

**INTERNATIONAL COMMISSION FOR THE CONSERVATION
OF ATLANTIC TUNAS**

**COMMISSION INTERNATIONALE POUR LA CONSERVATION
DES THONIDES DE L'ATLANTIQUE**

**COMISION INTERNACIONAL PARA LA CONSERVACION
DEL ATUN ATLANTICO**



ASSESSMENT PROGRAM DOCUMENTATION

Program: **VPA-2BOX (ver. 3.01)**

Fits age-structured population equations to catch, effort, abundance and tag-recapture data; accommodates two intermixing populations and sex-specific analyses.

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Cataloguing Committee

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NOTE: As part of its efforts to carry out Quality Management, ICCAT's Standing Committee on Research and Statistics is

developing a catalog of stock assessment applications. The purpose of the catalog is not to evaluate the relative merits of various assessment methods, but rather whether the software implementing the method works as intended and is adequately documented.

1. PROGRAM NAME

VPA-2BOX

2. VERSION (DATE)

Version 3.01, dated March, 2003

3. LANGUAGE

Fortran 90

4. PROGRAMMER / CONTACT PERSON

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5. DISTRIBUTION LIMITATIONS

Only executable code can routinely be distributed, along with the manual and example files. Source code is available from the author upon written request and with agreement to certain restrictions.

6. COMPILER NEEDS / STAND-ALONE

Does not require software other than an operating system with DOS-emulating capabilities such as Windows (Windows 9x, 2000 or NT). Users must be able to print and edit ASCII files.

7. PURPOSE

Assesses the abundance and mortality of animal populations by fitting age-structured population equations to catch, effort, abundance and tag-recapture data. An observation-error estimator is used with numerous options available. Accommodates two intermixing populations and sex-specific analyses.

8. DESCRIPTION

NOTE: Version 3.01 replaces Version 3.00. See Section 18 for a description of changes.

The program uses backwards recursions to fit age-structured models for one or two intermixing populations to catch, effort, abundance and tag-recapture data. The following is a brief description of the basic method.

Population dynamics

The program includes two types of intermixing: diffusion and overlap (**Table 1**). The former assumes a fraction of the population in management zone j transfers to zone k whereas the latter assumes a fraction \tilde{T}_{jk} of stock s transfers to zone k . Both models reduce to single-stock VPA's when the T (or \tilde{T}) are set to zero. For convenience T and \tilde{T} are both referred to as transfer coefficients, but the two are not directly comparable because the diffusion model allows fish born in one zone to accumulate in the other.

For example, if the transfer fractions for both stocks were both 10% (ignoring for the moment mortality), the diffusion model would calculate that 10% of the fish born in stock 1 will be living with stock 2 after one year, 18% after two years and 24.4% after three years.

Table 1. Overlap and diffusion model equations describing population dynamics (stock: s, age: a, year: y, zone: j or k, A: age of plus-group, Y: most recent year in analysis).

Equations and variables	Description
$C_{kay} = \tilde{N}_{kay} \frac{F_{kay}(1 - e^{-Z_{kay}})}{Z_{kay}}$	Catch at age a in year y from all stocks in management zone k
$Z_{kay} = F_{kay} + M_{kay}$	Total mortality rate in zone k
F_{kay}	Fishing mortality rate in zone k
M_{kay}	Natural mortality rate in zone k
Overlap model	
$N_{s,a+1,y+1} = N_{say} \sum_k T_{skay} e^{-Z_{kay}}$	Number of fish from stock s that are age a+1 at the beginning of year y (a+1<A)
$N_{s,A,y+1} = \sum_{a=A-1}^A N_{say} \sum_k T_{skay} e^{-Z_{kay}}$	Number of fish from stock s that are age A or older at the beginning of year y
$\tilde{N}_{kay} = \sum_s T_{skay} N_{say}$	Number of fish in zone k that are age a at the beginning of year y (all stocks combined)
T_{skay}	Fraction of stock s residing in zone k at the beginning of year y
Diffusion model	
$\tilde{N}_{k,a+1,y+1} = \sum_j \tilde{N}_{jay} \tilde{T}_{jkay} e^{-Z_{kay}}$	Number of fish in zone k that are age a+1 at the beginning of year y (a+1<A)
$\tilde{N}_{k,A,y+1} = \sum_{a=A-1}^A \sum_j \tilde{N}_{jay} \tilde{T}_{jkay} e^{-Z_{kay}}$	Number of fish in zone k that are age A or older at the beginning of year y
\tilde{T}_{jkay}	Fraction of population in zone j that moves to zone k at the beginning of year y

The equations in *Table 1* contain numerous variables representing the transfer coefficients, natural mortality rates, fishing mortality rates, catches and population abundances. Of these, it is often only the catches that are actually observed. The VPA approach to this problem is to develop a backwards recursion that determines the historical abundance and fishing mortality rate of each cohort from the observed catches and prescribed values for M , T , and the fishing mortality rate on the last age observed for the cohort (F_{Ay} or F_{ay}). This is illustrated for the overlap model in **Appendix 2** (A User's manual for VPA-2BOX).

The challenge that remains is to choose appropriate values for M , T , F_{ay} and F_{Ay} . One alternative is to fix those parameters to several values that seem plausible and compare the resulting solutions. Another is to estimate them by maximizing the model fits to auxiliary information such as indices of abundance or tag recovery data.

Estimation from indices of abundance

The parameters may be estimated from the indices of abundance by maximizing the log-likelihood function described in **Table 2**. This introduces several new variables that need to be accounted for-- the

index standard error σ , catchability q , and relative selectivity S . The values for σ may be estimated internally or fixed to values determined externally such as might be obtained from the index standardization procedures (see appendix for details). The values of q are usually assumed to be constant through time and estimated along with the other parameters. The values of S may be determined from the partial catches corresponding to each index (e.g., Powers and Restrepo, 1992; Butterworth and Geromont, 1999). Note that provisions are also made for tuning to indices of mortality (see appendix and Porch, 2000).

Table 2. Model for indices of abundance (index series: i , zone: k , age: a , year: y)

Equations and variables	Description
$\mathcal{L}(\bar{I}) = -\sum_i \sum_k \sum_y 0.5 \left(\frac{\ln(I_{iky}/\hat{I}_{iky})}{\sigma_{iky}} \right)^2 - \ln \sigma_{iky}$	log-likelihood term for lognormally distributed indices of abundance
$\hat{I}_{iky} = q_{iky} \sum_a s_{ika} w_{ikay} \tilde{N}_{kay}$	predicted value of index
$s_{ika} = \frac{\sum_y C_{ikay} F_{kay} / C_{kay}}{\text{MAX}_a \left\{ \sum_y C_{ikay} F_{kay} / C_{kay} \right\}}$	availability at age (see Butterworth and Geromont, 1999)
I_{iky}	observed value of index
σ_{iky}	standard error of index on log scale
q_{ikay}	catchability coefficient
w_{ikay}	adjustment for weight and time of year (if needed)
C_{ikay}	catch associated with index i in zone k

Estimation from tag recoveries

The temporal and spatial distribution of tag recoveries from a given group (cohort) of releases are assumed to be multinomial-distributed (Schweigert and Schwarz, 1993; Anganuzzi et al., 1994) as described in **Table 3**. The tag attrition model includes terms for the reporting rate (ρ), immediate loss of tags owing to misapplication or tagging-induced mortality (d), and chronic loss of tags owing to shedding or fouling (λ). The first two terms always occur together as the product $(1-d)\rho$ and cannot be distinguished using tag recovery data alone; therefore only one of the terms may be estimated and the other must be fixed. The chronic tag loss rate λ is similarly confounded with the natural mortality rate M , but independent estimation becomes possible when abundance indices are available in addition to the tagging data.

Table 3. Model for tag recoveries. The subscript τ denotes a unique group (cohort) of tag releases distinguished by the age (α), year (ψ) and zone (κ) of release. The remaining subscripts are as defined previously (stock: s , zone: k , year: y , age: $a = \alpha + y - \psi$).

Equations and variables	Description
$\mathcal{L}(\bar{r}) = \sum_{\tau} (R_{\tau} - \sum_{k,y} r_{k\tau y}) \ln \left[1 - \sum_{k,y} \frac{\hat{r}_{k\tau y}}{R_{\tau}} \right] - \sum_{k,y} r_{k\tau y} \ln \left[\frac{\hat{r}_{k\tau y}}{R_{\tau}} \right]$	log-likelihood for tag recoveries from all cohorts
R_{τ}	number of tag releases in cohort τ
$r_{k\tau y}$	observed recoveries from cohort τ
$\hat{r}_{k\tau y} = \rho_{kay} \tilde{n}_{k\tau y} \frac{f_{k\tau ay}}{z_{k\tau ay}} (1 - e^{-z_{k\tau ay}(1-t_{\tau y})})$	expected recoveries from cohort τ

Equations and variables	Description
$z_{k\tau y} = f_{k\tau y} + M_{k\tau y} + \lambda_{\tau y}$	total loss rate of cohort τ
$f_{k\tau y} = \gamma_{\tau y} F_{k\tau y}$	fishing mortality rate of cohort τ
$\gamma_{\tau y}$	pre-mixing adjustment for cohort τ
$\lambda_{\tau y}$	immediate tag loss of cohort τ
d_{τ}	immediate tag loss of cohort τ
$t_{\tau y}$	release date of cohort τ (= 0 for $y > \psi$)
$\rho_{k\tau y}$	reported fraction of recaptured tags
Overlap tag attrition model	
$\tilde{n}_{k\tau y} = \begin{cases} R_{\tau}(1-d_{\tau}) & (y = \psi, k = \kappa) \\ \sum_s T_{s\kappa y} n_{s\tau y} & (y > \psi) \end{cases}$	number of survivors with tags from cohort τ in zone k at start of year y
$n_{s, \tau, y+1} = \begin{cases} R_{s\tau}(1-d_{\tau}) e^{-z_{\kappa\tau y}(1-t_{\tau y})} & (y = \psi) \\ n_{s\tau y} \sum_k T_{s\kappa y} e^{-z_{k\tau y}} & (y > \psi) \end{cases}$	number of survivors with tags from cohort τ and stock s at start of year y ($R_{s\tau}$ is the number of releases by stock)
Diffusion tag attrition model	
$\tilde{n}_{k, \tau, y+1} = \begin{cases} R_{\tau}(1-d_{\tau}) e^{-z_{\kappa\tau y}(1-t_{\tau y})} & (y = \psi) \\ e^{-z_{k\tau y}} \sum_j T_{j\kappa y} \tilde{n}_{j\tau y} & (y > \psi) \end{cases}$	number of survivors with tags from cohort τ in zone k at start of year y

The model in **Table 3** also allows for the possibility that the effective fishing mortality on the tagged population may differ from that on the untagged population by use of pre-mixing adjustment factors $\gamma_{\tau y}$. The values of $\gamma_{\tau y}$ can be difficult to distinguish precisely from F when only tag recovery data are available (Hoenig et al., 1998), but the task is made easier when catch and abundance data are included because F is largely determined from them.

Finally, it usually will not be possible to distinguish members of the two stocks during the tagging process. In the case of the diffusion model this is unimportant because the two stocks are defined by area or management zone (rather than by origin)--fish born in zone 1 and tagged in the zone 2 are considered to be members of the zone 2 stock and vice versa. In the case of the overlap model, where the two stocks are defined by origin, fish from each stock are assumed to be tagged in proportion to their relative abundance in each management zone, i.e.,

$$R_{s\tau} = R_{\tau} \frac{T_{s\kappa y} N_{s\tau y}}{\sum_s T_{s\kappa y} N_{s\tau y}}$$

where the N and T values are the estimates from the VPA.

Sex-specific analyses

If the abundance of each sex were completely independent of the other, then it would be reasonable to conduct separate appraisals for each sex. The parameters for each sex would be estimated as discussed above by minimizing an objective function of the sex-specific indices of abundance and setting the transfer coefficients to zero. It could be argued however, that the sex ratio for many stocks is fixed at birth and changes with age in response to various selection factors. This is modeled by adding a term to the objective function that penalizes solutions where the predicted ratio of males (m) to females (f) at

birth differs from its expectation (R):

$$0.5 \sum_{y=1}^Y \left(\frac{\log(R^j N_{y,0} / {}^m N_{y,0})}{\sigma_R} \right)^2$$

(see Restrepo and Porch, 1998). This of course necessitates that both sexes be analyzed simultaneously. The influence of the penalty can be increased by decreasing σ_R (the expected deviation of R from one year to the next). Both R and σ_R must be specified.

Series weighting

Provisions are made whereby the indices of abundance can be de-emphasized relative to one another in the objective function. This may be done manually by fixing the σ to prescribed values or the program may be allowed to estimate them in various ways. The weight ascribed to the tagging data depends on the number of recoveries since a multinomial distribution is assumed, however the influence of the tagging data may be changed relative to the indices of abundance by a weighting multiplier. The estimation of variances for weighting different types of data is a controversial topic and there are many ways to do it, therefore the reader is referred to the user's guide in the appendix for more details.

Penalties

An autocorrelated stock recruitment penalty is available to discourage deviations from the Beverton and Holt stock-recruit relationship as described by Porch (1998). It is also possible to penalize year to year variations in recruitment, the most recent fishing mortality rates on each age group, and any estimated parameter (see the User's manual in **Appendix 2**).

Methods of estimation

In typical applications one minimizes the sum of the negative log-likelihood expressions pertaining to each type of data, and the parameters that correspond to the minimum are referred to as maximum likelihood estimates. However, it is also possible to impose Bayes priors on the parameters and incorporate various penalties. In that case the parameter estimates that minimize the objective function (likelihood terms + penalties + priors) are referred to as highest posterior density estimates (see Porch, 1998b or the User's manual in the appendix for more details).

The simplex algorithm AMOEBA (Press et al., 1992) is employed to find the values of the parameters that minimize the objective function (i.e., the maximum likelihood or highest posterior density estimates). The algorithm is restarted at multiple locations in the parameter space to avoid being fooled by local minima in the solution surface. The restarts continue until the solution for three consecutive restarts varies by less than one percent for all parameters.

Estimates of the bias and variance of each parameter may be obtained via either a parametric or nonparametric bootstrap (but see the cautions discussed in the manual, **Appendix 2**). The parametric bootstrap entails the following steps:

- (1) Fit the model to the actual data;
- (2) Create new "bootstrap" indices of abundance, ${}^b I_{ky}$, by drawing at random with replacement from normal or lognormal distributions with mean and standard deviation equal to the model expectations of I and σ , e.g., for lognormal-distributed indices,

$${}^b I_{ky} = \hat{I}_{ky} e^{b \pi_{ky}}$$

$${}^b \pi_{ky} \sim \text{Normal}(0, \hat{\sigma}_{ky})$$

- (3) Fit the model to the bootstrap data set created in step 2;
- (4) Repeat steps 2 and 3 until the required number of replications is obtained.

The nonparametric bootstrap is similar, but steps 1 and 2 become:

(1b) Fit the model to the actual data and standardize the residuals of the fits to each index of abundance by dividing the yearly values with their respective standard deviations, e.g, for lognormal-distributed indices—

$$r_{ky} = \frac{\log_e I_{ky} - \log_e \hat{I}_{ky}}{\sigma_{ky}}$$

$$\sigma_{ky} = \sqrt{\log_e (CV_{ky}^2 - 1)}$$

(2b) Create new “bootstrap” indices of abundance, ${}^b I_{ky}$, by drawing at random with replacement from the index-specific sets of standardized residuals, rescaling the sampled residuals by the standard deviation for that year and index (equations above), and adding the rescaled residual to the expected value from the original fitting—

$$\log_e {}^b I_{ky} = \log_e \hat{I}_{ky} + {}^b \pi_k \sigma_{ky}$$

$${}^b \pi_k \sim \{r_{ky}\}$$

The bias and variance of the point estimate $\hat{\phi}$ are computed via the estimators suggested by Efron (1990):

$$\text{bias}_B(\hat{\phi}) = \frac{\sum {}^b \phi}{B} - \phi(\bar{I})$$

$$V_B(\hat{\phi}) = \frac{\sum_{b=1}^B ({}^b \phi - \frac{\sum {}^b \phi}{B})^2}{B-1}$$

Summary of major assumptions

The assumptions required by the VPA in its most general form are enumerated below. Further assumptions, such as constant catchability through time, may be required with sparse data.

1. One closed population or two intermixing populations
2. Rapid mixing throughout the home range of each population or random fishing
3. A constant fraction of each age group moves outside their home range at the beginning of each year (transfer coefficients do not change through time)
4. The natural mortality rate on each age group is constant through time
5. The catch of each age group is known with negligible error
6. The abundance, mortality, and tagging data, however imprecise, accurately represent the population

9. REQUIRED INPUTS

1. Complete catch at age matrix (all ages for all years) for each stock considered
2. Starting guesses and constraints on parameters
3. Some control parameters are required (e.g., convergence criteria), but the sample input files provide values that are sufficient, and most changes result in worse results.
4. Items for user convenience, such as run title and text description of each data series.
5. As available, indices of abundance (e.g., CPUE series), tag recaptures, indices of mortality rate, weights at age

10. PROGRAM OUTPUTS

ASCII files are written after each run containing the following information:

For all runs:

1. Log file with program status information (i.e., did the program seem to converge on estimates?)
2. Estimates of all parameters with CV's and correlation coefficients retrieved from the asymptotic covariance matrix (inverse of the Hessian matrix of numerical second derivatives)
3. Estimated population trajectory through time for each age
4. Estimated F trajectory through time for each age
5. For each data series, trajectories of estimated and observed values through time.

For bootstrapped runs:

1. ASCII File with variances, correlation coefficients, and bias-corrections for all parameters, population abundance at age and fishing mortality rate at age.
2. Binary files with estimates from each bootstrap data set for all parameters, population abundance at age and fishing mortality rate at age. Used for projections and constructing certain types of bias-corrected confidence intervals.

11. DIAGNOSTICS

1. Goodness-of-fit criteria (AIC, AIC_c , Likelihood and posterior density values for all parameters and data components.
2. Limits on number of iterations allowed for convergence.
3. Warning messages if any parameter estimates are at constraints.
4. Optionally: Retrospective analyses and likelihood profiling.

12. OTHER FEATURES

1. VPA-2BOX does not include facilities for drawing graphs, however a separate file is created that outputs the results in a format that is easy to import into spreadsheets for further analysis
2. Can set any parameter constant, rather than estimating it
3. Can apply constraints to any parameter
4. Accommodates Bayesian priors

13. HISTORY OF METHOD PEER REVIEW

The basic recursive approach of VPA was described by Gulland (1965) and Murphy (1965). Parks (1976) appears to have been the first to estimate the terminal fishing mortality parameters using auxiliary data (F's derived independently from tagging experiments) and least squares. Subsequently, Doubleday (1981) and Parrack (1986) did the same with various types of abundance indices. The present program is based on the ADAPT framework, which is basically a suite of extensions to Parrack's model (see Gavaris, 1988; Conser and Powers, 1990; Powers and Restrepo, 1992; Butterworth and Geromont, 1999). Various implementations of ADAPT have been widely used in several different arenas, including ICCAT, the Canadian Atlantic Fisheries Scientific Advisory Committee (CAFSAC), the Convention for the Conservation of Southern Bluefin Tuna (CCSBT), the Bluefin WG of the Interim Scientific Committee (ISC), the North Pacific Albacore Workshop, and the Northwest Atlantic Fisheries Organization (NAFO). The approach has also been used in the United States for many of its domestic stocks.

Aldenberg (1975) was the first to apply VPA methods to two intermixing stocks. He examined the potential effect of various transfer rates on VPA appraisals of stock status, but did not attempt to estimate the transfer parameters for any stock in particular. Butterworth and Punt (1994) developed a similar model, hereafter referred to as the 'diffusion' model, and applied it to data for Atlantic bluefin tuna. They did not attempt to estimate the transfer coefficients, but did note that different assumed values gave different results, both in terms of stock status and least-squares fits to the indices of abundance. Subsequently, several versions of the diffusion VPA have been applied to Atlantic bluefin tuna (NRC,

1994; Porch et al., 1995; Punt and Butterworth, 1995) and to simulated data (Porch, 1995; Porch et al., 1998).

The present algorithm includes the original diffusion model as well as the overlap model described by Cooke and Lankester (1996), which assumes that fish migrate outside their home range only temporarily, coming back at the end of the year (see description above). The first VPA implementation of the overlap model was developed relatively recently by Porch and Turner (1998), therefore it has not undergone as much scrutiny as the diffusion model. However, both the original paper and a subsequent paper, Porch et al. (in press), have been reviewed by the SCRS.

Several methods of estimating the transfer coefficients have been developed (Punt and Butterworth, 1995; Porch and Turner, 1998), but these have all proven unsatisfactory for various reasons. The present algorithm, detailed in Porch et al. (in press) does so by use of a tag-recapture model that is rooted in well-established statistical principles (Brownie et al., 1985; Hilborn, 1990; Schwarz et al., 1993; Anganuzzi et al., 1994).

Other papers detailing specific capabilities of VPA-2BOX have been reviewed by the SCRS, including bootstrapping (Porch, 1999a), random-walk parameters (Porch, 1999b), stock-recruitment penalties (Porch, 1998), indices of mortality rate (Porch, in press), and sex-specific analyses (Restrepo and Porch, 2000).

14. STEPS TAKEN BY PROGRAMMER FOR VALIDATION

The author has written several spreadsheet programs to generate numerous simulated data sets without imposed errors. These were then analyzed by VPA-2BOX to verify that the routine performs as expected. This testing procedure has been applied to all of the options available in the program where it was possible to do so. However, it is not possible to test some of the options in this way. For example, a test of the model's ability to estimate the variance of an index requires a large number of data sets be generated with the assumed error structure (this was done for the concentrated-likelihood method, which is analogous to iterative reweighting, by Legault and Porch, 2000).

15. TESTS CONDUCTED BY OTHERS

Most of the available options have also been tested by comparing the results of VPA-2BOX with those of similar, but independently coded algorithms. The core single-stock computations and fitting procedures have been verified in this manner during every bluefin tuna (BFT) assessment since 1993 by comparisons with the outputs from code held by either J. E. Powers (STAATS), A. E. Punt or H. F. Geromont. This was also done during the 1996 yellowfin tuna assessment by duplicating results obtained with FADAPT (Restrepo, 1996) and during the 1996 swordfish assessment by duplicating the results obtained with APL code held by S. Gavaris. The calculations for the random-walk routine for the F-ratio have been confirmed by Y. Takeuchi (during the 1998 assessment of yellowfin tuna) and H. F. Geromont (during the 2000 assessment of BFT). The estimation of the overall variance parameter for equally-weighted indices of abundance has been verified by H. F. Geromont (BFT, 2000). The estimation of index-specific variances by maximum likelihood has been verified by A. E. Punt (BFT, 1994), H. F. Geromont (BFT, 1996), and C. Legault (USA domestic king mackerel assessment, 1999). Part of sex-specific analyses made during the 1999 ICCAT swordfish assessment was verified by Y. Takeuchi.

16. NOTES BY ICCAT

None.

17. SOURCES CITED

ALDENBERG, T. 1975. Virtual population analysis and migration; A theoretical treatment. ICES C.M> 1975/F: 32.
ANGANUZZI, A., Hilborn, R. and Skalski, J. R. 1994. Estimation of size selectivity and movement rates

- from mark-recovery data. *Can. J. Fish. Aquat. Sci.* 51: 734-742
- BROWNIE, C., Anderson, D. R., Burnham, K. P., and Robson, D. S. 1985. *Statistical inference from band recovery data: a handbook*. 2nd ed. U.S. Fish and Wildl. Serv. Resour. Publ. No. 156.
- BUTTERWORTH, D. S., and H. F. Geromont. 1999. Some aspects of ADAPT VPA as applied to North Atlantic bluefin tuna. *ICCAT Coll. Vol. Sci. Pap.* 49(2):233-241
- BUTTERWORTH, D. S., and A. E. Punt. 1994. The robustness of estimates of stock status for the western north Atlantic bluefin tuna population to violations of the assumptions underlying the associated assessment models. *ICCAT Coll. Vol. Sci. Pap.* 42(1): 192-210.
- CONSER, R. J., and J. E. Powers. 1990. Extensions of the ADAPT VPA tuning method designed to facilitate assessment work on tuna and swordfish stocks. *ICCAT Coll. Vol. Sci. Pap.* 32: 461-467.
- COOKE, J. G., and K. Lankester. 1996. Examination of alternative stock distribution models for the interpretation of bluefin tuna (*Thunnus thynnus*) tag-recovery data. *ICCAT Coll. Vol. Sci. Pap.* 45(2): 135-138.
- CONSER, R. J., and J. E. Powers. 1990. Extensions of the ADAPT VPA tuning method designed to facilitate assessment work on tuna and swordfish stocks. *ICCAT Coll. Vol. Sci. Pap.* 32: 461-467.
- DOUBLEDAY, W. G. 1981. A method for estimating the abundance of survivors of an exploited fish population using commercial catch-at-age and research vessel abundance indices. *Can. Spec. Pub. Fish. Aquat. Sci.* 58:164-178.
- GAVARIS, S. 1988. An adaptive framework for the estimation of population size. *Can. Atl. Fish. Sci. Adv. Comm. (CAFSAC) Res. Doc.* 88/29. 12 pp.
- GULLAND, J. A. 1965. Estimation of mortality rates. Annex to Arctic Fisheries Working Group Report. *ICES CM 1965, Doc. No. 3*, 9 pp.
- HILBORN, R. 1990. Determination of fish movement patterns from tag recoveries using maximum likelihood estimators. *Can. J. Fish. Aquat. Sci.* 47: 635-643.
- HOENIG, J. M., Barrowman, N. J., Pollock, K. H., Brooks, E. N., Hearn, W. S., and Polacheck, T. 1998. Models for tagging data that allow for incomplete mixing of newly tagged animals. *Can. J. Fish. Aquat. Sci.* 55: 1477-1483.
- LEGAULT, C. M. and Porch, C. E. 2000. Comparisons of Index Weighting Schemes for Tuned Virtual Population Analyses. *ICCAT Collective Volume of Scientific Papers SCRS/00/35*.
- MURPHY, G. I. A solution of the catch equation. *J. Fish. Res. Bd. Canada* 22(1):191-202.
- NRC. 1994. Report of the National Research Council review of Atlantic bluefin tuna. National Academy Press. Washington, D.C. 148 pp.
- PARKS, W. W. 1976. Cohort analysis, equilibrium yield per recruit analysis and predicted effects of minimum size limit regulation in the Atlantic bluefin tuna fisheries system. *ICCAT Coll. Vol. Sci. Pap.* 5: 313-331
- PARRACK, M. L. 1986. A method of analyzing catches and abundance indices from a fishery. *ICCAT Coll. Vol. Sci. Pap.* 24:209-221.
- PORCH, C. E. 1995. A two-area VPA with discrete mixing: Can we discriminate between mixing rates given the present condition of the data? *ICCAT Coll. Vol. Sci. Pap.* 44(1): 198-208.
- PORCH, C. E. 1998. Autocorrelated stock recruitment penalties applied to the 1996 SCRS assessment of West Atlantic bluefin tuna. *ICCAT Collective Volume of Scientific Papers* 48(1):43-46.
- PORCH, C. E. 1999a. Bootstrap estimates of the precision and bias of the 1996 base case assessment of West Atlantic bluefin tuna. *ICCAT Collective Volume of Scientific Papers* 49(2):306-313.
- PORCH, C. E. 1999b. A Bayesian VPA with randomly walking parameters. *ICCAT Collective Volume of Scientific Papers* 49(2):314-326.
- PORCH, C. E. In press. Still another option for ADAPT: Tuning to independent estimates of mortality rate with applications to West Atlantic bluefin tuna. *ICCAT Collective Volume of Scientific Papers. SCRS/00/99*
- PORCH, C. E. and S. C. Turner. 1998. Virtual population analyses of Atlantic bluefin tuna with alternative models of trans-Atlantic migration. *ICCAT Coll. Vol. Sci. Pap.* 49:291-305.
- PORCH, C., P. Kleiber, S. Turner, J. Sibert, R. Bailey and J. Cort. 1998. The efficacy of VPA models in the presence of complicated movement patterns. *Proceedings of the 25 Anniversary ICCAT Tuna Symposium.* *ICCAT Coll. Vol. Sci. Pap.* 50(2):591-622.
- PORCH, C. E., Restrepo, V. R., Turner, S. C., and G. P. Scott. 1995. Virtual population analyses of Atlantic bluefin tuna incorporating movement and tagging data. *ICCAT Coll. Vol. Sci. Pap.* 44(1): 183-190.
- PORCH, C. E., S. C. Turner, and J. E. Powers. In press. Virtual population analyses of Atlantic bluefin tuna with alternative models of transatlantic migration: 1970-1997. *ICCAT Collective Volume of Scientific Papers. SCRS/00/98*
- POWERS, J. E., and V. R. Restrepo. 1992. Additional options for age-sequenced analysis. *ICCAT Col.*

- Vol. Sci. Pap. 39(3):540-553.
- PRESS, W. H., B. P. Flannery, S. A. Teukolsky, and W. T. Vetterling. 1994. Numerical Recipes in Fortran. Cambridge University Press. Cambridge, MA. 963 pp.
- PUNT, A. E., and D. S. Butterworth. 1995. Use of tagging data within a VPA formalism to estimate migration rates of bluefin tuna across the north Atlantic. ICCAT Coll. Vol. Sci. Pap. 44(1): 166-182.
- RESTREPO, V. R. FADAPT Version 3.0: A Guide. Unpublished manuscript.
- RESTREPO, V. R. and Porch, C. E. 2000. Options for conducting swordfish sex-specific assessments. ICCAT Collective Volume of Scientific Papers 51:1375-1386.
- SCHWEIGERT, J. F., and Schwarz, C. J. 1993. Estimating migration rates for Pacific herring (*Clupea pallasii*) using tag-recovery data. Can. J. fish. Aquat. Sci. 50: 1530-1540.

18. AUTHOR'S NOTES

WHAT'S NEW IN VERSION 3.01?

This update of version 3.0 includes four changes:

1. Uses bisection routine, rather than Newton's method, for solution of 1-dimensional catch equation (1-area and 2-area diffusion model). This change appears to have little effect on the final results, but was made at the request of the 2002 bluefin tuna stock assessment working group.
2. The formulae for AIC and BIC are now based on the full likelihood expressions (with constants) rather than the deviance to allow more accurate comparisons between models where the index variances are estimated.
3. Correct formula for chi-square discrepancy in case of lognormal variates (formerly it was based on the predicted values of the indices as suggested in SCRS 2001, but in the case of lognormal variates the predicted values are the medians rather than the expectations).
4. Error message preventing use of overlap model when estimating terminal parameters on abundance scale while at the same time using different age groups for each stock (in that case it is not possible to solve the backwards recursion for the overlap model)

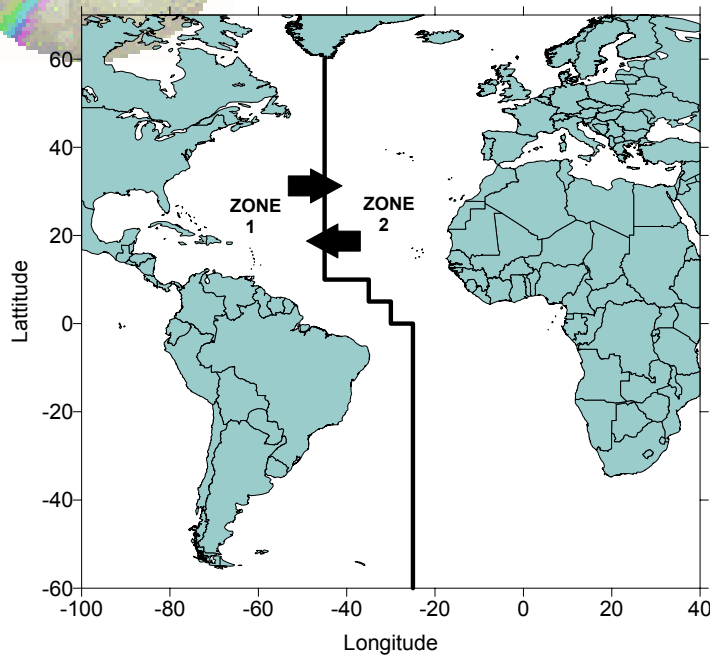
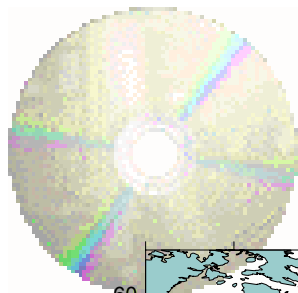
APPENDIX 1. ALGORITHM

See Methods of Estimation in **Section 8** the Users' Guide in **Appendix 2**.

Appendix 2

VPA-2BOX *Version 3.01*

User's guide



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1. GETTING STARTED

VPA-2BOX is a flexible software tool for analyzing the abundance and mortality of exploited animal populations that is based on the ADAPT framework developed by Parrack (1986) and Gavaris (1988). The primary difference between this package and other versions of ADAPT is the capability of analyzing two different stocks simultaneously, making possible routine quantitative analyses of the effect of sex-specific growth or stock intermixing. In addition, a wide variety of options are provided with respect to the types of data that may be used and the way the parameters are estimated.

WHAT'S NEW IN VERSION 3.01?

This update of version 3.0 includes four changes:

1. Uses bisection routine, rather than Newton's method, for solution of 1-dimensional catch equation (1-area and 2-area diffusion model). This change appears to have little effect on the final results, but was made at the request of the 2002 bluefin tuna stock assessment working group.
2. The formulae for AIC and BIC are now based on the full likelihood expressions (with constants) rather than the deviance to allow more accurate comparisons between models where the index variances are estimated.
3. Correct formula for chi-square discrepancy in case of lognormal variates (formerly it was based on the predicted values of the indices as suggested in SCRS 2001, but in the case of lognormal variates the predicted values are the medians rather than the expectations).
4. Error message preventing use of overlap model when estimating terminal parameters on abundance scale while at the same time using different age groups for each stock (in that case it is not possible to solve the backwards recursion for the overlap model)

DISCLAIMER

The development of VPA-2BOX is ongoing. Executable versions may be obtained from the author free of charge, however there is no warranty of any kind. The author appreciates comments regarding the program, including any suspected bugs, but does not offer formal technical support.

Copies of the executable code and manual for VPA-2BOX may be distributed without restriction. Those desiring source code are requested to send a written request directly to the author¹

¹Address on front cover of this manual.

and will be asked to abide by certain restrictions.

SYSTEM REQUIREMENTS

- 80486, Pentium series, or compatible processor (standard PC's and clones)
- MS-DOS, IBM OS/2, or Microsoft Windows (9x, 2000, NT) operating systems²
- 1 MB of available hard disk space (30 MB for some bootstrap applications)

NOTATIONAL CONVENTIONS

The following notations are used:

- *Italics* indicate mathematical variables or text to be replaced by the user.
- Courier font indicates text in a file or keystrokes.

INSTALLING AND RUNNING VPA-2BOX

The files needed for a complete installation are normally sent as a self-extracting PKZIP file. The only steps required are:

- Copy file *VPA-ZIP.exe* to a directory on your hard drive
- Run *VPA-ZIP.exe* (or open a DOS window, move to the chosen directory, and enter *VPA-ZIP*)
- Add the chosen directory to your PATH statement as described in the documentation for your operating system and reboot your system (or place a copy of VPA-2BOX.exe in the directory where you plan to do the analyses)

The program may then be started using the Windows Run dialog, by double clicking on the VPA-2BOX.EXE icon or by entering the name VPA-2BOX at a DOS prompt. When the latter approach is taken, the name of the ASC-II text file that contains the control specifications may (optionally) be included as a command-line argument up to 50 characters long, e.g,

```
VPA-2BOX your_control_file_name
```

Otherwise, following screen display will appear:

²Reference to trade names does not imply endorsement by NOAA or the U.S. Government.

```
Command Prompt - vpa-2box
+-----+
| Program UPA-2BOX.F90, Version 3.0 (Nov. 1, 2001)
|
| A virtual population analysis tool that uses catch-at-age, indices of
| abundance, indices of mortality rates, and tag-recoveries to estimate
| the abundance and mortality of one or two (intermixing) populations.
|
| based on the methods of
|   Porch, C. E., Turner, S. C., and Powers, J. E. 2001
|   Virtual population analyses of Atlantic bluefin tuna with alternative
|   models of transatlantic migration: 1970-1997. Int. Comm. Conserv. Atl.
|   Tunas, Coll. Vol. Sci. Pap. 52: 1022-1045
|
| programmed by
|   Clay E. Porch
|   NOAA Fisheries
|   75 Virginia Beach Drive
|   Miami, Fl 33149 (USA)
+-----+
ENTER THE NAME OF THE CONTROL FILE:
```

The line at the bottom of the screen prompts the user for the name of the ASC-II control file. There is no graphical user interface; VPA-2BOX runs only as a console-mode program that takes all input from ASC-II text files (described in chapter 3). The screen is used only to enter the name of the control file and to display certain error and advisory messages. Hence, the user must be able to create and edit ASC-II text files.

2. THEORY BEHIND VPA-2BOX

Virtual population analysis (VPA) describes a family of techniques rooted in the seminal papers of Murphy (1965) and Gulland (1965). The method assumes that the catch history of any given year class is known without error, permitting the historical abundance and fishing mortality rates to be computed deterministically from a guess of the abundance or fishing mortality rate on the oldest (terminal) age of the year class. Various *ad hoc* methods have been proposed for fine tuning the guesses for the terminal parameters, but they invariably involve subjective criteria that may not be applicable to fisheries other than those for which they were developed. Parks (1976) appears to have been the first to estimate the terminal parameters from auxiliary data. He used least-squares to tune the VPA back-calculated fishing mortality rates to fishing mortality rates derived from tagging experiments. Subsequently, Gray (1977), Doubleday (1981) and Parrack (1986) developed similar tuning procedures for use with various types of abundance indices.

VPA is not the only method available for analyzing catch-at-age data. A plethora of statistical models now exist that allow for errors in the catch data and a more detailed accounting of the dynamics of the fishery (e.g., Deriso *et al.*, 1985; Methot, 1990; Fournier *et al.*, 1999). Nevertheless, tuned VPA's remain popular, in part because of their long history and relative simplicity, but also because they have many fewer estimable parameters and reach a solution much faster than their more sophisticated counterparts. Some investigators also find it advantageous that tuned VPA's place no restrictions on the degree to which the fishing mortality rate may vary from year to year and age to age.

The present program is based on the ADAPT framework, which is essentially an extension of Parrack's (1986) model (see Gavaris, 1988; Conser and Powers, 1990; Powers and Restrepo, 1992). Various implementations of ADAPT have been widely used for domestic fisheries in the United States, South Africa and Canada; as well as in several international arenas, including the International Commission of the Conservation of Atlantic Tuna (ICCAT) and the Northwest Atlantic Fisheries Organization (NAFO).

The most distinctive feature of VPA-2BOX is of course its ability to examine two distinct groups simultaneously, making it amenable to sex-specific or stock-specific analyses where the two groups interact at some level. Aldenberg (1975) was the first to apply VPA methods to two intermixing stocks; solving the catch equations associated with the box-transfer model proposed by Beverton and Holt (1957). He examined the potential effect of various transfer rates on VPA appraisals of stock status, but did not attempt to estimate the transfer parameters for any stock in particular. Butterworth and Punt (1994) applied a similar box-transfer model to data for Atlantic bluefin tuna and showed that the magnitude of the transfer coefficients affected the model's ability to fit the indices of abundance. Subsequently, several versions of the box-transfer VPA were applied to Atlantic bluefin tuna in an attempt to estimate the transfer rates (NRC, 1994; Porch *et al.*, 1995; Punt and Butterworth, 1995; Porch *et al.*, 1998, 2001).

The box-transfer models mentioned above all assume that two populations exist, one in each of two management zones (see cover figure). Each year a fraction T_1 of the fish present in zone (box) 1 stray into zone 2 and a fraction T_2 in zone 2 stray into zone 1. Once a fish moves into a zone it is

assumed to move in the same manner as the native population. When a spawner-recruit relationship is to be generated from the VPA results, then there is also the implicit assumption that immigrating fish will adopt the spawning habits of the native population as well. This assumption may be biologically unrealistic for some stocks (ICCAT, 1995: pp.108-110). As an alternative, Cooke and Lankester (1996) suggested the so-called ‘overlap’ model, which assumes that a fraction \tilde{T}_1 of the fish born in zone 1 will reside in zone 2 and a fraction \tilde{T}_2 of the fish born in zone 2 will reside in zone 1. Thus, fish movement in the overlap model depends on where they were spawned rather than their present location. VPA-2BOX includes algorithms for the Butterworth and Punt (1994) box-transfer model as well as the Cooke and Lankester (1996) ‘overlap’ model. Both models and their implementation are described in detail below, and also in Porch and Turner (1998) and Porch et al. (2001).

POPULATION DYNAMICS

The program includes two types of box-transfer models: Diffusion and overlap (see Tables 1 and 2 below). The former assumes a fraction T_{jk} of the population in zone j transfers to zone k whereas the latter assumes a fraction \tilde{T}_{sk} of stock s transfers to zone k . Both models reduce to single-stock VPA’s when the transfer fractions are set to zero, otherwise T and \tilde{T} are not directly comparable inasmuch as the diffusion model allows fish born in one zone to accumulate in the other. For example, if the transfer fractions for both stocks were both 10%, the diffusion model (without mortality) would calculate that 10% of the fish born in zone 1 will be living in zone 2 after one year, 18% after two years and 24.4% after three years.

Table 1. Standard catch equation assumed in program VPA-2BOX

Catch equation	Description
$C_{kay} = \tilde{N}_{kay} \frac{F_{kay}(1 - e^{-Z_{kay}})}{Z_{kay}}$	Catch of age a in year y from all stocks in management zone k
$Z_{kay} = F_{kay} + M_{kay}$	Total mortality rate in zone k
F_{kay}	Fishing mortality rate in zone k
M_{kay}	Natural mortality rate in zone k
\tilde{N}_{kay}	Number of fish in zone k that are age a at the beginning of year y (all stocks combined)

Table 2. Overlap and diffusion equations for population dynamics.

Overlap model equations	Description
$N_{s,a+1,y+1} = N_{say} \sum_k T_{skay} e^{-Z_{kay}}$	Number of fish from stock s that are age $a+1$ at the beginning of year y ($a+1 < A$)
$N_{s,A,y+1} = \sum_{a=A-1}^A N_{say} \sum_k T_{skay} e^{-Z_{kay}}$	Number of fish from stock s that are age A or older at the beginning of year y
$\tilde{N}_{kay} = \sum_s T_{skay} N_{say}$	Number of fish in zone k that are age a at the beginning of year y (all stocks combined)
T_{skay}	Fraction of stock s residing in zone k at the beginning of year y
Diffusion model equations	Description
$\tilde{N}_{k,a+1,y+1} = \sum_j \tilde{N}_{jay} \tilde{T}_{jkay} e^{-Z_{kay}}$	Number of fish in zone k that are age $a+1$ at the beginning of year y ($a+1 < A$)
$\tilde{N}_{k,A,y+1} = \sum_{a=A-1}^A \sum_j \tilde{N}_{jay} \tilde{T}_{jkay} e^{-Z_{kay}}$	Number of fish in zone k that are age A or older at the beginning of year y
\tilde{T}_{jkay}	Fraction of population in zone j that moves to zone k at the beginning of year y

PARAMETER ESTIMATION

The equations describing the catch and population dynamics (above) include a large number of variables representing the transfer coefficients, natural mortality rates, fishing mortality rates, catches and population abundances. Of these, it is often only the catches that are actually observed. The VPA approach to this problem is to develop an explicit recursion that determines the historical abundance and fishing mortality rate of each cohort from the observed catches and prescribed values for M , T , and the fishing mortality rate on the last age observed for each cohort (F_{Ay} or F_{ay}).

Successful application of the VPA approach depends on three assumptions: (1) the catch equation correctly describes the dynamics of the fishery, (2) the observed catches are known with negligible error, and (3) reasonable values of M , T , F_{Ay} and F_{ay} can be derived. The first assumption is common to all modeling exercises and is discussed further in the section on Model Selection. The

second assumption determines whether or not the VPA approach is suitable; if the catches are not well known, then a statistical catch-at-age model may be more appropriate.

The third assumption has often been addressed by fixing M , T , F_{Ay} and F_{aY} to several values that seem plausible and then comparing the resulting solutions. The approach taken by ADAPT and related methods differs from this in that at least some of these parameters are estimated internally by use of auxiliary data such as indices of abundance or tag recoveries (a process sometimes referred to as ‘tuning’ the VPA). The tuning procedure occurs in two phases. The first phase is the explicit recursion, which determines the historical abundance and mortality rates from the latest estimates for M , T , F_{Ay} and F_{aY} . The second phase uses the abundance and mortality rate estimates from the first step to predict the values of the data. New values of M , T , F_{Ay} and F_{aY} are then selected so as to minimize the discrepancy between the model predictions and the observed values of the data as measured by an appropriate statistical model. These values are in turn used to reinitiate phase 1 and the process continues in iterative fashion until certain stopping criteria are met.

The explicit recursion itself involves two steps. Consider for example the simplest case of a single stock in one zone. In the first step the abundance at the beginning of the year for any given cohort is determined from the fishing mortality rate during that year by solving the catch equation

$$N_{a,y} = \frac{C_{a,y}Z_{a,y}}{F_{a,y}(1 - e^{-Z_{a,y}})} .$$

In the second step, $F_{a-1,y-1}$ is determined by numerically solving the equation derived by combining the catch and abundance equations for the next younger age,

$$C_{a-1,y-1} = \frac{F_{a-1,y-1}(1 - e^{-Z_{a-1,y-1}})}{Z_{a-1,y-1} e^{-Z_{a-1,y-1}}} N_{a,y}$$

using the values of $N_{a,y}$ obtained from the first step. This two-step cycle is repeated to obtain $F_{k,a-2}$ from $F_{k,a-1}$ and so on back to the youngest age class in the analysis.

If the oldest age is a plus-group (age A and older fish lumped together), the fishing mortality rate on the next youngest age must be computed somewhat differently. In the first step $N_{A,y}$ is determined from $F_{A,y}$ by use of the catch equation as before, but it is also necessary to obtain $N_{A,y-1}$ from $F_{A,y-1}$. The second step then substitutes the values for $N_{A,y}$ and $N_{A,y-1}$ into the equation

$$C_{k,A-1,y-1} = \frac{F_{k,A-1,y-1}(1 - e^{-Z_{k,A-1,y-1}})}{Z_{k,A-1,y-1}} \frac{\sum_{s=1}^J T_{s,k,A-1,y-1} \left(\frac{N_{s,A,y} - N_{s,A,y-1} \sum_{k=1}^J T_{s,k,A,y-1} e^{-Z_{k,A,y-1}}}{\sum_{k=1}^J T_{s,k,A-1,y-1} e^{-Z_{k,A-1,y-1}}} \right)}{\sum_{s=1}^J T_{s,k,A-1,y-1}}$$

which is solved numerically for $F_{A-1,y-1}$. The value of $F_{A-1,y-1}$ is in turn is used to initiate the recursive sequence for the younger age classes discussed in the preceding paragraph.

The recursion for a plus-group requires starting guesses for the fishing mortality rate on the oldest age in two years ($F_{k,A,y}$ and $F_{k,A,y-1}$), whereas the recursion without a plus-group requires only $F_{k,A,y}$. This is of little consequence where a succession of cohorts is to be analyzed because starting values must be supplied for all years regardless. However, determining those starting values can be

problematic. Program VPA-2BOX adopts the common convention of expressing the fishing mortality rate on the plus-group as a fraction φ of the fishing mortality rate on the next younger group, $F_{k,A,y} = \varphi_{k,y} F_{k,A-1,y}$. The value of φ should be less variable from year to year than the value of F inasmuch as changes in effort are to some degree factored out. In some applications the value of φ is assumed to be 1.0 while in others they are estimated.

The recursion for the overlap and diffusion models for two stocks is similar in principle to that above, but requires the linear decomposition of a system of equations (see Porch and Turner (1998) and Porch et al., in press).

The challenge that remains is to choose appropriate values for M_{kay} , T_{kay} and the parameters that represent the fishing mortality on the oldest age in the cohort, $\varphi_{k,y}$, or in the case of incomplete cohorts represented by the last year of data, F_{kay} . This involves the second phase of the tuning procedure discussed earlier, which is discussed in detail below.

Basic theory of parameter estimation

The basic tenet behind any statistical estimation procedure is that any data element d_j may be described as a scalar function f of a covariate vector \mathbf{X}_j (e.g., time), parameter vector Θ , and random noise. The most popular estimation approach historically has been the method of least squares where the random noise is considered either to be additive ($d_j = f[\mathbf{X}_j, \Theta] + \epsilon$) or multiplicative ($d_j = f[\mathbf{X}_j, \Theta]e^\epsilon$) such that the best estimate of Θ is taken to be that which minimizes, respectively,

$$\sum_j (d_j - f[\Theta, \mathbf{X}_j])^2 \quad (2.1)$$

or

$$\sum_j (\log_e d_j - \log_e f[\Theta, \mathbf{X}_j])^2 \quad (2.2)$$

Another popular approach is the method of maximum likelihood, where the probability of observing the data matrix \mathcal{D} under a proposed model structure is expressed as a probability function:

$$P(\mathcal{D} | \Theta, \mathbf{X}) = \prod_j P(d_j | \Theta, \mathbf{X}_j) \quad (2.3)$$

This probability expression is typically referred to as the likelihood function. According to classical maximum likelihood theory, the values of Θ that maximize $P(\mathcal{D} | \Theta, \mathbf{X})$ will be asymptotically efficient unbiased estimates of the true values provided the covariates are known without error.

To see how the maximum likelihood method is prosecuted, consider the special case where the likelihood function P has the form of a normal distribution with constant variance σ . In that case,

$$P(\mathcal{D} | \Theta, \mathbf{X}) = \prod_j \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(d_j - f[\Theta, \mathbf{X}_j])^2}{2\sigma^2}\right). \quad (2.4)$$

Now the maximum of $P(\mathcal{D} | \Theta, \mathbf{X})$ occurs at the same values of Θ as the minimum of its negative logarithm;

$$-\log_e P(\mathcal{D}|\Theta, \mathbf{X}) = \sum_j \frac{(d_j - f[\Theta, \mathbf{X}_j])^2}{2\sigma^2} - \log_e \sqrt{2\pi}\sigma \quad (2.5)$$

Notice that (2.5) has a form very similar to the least-squares estimator in (2.1); in fact they are minimized at exactly the same values of Θ inasmuch as σ and 2π are merely constants. Thus, it can be said that the additive least-squares estimator is equivalent to the maximum likelihood estimator under a normal distribution with constant variance. A similar equivalency can be shown for the multiplicative least-squares estimator (2.2) and the maximum likelihood estimator under a lognormal distribution with constant coefficient of variation.

As mentioned previously, one of the desirable properties of the maximum likelihood method is that, if an efficient unbiased estimator exists, the maximum likelihood method will produce it--provided the covariates \mathbf{X} are known without error. However, in most stock assessment models some of the covariates will be error-prone and alternative methods of estimation may be required (see Seber and Wild, 1989). One general class of models that deals explicitly with error prone covariates is the state space model. Typically the observations \mathcal{D}_t (e.g., indices of abundance) are expressed as functions of time-independent parameters Θ and time-dependent covariates \mathbf{X}_t that include the unobserved states of the system. A stochastic representation of a state space model is therefore defined by two probability statements: $P(\mathcal{D} | \Theta, \mathbf{X})$, quantifying the likelihood of observation errors in the data, and $P(\mathbf{X} | \Theta)$, quantifying the likelihood of process errors in the covariates (states).

A statistically rigorous Bayesian treatment of state space models is straightforward (see Schnute, 1994). By Bayes theorem, $P(\Theta, \mathbf{X} | \mathcal{D}) P(\mathcal{D}) = P(\mathcal{D} | \Theta, \mathbf{X}) P(\Theta, \mathbf{X})$. Inasmuch as $P(\mathcal{D})$ is a constant and $P(\Theta, \mathbf{X})$ may be expressed as $P(\mathbf{X} | \Theta) P(\Theta)$,

$$P(\Theta, \mathbf{X} | \mathcal{D}) \propto P(\mathcal{D} | \Theta, \mathbf{X}) P(\mathbf{X} | \Theta) P(\Theta) \quad (2.6)$$

Here $P(\Theta)$ is the so-called ‘Bayes prior’, the analyst’s best guess of the probability density for Θ .

Estimates for Θ (and therefore also \mathbf{X}) may be obtained by maximizing (2.6), known as the method of highest posterior density (HPD), which of course is equivalent to minimizing

$$\Psi = -\log P(\mathcal{D} | \Theta, \mathbf{X}) - \log P(\mathbf{X} | \Theta) - \log P(\Theta) \quad (2.7)$$

Alternatively, one may employ the classical Bayes moment estimator

$$\hat{\theta}_i = \int \theta_i P(\mathcal{D} | \Theta, \mathbf{X}) P(\mathbf{X} | \Theta) P(\Theta) d\theta_i \quad , \quad \theta_i \in \{\Theta, \mathbf{X}\} \quad (2.8)$$

Covariances may be obtained from the classical Bayes estimator

$$\hat{\sigma}_{ij} = \int (\theta_i - \hat{\theta}_i)(\theta_j - \hat{\theta}_j) P(\mathcal{D} | \Theta, \mathbf{X}) P(\mathbf{X} | \Theta) P(\Theta) d\theta_i \theta_j \quad (2.9)$$

Notice that when process errors and priors are ignored equation (2.7) reduces to the classical negative log-likelihood expression and the HPD estimates are equivalent to the maximum likelihood

(ML) solution. In that case the covariance matrix may be obtained from the inverse of the matrix of second derivatives with respect to Θ .

To the uninitiated this brief review of statistical theory and state space modeling may seem a bit esoteric. However, it is not quite so complicated as it seems. Consider a single time series of abundance indices where the year observations I_y are modeled as

$$\begin{aligned} I_y &= q_y N_y + \varepsilon_y \\ q_y &= q_0 + \chi_y \\ \varepsilon &\sim \mathcal{N}(0, \sigma_I); \chi \sim \mathcal{N}(0, \sigma_q); q_0 \sim \mathcal{N}(\mu_{q_0}, \sigma_{q_0}) \end{aligned} \quad (2.10)$$

Here N_y is the abundance (assumed for this example to be measured without error), q_y is the unobserved catchability coefficient for year y (a state variable), q_0 is the overall expected catchability (a parameter), χ is the process error (accounts for inter-annual variations in catchability) and ε is the observation error (accounts for errors in measuring the actual value of the index I). The notation $\mathcal{N}(\mu, \sigma)$ denotes a normal distribution with mean μ and standard error σ .

The HPD estimates of q_0 and the state variables q_y would be obtained by minimizing

$$\Psi = \sum_y \left(\frac{(I_y - q_y N_y)^2}{\sigma_I^2} + \ln \sigma_{Iq} \right) + \sum_y \left(\frac{(q_y - q_0)^2}{\sigma_q^2} + \ln \sigma_q \right) + \frac{(q_0 - \mu_{q_0})^2}{\sigma_{q_0}^2} + \ln \sigma_{q_0} + C \quad (2.11)$$

$\begin{array}{c} | \\ \text{-log P}(\mathcal{D} | \Theta, \mathbf{X}), \text{ negative log-likelihood (negative logarithm of observation density)} \\ \text{-log P}(\Theta, \mathbf{X}), \text{ negative logarithm of process density} \\ \text{-log P}(\Theta), \text{ negative log-prior} \\ \text{constant terms} \end{array}$

In comparison, the method of maximum likelihood (ML) minimizes only the negative loglikelihood term $-\log P(\mathcal{D} | \Theta, \mathbf{X})$, which in this case is equivalent to the method of least squares because the I_y are normal-distributed with constant σ_I .

Under certain conditions the HPD and ML estimators are equivalent. For example, as the process error variance tends to infinity, equation (2.11) reduces to

$$-\sum_y \left(\frac{(I_y - q_y N_y)^2}{\sigma_I^2} + \ln \sigma_{Iq} \right) - \frac{(q_0 - \mu_{q_0})^2}{\sigma_{q_0}^2} + \ln \sigma_{q_0} + C \quad (2.12)$$

where q_0 is uniquely determined by the prior and is otherwise irrelevant. Thus, minimizing (2.8) is effectively equivalent to minimizing the negative log-likelihood by itself:

$$\sum_y \left(\frac{(I_y - q_y N_y)^2}{\sigma_I^2} + \ln \sigma_{Iq} \right) + C \quad (2.13)$$

The state variables q_y now act as free parameters and the values that minimize (2.9) are therefore equivalent to the ML (and least-squares) estimates.

Similarly, if there is no process error ($q_y = q_0$) and the prior is uninformative (infinite variance), equation (2.7) again reduces to the negative log-likelihood term

$$\sum_y \left(\frac{(I_y - q_0 N_y)^2}{\sigma_I^2} + \ln \sigma_I \right) + C \quad (2.14)$$

This time, however, there is only one free parameter— q_0 .

At this point one might ask “Why bother with process error and priors? Couldn’t you just use maximum likelihood techniques and treat all the parameters as free parameters?” In this particular example, that sort of approach would indeed be possible because the abundance covariate is known without error, so the q_y are uniquely determined as I_y/N_y . Doing so, however, is equivalent to assuming there is no observation error in I_y and that all of the variation is due to changes in q ; this despite the fact that σ_I was imposed specifically to account for observation errors! Furthermore, such an approach is not even possible when the N_y themselves are functions of other parameters because the number of parameters exceeds the number of data points. The only recourse within the ML paradigm is to reduce the number of parameters to be estimated either by fixing some of them to predetermined guesses or by assuming they are constant over certain strata. Here the HPD paradigm provides a useful alternative.

Recall from the example above that the HPD and ML methods were shown to be equivalent for two extremes-- unconstrained inter-annual variations in q_y (infinite process variance) and $q_y = q_0$ for all y (zero process variance). In the former case the solution would generally be indeterminate (infinitely many possible answers) and in the latter case the solution would be inaccurate if q really did change from year to year. The imposition of a finite process variance therefore provides a middle ground whereby q can be allowed to change, but slowly enough that unique estimates may be obtained with reasonable precision. In fact, one can think of the HPD approach as an elegant way of constraining the ML solution.

The use of Bayes priors has the added advantage of being able to impose a guess for a particular parameter without barring the model from choosing another value if the data warrant it. Moreover, Bayes priors provide a convenient way of incorporating the uncertainty in expert judgement into the assessment. The primary disadvantage of the use of Bayes priors is that the results tend to be sensitive to the shape of the prior distribution assumed (see Gelman et al., 2000).

Estimation from abundance indices

Program VPA-2BOX allows parameters to be estimated by minimizing the negative log-likelihood function of the observed and predicted values for various indices of abundance (Table 3). This introduces several new variables that need to be accounted for-- the index standard error σ , catchability q , and relative vulnerability to the gear v (which implicitly includes factors such as gear selectivity and the fraction of the population available to be caught). There are many options available in VPA-2BOX pertaining to how these variables may be treated and the reader is referred to the documentation on the input files for a detailed accounting.

One aspect about VPA-2BOX that is important to understand is the way the variance parameter σ^2 is represented. There are two basic components-- a fixed value that is determined

externally and entered in the data file (INPUT) and an estimable parameter (ν) that scales the input value. The input value is interpreted as a coefficient of variation (CV) if it is positive and a standard error if it is negative. The scaling parameters may be multiplicative or additive (see line 47 of the CONTROL file). In the multiplicative case

$$\begin{aligned}\sigma_{iky}^2 &= (\text{INPUT}_{iky} * \hat{I}_{iky} * \nu_{ik})^2 && \text{if input value is a positive CV} && (2.15a) \\ \sigma_{iky}^2 &= (\text{INPUT}_{iky} * \nu_{ik})^2 && \text{if input value is a negative std. error}\end{aligned}$$

or, in the additive case

$$\begin{aligned}\sigma_{iky}^2 &= (\text{INPUT}_{iky} * \hat{I}_{iky})^2 + \nu_{ik}^2 && \text{if input value is a positive CV} && (2.15b) \\ \sigma_{iky}^2 &= (\text{INPUT}_{iky})^2 + \nu_{ik}^2 && \text{if input value is a negative std. error}\end{aligned}$$

where i is the index series identifier, k is the management zone and y is the year.

The multiplicative ν approach corresponds to the approaches used by Quinn and Deriso (1999) and Sullivan (1999), where the INPUT_{iky} values are interpreted as expert judgments of the relative variance of each annual observation of each index, presumably reflecting knowledge about how the data were obtained and their representativeness of the overall system (e.g., spatial and temporal coverage). The ν 's then simply scale the inputs up or down to reflect the overall variance of the system. The additive approach corresponds to the 'additional variance' approach of Geromont and Butterworth (2001), where INPUT_{iky} values are interpreted as the variance of the index associated with observation errors (such as might be obtained from the GLM standardization approach) and the ν^2 are interpreted as the additional variance characterizing the uncertainty in the index as a reflection of the true abundance trends (as might occur when the proportion of the stock sampled by the index varies from year to year). A detailed review of the pro's and con's of the additive and multiplicative approaches is beyond the scope of this manual, but some interesting discussions can be found in Legault and Porch (1999) and McAllister et al.(2001).

It is useful to note that the 'equal weighting' approach used by many investigators (when presumably they find no basis for weighting one index more than another) can be achieved by setting the INPUT values to 1.0 and then estimating (or fixing) a single, multiplicative value of ν for all indices. Conversely, the 'input variance' approach can be affected by fixing the ν 's to a value of 1.0.

Estimation from mortality indices

Parks (1976) estimated the VPA terminal fishing mortality parameters by use of a least-squares fitting to from fishing mortality rates obtained from tagging experiments, i.e.,

$$\min \sum_y \sum_a (F_{ay} - {}^\tau F_{ay})^2, \quad (2.16)$$

where the superscript τ denotes the tagging-based values. This procedure assumes that the fishing

mortality on the tagged population is the same as on the untagged population, however this may not be true for a number of reasons (see the next section). A less restrictive assumption would be to assume that F is proportional to ${}^{\tau}F$ by a factor q , i.e.,

$$\min \sum_y \sum_a (qF_{ay} - {}^{\tau}F_{ay})^2 \quad . \quad (2.17)$$

More generally, the objective is to make inferences about the loss rate of a certain target population based on estimates of the loss rate from a subpopulation τ . Suppose that the loss rate experienced by τ has some elements in common with the target population, some elements that are different, and some elements that are proportional. The two mortality rates could then be represented by the formulas $Z = M+F$ and ${}^{\tau}Z = M + L+qF$. When τ represents a group of tagged fish, for example, these equations could be interpreted to mean that tagged and untagged fish have the same natural loss rate M , tagged fish have an additional loss rate L owing to tag shedding or other factors, and the fishing mortality rate on tagged fish is proportional to that on the untagged population owing to incomplete mixing or a change in catchability.

If the factors q , M and L can be considered relatively constant through time, then M and L may be removed simply by subtracting the observed values of ${}^{\tau}Z_y$ from the value for one standard year ${}^{\tau}Z_{\psi}$

$${}^{\tau}Z_{\psi} - {}^{\tau}Z_y = q(F_{\psi} - F_y) \quad , \quad (2.18)$$

where ψ is the standard year (perhaps the year with the maximum value of ${}^{\tau}Z$ to keep the deviations positive). Thus, a least squares estimation procedure analogous to (2.16) and (2.17) would be

$$\min \sum_{y \neq \psi} \sum_a (q(F_{\psi a} - F_{ya}) - ({}^{\tau}Z_{\psi a} - {}^{\tau}Z_{ya}))^2 \quad . \quad (2.19)$$

Note that this is an implicitly less assuming procedure than (2.17) because it does not require the total loss rate estimates for the subpopulation to be partitioned into fishing and non-fishing components. Moreover there is little to gain in using (2.17) even when external estimates of fishing mortality rates are available unless q is known to be 1.0. It should also be noted that the least-squares formulations above have essentially the same form as those for the indices of abundance, in which case the proportionality factor q is termed the catchability coefficient. It is a trivial matter to derive analogous maximum likelihood formulations (contrast Tables 3 and 4).

Two extensions of the above methodology are included as options in the current software. The first allows for a slightly different model, ${}^{\tau}Z = qZ+b$ (so ${}^{\tau}Z_{\psi} - {}^{\tau}Z_y = q[Z_{\psi} - Z_y]$). The second option accommodates the possibility that ${}^{\tau}F$ or ${}^{\tau}Z$, when they represent the effective mortality rate on multiple age groups, may not represent those age groups in the same proportion as they exist in target population. This may be useful when it is possible to derive these proportions external to the VPA, but not otherwise as they cannot be estimated from the partial catches as is done for indices of abundance. See the data file section and Table 4 for further details.

Table 3. Models for indices of abundance (index series: i , zone: k , age: a , year: y) that are available in VPA-2BOX.

Equations and variables	Description
$\sum_i \sum_k \sum_y 0.5 \left(\frac{\ln(I_{iky}/\hat{I}_{iky})}{\tilde{\sigma}_{iky}} \right)^2 + \ln \tilde{\sigma}_{iky}$	lognormal negative log-likelihood terms $L(\tilde{I})$ for various error distributions.
$\sum_i \sum_k \sum_y 0.5 \left(\frac{I_{iky} - \hat{I}_{iky}}{\sigma_{iky}} \right)^2 + \ln \sigma_{iky}$	normal Note: for the lognormal distribution σ' is the variance on a logarithmic scale,
$\sum_i \sum_k \sum_y \hat{I}_{iky} - I_{iky} \ln(\hat{I}_{iky})$	Poisson $\tilde{\sigma}_{iky} = \sqrt{\log_e \left\{ \left(\frac{\sigma_{iky}}{\hat{I}_{iky}} \right)^2 + 1 \right\}}$,
$\sum_i \sum_k \sum_y 0.5 \frac{(I_{iky} - \hat{I}_{iky})^2}{\sigma_{iky}^2 (\hat{I}_{iky} + 1)}$	Chi - square and for the gamma distribution:
$\sum_i \sum_k \sum_y \left(\frac{\sqrt{2} I_{iky} - \hat{I}_{iky} }{\sigma_{iky}} \right)^2 + \ln \sigma_{iky}$	Laplace $\alpha = (\hat{I}_{iky}/\sigma_{iky})^2$ and
$\sum_i \sum_k \sum_y C \ln \beta - (\alpha - 1) \ln I_{iky} - \frac{I_{iky}}{\beta} - \ln \Gamma(\alpha)$	gamma $\beta = \hat{I}_{iky}/\alpha$
I_{iky}	observed value of index
$\hat{I}_{iky} = q_{iky} \Delta_{ik} \sum_a v_{ikay} w_{ikay} \tilde{N}_{kay}$	predicted value of index
v_{ikay}	relative selectivity/availability at age
σ_{iky}	standard error of index
q_{iky}	catchability coefficient
w_{ikay}	weight
Δ_{ik}	adjustment for time of year

Table 4. Models for indices of mortality rate (index series: i , zone: k , age: a , year: y) available in VPA-2BOX. Options 3-6 refer to the third entry on line 56 of the catch data file.

Equations and variables	Description
$\sum_i \sum_k \sum_y 0.5 \left(\frac{\ln(D_{iky}/\hat{D}_{iky})}{\tilde{\sigma}_{iky}} \right)^2 + \ln \tilde{\sigma}_{iky}$	lognormal negative log-likelihood terms $L(\bar{D})$ for various error distributions.
$\sum_i \sum_k \sum_y 0.5 \left(\frac{D_{iky} - \hat{D}_{iky}}{\sigma_{iky}} \right)^2 + \ln \sigma_{iky}$	normal Note: for the lognormal distribution σ' is the variance on a logarithmic scale,
$\sum_i \sum_k \sum_y \hat{D}_{iky} - D_{iky} \ln(\hat{D}_{iky})$	Poisson $\tilde{\sigma}_{iky} = \sqrt{\log e \left\{ \left(\frac{\sigma_{iky}}{\hat{D}_{iky}} \right)^2 + 1 \right\}}$,
$\sum_i \sum_k \sum_y 0.5 \frac{(D_{iky} - \hat{D}_{iky})^2}{\sigma_{iky}^2 (\hat{D}_{iky} + 1)}$	Chi - square
$\sum_i \sum_k \sum_y \left(\frac{\sqrt{2} D_{iky} - \hat{D}_{iky} }{\sigma_{iky}} \right)^2 + \ln \sigma_{iky}$	Laplace and for the gamma distribution: $\alpha = (\hat{D}_{iky}/\sigma_{iky})^2$ and $\beta = \hat{D}_{iky}/\alpha$
$\sum_i \sum_k \sum_y C \ln \beta - (\alpha - 1) \ln D_{iky} - \frac{D_{iky}}{\beta} - \ln \Gamma(\alpha)$	gamma
$D_{iky} = \begin{cases} \text{Max}_y \{Z_{iky}\} - Z_{iky} & \text{options 3 or 4} \\ F_{iky} & \text{option 5} \\ Z_{iky} & \text{option 6} \end{cases}$	observed value of standardized mortality rate index
$\hat{D}_{iky} = \begin{cases} q_{iky} \sum_a v_{ikay} (\hat{F}_{kay} - \hat{F}_{kay}) & \text{option 3} \\ q_{iky} \sum_a v_{ikay} (\hat{Z}_{kay} - \hat{Z}_{kay}) & \text{option 4} \\ q_{iky} \sum_a v_{ikay} \hat{F}_{kay} & \text{option 5} \\ q_{iky} \sum_a v_{ikay} \hat{Z}_{kay} & \text{option 6} \end{cases}$	predicted value of standardized mortality rate index
v_{ikay}	age-specific scaling factor
σ_{iky}	standard error of index
q_{iky}	proportionality coefficient

Estimation from tag recoveries

Program VPA-2box assumes the temporal and spatial distribution of tag recoveries from a given group (cohort) of releases are multinomial-distributed (Schweigert and Schwarz, 1993; Anganuzzi et al., 1994) as described in Table 5. The tag attrition model includes terms for the reporting rate (ρ), immediate loss of tags owing to misapplication or tagging-induced mortality (d), and chronic loss of tags owing to shedding or fouling (λ). The first two terms always occur together as the product $(1-d)\rho$ and cannot be distinguished using tag recovery data alone; therefore only one of the terms may be estimated and the other must be fixed. The chronic tag loss rate λ is similarly confounded with the natural mortality rate M , but independent estimation becomes possible when abundance indices are available in addition to the tagging data.

The model in Table 5 also allows for the possibility that the effective fishing mortality on the tagged population may differ from that on the untagged population by use of pre-mixing adjustment factors $\gamma_{\mathcal{D}}$. The values of $\gamma_{\mathcal{D}}$ can be difficult to distinguish precisely from F when only tag recovery data are available (Hoenig et al., 1998), but the task is made easier when catch and abundance data are included because F is largely determined from them.

Another necessary adjustment has to do with the fact that the VPA accounting is by year, but tag releases tend to occur at various times within a year—sometimes before and sometimes after the periods of most intense fishing. Consider, for example, a group of fish that were tagged and released at the end of the 7th month after the major fishery was over. In that case the tagged fish would be exposed to five months of tag loss and natural mortality, but none would be recaptured. If no adjustments are made to account for this, the model would erroneously interpret the lack of recaptures for that year as no fishing for the year, when in fact the fishing pressure could have been very high. The fishing fraction parameter ϕ in Table 5 adjusts the fishing mortality rate parameter by the fraction of the total fishing pressure exerted during the year that was experienced by tags. This requires information on the seasonality of the fisheries beyond that which is normally required by VPA (see discussion on line 34 of the control file). Of course this sort of problem only occurs for the year when the fish were first tagged. In subsequent years the tagged population will face the full cycle of fishing such that $\phi=1$.

Finally, it usually will not be possible to distinguish members of the two stocks during the tagging process. In the case of the diffusion model this is unimportant because the two stocks are defined by management zone (rather than by origin)—fish born in zone 1 and tagged in the zone 2 are considered to be members of the zone 2 stock and vice versa. In the case of the overlap model, where the two stocks are defined by origin, fish from each stock are assumed to be tagged in proportion to their relative abundance in each management zone, i.e.,

$$R_{s\tau} = R_{\tau} \frac{T_{s\kappa\tau y} N_{say}}{\sum_s T_{s\kappa\tau y} N_{say}} \quad (2.17)$$

where the N and T values are the estimates from the VPA.

Table 5. Model for tag recoveries. The subscript τ denotes a unique group (cohort) of tag releases distinguished by the zone (κ), year (ψ) and age (α) of release. The remaining subscripts are as defined previously (stock: s , zone: k , year: y , age: $a = \alpha + y - \psi$).

Equations and variables	Description
$\mathcal{L}(\bar{r}) = \sum_{\tau} \frac{1}{\omega_{\tau}^2} \left\{ (R_{\tau} - \sum_{k,y} r_{k\tau y}) \ln \left[1 - \sum_{k,y} \frac{\hat{r}_{k\tau y}}{R_{\tau}} \right] - \sum_{k,y} r_{k\tau y} \ln \left[\frac{\hat{r}_{k\tau y}}{R_{\tau}} \right] \right\}$	negative log-likelihood for tag recoveries from all cohorts
R_{τ}	number of tag releases in cohort τ
$r_{k\tau y}$	observed recoveries from cohort τ
$\hat{r}_{k\tau y} = \rho_{kay} \tilde{n}_{k\tau y} \frac{f_{k\tau ay}}{z_{k\tau ay}} (1 - e^{-z_{k\tau ay}})$	expected recoveries from cohort τ
$z_{k\tau ay} = f_{k\tau ay} + (M_{kay} + \lambda_{\tau y})(1 - t_{\tau y})$	total loss rate of cohort τ
$f_{k\tau ay} = \phi_{\tau y} \gamma_{\tau y} F_{kay}$	fishing mortality rate of cohort τ
$\gamma_{\tau y}$	pre-mixing adjustment for cohort τ
$\phi_{\tau y}$	fishing fraction (= 1 for $y > \psi$)
$\lambda_{\tau y}$	chronic tag loss rate of cohort τ
d_{τ}	immediate tag loss of cohort τ
$t_{\tau y}$	release date of cohort τ (= 0 for $y > \psi$)
ρ_{kay}	reported fraction of recaptured tags
<i>Overlap tag attrition model</i>	
$\tilde{n}_{k\tau y} = \begin{cases} R_{\tau}(1-d_{\tau}) & (y = \psi, k = \kappa) \\ \sum_s T_{skay} n_{s\tau y} & (y > \psi) \end{cases}$	number of survivors with tags from cohort τ in zone k at start of year y
$n_{s, \tau, y+1} = \begin{cases} R_{s\tau}(1-d_{\tau}) e^{-z_{\kappa\tau ay}(1-t_{\tau y})} & (y = \psi) \\ n_{s\tau y} \sum_k T_{skay} e^{-z_{k\tau ay}} & (y > \psi) \end{cases}$	number of survivors with tags from cohort τ and stock s at start of year y ($R_{s\tau}$ is the number of releases by stock)
<i>Diffusion tag attrition model</i>	
$\tilde{n}_{k, \tau, y+1} = \begin{cases} R_{\tau}(1-d_{\tau}) e^{-z_{\kappa\tau ay}(1-t_{\tau y})} & (y = \psi) \\ e^{-z_{k\tau ay}} \sum_j T_{jkay} \tilde{n}_{j\tau y} & (y > \psi) \end{cases}$	number of survivors with tags from cohort τ in zone k at start of year y

BIAS AND UNCERTAINTY

In any statistical analysis there is a tradeoff between precision and accuracy. Generally, adding parameters to a model should improve its ability to reflect the dynamics of the population (making it more accurate). However, if the data are limited, adding too many parameters will lead to a situation where the estimates are highly imprecise, i.e., many combinations of parameter values can explain the data equally well (give the same posterior/likelihood values). In this regard, one of the challenges to the investigator is to determine whether the additional parameters improve the model's ability to fit the data in a statistically significant way. If not, the new model is generally rejected in favor of the simpler model (see the section on model selection below). Subsequent inferences are usually made under the implicit assumption that the selected model is correct and the parameter estimates obtained by the nonlinear optimization are unbiased.

Maximum likelihood estimators, where the objective function being minimized is the negative log-likelihood, are asymptotically unbiased under fairly general conditions (Hoel et al., 1980). In principle, asymptotically efficient estimates of the covariances of the parameters may be obtained from the inverse of the Hessian matrix (matrix of second derivatives), allowing one to quantify the precision with which the parameters were estimated. However, in most stock assessments the number of data points available is seldom much larger than the number of parameters, so the asymptotic theory may not apply and a substantial bias can be incurred in both the point estimates and their corresponding Hessian matrix covariances. Moreover, the asymptotic covariance matrix is not generally given by the inverse of the expected Hessian matrix when penalties, priors or process errors are imposed (Seber and Wild, 1989).

The best way to ascertain the bias and variance of any given estimator is to apply that estimator to a large number of random samples from a population with known distributional characteristics. In practice of course, one does not know the distribution of the population in question and, in many cases, does not have the capacity to resample that population multiple times. Therefore one must turn to various approximations, such as Box's (1971) linear approach, which involves computing both first and second derivatives (see discussion in Gavaris, 1993). I am unaware of an analogous technique for determining the bias of the corresponding covariance estimators. Moreover, it is unclear how the Box (1971) approach would apply when the objective function is not simply the negative log-likelihood, but also includes process error, priors and other penalties.

An alternative way of determining the bias and covariances of the point estimates is by use of a technique known as bootstrapping. Punt and Butterworth (1993) found that, on average, the estimates of variance from the inverse of the Hessian matrix were about the same as the estimates from bootstrapping, but it is not clear that this will always be the case for the reasons discussed above. In practice, the bootstrap estimator may often perform better than the inverse of the Hessian matrix because the latter is based only on the shape of the negative log-likelihood surface in the vicinity of the minimum, which of course presupposes that the true minimum has in fact been found and is based on a single configuration of the data. The bootstrap estimator, on the other hand, implicitly takes into account the possibility that the minimum may not always be found and the sensitivity of the solution to perturbations in the data.

Bootstrap procedures

The concept behind bootstrapping is that the distribution of values from any given random sample is the best guide to the distribution of values in the population the sample came from. Therefore, the next best thing to resampling a population is resampling the sample. Regression analyses may be bootstrapped either by resampling the regression residuals or by resampling the data (Manly, 1998, p 167), but the latter is seldom an option for VPA tuning approaches because there is only one observation for each index for any given time unit (year). Accordingly, most of the literature on bootstrapping VPA's involves resampling the residuals.

There are two principal ways of bootstrapping from regression residuals: parametrically by sampling from a known distribution with a prescribed variance and non-parametrically by sampling directly from the residuals of the model fit (random draws with replacement). In either case, the sampled residuals are added to the model expectation (not the observations themselves) to generate a pseudo-data set. The model is then refit to each of B number of pseudo data sets and the results used to construct the sampling distributions of the estimators in question.

VPA-2BOX can presently conduct parametric and non-parametric bootstrap analyses of the indices of abundance and indices of mortality. In principle, one should choose the parametric approach only if the distribution of the statistic being bootstrapped is known (e.g., lognormal with a variance of 0.2). Punt and Butterworth (1993) found that the non-parametric and parametric bootstrap procedures gave similar results in their examples, but Freedman and Peters (1984) and others have found that the non-parametric approach generally gives less-biased results.

The parametric bootstrap entails the following steps:

- (1) Fit the model to the actual data;
- (2) Create new "bootstrap" indices, ${}^b I_{ky}$, by drawing at random with replacement from normal or lognormal distributions with mean and standard deviation equal to the model expectations of I and σ (k denotes a particular series and y denotes a particular year):

$${}^b I_{ky} = \begin{cases} \hat{I}_{ky} + {}^b \pi_{ky} & \text{additive (normal) error} \\ \hat{I}_{ky} e^{{}^b \pi_{ky}} & \text{multiplicative (lognormal) error} \end{cases} \quad (2.18)$$

$${}^b \pi_{ky} \sim \mathcal{N}(\hat{I}_{ky}, \sigma_{ky})$$

- (3) Fit the model to the bootstrap data set created in step 2;
- (4) Repeat steps 2 and 3 until the required number of replications is obtained.

A potential problem with this approach occurs when the standard error term σ is not known and is instead replaced by a value estimated in the model, $\hat{\sigma}$. In many cases the estimated value $\hat{\sigma}$ may be smaller than the true value, causing the bootstrap residuals π to be smaller than they should be. As a result, the bootstrap could indicate that the model parameters are well-estimated when in fact they are poorly estimated and $\hat{\sigma}$ just happens to be too low. For this reason I recommend against using the parametric approach unless one is confident in the values being used for σ .

The non-parametric bootstrap is similar in principle, but steps 1 and 2 become:

(1) Fit the model to the actual data and store the residuals--

$$r_{ky} = \begin{cases} I_{ky} - \hat{I}_{ky} \\ \log_e I_{ky} - \log_e \hat{I}_{ky} \end{cases} \quad (2.19a)$$

(2) Create new “bootstrap” indices of abundance, ${}^b I_{ky}$, by drawing at random with replacement from the index-specific sets of residuals--

$${}^b I_{ky} = \begin{cases} \hat{I}_{ky} + {}^b \pi_{ky} & \text{additive (normal) error} \\ \hat{I}_{ky} e^{b\pi_{ky}} & \text{multiplicative (lognormal) error} \end{cases} \quad (2.19b)$$

$${}^b \pi_{ky} \sim \{r_{ky}\}$$

As it stands, this approach tends to perform poorly when the number of estimated parameters is large relative to the number of data points. In such cases the model may be able to provide a near perfect fit to the data with many different combinations of parameter values. The small residuals in turn will lead to bootstrap data sets that are essentially identical to the original data set, ultimately leading to artificially small bootstrap estimates of the parameter variances. The reason for this is easy to see in the context of a regression involving a single index of abundance. In that case the variance of the bootstrap residuals (being random draws from the finite population r_y) is

$$\text{VAR}({}^b \pi_y) = \frac{n_{\Theta} - n_{\mathcal{D}}}{n_{\mathcal{D}}} \hat{\sigma}^2, \quad (2.20)$$

where n_{Θ} is the number of estimated parameters and $n_{\mathcal{D}}$ is the number of observations. Hence, the variance of the residuals is too small by a factor of $1 - n_{\Theta}/n_{\mathcal{D}}$.

Tukey (1987) and Stine (1990) recommend ‘fattening’ the residuals from linear regressions by dividing each by a factor $(1 - n_{\Theta}/n_{\mathcal{D}})^{1/2}$. However, this may not be the correct adjustment in more complicated regressions, such as when more than one index of abundance is being used. Efron and Tibshirani (1993) suggest that the random variability in the estimates of variance is more important than the bias caused by factors such as $(1 - n_{\Theta}/n_{\mathcal{D}})^{1/2}$ and that the problem is not too worrisome unless $n_{\Theta}/n_{\mathcal{D}}$ is greater than about 0.25. Nevertheless, in the case of multiple indices it is reasonable to take an intermediate position and at least adjust for the number of estimated parameters unique to each index (optional in VPA-2BOX). Thus, step 1 of the non-parametric procedure becomes

$${}^b I_{ky} = \begin{cases} \hat{I}_{ky} + {}^b \pi_{ky} & \text{normal} \\ \hat{I}_{ky} e^{b\pi_{ky}} & \text{lognormal} \end{cases} \quad (2.21)$$

$${}^b \pi_{ky} \sim \left\{ \frac{r_{ky}}{\sqrt{1 - n_{\Theta k}/n_{\mathcal{D}k}}} \right\}$$

where $n_{\mathcal{D}k}$ and $n_{\Theta k}$ indicates the number of observations and estimated parameters unique to index

k (namely the catchability coefficients q_k and variances σ_k). In point of fact the above adjustment is still too low owing to the bias caused by not adjusting for the parameters shared by each index, but it is not clear how such further adjustments should be accomplished. Therefore, a warning message is output by program VPA-2BOX whenever $n_{\Theta}/n_{\mathcal{Q}} > 0.25$.

Finally, it may sometimes happen that the variance of an index differs from one year to the next owing to differences in sample size or other factors and that the investigator may wish to deal with this heterogeneity explicitly. With the parametric approach this is straightforward and no further modifications are required, but the non-parametric approach will lead to homoscedastic bootstrap samples. In such cases residuals r may be transformed to standard normal deviates by dividing by the standard errors. Thus, steps 1 and 2 become

- (1) Fit the model to the actual data, standardize the residuals by the known (or estimated) standard errors and store them (Note: for the lognormal case σ is the standard error on a logarithmic scale.)—

$$r_{ky} = \begin{cases} (I_{ky} - \hat{I}_{ky}) / \sigma_{ky} & \text{normal} \\ (\log_e I_{ky} - \log_e \hat{I}_{ky}) / \sigma_{ky} & \text{lognormal} \end{cases} \quad (2.22)$$

- (2) Create new “bootstrap” indices of abundance, ${}^b I_{ky}$, by drawing at random with replacement from the index-specific sets of residuals and then renormalizing by the appropriate standard errors—

$${}^b I_{ky} = \begin{cases} \hat{I}_{ky} + {}^b \pi_{ky} \sigma_{ky} & \text{normal} \\ \hat{I}_{ky} e^{b \pi_{ky} \sigma_{ky}} & \text{lognormal} \end{cases} \quad (2.23)$$

$${}^b \pi_{ky} \sim \left\{ \frac{r_{ky}}{\sqrt{1 - n_{\Theta k} / n_{\mathcal{Q}k}}} \right\}$$

Note: This standardization procedure is an *ad hoc* approach employed by the author to account for heterogeneous variances among years; it would not be necessary if multiple observations were available for each year, in which case one could simply resample the data.

Bootstrap estimates of bias and variance

The expected value of an estimator applied to bootstrap pseudo-data sets is, by definition, the point estimate associated with original model fit. Therefore, in the absence of any methodological bias, the mean of the estimates from each of the bootstrap fits should be the same as the original point estimate. Otherwise, the difference between the mean and the point estimate is taken to be an indicator of the bias, i.e., the difference between the point estimate and the true value. Program VPA-2BOX computes the bias and variance of any given point estimate $\hat{\phi}$ via the estimators suggested by Efron (1990):

$$\begin{aligned} \text{bias}_B(\hat{\phi}) &= \frac{\sum^b \phi}{B} - \phi(\bar{\mathbf{I}}) \\ V_B(\hat{\phi}) &= \frac{\sum_{b=1}^B (\phi - \frac{\sum^b \phi}{B})^2}{B-1} \end{aligned} \quad (2.24)$$

where $\phi(\bar{\mathbf{I}})$ denotes the estimate obtained by fitting the model to the average of the bootstrap data sets (i.e., $\bar{I}_{ky} = \sum^b I_{ky}/B$). Note that some investigators prefer to use the median of the bootstraps to calculate the bias rather than the mean because it is less sensitive to rare, large aberrations:

$$\text{bias}_B(\hat{\phi}) = \text{median}\{^b \phi\} - \hat{\phi}. \quad (2.25)$$

This has not yet been automated in VPA-2BOX, but can be computed from the binary output files.

Frequently one may wish to correct the statistic $\hat{\phi}$ in order to make it less biased:

$$\phi_{corrected} = \hat{\phi} - \text{bias}_B(\hat{\phi}). \quad (2.26)$$

Note that $\phi_{corrected}$ is not equivalent to the median or mean of the bootstraps, a fairly common mistake (in fact, if $\hat{\phi}$ is biased then, by definition, the bootstrap mean and median are even more so). Efron and Tibshirani (1993) point out that bias-correcting is a dangerous affair; even if $\phi_{corrected}$ is less biased than $\hat{\phi}$, its standard error may be much greater. For this reason they suggest that the bias statistic is most useful as a diagnostic tool and that it is safer to use $\hat{\phi}$ than $\phi_{corrected}$ if the bias is small relative to the estimated standard error. On the other hand, a large bias relative to the standard error may indicate that the statistic $\hat{\phi}$ is too poorly determined to be useful.

How many bootstraps?

Porch (1999) found that the estimates of bias and coefficients of variation converged to stable values as the number of bootstrap replicates increased to 200 or more (Figures 1 and 2). However, even as few as 50 replicates gave reasonably good estimates. Therefore, there seems to be little to gain from using more than 200 replicates and as few as 50 may be adequate when computing time is limited. This conclusion seems to be typical of many bootstrap problems (Efron, 1987; Punt and Butterworth, 1993; Smith and Gavaris, 1993), although it is possible that very large data sets may require more replicates.

Cautions

It must be emphasized that the bootstrapping procedure only addresses errors that arise specifically because a nonlinear model is being applied to a relatively small data set. Other biases may occur when the error structure of the dependent variables is mis-specified or because the independent variables (e.g., the predicted indices of abundance) are treated as though they were error-free when in fact they do have error. In case of the latter, for example, the inverse of the Hessian matrix will usually lead to underestimates of variance (page 496 in Seber and Wild, 1989).

Still other uncertainties may arise because the catches (and even some of the model parameters) are treated as though they were perfectly known. In the case of catches, VPA-2BOX does include an option to generate pseudo-catch-at-age data from the observed values assuming a particular distribution type and variance (or cv) analogous to the parametric bootstrap discussed above. This approach is useful for characterizing the additional uncertainty attributable to the catches, but is biased because it is centered on the data (see Poole et al., 1999) and should not be used for bias-correction.

Retrospective pattern analysis

One means of detecting some potential biases not discernable from the bootstrap is retrospective pattern analysis. The idea here is to determine if there is a systematic trend in the model estimates when the same model is applied to successively shorter data sets. For example, one might compare the fishing mortality estimates when the model was applied to the data from 1975 to 1999, then again to the data from 1975 to 1998, then again to the data from 1975 to 1997, and again to the data from 1975 to 1996. A systematic trend in the F estimates could suggest a number of possible biases, including mis-specification of some of the fixed parameters (often the natural mortality rate), consistent under or over-reporting of catches, indices of abundance that do not represent abundance, and ageing errors.

Various *ad hoc* procedures have been developed to try to adjust the estimates to account for potential biases indicated by the retrospective pattern (e.g., ICCAT 1995, page 48), however the statistical properties of these adjustments are unclear. Certainly no adjustment should be attempted if the standard errors of the estimates are larger than the indicated retrospective bias inasmuch as the bias adjustment itself is likely to be poorly estimated. Moreover, retrospective patterns usually dissipate as more data are added owing to the convergent properties of the VPA, so it is unclear how the estimates farther back in time should be adjusted. For these reasons I recommend retrospective analyses only as a diagnostic tool to help identify failings in the model or data.

MODEL SELECTION

Model selection is the process of identifying the model that provides the ‘best’ description of a given set of data from a suite of competing models. There are two important caveats that must be addressed at the outset. First, none of the comparative methods discussed below are useful for comparing models applied to different data sets-- they all assume the same data are used. Second, one should have an idea of the most theoretically plausible model structures to examine and then limit the comparisons to these. The strategy should never be to try every model under the sun and then select the one that provides the best fit, the danger being that the selection process will identify a model that explains much of the variation in the data but has little connection to reality. Draper (1995), for example, has shown that traditional methods of model selection can lead to models with apparently strong predictive power even for randomly generated data. This problem is analogous to what happens in step-wise regression procedures with a very large number of potential covariates: the probability of finding some combination of covariates that accounts for the variation in the data may be great even when none of the covariates are related to the data (Manly, 1998).

Hypothesis tests

Hypothesis tests are often used to select the best approximating model. If the models are fitted by maximum likelihood, for example, the standard likelihood ratio test may be used to determine if the addition of n number of parameters to a previous model significantly improved the fit to the data. The test statistic,

$$-2 \log \left\{ \frac{P(\mathcal{D} | \Theta_2, \mathbf{X}_2)}{P(\mathcal{D} | \Theta_1, \mathbf{X}_1)} \right\}, \quad (2.27)$$

is chi-square distributed with n degrees of freedom (Hoel et al., 1981). Thus, the augmented model (2) would be judged significantly better than its simpler predecessor (1) if the test statistic was greater than the value from the chi-square distribution with n degree of freedom and the prescribed probability level (say 5%).

The primary drawback to likelihood ratio tests is that they are made with the understanding that one model is a reduced version of the other. Accordingly, models with different distributional assumptions about the data (e.g., lognormal versus normal distributed indices) cannot be compared with likelihood ratio tests. For this reason it is often preferable to work with information criteria, which do not require the competing hypotheses to be nested.

Information criteria

Perhaps the most familiar information criterion is Akaike's (1973) AIC metric,

$$\text{AIC} = -2 \log P(\mathcal{D} | \Theta, \mathbf{X}) + 2n_{\Theta}, \quad (2.28)$$

and the small sample bias-adjusted version AIC_c (Hurvich and Tsai, 1995),

$$\text{AIC}_c = -2 \log P(\mathcal{D} | \Theta, \mathbf{X}) + 2n_{\Theta} \left(1 + \frac{n_{\Theta} + 1}{n_{\mathcal{D}} - n_{\Theta} - 1} \right). \quad (2.29)$$

The variables n_{Θ} and $n_{\mathcal{D}}$ represent the number of estimated parameters and number of data points, respectively. The philosophy behind the AIC is that reality is high-dimensional, possibly requiring infinitely many parameters to describe it. Model selection is therefore seen as a process of identifying the best approximating model. The dimension of this 'best' approximation would be expected to be low when the data are sparse and increase with the quantity and quality of the available data. The 'best' model is taken to be that with the lowest AIC (AIC_c) value.

Another metric that is sometimes used is the Bayes Information Criterion BIC,

$$\text{BIC} = -2 \log P(\mathcal{D} | \Theta, \mathbf{X}) + n_{\Theta} \log(n_{\mathcal{D}}). \quad (2.30)$$

The philosophy underlying the BIC criterion is that reality is low dimensional and model selection is seen as the process of identifying the true model (the usual Bayesian approach). As with AIC, the

‘best’ model is taken to be that with the lowest BIC value. An interesting implication of the BIC is that it should be proportionately harder to add parameters as more data become available, which seems somewhat counterintuitive.

Burnham et al. (1994) and Buckland et al. (1997) favor the AIC/AIC_c approach over BIC, arguing that reality is rarely low-dimensional. VPA-2BOX includes both metrics, but I do not generally recommend the BIC because the systems one is likely to analyze with VPA are likely to be very much more complex than any model that can be supported by the data. I generally use the AIC_c metric rather than AIC because of the relatively small ratio of data to parameters in most VPA applications.

It is important to note that the negative log-likelihood expression $-\log P(\mathcal{D} | \Theta, \mathbf{X})$ used in criteria (2.28 -2.30) must include all constant terms if comparisons are to be made between models with different distributional assumptions (e.g., normal versus lognormal distributed indices of abundance). An alternative form of the criteria uses the model *deviance* in place of $-2\log P(\mathcal{D} | \Theta, \mathbf{X})$, however it is unclear how this form could be applied when the variance terms are estimated. (Model deviance is twice the difference between the negative loglikelihood function associated with the model fit and the negative loglikelihood that would be obtained if the model were able to fit the data perfectly.)

Bayes factors

A related point to keep in mind is that the AIC, BIC, likelihood ratio tests, and related criteria are based on likelihood theory and should not be applied when Bayesian priors and penalty functions are incorporated unless the priors and penalties are relatively uninformative (and so have little influence on the likelihood function). Strictly speaking, a discrete set of Bayesian models should be compared by contrasting their posterior densities,

$$P(H_i | \mathcal{D}) = \frac{P(\mathcal{D} | H_i)P(H_i)}{P(\mathcal{D})}, \quad (2.31)$$

where H_i denotes the i 'th of several alternative models to be tested, $P(\mathcal{D} | H_i)$ is the marginal density of observing the data if hypothesis H_i were true, $P(H_i)$ is the prior representing expert opinions on probability that H_i is true relative to the competing hypotheses, and $P(\mathcal{D})$ is the unknown probability density of the data. If the same data are used for all models, $P(\mathcal{D})$ is a constant that can be ignored. In that case the ratios of $P(H_i | \mathcal{D})$ for two competing models (H_1 and H_2) may be compared:

$$\frac{P(H_2 | \mathcal{D})}{P(H_1 | \mathcal{D})} = \frac{P(\mathcal{D} | H_2)P(H_2)}{P(\mathcal{D} | H_1)P(H_1)}. \quad (2.32)$$

Model H_2 would then be interpreted as ‘better’ than H_1 if the ratio were greater than 1.

Unfortunately, the computation of the ratio $P(\mathcal{D} | H_2) / P(\mathcal{D} | H_1)$, known as the Bayes factor, has a number of practical limitations. One of the most important of these limitations is that they cannot reasonably be applied to noninformative priors (See Gelman et al. 2000, pp. 175-177). Another is that their computation requires performing the multidimensional integration

$$P(\mathcal{D} | H_i) = \int_{\Theta_i} P(\mathcal{D} | \Theta_i, \mathbf{X}_i) P(\mathbf{X}_i | \Theta_i) P(\Theta_i) d\Theta_i, \quad (2.33)$$

which may demand considerable computing time. A number of alternatives to the Bayes factor have been suggested, including the controversial ‘posterior Bayes factor’ suggested by Aitkin (1991) and appropriated (in one of its limiting forms) for stock assessments by Fournier et al., (1998). Each such alternative has its own peculiarities and, at this point, none have been programmed into VPA-2BOX.

Chi-square discrepancy statistic

One useful check of model performance that can be applied in both Bayesian and non-Bayesian constructs is the Chi-square discrepancy statistic (Gelman et al., 1995; BFT, 2001):

$$\chi^2 \text{ discrepancy} = \sum_j \frac{(d_j - f[\hat{\Theta}, \mathbf{X}_j])^2}{V(d_j)}, \quad (2.34)$$

where $f[\hat{\Theta}, \mathbf{X}_j]$ is the model expectation of d_j given the estimated parameter vector and $V(d_j)$ is the variance. This statistic is approximately Chi-square distributed with $n_{\mathcal{D}} - n_{\Theta}$ degrees of freedom, so the probability p of observing a value of χ^2 that exceed the calculated value may be read from a standard Chi-square table. The idea here is to assess whether the observed discrepancies between the data and model predictions could have arisen by chance under the model’s own assumptions. Major failures of the model should lead to either very high p -values (say, over 0.99, in which case the model probably has too many parameters) or very low p -values (say, less than 0.01, in which case the model is inconsistent with the data). The chi-square statistic can also be used to identify changes in the model, other than error structure, that augment its performance and bring the p -values to a reasonable range. It should not be used to compare different assumptions about error structure because it would, by its very nature, always favor weighted least-squares estimators. Note that VPA-2BOX computes this statistic for the indices of abundance/mortality only; it does not compute it for tag-recapture data.

NUMERICAL OPTIMIZATION

The section on parameter estimation discussed how the ability of a model to fit the data could be expressed as a single objective function Ψ that depends on a number of independent variables (parameters). The goal was to find the values of those variables where Ψ takes on its lowest possible value, i.e., the minimum. In certain special cases, such as when the model is a linear in its parameters, the minimum can be found exactly by setting the derivatives of Ψ with respect to the parameters equal to zero and solving the resulting system of equations analytically. In the case of nonlinear models, however, it is seldom possible to find a solution analytically and numerical procedures must be employed.

Numerical optimization methods essentially amount to trying a large number of different combinations of parameter values and finding the combination with the optimal (in this case lowest) value of Ψ . Ideally, one would like to try compare the values of Ψ obtained with every possible combination of feasible parameter values (or increments of values in the case of continuous variables). Unfortunately, the number of function evaluations (parameter combinations) required for this strategy increases geometrically with the number of values (n) evaluated and parameters considered (p): evaluations = n^p . Thus, the use of even a very coarse grid with only ten values for each parameter would require ten million function evaluations for seven parameters (a fairly modest number). At this writing, even the fastest PC processors require several hours to compute a typical VPA-type objective functions ten-million times. Grid searches with any more than 7 parameters or ten values can therefore be seen to be completely impractical. For this reason a number of algorithms have been developed to reduce the number of parameter combinations that must be evaluated in an intelligent way.

Unfortunately, by trying to intelligently select from among all possible parameter combinations, any given algorithm is prone to be 'fooled' in certain situations. Perhaps the most common failure involves mistaking a local minimum in the solution surface for the overall (global) minimum. It is beyond the scope of this manual to discuss the pros and cons of the innumerable number of search algorithms that have been developed. Interested readers are referred to any standard text on the subject (e.g., Press et al., 1992).

A two-step approach is used in VPA-2BOX. The first step involves the OSSRS algorithm of Sheela (1979), which was designed to rapidly converge on the general vicinity of the global minimum. Once in that vicinity, however, the OSRSS algorithm converges very slowly. At that point VPA-2BOX automatically swithes to the Nelder-Mead simplex routine AMOEBA of Press et al. (1992). This routine has the advantage of not requiring analytical or numerical derivatives, as do quasi-Newton and related algorithms.

The AMOEBA algorithm is restarted multiple times to avoid being fooled by local minima. New initial vertices are selected for each such restart using the formula

$$\theta_{ij} = \theta_{0j} e^{\sigma\eta\delta} \quad (i,j = 1, 2, \dots, p) \quad (2.35)$$

where θ_{0j} is the value of the j 'th parameter at the presumed minimum, θ_{ij} is the value of the j 'th coordinate (parameter) in the i 'th vertex of the initial simplex, η is a standard normal variate, σ is a user-prescribed standard deviation, and δ is equal to one if i equals j and zero otherwise. Subsequent 'restarts' continue until a prescribed number of consecutive sets of parameter estimates differ by less than one percent.

It should be reiterated that no algorithm is foolproof and the combination of OSSRS and AMOEBA used here is no exception. However, this combination has fared well in extensive comparisons with several other VPA programs that use different search algorithms, usually finding the same minimum and often a lower one.

3. INPUT FILES

Program VPA-2BOX reads four input files: 1) a control file that designates the type of model to be run, 2) a parameter file that specifies how the parameters should be estimated, 3) a data file containing the catches, weights and indices of abundance, and 4) a data file containing the tag-recovery information. Each of the files is read in free-format fashion, that is, the input data need not be in any particular column. Of course, if there are multiple entries on one line, it is necessary to enter the data in the proper sequence. For example, catch-at-age information must be entered in the sequence {year, catch-at-youngest-age, catch-at-youngest-age+1, ..., catch-at-oldest-age}.

Comments may be inserted anywhere in any of the input files provided they are preceded by a # symbol in the first column of the file. Data placed after a # symbol will not be read. Comments may also be safely inserted at the end of a complete data stream (without need of a # symbol). For example, the following comments are acceptable:

```
# the catches of ages 1 and 2 in 1995 are unknown (1996 catches are used)
1995 13456 23454 68906 80001 25501
1996 13456 23454 78906 90001 24565
```

or

```
1995 13456 23454 68906 80001 25501 the catches of ages 1 and 2 in 1995
1996 13456 23454 78906 90001 24565 are unknown (1996 catches are used)
```

In contrast, the comment forms below are unacceptable:

```
# the catches of ages 1 and 2 in 1995 are unknown (1996 catches are used)
1995 13456 23454 68906 80001 25501
1996 13456 23454 78906 90001 24565
```

or

```
1995 13456 23454 the catches of ages 1 and 2 in 1995 68906 80001 25501
1996 13456 23454 are unknown (1996 catches are used) 78906 90001 24565
```

A template for each input file appears as an appendix. The explanation for each line item in the appropriate appendix is then given under the corresponding heading below.

CONTROL FILE: Appendix 1

This is the only file VPA-2BOX will prompt the user for. It contains the file names of all the other input files. Among other things, it specifies the type of model being used (one stock or two,

overlap versus diffusion), imposes certain constraints on the model (e.g., a stock recruitment penalty), controls the performance of the search algorithm, and conducts bootstrap or retrospective analyses. What follows is a line by line explanation of the entries in Appendix 1.

Line Explanation

Comments

1 - 13 Comments preceded by the # symbol in the first column.

Names (must be placed within single quotes)

- 14 The title of the run, which may be up to 50 characters long.
- 15 The name of the file with the catch, weight and index data (50 characters).
- 16 The name of the file with the parameter specifications (50 characters).
- 17 The name of the output file with the results (50 characters).
- 18 The name of the output file with the parameter estimates (50 characters).
- 19 The name of the output file with the results in a spreadsheet friendly format (50 char.)
- 20 The name of the file with the tag-recovery data (50 characters). The name of this file is immaterial if the tagging data switch on line 34 is set to 0, but some kind of name must still be entered

Model type

- 24 Number of zones or stocks being considered (either 1 or 2)
- 25 The class of model being used (overlap or diffusion, see Table 2). If only 1 stock is considered then the overlap and diffusion models are exactly the same.

Tagging data controls

34 Fourteen specifications must be entered here. The first is the tagging data switch: a value less than or equal to 0 tells the program to ignore the tag-recovery information and the other 13 entries can be left out. Otherwise, a positive value tells the program to use the tag-recovery information and the second entry is interpreted as a multiplicative weighting factor ω that controls the influence that the tagging data has on the estimation procedure. The objective function minimized in program VPA-2BOX is

$$\Psi(\Theta, X) = \mathcal{L}(\bar{I}) + \omega \mathcal{L}(\bar{r}) + \text{priors and other terms} \quad (3.1)$$

Thus, a value of ω greater than 1.0 magnifies the influence of the tagging, whereas a value less than 1.0 decreases its influence.

The next 12 entries give the relative amount of fishing E_j expected to occur in each month j . These are used to calculate the fraction of the annual fishing pressure ϕ_τ each cohort of tags was exposed to during the calendar year they were released (see Table 5):

$$\phi_\tau = \frac{(J_\tau - t_\tau)E_{J_\tau} + \sum_{j>t_\tau}^{12} E_j}{\sum_{j=1}^{12} E_j} \quad (3.2)$$

where t_τ is the time of release in terms of elapsed months and J_τ is the month the release occurred (an integer value from 1 to 12). The monthly effort indices E can be in any

units so long as they are consistent. Note, however, that the above formula implicitly assumes that the E values are fairly constant from year to year. If they are not, the release dates should be somehow adjusted outside program VPA-2BOX and the monthly values for E all set to the same value (say 1) so that VPA-2BOX does not modify them.

Search algorithm controls

- 38 The seed for the random number generator, which can be any negative integer. You would want to change this if you were running separate bootstrap analyses (perhaps on different machines) and planned later to combine the results into one grand bootstrap analysis. If you do not change the random number seed the bootstrap runs will be identical whether you run them at different times or on different machines.
- 39 The maximum number of Amoeba simplex restarts (see Numerical Optimization section) can be fixed to prevent the algorithm from running too long. Most applications will converge within 10 restarts, however some two-stock analyses with tagging data can take 50 or more. Usually, this many restarts does not lead to a noticeable improvement in the model fit and is the result of one or two parameters being poorly determined. Therefore one may wish to cap the number of restarts at the point where noticeable improvements cease, particularly when doing bootstrap analyses.
- 40 The number of consecutive restarts over which the parameter estimates must not vary by more than one percent (see discussion of equation 2.35). Usually three is enough, but one may wish to use four or five with especially difficult problems.
- 41 This is the standard deviation parameter used in equation (2.35). It controls the extent to which the restart vertices span the parameter space. If the value is large, the initial simplex at each restart will be large, which will lead to rapid convergence initially, but slower convergence when the algorithm gets closer to the minimum. Conversely, small values tend to enhance the performance in the vicinity of the minimum, but the initial rate of convergence will be slow. Experience has shown that, for VPA analyses, the best tradeoff usually occurs with values of 0.4 - 0.5.

Index weighting controls

- 45 This option allows one to divide each index of abundance by its arithmetic mean (to do so enter any positive nonzero value). This scales all of the indices to an order of 1. It is important to do this if you are assuming the indices are normally distributed and wish to weight all of the indices the same (choice -1 at line 46 below). Otherwise, the objective function will be dominated by the indices with the largest values. If you are assuming the indices are lognormally distributed or are allowing each series to be weighted by different variances, then no scaling is necessary.
- 46 This option allows one to substitute a default value for the index variance inputs discussed in connection with line 63 of the data file. The available options are:

<u>Option</u>	<u>Result</u>
0	no action, program uses the $INPUT_{iky}$ values specified in the data file
+ value	any positive nonzero input is read as a default CV, and $\sigma_{iky}^2 = (\text{value} * \hat{I}_{iky})^2$.
- value	any negative input is read as a default standard error, and $\sigma_{iky}^2 = (\text{value})^2$
999	a value with the integer part equal to 999 causes the variance for each index to be estimated by the concentrated maximum likelihood formulae

$$\sigma_{iky}^2 = \sqrt{\frac{\sum_y (I_{iky} - \hat{I}_{iky})^2}{\sum_y 1.0}} \quad (\text{Normal distribution}) \quad (3.3)$$

$$\tilde{\sigma}_{iky}^2 = \sqrt{\frac{\sum_y (\ln I_{iky} - \ln \hat{I}_{iky})^2}{\sum_y 1.0}} \quad (\text{Lognormal distribution}) \quad (3.4)$$

This option is included for comparison with previous ADAPT programs and should only be used if the indices of abundance are being modeled as normal or lognormal distributed variates. The concentrated likelihood approach is effectively equivalent to the method of iterative re-weighting used by some other ADAPT programs such as STAATS (J. E. Powers, National Oceanic and Atmospheric Administration, Southeast Fisheries Science Center, Miami Laboratory, USA). Note that VPA-2BOX also allows the variances to be represented by parameters estimated in the search (see discussion on line 47 below). If the solution is well-determined, the maximum likelihood and concentrated maximum likelihood estimates should be the same.

47 This option tells the program whether the variance scaling parameters (v_{ik}) specified in the parameter file (see line 77 of Appendix 4) should be multiplied or added to the input values entered in the data file or line 46 above. It is important to remember that the input values may be either CV's or negative standard errors. The scaling parameters therefore modify those values as follow

<u>Option</u>	<u>Result</u>	
0	$\sigma_{iky}^2 = (\text{INPUT}_{iky} * \hat{I}_{iky} * v_{ik})^2$	if input value is a positive CV
	$\sigma_{iky}^2 = (\text{INPUT}_{iky} * v_{ik})^2$	if input value is a negative std. error
1	$\sigma_{iky}^2 = (\text{INPUT}_{iky} * \hat{I}_{iky})^2 + v_{ik}^2$	if input value is a positive CV
	$\sigma_{iky}^2 = (\text{INPUT}_{iky})^2 + v_{ik}^2$	if input value is a negative std. error

As is true of any parameter listed in the parameter file, the variance parameters may be fixed or estimated in various ways. However, the program will send an error message if you enter 999 at line 46 and then try to estimate the variance parameters entered in the parameter file since they are merely different ways of estimating the same quantity.

One very important item to remember is that the multiplicative factors are made after the inputs are converted into the appropriate variances. Therefore, when a lognormal distribution is specified the v_i^2 values are added or multiplied to the inputs after they are converted to logscale variances $\tilde{\sigma}_{iky}^2$, i.e.,

Option Result

$$\begin{array}{ll}
0 & \tilde{\sigma}_{iky}^2 = \ln(\text{INPUT}_{iky}^2 + 1) * \nu_{ik}^2 \quad \text{if input value is a positive CV} \\
& \tilde{\sigma}_{iky}^2 = \ln((\text{INPUT}_{iky}/I_{iky})^2 + 1) * \nu_{ik}^2 \quad \text{if input value is a negative std. error} \\
1 & \tilde{\sigma}_{iky}^2 = \ln(\text{INPUT}_{iky}^2 + 1) + \nu_{ik}^2 \quad \text{if input value is a positive CV} \\
& \tilde{\sigma}_{iky}^2 = \ln((\text{INPUT}_{iky}/I_{iky})^2 + 1) + \nu_{ik}^2 \quad \text{if input value is a negative std. error}
\end{array}$$

Note that constant variance scenarios equivalent to the concentrated likelihood method (line 46) may be imposed by use of the additive structure with INPUT=0 or by use of the multiplicative structure with INPUT=1.

Constraints on vulnerability

56 The vulnerability (partial recruitment) for a subset of age groups can be constrained to change slowly over the last several years of the time series. The number of years included in the penalty (n) is entered first, followed by the log-scale standard error σ_v (which controls the severity of the penalty) and the youngest age (α) and oldest age (A). If n is less than 2, no penalty is imposed and the program does not attempt to read σ_v , α and A , so they do not need to be entered.

The penalty term that is added to the objective function is a correlated random walk:

$$\sum_{y=Y-n+2}^Y \sum_{a=\alpha}^A \left\{ 0.5 \left(\frac{\ln v_{k,a,y} - \ln v_{k,a,y-1}}{\sigma_v} \right)^2 + \ln \sigma_v \right\} \quad , \quad (3.5)$$

$$v_{k,a,y} = \frac{F_{k,a,y}}{\max_a F_{k,a,y}}$$

where Y is the last year in the time series and v is the relative vulnerability. Note that the maximization in the vulnerability computation is over all ages, not just those from α to A . Also, the penalty is on the relative vulnerability, not the fishing mortality rates themselves (which are more likely to vary from year to year owing to changes in effort).

The vulnerability penalty can be very useful in situations where there are few data covering several age groups during the recent time period. Usually, the VPA solution can be stabilized by linking the last two or three years with a σ_v between 0.2 and 1.0, although one should be careful not to impose values of σ_v too much smaller than the standard errors of the indices abundance or the penalty will dominate the objective function. Furthermore, I do not recommend the use of a σ_v value much below 0.2 because the VPA must achieve an exact match to the catch-at-age and, if the penalty is too strong, sometimes will require rather strange solutions to do so. Again, this is strictly an artifact of having to match the catches exactly. Of course the value of σ_v should be large (> 1.0) if there is evidence to suggest that the vulnerability has changed substantially during the last n years of the time series. Alternatively, one could set $n =$

0 to eliminate the vulnerability penalty altogether and then fix the partial recruitments to some predetermined values (see discussion of line 41 in the parameter file).

Constraints on recruitment

62 The recruitments R (abundance of youngest age group) can be linked as a correlated random walk. The number of years included in the penalty (n) is entered first, followed by the log-scale standard error σ_R (which controls the severity of the penalty):

$$\sum_{y=Y-n+2}^Y \left\{ 0.5 \left(\frac{\ln R_{k,y} - \ln R_{k,y-1}}{\sigma_R} \right)^2 + \ln \sigma_R \right\} . \quad (3.6)$$

As with the vulnerability penalty above, this recruitment penalty is most useful where there is little information to determine the last several recruitments (which is almost always true). A strong penalty can force nearly constant recruitment over the most recent two or three years, but earlier recruitment estimates are seldom affected, even when n is set to include the entire time period, owing to the well known convergent properties of VPA. However, bizarre solutions can arise if the penalty is too strong ($\sigma_R \ll 0.1$) because the penalty will try to force essentially constant recruitment, but the VPA must still match the catches.

63 The recruitments R of the two separate stocks may be linked by the penalty term

$$\sum_{y=Y-n+2}^Y \left\{ 0.5 \left(\frac{\ln rR_{2,y} - \ln R_{1,y-1}}{\sigma_r} \right)^2 + \ln \sigma_r \right\} \quad (3.7)$$

Here n refers to the number of years to link (including the most recent year Y), σ_r is the standard error and r is the recruitment ratio (number of recruits from stock 1 divided by the number from stock 2). The entries for σ_r and r are not read if n is set to 0.

The main purpose for this penalty is to accommodate situations where the growth and fishing pressure on a stock may differ by sex, but the sex ratio is fixed at the time of recruitment. Restrepo and Porch (2000) applied this penalty to Atlantic swordfish and found that it had a strong effect on the recruitments during the most recent years, but little effect farther back in time (again, owing to the well known convergent properties of VPA). As with the other penalties, setting σ_R much lower than 0.1 can lead to aberrant solutions and poor fits to the data.

Constraint on spawner-recruit relationship

72 This constraint penalizes departures from the Beverton and Holt (1957) spawner-recruit relationship assuming a first-order autoregressive error structure. It is invoked by entering either 1, 2, -1, or -2; followed by the first and last years corresponding to the range of recruitments one wishes to use (ψ and Ψ):

$$\sum_k \frac{1}{2\sigma_{BH,k}^2} \left[(1 - \rho_k^2) \varepsilon_{k,\psi}^2 + \sum_{y=\psi}^{\Psi-1} (\varepsilon_{k,y+1} - \rho \varepsilon_{k,y})^2 \right] + n_k \ln \sigma_{BH,k} - \frac{\ln(1 - \rho_k^2)}{2} \quad (3.8)$$

where the form of the ε 's depends on the distribution specified by the first entry

$$\varepsilon_{k,y} = \begin{cases} \ln(R_{k,y}) - \ln\left(\frac{a_k SSF_{k,y-\alpha}}{b_k + SSF_{k,y-\alpha}}\right) & \text{lognormal (entry = 1 or -1)} \\ R_{k,y} - \frac{a_k SSF_{k,y-\alpha}}{b_k + SSF_{k,y-\alpha}} & \text{normal (entry = 2 or -2)} \end{cases} \quad (3.9)$$

Here n_k is the number of spawner-recruitment pairs, α is the youngest age in the VPA, and SSF is the average spawning stock fecundity computed from user-supplied fecundity-at-age data as described for line 147 in the data file section. The variables a and b are parameters of the Beverton and Holt spawner-recruit relationship and ρ is the correlation coefficient, all three of which must be specified in the parameter file. The term σ_{BH} , which refers to the standard error of the random component of the recruitment deviations, may either be specified in the parameter file (if the first entry is 1 or 2) or else estimated by the concentrated likelihood approach (if the entry is -1 or -2):

$$\sigma_{BH,k}^2 = \frac{1}{n_k} \left[(1 - \rho_k^2) \varepsilon_{k,\psi}^2 + \sum_{y=\psi}^{\Psi-1} (\varepsilon_{k,y+1} - \rho \varepsilon_{k,y})^2 \right] \quad (3.10)$$

As for the previous two stock-recruitment penalties, most of the effect is on the recruitment estimates for the most recent years. Strong effects on the early part of the time series are usually not achieved without a very strong penalty (under about 0.1), in which case there is a danger of bizarre solutions because of the conflicting need to match the catch-at-age history exactly.

Parameter estimation options

78 The parameters for each age group a on the last year Y may be represented by the fishing mortality rate in that year $F_{a,Y}$ (entry = 1) or the abundance at the beginning of the next year after mixing $N_{a+1,Y+1}$ (entry = 2). Normally the first option is to be preferred because it is easier to guess the magnitude of F than of N , but the latter is useful to facilitate comparisons with older ADAPT programs.

79 This option allows one to estimate the catchability parameters q_{ki} by the concentrated likelihood approach (enter 0) rather than include them in the search list specified by the parameter file (enter 1). The concentrated likelihood approach is computationally more efficient and generally is the method of choice if one is willing to assume catchability does not change with time. Otherwise, one should specify the q 's in the parameter file.

The concentrated likelihood approach is available for three distributions:

$$q_{ik} = \left\{ \begin{array}{l} \exp \left[\frac{\sum_y \frac{\ln I_{iky} - \ln(\sum_a v_{ikay} w_{ikay} \tilde{N}_{kay})}{\tilde{\sigma}_{iky}^2}}{\sum_y \frac{1}{\tilde{\sigma}_{iky}^2}} \right] \quad \text{lognormal} \\ \frac{\sum_y \frac{I_{iky} \sum_a v_{ikay} w_{ikay} \tilde{N}_{kay}}{\sigma_{iky}^2}}{\sum_y \frac{(\sum_a v_{ikay} w_{ikay} \tilde{N}_{kay})^2}{\sigma_{iky}^2}} \quad \text{normal} \\ \frac{\sum_y I_{iky}}{\sum_y \sum_a v_{ikay} w_{ikay} \tilde{N}_{kay}} \quad \text{Poisson} \end{array} \right. \quad (3.11)$$

If the chi-square, Laplace or gamma distributions are selected for the indices (see Table 4), then one should specify the q 's in the parameter file (otherwise the program will substitute the concentration formula for the normal distribution).

Bootstrap analyses

86 This is the number of bootstraps you wish to conduct. A positive integer indicates they are to be nonparametric bootstraps and a negative integer indicates they are to be parametric bootstraps (e.g., entering -500 would tell the program to do 500 parametric bootstraps). Of course an input value of 0 means no bootstraps are to be conducted. If you chose to conduct a nonparametric bootstrap, then you must enter another integer on the same line that specifies whether or not to inflate the bootstrap residuals by use of the Stine correction factor discussed in regards to equations 2.20 - 2.23 (1 = yes, do it; 0 = no, do not do it).

Retrospective analyses

90 This entry specifies the number of years to go back for annual retrospective analyses (up to 20). The program automatically removes one year from the data and relevant parameters and then performs the VPA on the reduced data set. This procedure is repeated in annual steps until the data are reduced by the specified number of year (no retrospective analyses will be conducted if a 0 is entered). The results from each successive retrospective run (\underline{x}) are written to files with the same format as the output files from the base run: MINUS \underline{x} .R gives the diagnostic output, MINUS \underline{x} .EST gives the parameter estimates, and MINUS \underline{x} .SPD gives the spreadsheet friendly output (see the explanation of the output files in chapter 4).

One potential pitfall of automating this process occurs when some of the data do not go as far back in time as the specified retrospective analyses. For example, suppose there is an index of abundance that only goes back 7 years and you are attempting to estimate both a catchability q and standard error σ for that index. The fifth retrospective run will have to estimate those two parameters from only two index points and any subsequent run will not be able to estimate them at all. A similar problem would be encountered when estimating tagging parameters from too few data. The user should be mindful that the program will attempt to run retrospective VPA's regardless of whether they make sense or not. The nonsensical results should be evident from the output files and the user should consider setting up those retrospective analyses by hand.

Note that you cannot run a retrospective analysis and a bootstrap analysis with the same call to the program. You will need to initiate two different runs with the same random number seed (line 38 above), one with the control file pointing to retrospectives and another with it pointing to bootstraps

91 The @ symbol is read as the end of the file, but is not necessary here.

CATCH DATA FILE: Appendix 2

This file contains all the information pertaining to the data used in the VPA with the exception of the tag-recoveries. One feature that distinguishes the format of this file from the control and parameter files is the use of negative entries to demarcate the end of a data input stream.

Remember, the line numbers given here are only for referencing the example file in Appendix 2; they will change depending on the placement of comments and the length of the data series. What is important is to enter the data and specifications in the correct order, not the specific line number.

Line Explanation

Comments

1 - 6 Comments preceded by the # symbol in the first column.

General specifications

7 The first and last year in the data. It is not necessary to use four digit years, but of course you must be consistent in whatever accounting you use.

8 The youngest and oldest age classes in the data followed by the age of the plus-group. If the plus-group is less than the oldest age, the program reads the data from the youngest age to the oldest age and automatically accumulates the catch of age classes greater than or equal to the plus-group. If there is weight information given in the data file, the average weight of the plus-group is computed from the weights of the older age classes as leveraged by the corresponding catches (see discussion of lines 141 and 147). The oldest age is then reset to the value of the plus-group and all subsequent calculations use the plus-group age as the maximum age. (This makes it easier to examine the effect of changing the age of the plus-group).

Input for first stock/zone

9-11 These comments remind the user to begin inputting all the data that pertains specifically

to the first zone or stock in the analysis. If only one zone/stock is specified in the control file, then the information will only be read for that one zone and the user can disregard the comment on line 174.

- 12 Number of indices of abundance (or mortality) to be read. This should include any indices that you list later in the data file, even if you do not intend to use them in the analysis.
- 13 Spawning date ($spawntime_k$), in months elapsed. A value of 0 indicates the beginning of the year and a value of 12 indicates the end of the year (but before mixing occurs, if applicable).
- 14 Fecundity modifier (MAT) for each age class. This is used to determine the spawning stock fecundity SSF as follows:

$$SSF_{kay} = \begin{cases} \sum_a MAT_{ka} FEC_{kay} N_{kay} e^{-Z(spawntime_k/12)} & \text{if } spawntime_k \geq 0 \\ \sum_a MAT_{ka} FEC_{kay} N_{kay} \frac{(1 - e^{-Z})}{Z} & \text{if } spawntime_k < 0 \end{cases} \quad (3.12)$$

where the fecundity information (FEC) is specified at the bottom of the file (line 147). The fecundity modifier can be used, for example, as an index of maturity when computing spawning stock biomass from weight information.

- 17 Title of the stock/zone to which the following catch data apply (must be 50 characters or less) followed by the probability density (pdf) the catch data are expected to follow and a measure of its standard error σ_C (a positive value is interpreted as a CV and a negative value as a standard error). The pdf and σ_C specifications are only used if a bootstrap analysis is specified in the control file. If the pdf is set to 0 the catches are held constant, otherwise a parametric bootstrap of the catches is carried out according to the specified distribution (where the expectation is set equal to the observed catch at age). The options available for the pdf are summarized in Table 6.

Catch data input

- 22 - 46 Here is where the catch at age vectors are input. Each line must include the year followed by the catch observations for every age class from youngest to oldest (recall that if the age of the plus-group is less than the oldest age indicated on line 8, then the program will read from youngest to oldest and automatically combine the catches into a plus-group).

Years with no catch need not be input; the missing years will automatically be assigned catch-at-age values of 1.0. Also, catch-at-age entries that are less than or equal to zero are replaced by a value of 1.0. Zero catches are not acceptable because the explicit VPA recursion would be undefined, so a small value of 1 fish is used instead. If vectors for the same year are entered on more than one line, the catches corresponding to the last line with that year will be used.

- 47 A negative value (e.g., -1) must be entered after the catch-at-age matrix to tell the program to move on to the index specifications.

Table 6. Probability density functions available for parametric bootstraps of catch and index data. In case of catch data the expectation μ is set equal to the observed catch-at-age, whereas with the index data μ is set equal to the model prediction of the index value. The methods of generating the variables are described in Law and Kelton (1982).

Option	Mathematical representation	How x is generated
1: lognormal	$\frac{1}{\sqrt{2\pi\tilde{\sigma}^2}x} e^{-0.5(\log_e [x] - \mu)^2 / \tilde{\sigma}^2}$	polar method to get normal variate y , then take $x = e^y$
2: normal	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-0.5(x - \mu)^2 / \sigma^2}$	polar method
4: Poisson	$\frac{\mu^x e^{-\mu}}{x!}$	Law and Kelton (1982)
7: uniform	$\begin{cases} \frac{1}{\sqrt{12}\sigma} & \text{for } \mu(1 - \frac{\sqrt{3}\sigma}{\mu}) \leq x \leq \mu(1 + \frac{\sqrt{3}\sigma}{\mu}) \\ 0 & \text{otherwise} \end{cases}$	3 linear congruential generators (see Press et al., 1995)
8: triangular (centered at μ)	$\begin{cases} \frac{x - \mu + \sqrt{6}\sigma}{6\sigma^2} & \text{if } -\sqrt{6}\sigma \leq x - \mu \leq 0 \\ \frac{\mu + \sqrt{6}\sigma - x}{6\sigma^2} & \text{if } 0 \leq x - \mu \leq \sqrt{6}\sigma \\ 0 & \text{otherwise} \end{cases}$	Law and Kelton (1982)

Index specifications

56-57 There are 8 entries on each line that tell the program how to interpret the index time series that follow. There should be one line for each index. The **first entry** identifies the index and must be an integer between 1 and the number entered on line 12.

The **second entry** identifies the error structure one wishes to employ (see Table 6) and must be one of the following choices: 0 = do not use this index, 1 = lognormal, 2 = normal, 4 = Poisson, 5 = robust Chi-square, 6 = Laplace double exponential, 7 = gamma, 12 = standard normal. Please note, however, that only the lognormal, normal and Poisson forms can be used for parametric bootstraps. The last choice, 12 = standard normal, uses the same formula as choice 2 (normal), but the input data are interpreted as standard normal deviates created by subtracting the series mean from each observation and then dividing by the series standard deviation. I included this option because I have encountered situations where the only available indices had been standardized in this manner. However I recommend against the use of this standardization approach if at all possible inasmuch as the difference between a fairly flat trend with low variance and a steep trend with high variance is obscured.

The **third entry** is an integer that specifies the units of the index as follows:

<u>Option</u>	<u>Prescription</u>
1	index of abundance in numbers
2	index of biomass (abundance in terms of weight)
3	index of relative fishing mortality rate, $\text{Max}\{F_y\} - F_y$
4	index of relative total mortality rate, $\text{Max}\{Z_y\} - Z_y$
5	index of absolute fishing mortality rate
6	index of absolute total mortality rate

The first two options relate to indices of abundance and correspond to Table 3, where for choice (1) $w_{kiay} = 1.0$ and for choice (2) w_{kiay} = the weight-at-age specified later in the data file. Options 3, 4, 5 and 6 relate to indices of mortality and correspond to Table 4.

The **fourth entry** is an integer that specifies the method that is to be used to determine the index-specific vulnerability vector v_{ikay} . There are three basic choices here:

<u>Option</u>	<u>Prescription</u>
1	Vulnerability vector read as input (line 111)

$$2 - 3 \quad v_{ikay} = \frac{C_{ikay} F_{kay} / C_{kay}}{\text{MAX}_a \{C_{ikay} F_{kay} / C_{kay}\}} \quad (3.13)$$

$$4 \quad v_{ika} = \frac{\sum_y C_{ikay} F_{kay} / C_{kay}}{\text{MAX}_a \left\{ \sum_y C_{ikay} F_{kay} / C_{kay} \right\}} \quad (3.14)$$

When options (3) or (4) are selected, the values read from the file (see line 111) are assumed to be the fishery-specific (partial) catches C_{ikay} . When option (2) is selected, the values from line 111 are assumed to be the fractions C_{ikay}/C_{kay} (but otherwise the

computations are identical to option 3). The value of F_{kay} is the fishing mortality rate estimated by the VPA at the current iteration.

Option 1 should be used whenever the index represents a single age class, in which case one would normally assume the vulnerability is constant at 1.0 (the default value if no vulnerabilities are input). Option 1 is the only option available for indices of mortality. The choice between options 2 or 3 (Powers and Restrepo, 1992) and option 4 (Geromont and Butterworth, 1999) depends upon how stable one believes the vulnerability-at-age vector is likely to be. The former allows the vector to change from year to year whereas the latter assumes it is constant over all of the years covered by the index. One may be tempted to go with the seemingly more flexible approach of option 2-3, however it turns out that option 4 nearly always produces a better fit to the indices of abundance (and a lower value of the objective function). There reasons for this are two inherent inconsistencies in the method of options 2-3. The first inconsistency arises because the partial catches are usually observed with some error and yet must be matched exactly; large random errors in the partial catches will tend to skew the estimated vulnerabilities too far towards younger ages in some years and too far towards older ages in other years, making it difficult for the model to fit the index data. The method of option 4 will tend to average these random errors away. The second inconsistency arises with the usual practice of holding the catchability coefficient q constant. In point of fact, one would expect a change in S to be accompanied by an effective change in q since some of the same factors affect both; one would, for example, generally expect very different q values to accompany the relative vulnerability vectors $v=\{1,1,1,1,1\}$ and $v=\{0,0,0,0,1\}$. However, when option 4 is used and q is at the same time held constant, this likely scenario is ruled out, creating a potentially serious model mis-specification problem. In general, I do not recommend the use of options 2 and 3 unless q is allowed to vary from year to year (see the discussion on specifications for the q parameters in the parameter file).

The **fifth entry** specifies when the index observations were made in terms of months elapsed ($indextime_{ki}$). A negative integer (e.g., -1) indicates the observations represent the average abundance during the year. The value of $indextime_{ki}$ is used to determine the value of the adjustment factor Δ :

$$\Delta = \begin{cases} e^{-Z_{kay}(indextime_{ki} / 12)} & \text{if } indextime_{ki} \geq 0 \\ \frac{1 - e^{-Z_{kay}(indextime_{ki} / 12)}}{Z_{kay}} & \text{if } indextime_{ki} < 0 \end{cases} \quad (3.15)$$

The **sixth** and **seventh entries** give the youngest and oldest age represented by the index. The oldest age should not exceed the age of the plus-group. The **eighth entry** is the title of the index you want to appear in the output (must be 50 characters or less).

58 Again, a negative value (e.g., -1) must be entered after the index specifications to tell the program to move on to reading the index data.

Index data

63-105 Here the actual values of the indices of abundance or mortality are read. The **first entry**

is the integer identifying the index and the **second entry** is the year. The **third entry** is the value of the index, which is ignored if it is negative unless the standard normal option is selected. The **fourth entry** is interpreted as a coefficient of variation if it is positive and a standard error if it is negative. It corresponds to the value labeled $INPUT_{iky}$ in the discussion on line 47 of the control file.

106 A negative value (e.g., -1) must be entered after the index specifications to tell the program to move on to reading the vulnerability data.

Index vulnerability information

111-135 Here the values of the vulnerabilities or partial catches for the indices are read. The **first entry** is the integer identifying the index and the **second entry** is the year. After these must come the vulnerability-at-age vector for that year, starting with the youngest age and continuing to the oldest age (as per line 8). If no lines are input for a given index or year a value of 1.0 is assumed for all ages (thus you do not need to list an index where the vulnerabilities are the same for all ages in all years).

If the plus-group age is less than the oldest age and the inputs are fixed vulnerabilities, the vulnerability given for the plus-group age will be used. Otherwise, the partial catches or fractional catches of the age classes older than the plus-group age will be combined into the plus-group. Whether the values are read as vulnerabilities, partial catches or catch fractions is specified by the fourth entry on line 56.

136 A negative value (e.g., -1) must be entered after the index specifications to tell the program to move on to reading the index weight data.

Index weight information

141 Here the weight-at-age vectors for the indices are read. This information is only used if the third entry on line 56 is set to 2 (for biomass units). The **first entry** is the integer identifying the index and the **second entry** is the year. After these must come the weight-at-age vector for that year, starting with the youngest age and continuing to the oldest age (as per line 8). If the plus-group age is less than the oldest age, the weight of the plus-group is computed from the partial catches if they are available and the total catch otherwise, i.e., as $\sum C_{ikay} w_{ikay} / \sum C_{ikay}$ or $\sum C_{kay} w_{ikay} / \sum C_{kay}$.

142 A negative value (e.g., -1) must be entered after the index specifications to tell the program to move on to reading the fecundity data.

Fecundity information

147 Here the fecundity-at-age data are entered (the variable *FEC* discussed in connection with line 14 and equation 3.12). This can be weight-at-age for computation of spawning stock biomass or the per capita fecundity (e.g., average gonad weight, average number of eggs per female, etc.). The **first entry** is the integer identifying the index and the **second entry** is the year. After these must come the fecundity-at-age vector for that year, starting with the youngest age and continuing to the oldest age (as per line 8). If the plus-group age is less than the oldest age, the fecundity of the plus-group is computed from the total catch as $\sum C_{kay} FEC_{kay} / \sum C_{kay}$.

172 A negative value (e.g., -1) must be entered after the index specifications to tell the program to move on to the next zone/stock.

Input for second stock/zone

173-175 These comments remind the user to begin inputting all the data that pertains specifically

to the second zone or stock in the analysis. If only one zone/stock is specified in the control file, then any information entered from here on will not be read. Otherwise, the information in lines 12 to 172 will need to be repeated for the second stock (the number of lines will of course change, but the order and formats must be identical to those used for the information on lines 12 to 172).

TAG RECOVERY FILE: Appendix 3

This file contains all the information pertaining to the tag-recovery data. The example in Appendix 3 has been abridged to appear as though there were only two years of releases and 6 years of recoveries; the reader is reminded that the line numbers given here are only for referencing the example file in Appendix 3; they will change depending on the placement of comments and the length of the data series. What is important is to enter the data and specifications in the correct order, not the specific line number.

Line Explanation

Comments

1 - 17 Comments preceded by the # symbol in the first column.

Release information

7-53 Here you must indicate the zone, year, and integer age of the fish when they were tagged and released (in that order), which defines the tag-release cohort τ . On the same line, this information must be followed by the number of fish tagged, the average time of the year when they were tagged (in months), and a weighting factor. The average time of the year (t_τ) is used in the calculation to determine the fraction of the fishing year that this group of tags was exposed to (see discussion of line 34 in the control file and equation 3.2).

The weighting factor is used to discount tag-recovery information that is deemed somehow less reliable than that of other cohorts (one might wish to do this, for example, if the number of releases that survived the tagging process that year was more uncertain than in other years). It takes the form of a variance (ω_τ^2 in Table 5). If you do not wish to include any special weighting, just set all the ω_τ^2 values to 1.0, otherwise values greater than 1.0 will decrease the weight attributed to the tagging data for that cohort (one can also down-weight the entire tagging data set using the default weighting factor discussed on line 32 of the example control file).

54 A negative value (e.g., -1) must be entered after the release information to tell the program to move on to reading the recovery data

Recovery data

64-135 Here you must indicate the zone, year, and integer age of the fish when they were tagged and released (in that order), which defines the tag-release cohort τ . On the same line, this information must be followed by the zone of recovery and the number of tags recovered from the cohort in that zone during each year of the analysis—not just the years of the tagging experiment, but the first and last years indicated in the catch data file. Thus, there should be zero values for every year prior to the year when the fish in that cohort were tagged. For example, in the sample tag data file there is a 0 value for the column

labeled 1975 for all of the tag cohorts released in 1976 (it is not possible to recapture a tag before it was released, so a zero is entered).

136 A negative value (e.g., -1) can be entered after the recovery information to tell the program to stop reading data.

PARAMETER SPECIFICATIONS FILE: Appendix 4

This file determines how the parameters of the model will be estimated. The format for all parameter specifications is as follows:

```

lower bound
|
|
|
0.1
|
|
|
best estimate (prior expectation)
|
|
|
1.2
|
|
|
upper bound
|
|
|
2.0
|
|
|
method of estimation
|
|
|
1
|
|
|
log-scale standard error of prior
|
|
|
0.1 {anything after the fifth entry is not read}

```

There must be one line of specifications for each parameter, however several consecutive parameters with exactly the same prescription may be represented by a single line if it is preceded by a \$ symbol in the first column followed by an integer value that indicates the number of parameters the line represents. For example, writing the line

```
$ 3 0.1 1.2 2.0 1 0.1
```

is equivalent to writing

```
0.1 1.2 2.0 1 0.1
0.1 1.2 2.0 1 0.1
0.1 1.2 2.0 1 0.1
```

The lower bound (l) refers to the lowest reasonable value of the parameter you will accept, the best starting estimate (b) refers to the value of the parameter you think is most likely, and the upper bound (u) refers to the highest reasonable value of the parameter you will accept. Solutions with parameter values (θ) that are outside the upper and lower bounds incur a penalty,

$$penalty = \begin{cases} 10 + 1000 \left(\frac{\theta - u}{b} \right)^2 & \text{if } \theta > u \\ 10 + 1000 \left(\frac{\theta - l}{b} \right)^2 & \text{if } \theta < l \end{cases}, \quad (3.16)$$

which is added to the objective function. This usually helps the search algorithm find a solution faster by forcing it to concentrate on parameter values within the feasible range. A judicious choice for the starting value b will also usually improve the search algorithm's performance.

The 'method of estimation' indicator tells the program how to handle each parameter θ_j :

Method	Parameter structure	
0	$\theta_j \equiv b_j$	fixed constant at best starting guess
1	$\theta_j = \theta_j$	estimated as 'frequentist' parameter (no Bayes prior)
2 (0.3)	$\theta_j = b_j e^{\varepsilon_k}$	estimated with Bayes prior
3 (0.1)	$\theta_j = \theta_{j-1} e^{\varepsilon_j}$	estimated with correlated process error (random walk)
4 (0.2)	$\theta_j = \theta_{ref} e^{\varepsilon_j}$	estimated with uncorrelated process error
-0.1	$\theta_j = \theta_{est}$	set to value of the closest previous estimated parameter
-n	$\theta_j = \theta_n$	set to value of n th parameter in the list (whether estimated or not)

where $\varepsilon_k \rightarrow \text{Normal}(0, \tilde{\sigma}_k)$

Note: the Bayesian method designations in parentheses--0.1, 0.2 and 0.3--were used in previous versions of VPA-2BOX and are still accommodated (i.e., the old parameter files can still be used). The variable θ_{ref} refers to the closest previous parameter determined by any method other than method 4 (an uncorrelated random deviation from the preceding uncorrelated random deviation becomes effectively a random walk). The variable θ_{est} refers to the closest previous parameter that was actually estimated (methods 1 to 4). The variable $\tilde{\sigma}_k$ is the log-scale standard error and is specified by the last entry on the parameter specification line (which is read but not used with options 0, 1, -n, and -0.1).

The choice of methods 1 to 4 causes the program to estimate the parameter by searching for the value that minimizes the objective function. Method 1 takes the usual frequentist approach of minimizing the negative log-likelihood function that measures the discrepancy between the data and the model predictions (subject to the constraints discussed in the description of the control file). Methods 2, 3 and 4 however, expand the objective function to include terms that penalize discrepancies between the parameter estimates and their preconceived values:

Method	Term added to objective function
2 (0.3)	$0.5 \left(\frac{\ln \theta_k - \ln b_k}{\tilde{\sigma}_k} \right)^2 + \ln \tilde{\sigma}_k$
3 (0.1)	$0.5 \left(\frac{\ln \theta_k - \ln \theta_{k-1}}{\tilde{\sigma}_k} \right)^2 + \ln \tilde{\sigma}_k$
4 (0.2)	$0.5 \left(\frac{\ln \theta_k - \ln \theta_{ref}}{\tilde{\sigma}_k} \right)^2 + \ln \tilde{\sigma}_k$

Method 2 invokes a lognormal Bayesian prior for the parameter centered on the input best guess b and having a log-scale standard error of $\tilde{\sigma}_k = \sqrt{\log_e(CV^2+1)}$. This construct is useful when there

is some external information on a parameter, but additional insight may be gained from the data used in the VPA. For example, the natural mortality rate is notoriously difficult to estimate and is usually fixed to some predetermined constant. An alternative is to impose a prior centered at that predetermined value with a variance term that reflects its uncertainty.

Methods 3 and 4 may be interpreted as autocorrelated process errors with correlation coefficients of 1 and 0, respectively (see section xx). From this perspective the parameter θ_k is viewed as a state variable (see Chapter 2, Parameter Estimation) with expectation θ_{k-1} or θ_{ref} (if θ_{ref} is estimated). The two methods are identical when $\theta_{ref} = \theta_{k-1}$, however they have very different implications when a long series of parameters are linked. Generally, one should chose method 3 (known as a random walk; see Porch, 1999) if there is likely to be a consistent trend and method 4 otherwise. For example, the catchability coefficient q of a catch per unit effort series might be expected to increase through time owing to technological improvements made by the fishing fleet, in which case one might prefer the random walk. On the other hand, the catchability coefficient for a research survey might be expected to be devoid of any trends yet still vary owing to fluctuations in the spatial distribution of the stock relative to the locations where the survey was conducted, in which case method 4 might be preferred.

The process error approach tends to the frequentist approach as the process variance becomes either very small ($\tilde{\sigma}_k \rightarrow 0$) or very large ($\tilde{\sigma}_k \rightarrow \infty$). In case of the former, it is as if only θ_{ref} were being estimated, whereas in the case of the latter it is as if one were trying to estimate every θ_k , as a free parameter (generally impossible because of insufficient data). Thus, moderate values of $\tilde{\sigma}_k$ (say between 0.1 and 1.0) can be thought of as a middle ground adding flexibility to the model while still preserving the estimability of the parameters. The best choice for $\tilde{\sigma}_k$ depends on how many other parameters are being estimated, what data are available, and how variable the state variables are likely to be. The bootstrap and other diagnostic tools may give some insight as to when the value of $\tilde{\sigma}_k$ is too large, but the choice is really more of an art than a science.

As mentioned previously, all of the parameters in this file are represented in the same fashion (with one exception to be discussed). However, the order of parameter input is very important. The following discussion is based on the file in Appendix 4 and the reader is reminded that the line numbers given here are only for referencing that example; they will change depending on the placement of comments and the number of parameters. What is important is to enter the specifications in the correct order, not the specific line number. It is also important to recognize that a single parameter can be used to represent several categories (age class, year, or index) simply by estimating the value for one category and then using the -0.1 or -n method prescriptions to set subsequent parameters equal to that estimated value. Also, one should take care not to try to estimate parameters where there is no data to do so, as might happen if you try to estimate the variance scaling factor for an index that you have in the data file but told the program not to use (by setting the pdf in the data file to 0).

Line Explanation

Comments

1 - 40 Comments preceded by the # symbol in the first column.

Terminal-year parameters

41-47 The parameters for each age group a on the last year Y may be represented by the fishing

mortality rate in that year $F_{a,Y}$ or the abundance at the beginning of the next year after mixing $N_{a+1,Y+1}$, depending on the prescription on line 78 of the control file. Each age must be represented by one specification line with the exception of the oldest age, which is represented by the F-ratio parameter discussed in connection with line 51. Thus, the youngest age is represented by the first parameter (first specification line) in the file.

The format used to specify the terminal-year parameters is the same as for the other parameters below, with one exception. If the method indicator is set to 0 and the value of the best estimate is less than 9, then the best estimate is interpreted as the vulnerability on that age a relative to a reference age j (which is entered in place of the standard deviation) such that $F_{a,Y} = b_a F_{j,Y}$.

If the option to estimate $N_{a+1,Y+1}$ (rather than $F_{a,Y}$) is chosen, then the specifications for $N_{a+1,Y+1}$ are entered in the same position as for $F_{a,Y}$ and the reference age j must still refer to the age during the terminal year (not the age +1). Note that when the overlap model is specified, the program will attempt to solve for $F_{1,a,Y}$ and $F_{2,a,Y}$ simultaneously from $N_{1,a+1,Y+1}$ and $N_{2,a+1,Y+1}$; therefore the same age groups must be used for both stocks (an error message will be generated if you attempt otherwise).

The terminal parameters for the first three or four age groups tend to be rather poorly determined because they are affected by relatively few data points, but their estimability can be improved by implementing the vulnerability or recruitment constraints discussed in the control file. Where those constraints do not seem plausible, one may fix the relative vulnerabilities to some predetermined values and link them to a reference age that can reasonably be estimated.

In the example file (Appendix 4), line 41 tells the program that $F_{1,Y} = 0.2 F_{2,Y}$ and line 42 tells the program to estimate $F_{2,Y}$ with a starting value of 0.4886. Lines 43 to 46 likewise tell the program to estimate the F's on ages 3 to 6, but line 47 tells the program to link age 7 to age 6 such that $F_{7,Y} = 0.9 F_{6,Y}$.

F-ratio parameters

51 This is the ratio of the fishing mortality on the plus-group to the next younger age, $\phi_{ky} = F_{k,A,y}/F_{k,A-1,y}$. There must be one F-ratio specification for each year. Typically the values are fixed to 1.0 unless there is some compelling biological reason to suggest otherwise. VPA-2BOX allows separate values of ϕ_{ky} to be estimated as free parameters for every year, but this is seldom practical owing to the scarcity of data. Generally one will have to limit the number of parameters by assuming ϕ_{ky} is constant during several blocks of years or limit the amount ϕ_{ky} can vary from year to year by use of the process error formulations with moderate $\tilde{\sigma}_k$.

Natural mortality parameters

57 One natural mortality parameter M_{ka} must be specified for each age class (inter-annual variations are not accommodated). In the example file there are two M parameters being estimated, one for age 1 and another for age 2 and older (both with starting values of 0.3). In general, the natural mortality rate will not be well-estimated unless the indices of abundance cover a time without fishing or the tag-recovery data come from a well-executed experiment. In most cases it will be necessary to impose informative Bayesian priors on the M_{ka} 's or else fix them to some externally derived constants.

Mixing parameters

61 One mixing parameter T_{ka} must be specified for each age class (inter-annual variations are not accommodated). These parameter are very unlikely to be well-estimated without tag-recovery data, in which case one must either fix them or impose tight Bayesian priors. If the one stock option is chosen these parameters are read, but ignored.

Stock recruit parameters

65-69 Here are specified five parameters that dictate the autocorrelated stock recruit relationship discussed in connection with line 72 of the control file. The first two parameters represent a_k and b_k of the Beverton and Holt (1957) spawner-recruit curve:

$$R_{k,y} = \frac{a_k SSF_{k,y-\alpha}}{b_k + SSF_{k,y-\alpha}} \quad (3.17)$$

The third specification refers to a parameter that will be used to introduce a three parameter spawner-recruit curve in a later version, but is not now being used and should have the estimation method set to 0. The fourth and fifth specifications are the correlation coefficient ρ_k and standard error σ_k ($\tilde{\sigma}_k$ in the lognormal case) of the process error, respectively. Obviously one cannot estimate any of these parameters unless the stock-recruit penalty on line 72 of the control file is turned on.

Variance scaling parameters

77-78 These are the scaling parameters v_{ik} discussed in connection with equation 2.15 and line 47 of the control file. One v parameter must be specified for each index listed in the data file. Obviously the values of the v_{ik} parameters cannot be estimated if the corresponding index is not being used, so be sure to check that the estimation method for these parameters is either set to zero or equated to a previous parameter as in the example here.

Catchability parameters

83-88 These represent the catchability coefficients for the indices of abundance and proportionality coefficients for the indices of mortality (q_{iky}). This section must not appear if the option on line 79 of the control file specifies for the q values to be estimated by the concentrated likelihood method. Otherwise, there must be one specification line for every year regardless of the number of years for which there are data. If you intend to estimate only a single value of q for all years, then you can estimate the value for the first year and set the values for the remaining years equal to that value as in lines 83-84. However, if you intend to allow q to vary from year to year, it generally does not make sense to try to estimate q for the years where there is no data and you should fix the q values for the years without data to some arbitrary constant (as done in line 88, since the second index in the corresponding data file does not include 1999) or to the value estimated in a preceding year (the program won't predict the value of the index for years with no data). If you do try to estimate a q parameter for a year with no data, the program will try to estimate it and the search algorithm will take unnecessarily long. One exception to this rule might be when the index is missing a year or two in the midst of the time series. In that case it would still be appropriate to try to estimate the q values for the missing year using one of the process error approaches (provided the imposed $\tilde{\sigma}_k$ is not too large),

Tag-recovery parameters

- 89-110 The rest of the specifications in this example file pertain to the tag recovery parameters. This section must not appear if tag-recovery information is not being used (or be placed after the @ symbol discussed below at line 111).
- 92 This line specifies the immediate loss of tags owing to misapplication or tagging-induced mortality (d_{τ} of Table 5). One parameter must be specified for each age class (inter-annual variations are not accommodated but see discussion on line 100).
- 96 This line specifies the chronic loss of tags owing to shedding or fouling (λ_{τ} of Table 5). One parameter must be specified for each age class (inter-annual variations are not accommodated). If indices of abundance are available this parameter is estimable, otherwise it is confounded with the natural mortality rate M and one may prefer to set it equal to values determined from double tagging experiments.
- 100 This line specifies the reporting rate ($\rho_{kay\tau}$ of Table 5). One parameter must be specified for each year (age-specific variations are not accommodated, but see below). Of course the parameters corresponding to years with no tag releases should be assigned arbitrary constants.

It is important to notice that this term always occurs together with d (see line 92) as the product $(1-d)\rho$ in the tag-recovery equations, therefore the two sets of parameters may not be estimated independently for every age and year combination no matter how good the tag-recovery data are. For this reason the formulation used by VPA-2BOX limits changes in d to age specific effects and changes in p to year specific effects. Together, these parameters can be thought of as constituting a separable model of the quantity $(1-d)\rho$, that is, as a model of $(1-d)\rho$ where the year/age interactions are considered negligible. With sufficient data, all of the age and year effects will be estimable. The absolute magnitudes of the d_a and ρ_y parameters however, will remain indistinguishable inasmuch as the age and year effects are multiplicative. Therefore, I recommend fixing either one of the d_a parameters or one of the ρ_y parameters to some value determined external to the model (via captive studies or tag seeding experiments) and estimating the others.

- 105-106 These are the pre-mixing adjustment factors for the first calendar year after the release $\gamma_{\tau\psi}$. Values must be specified for every age in every year (making these the most tedious parameters to specify). The example in Appendix 4 simply assumes this value is the same for every year and age of release, but one can in principle estimate different values for every year/age combination where tags were actually released (see the bluefin tuna mixing example files included with the electronic copies of this manual). Hoenig et al. (1998) points out that the values of γ can be difficult to distinguish precisely from F when only tag recovery data are available, but this should not be too serious of a problem here because F is largely determined from the catch and index data.
- 110 These are the pre-mixing adjustment factors for the second calendar year after the release $\gamma_{\tau,\psi+1}$. Values must be specified for every age in every year. The example in Appendix 4 simply assumes this value is 1.0 for every year and age of release, but one can in principle estimate different values for every year/age combination where tags were actually released (just as for the first-year pre-mixing factors).

@ The end of file indicator

111 The appearance of an @ symbol in the first column tells the program to stop reading the parameter file at that point. It is superfluous if it comes at the end of the file, but is useful if you want to store alternative parameter specifications in the same file. For example, if the concentrated likelihood method were to be used in runs that did not use the tagging data, then an @ could be placed in the first column of line 79 to avoid having delete or comment out all the q and tagging parameters.

4. OUTPUT FILES

Program VPA-2BOX always produces four output files containing the: 1) parameter estimates, 2) diagnostic statistics and derived quantities, 3) derived quantities in a spreadsheet friendly format and 4) log of performance statistics. If a retrospective analysis is conducted, then each of the first three files is reproduced for every retrospective run as explained for line 90 of the control file. If a bootstrap analysis is conducted, then a summary file is produced along with a set of binary files with the output from each individual bootstrap run.

PARAMETER ESTIMATE FILE

This format of this file is very much like that of the parameter specification file and can be used as the parameter specification file for subsequent runs simply by changing its name to the pointer in line 16 of the control file³. The only differences are that the estimated value is substituted for the ‘best guess’, the parameters are enumerated, a coefficient of variation (CV) is computed and an exponential format is used. Also, the flag BOUND appears when the parameter is close to the constraints.

lower bound	estimated value	upper bound	method of estimation	log-scale std. error of prior	parameter ID	estimate ID	CV (%)	Flag
0.0000E+00	0.6000E+00	0.3000E+01	0.0	0.2000E+01	1			
0.1000E-01	0.7337E+00	0.5000E+01	1.0	0.1000E+00	2	1	21.	
0.1000E-01	0.4999E+01	0.5000E+01	1.0	0.1000E+00	2	1	1.	BOUND

The column labeled ‘parameter ID’ identifies the numerical order of the adjacent parameter specification. The column labeled ‘estimate ID’ is similar, but refers to the numerical order of the parameters that are estimated. Both identifiers are useful when trying to reference certain error messages produced by VPA-2BOX. The parameter ID is also useful when one wishes to link one parameter to another parameter specified earlier in the file (estimation method -n discussed above).

The coefficient of variation (CV) is the standard error of the estimator divided by the value of

³Note, however, that the new estimates will be used as the central tendencies for any Bayes priors that are imposed (estimation method 2). If you wish to preserve the old priors, you will have to manually change the values in the second column to the ‘best’ values specified in the original parameter file..

the estimate, here expressed as a percentage. Typically, values of less than 10 or 20% are interpreted as indicating the parameter estimates are fairly precise, whereas values of more than 50% indicate the parameters are poorly estimated. However, it is important to realize that the standard errors are themselves estimated by inverting the Hessian matrix, which assumes the likelihood⁴ surface is quadratic near the minimum. In practice, this is only approximately true and the estimates of standard error tend to be less precise than the estimates of the parameters themselves. In extreme cases a true minimum may not have been found or the surface may be so far from quadratic that the Hessian is not positive semi-definite and estimates of the CV cannot be produced. Furthermore, the CV's will tend to be biased if the variance parameters for the indices of abundance/mortality are incorrectly specified. Hence, it is recommended that the CV's derived from the Hessian matrix not be trusted unless the variance terms for the indices are estimated (either in the search or by the concentrated likelihood method) and the Hessian appears well-behaved (see discussion on the log file below).

DIAGNOSTIC AND DERIVED STATISTICS FILE

This file contains most of the output statistics one might expect from a VPA program in a format that is easy to read. The first set of information presented is a synopsis of the model's performance:

Total objective function =	10602.56	<i>value of the negative log posterior function at its minimum</i>
(With constants) =	10602.56	<i>value of the negative log posterior with constant terms</i>
Number of parameters (P) =	73	<i>number of parameters that are estimated</i>
Number of data points (D)=	8691	
AIC : 2*objective+2p =	2531.44	
AICc: 2*objective+2p(...)=	2532.69	
BIC : 2*objective+Plog(D)=	3047.55	
Chi-square discrepancy =	869.30	
Log-likelihood (deviance)=	-10600.77 (2385.44)	<i>the values in parentheses are the deviances</i>
effort data =	-54.67 (326.16)	
tagging data =	-10546.10 (2059.27)	
Log-posteriors =	-1.79	
catchability =	0.00	
f-ratio =	-1.79	
natural mortality =	0.00	
mixing coeff. =	0.00	
initial tag survival =	0.00	
tag shedding rate =	0.00	
tag reporting rate =	0.00	
tag non-mixing factor =	0.00	
Constraints =	0.00	
terminal F =	0.00	
stock-rec./sex ratio =	0.00	
Out of bounds penalty =	0.00	

⁴The asymptotic covariance matrix is not generally given by the inverse of the Hessian matrix when informative Bayes priors or process errors are incorporated since the posterior is no longer a true likelihood. It may, however, be given to good approximation if the variances of any penalties, priors or process errors are much larger than those associated with the data observation errors (the posterior effectively reducing to a likelihood).

Explanations of these output statistics are provided in previous sections of this manual (see index). Note that the components of the objective function pertaining to the data, priors and process errors and constraints are the positive logarithms of the respective likelihood and posterior function— not the negative logarithms. Thus, a better fit is indicated by larger (less negative) values. The quantity being minimized (first entry above), therefore, is the negative of the sum of the components listed below it.

The remaining components are fairly self explanatory. The first three tables give the estimated fishing mortality rates, estimated abundances and observed catches for each year and age group.

TABLE 1.1 FISHING MORTALITY RATE FOR EAST

```

=====
          1      2      3      4      5
-----
70      0.219  0.231  0.129  0.099  0.037
71      0.011  0.281  0.267  0.112  0.098
72      0.171  0.235  0.433  0.140  0.094
73      0.145  0.178  0.200  0.111  0.042
74      0.127  0.234  0.273  0.237  0.168

```

TABLE 2.1 ABUNDANCE AT THE BEGINNING OF THE YEAR [BY AREA] FOR EAST

```

=====
          1      2      3      4      5
-----
70      839440.  407538.  256252.  207707.  305586.
71      1244733.  413005.  247664.  172667.  150988.
72      933262.  754513.  238717.  145232.  123160.
73      1313402.  481718.  456478.  118423.  100363.
74      1931654.  696225.  308705.  285930.  83930.
75      1042334.  421733.  179783.  177808.

```

TABLE 3.1 CATCH OF EAST

```

=====
          1      2      3      4      5
6         7         8         9        10
-----
70      131834.  73211.  26994.  17842.  9793.
71      10384.  88198.  50413.  16589.  12777.
72      116980.  137100.  73231.  17152.  9923.
73      140707.  68048.  71707.  11121.  3710.
74      182955.  125976.  64125.  54045.  11608.

```

A fourth table is included that gives the abundance by stock (rather than area) when the overlap model is specified for analyzing two stocks simultaneously.

The next set of tables gives the spawning stock biomass, which is computed from the weights and other specifications given in the catch data file:

TABLE 4.1 SPAWNING STOCK FECUNDITY AND RECRUITMENT OF EAST

```

=====
year      spawning      recruits
         biomass        from VPA
-----
70        161011.         839440.
71        183815.         1244733.
72        191700.         933262.
73        188799.         1313402.
74        194959.         1931654.

```

An additional column containing the expected value of recruitment from the spawner-recruit relationship is included if that constraint is employed (see discussion of line 72 in the control file).

The next set of Tables summarizes the fits to the indices of abundance and indices of mortality.

TABLE 5 FITS TO INDEX DATA EAST

```

=====
-----
5.1
-----
Lognormal dist.
average numbers
Ages 8 - 10
log-likelihood = 1.46
deviance = 64.17
Chi-sq. discrepancy= 75.96

Year  Observed  Predicted  Residuals  Standard  Q  Untransformed  Chi-square
      (Obs-pred)  Deviation  Catchabil.  Observed  Predicted  Discrepancy
-----
70    -0.456    -0.295    -0.161    0.226    0.136E-05    0.634    0.745    0.420
71    -0.177    -0.398    0.221    0.227    0.136E-05    0.838    0.672    1.156
72     0.232    -0.509    0.741    0.232    0.136E-05    1.261    0.601    21.786
73    -0.498    -0.518    0.020    0.230    0.136E-05    0.608    0.596    0.007
74    -0.708    -0.553    -0.155    0.246    0.136E-05    0.493    0.575    0.331

Selectivities by age
Year      8      9      10
-----
70    0.810  1.000  0.791
71    0.810  1.000  0.791
72    0.810  1.000  0.791
73    0.810  1.000  0.791
74    0.810  1.000  0.791

```

Note that the columns labeled ‘untransformed’ refer to the value of the indices on an arithmetic scale. They should be the same as the original input values unless the user specified in the control file that they should be divided by the series mean. The columns labeled ‘observed’, ‘predicted’, ‘residuals’, and ‘standard deviation’ contain the observed values and model predictions on a log scale when the lognormal distribution is specified in the data file, but otherwise are presented on an arithmetic scale (in which case the ‘untransformed’ columns do not appear). The chi-square discrepancy is computed for each index point for ease of identifying possible outliers (they should sum to the total given at the top of the file, but in this case the entire table has not been presented).

Finally, the last tables in this output file give the fits to the tag-recovery data:

TABLE 6.1 FITS TO TAGS RELEASED IN AREA OF EAST

Multinomial dist.
log-likelihood = -1770.26
deviance = 367.20

Release Year	Age	Recapture Area	Type	Recaptures by year following release			
				1	2	3	4
70	1	1	obsd	3.00	2.00	0.00	0.00
			pred	0.60	0.36	0.03	0.01
71	1	1	obsd	23.00	1.00	3.00	2.00
			pred	7.28	2.18	1.13	0.13

Note that chi-square discrepancy statistics are not computed for tag-recapture data.

DERIVED STATISTICS IN SPREADSHEET FRIENDLY FORMAT

This file contains the fishing mortality rate estimates, abundance estimates, observed catches, input weight at age for spawners, and the observed and predicted values of the indices. There are 100 spaces (for up to 100 years) devoted to each matrix, enabling the user to set up a spreadsheet file that need not be readjusted for every particular application. The index matrix has two columns devoted to each index for each area; the first contains the observed values and the second contains the predicted values (-9's are written as place holders where data are missing).

LOG OF PERFORMANCE STATISTICS

This file, called VPA-2BOX.LOG, records the value of the objective function after each restart of the objective function. Then it displays the results of a first derivative test to see if the proposed minimum point is in fact a local extremum (the hope of course is that it is also a minimum rather than a saddle point, in which case the Hessian matrix must also be positive semi-definite).

The first derivative test results are presented in a table that looks like the following:

```
FIRST DERIVATIVE TEST
=====
          -h          central          +h
-----
1 : -0.1003D-01  0.1703D-01  0.1904D-01
2 : -0.1001D-01  0.1621D-01  0.1821D-01
3 :  0.8303D-02  0.8309D-02  0.9315D-02      FAIL: Backward step :
```

where in this case there are three estimated parameters. If a local extremum has been found, then all of the first derivatives should be zero at that point. Owing to the large number of options available, VPA-2BOX does not compute analytical derivatives, but instead employs finite difference approximations. In that case, a good indication of whether a true minimum has been reached is if the central difference approximation is close to zero while the backwards difference (-h) is slightly negative and the forward difference (+h) is slightly positive. Several flags are written to alert the

user when these criteria are not met (as for the third parameter in the example above). Such failures may occur for a number of reasons, including (1) one or more parameters are estimated near the boundary constraints, (2) the simplex search has not found a true minimum and (3) surface of objective function is not approximately quadratic near the minimum (either very flat or very jagged). The first possibility can easily be checked by inspection of the parameter estimate file discussed above. The second possibility can be addressed by restarting the algorithm with several different initial values for the parameters; if the same minimum is found each time then it is likely that the lowest point has been found. One should also check to see if the search was terminated prematurely because the number of restarts exceeded the limit indicated in the control file. The third possibility suggests either the data are too noisy, conflicting or sparse to provide useful parameter estimates; the user should consider reducing the number of estimable parameters.

It may happen that the first derivative test above indicates that a minimum had been found, but the Hessian is not positive semi-definite and therefore not invertible. This may occur for the same reasons outline above, and the remedies are the same. When the Hessian matrix is invertible, the resulting covariance matrix is printed as well as the corresponding matrix of correlation coefficients. As mentioned previously, the covariance matrix will be biased if the variances of the index data are incorrectly specified or the objective function is not a true likelihood. Moreover, the numerical derivatives in the Hessian matrix are sometimes very sensitive to the step-size used owing to the jagged terrain of the solution surface in the vicinity of the lowest point found by the simplex algorithm (which may not be a well-behaved minima). The correlation coefficients derived from the inverse-Hessian covariances,

$$\hat{\rho}_{ij} = \frac{\hat{\sigma}_{ij}}{\hat{\sigma}_i \hat{\sigma}_j} ,$$

appear to be more stable than the covariance estimates themselves inasmuch as some of the biases cancel out. Accordingly, they are probably a more reliable indicator of the quality of the solution than the magnitudes of the covariances (correlations of 0.1 or 0.2 are considered very low, whereas correlations above 0.9 are excessively high and may indicate that some of the parameters involved should somehow be combined or eliminated altogether). In summary, I do not recommend placing much confidence in the inverse-Hessian covariance estimates or the coefficients of variation derived from them. I have found the correlation coefficients to be somewhat useful during the model development phase, but recommend the bootstrap procedure for characterizing the uncertainty in any model used to generate management advice.

BOOTSTRAP OUTPUT FILES

The file BOOTSTRP.OUT records the bias and standard error of the fishing mortality rate and abundance estimates, which are computed according to the methods discussed in chapter two. The bias and standard errors are also computed for the parameter estimates with the following format

TABLE 1E. PARAMETER ESTIMATES FOR Northern Albacore

```
=====
```

TERMINAL AGE STRUCTURE OF POPULATION ABUNDANCE					
Age	MLE	Average of bootstraps	Bias	Std. Error	% CV
2	0.125E+08	0.134E+08	0.657E+06	0.491E+07	36.6
3	0.167E+07	0.183E+07	0.118E+06	0.834E+06	45.6
4	0.784E+06	0.882E+06	0.353E+05	0.267E+06	30.3
5	0.625E+06	0.610E+06	-0.258E+05	0.155E+06	25.4
6	0.454E+06	0.433E+06	0.664E+04	0.124E+06	28.7
7	0.145E+06	0.147E+06	0.151E+05	0.700E+05	47.5
8	0.458E+06	0.492E+06	0.111E+05	0.779E+05	15.8

Here the column labeled “MLE” stands for the best (maximum likelihood or highest posterior density) estimates, the “average of bootstraps” is the mean value of the parameter estimates from all of the bootstrap runs, and the bias is computed from the “average of bootstraps” and a run using the averages of the bootstrap data as described in chapter two.

The results from each individual bootstrap run are stored in a set of 4-bit binary files (.bin extension) with the following formats:

Abundance, fishing mortality, catch, natural mortality, and transfer rate coefficients

```
record length = 4*(Y-y0+1)*(A-firstage+1)*NBOX
NAA.bin: ((N(k,a,y),y=y0,Y),a=firstage,A),k=1,NBOX)
FAA.bin: ((F(k,a,y),y=y0,Y),a=firstage,A),k=1,NBOX)
CAA.bin: ((C(k,a,y),y=y0,Y),a=firstage,A),k=1,NBOX)
MAA.bin: ((M(k,a,y),y=y0,Y),a=firstage,A),k=1,NBOX)
TAA.bin: ((T(k,a,y),y=y0,Y),a=firstage,A),k=1,NBOX)
```

Observed indices of abundance and mortality

```
record length = 4*(Y-y0+1)*(number of indices)
IND.bin ((I(i,1,y),y=y0,Y),i=1,Nind(1)),((I(i,2,y),Y=y0,Y),i=1,Nind(2))
```

Terminal vulnerabilities (during last year)

```
record length = 4*(A-firstage+1)*NBOX
TERM.bin:((Term(k,a),a=firstage,A),k=1,NBOX)
```

Stock recruitment parameters

```
record length = 4*(5+Y-y0+1)*NBOX
SR.bin:((SR(k,Y),Y=1,5+Y),k=1,NBOX)
```

where y_0 and Y are the first and last years in the model, A is the age of the plus-group, $NBOX$ is the number of zones (1 or 2), and $Nind$ is the number of indices representing each zone.

These files are useful if one wishes to use other software to compute confidence limits and alternative forms of bias correction. They may also be read into programs designed to project the VPA results into the future (such as the companion program to VPA-2BOX, called PROJECT). Note that an ASC-II file called BAD.OUT is also produced that identifies bootstrap runs that may not have converged or gave otherwise unreasonable results (which the careful investigator may wish to exclude from any further calculations).

5. LITERATURE CITED

- Anganuzzi, A., Hilborn, R. and Skalski, J. R. 1994. Estimation of size selectivity and movement rates from mark-recovery data. *Can. J. Fish. Aquat. Sci.* 51: 734-742
- Baglin, R. E., Farber, M. I., Lenarz, W. H. and Mason, J. M. 1980. Shedding rates of plastic and metal dart tags from Atlantic bluefin tuna, *Thunnus thynnus*. *Fishery Bulletin (US)* 78: 179-185.
- Block, B. A., Dewar, H., Blackwell, S. B., Williams, T., Prince, E. D., Farwell, C., Boustany, A., and Seitz, A. In press. Archival tagging of Atlantic bluefin tuna. ICCAT Coll. Vol. Sci. Pap. (SCRS/99/103)
- Brown, B., and M. L. Parrack, 1985. Status of the Atlantic bluefin tuna resource. Pages 279-289 in Stroud, R. H., ed., *World Angling Resources and Challenges*. Int. Game Fish Assoc. 390 pp.
- Brownie, C., Anderson, D. R., Burnham, K. P., and Robson, D. S. 1985. *Statistical inference from band recovery data: a handbook*. 2nd ed. U.S. Fish and Wildl. Serv. Resour. Publ. No. 156.
- Buckland, S. T., Burnham, K. P., and Augustin, N. H. 1997. Model selection: An integral part of inference. *Biometrics* 53: 603-618
- Butterworth, D. S., and A. E. Punt. 1994. The robustness of estimates of stock status for the western north Atlantic bluefin tuna population to violations of the assumptions underlying the associated assessment models. ICCAT Coll. Vol. Sci. Pap. 42(1): 192-210.
- Cooke, J. G., and K. Lankester. 1996. Examination of alternative stock distribution models for the interpretation of bluefin tuna (*Thunnus thynnus*) tag-recovery data. ICCAT Coll. Vol. Sci. Pap. 45(2): 135-138.
- Hilborn, R. 1990. Determination of fish movement patterns from tag recoveries using maximum likelihood estimators. *Can. J. Fish. Aquat. Sci.* 47: 635-643.
- Hoening, J. M., Barrowman, N. J., Pollock, K. H., Brooks, E. N., Hearn, W. S., and Polacheck, T. 1998. Models for tagging data that allow for incomplete mixing of newly tagged animals. *Can. J. Fish. Aquat. Sci.* 55: 1477-1483.
- Hurvich, C. M., and Tsai, C. 1995. Model selection for extended quasi-likelihood models in small samples. *Biometrics* 51: 1077-1084.
- ICCAT. 1994. Report for the biennial period 1992-1993. Part II (1993). 395 pp.
- ICCAT. 1995. Report for the biennial period 1994-1995. Part I (1994). 395 pp.
- Lutcavage, M. E., Brill, R. W., Skomal, G. B., Chase, B. C., and Howey, P. W. 1999. Results of pop-up satellite tagging on spawning size class fish in the Gulf of Maine: Do North Atlantic bluefin tuna spawn in the mid-Atlantic? *Can. J. Fish. Aquat. Sci.* 56: 173-177.
- Mather, F. J. 1980. A preliminary note on migratory tendencies and distributional patterns of Atlantic bluefin tuna on recently acquired and cumulative tagging results. ICCAT Coll. Vol. Sci. Pap. 11: 478-490.
- Mather, F. J., Rothschild, B. J., Paulik, G. J. and Lenarz, W. H. 1974. Analysis of migrations and mortality of bluefin tuna, *Thunnus thynnus*, tagged in the northwestern Atlantic Ocean. *Fishery Bulletin (US)* 72: 900-911.
- Mather, F. J., Mason, J. M., and Jones, A. C. 1995. Historical Document: Life history and fisheries of Atlantic bluefin tuna. 1995. NOAA Tech. Memo. NMFS-SEFSC-370. 165 p.

- NRC. 1994. Report of the National Research Council review of Atlantic bluefin tuna. National Academy Press. Washington, D.C. 148 pp.
- Porch, C. E. 1995. A two-area VPA with discrete mixing: Can we discriminate between mixing rates given the present condition of the data? ICCAT Coll. Vol. Sci. Pap. 44(1): 198-208.
- Porch, C., P. Kleiber, S. Turner, J. Sibert, R. Bailey and J. Cort. 1998. The efficacy of VPA models in the presence of complicated movement patterns. Proceedings of the 25 Anniversary ICCAT Tuna Symposium. ICCAT Coll. Vol. Sci. Pap. 50(2):591-622.
- Porch, C. E., Restrepo, V. R., Turner, S. C., and G. P. Scott. 1995. Virtual population analyses of Atlantic bluefin tuna incorporating movement and tagging data. ICCAT Coll. Vol. Sci. Pap. 44(1): 183-190.
- Porch, C. E. and S. C. Turner. 1998. Virtual population analyses of Atlantic bluefin tuna with alternative models of trans-Atlantic migration. ICCAT Coll. Vol. Sci. Pap. 49:291-305.
- Powers J.E.; Conser R.J and Parrack M.L. 1983. An assessment of Atlantic bluefin tuna resources. ICCAT Coll. Vol. Sci. Pap. 18(2): 563-611
- Powers, J. E., and J. Cramer. 1996. An exploration of the nature of Atlantic bluefin tuna mixing. ICCAT Coll. Vol. Sci. Pap. 45(2): 173-181.
- Punt, A. E., and D. S. Butterworth. 1995. Use of tagging data within a VPA formalism to estimate migration rates of bluefin tuna across the north Atlantic. ICCAT Coll. Vol. Sci. Pap. 44(1): 166-182.
- Restrepo, V. R. and Porch, C. E. 2000. Options for conducting swordfish sex-specific assessments. ICCAT Collect. Vol. Sci. Pap. 51:1375-1386.
- Schweigert, J. F., and Schwarz, C. J. 1993. Estimating migration rates for Pacific herring (*Clupea pallasii*) using tag-recovery data. Can. J. fish. Aquat. Sci. 50: 1530-1540.
- Sibert, R., and D. A. Fournier. 1994. Evaluation of advection-diffusion equations for estimation of movement patterns from tag recapture data. FAO Fish. Tech. Pap. 336/1:108-121.
- SCRS. 2001. Report of the ICCAT SCRS West Atlantic Bluefin Tuna Stock Assessment Session (Madrid, Spain, September 18 - 22, 2000). ICCAT Col. Vol. Sci. Pap. 52: 831-958.
- Turner, S. C. 1986. An analysis of recaptures of tagged bluefin with respect to the mixing assumption. ICCAT Col. Vol. Sci. Pap. 24: 196-202.
- Turner, S. C., and J. E. Powers. 1995. Review of information related to Atlantic bluefin tuna east-west movement. ICCAT Col. Vol. Sci. Pap. 44(1): 191-197.

6. APPENDICES

APPENDIX 1. Sample control file with line numbers

```

First column of file
Line |
1 #####
2 ###          CONTROL FILE FOR PROGRAM VPA-2BOX, Version 3.0      ###
3 #####
4 # INSTRUCTIONS: the control options are entered in the order specified.
5 #           Additional comment lines may be inserted anywhere in this
6 #           file provided they are preceded by a # symbol in the FIRST
7 #           column, otherwise the line is perceived as free-format data.
8 #####
9 #
10 #####
11 # TITLES AND FILE NAMES (MUST BE PLACED WITHIN SINGLE QUOTES)
12 #####
13 #|-----must be 50 characters or fewer-----|
14 'NORTHERN ALBACORE 1975-97'          TITLE OF RUN
15 'ALB00.d01'                          DATA FILE NAME (INPUT)
16 'ALB00.p01'                          PARAMETER SPECIFICATION FILE (INPUT)
17 'ALB00.r01'                          RESULTS FILE NAME (OUTPUT)
18 'ALB00.e01'                          PARAMETER ESTIMATE FILE NAME (OUTPUT)
19 'ALB00.SPD'                          SPREADSHEET FRIENDLY RESULTS (OUTPUT)
20 'none for ALB '                      TAGGING DATA FILE (INPUT)
21 #####
22 # MODEL TYPE OPTIONS
23 #####
24 1          NUMBER OF ZONES (1 OR 2)
25 1          MODEL_TYPE (1=DIFFUSION, 2=OVERLAP)
26 #####
27 # TAGGING DATA SWITCH
28 #####
29 # tagging data switch (0=do not use tagging data, 1=use tagging data)
30 # | weighting factor for modifying importance of tagging data in objective function
31 # | Relative amount of fishing in each month (not necessary tag data switch = 0)
32 # |
33 # |
34 0 1.0 0 0 0 1 1 1 1 1 1 0 0 0          TAGGING MODEL CONTROLS
35 #####
36 # SEARCH ALGORITHM CONTROLS
37 #####
38 -911    RANDOM NUMBER SEED
39 20     MAXIMUM NUMBER OF AMOEBASIMPLEX SEARCH RESTARTS
40 3     NUMBER OF CONSECUTIVE RESTARTS THAT MUST VARY BY LESS THAN 1% TO STOP SEARCH
41 .4    PDEV (standard deviation controlling vertices for Initial simplex of each restart)
42 #####
43 # INDEX WEIGHTING CONTROLS
44 #####
45 0     SCALE (DIVIDE INDEX VALUES BY THEIR MEAN)- ANY VALUE > 0 = YES
46 1.0  INDEX WEIGHTING:(0)INPUT CV's, (+)DEFAULT CV, (-)DEFAULT STD. DEV., (999)MLE
47 0     (0) MULTIPLICATIVE VARIANCE SCALING FACTOR or (1) ADDITIVE VARIANCE SCALING FACTOR
48 #####
49 # CONSTRAINT ON VULNERABILITY (PARTIAL RECRUITMENT)
50 #####
51 # apply this penalty to the last N years (SET N = 0 TO IGNORE)
52 # | standard deviation controlling the severity of the penalty
53 # | first age affected
54 # | last age affected
55 # |
56 0 .4 1 9    LINKS THE VULNERABILITIES IN THE LAST N YEARS

```

```

57 #####
58 # CONSTRAINTS ON RECRUITMENT
59 #####
60 # apply this penalty to the last N years (SET N = 0 TO IGNORE)
61 # | standard deviation controlling the severity of the penalty
62 0 .1 LINKS THE RECRUITMENTS IN THE LAST N YEARS
63 0 .1 1 LINKS THE RECRUITMENTS OF THE TWO STOCKS
64 #
65 # | ratio of stock (sex) 1 to stock (sex) 2 {a value of 1 means a 1:1 ratio}
66 #####
67 # CONSTRAINT ON SPawner-RECRUIT RELATIONSHIP
68 #####
69 # PDF of spawner-recruit penalty: 0=none, 1=lognormal, 2=normal (-)=estimate sigma by MLE
70 # | first and last years to use in fitting (in terms of recruits)
71 # |
72 0 1975 1996 PENALIZES DEPARTURES FROM BEVERTON AND HOLT STOCK-RECRUIT CURVE
73 # (note: check the parameter file to make sure you are estimating the S/R
74 # parameters when pdf not 0, or not estimating them when pdf=0))
75 #####
76 # PARAMETER ESTIMATION OPTIONS
77 #####
78 1 OPTION TO USE (1) F'S OR (2) N'S AS TERMINAL YEAR PARAMETERS
79 -1 ESTIMATE Q IN (+) SEARCH or (<0) by concentrated MLE's
80 #####
81 # BOOTSTRAP ANALYSES
82 #####
83 # Number of bootstraps to run (negative value = do a parametric bootstrap)
84 # | Use Stine correction to inflate bootstrap residuals (0=NO)
85 # |
86 0 1 BOOTSTRAP OPTION
87 #####
88 # RETROSPECTIVE ANALYSES (CANNOT DO RETROSPECTIVE ANALYSES AND BOOTSTRAPS AT SAME TIME)
89 #####
90 4 NUMBER OF YEARS TO GO BACK FOR RETROSPECTIVE ANALYSES
91 @EOF@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@

```

APPENDIX 2. Sample data file with line numbers

```

=====
First column of file
Line |
1 #####
2 # DATA FILE FOR PROGRAM VPA-2BOX, Version 3.0
3 #
4 # The data and specifications are entered in the order indicated
5 # by the existing comments. Additional comments must be preceded by a # symbol
6 # in the first column, otherwise the line is perceived as free format input.
7 #####
8 1975 1999 FIRST AND LAST YEAR
9 1 8 8 FIRST AGE, LAST AGE AND PLUSGROUP AGE
10 #####
11 # BEGIN INPUT FOR Zone/STOCK 1
12 #####
13 2 NUMBER OF INDICES in this file (whether used or not)
14 6 SPAWNING SEASON (elapsed months, 0 is beginning of year)
15 0 0 0 0 0.5 1 1 1 FECUNDITY MODIFIER (MATURITY) AT AGE
16 # 50 character title within single quotes ' ' ---->] PDF OF CATCH
17 # | SIGMA CATCH
18 'Northern Albacore' | 0 1
19 #-----
20 # NOW ENTER THE CATCH-AT-AGE DATA. ROW=YEAR, COLUMN=AGE
21 #-----
22 #YEAR 1 2 3 4 5 6 7 8+ <--AGE
23 1975 315733 1066318 1237487 299015 280100 186106 212809 68034
24 1976 931707 2228301 935988 823222 448893 313768 151055 68898
25 1977 428823 2433768 1397655 321475 454251 277723 108428 72114
26 1978 2487904 2179912 1182421 418111 219033 213060 84188 31706
27 1979 883487 3295114 1767666 179078 150122 108815 51052 121773
28 1980 1661960 1372292 1533717 280723 85452 49805 31750 67929
29 1981 1127638 1524756 1019549 302997 74073 51145 42296 99892
30 1982 239468 1844670 1610921 284073 77559 70137 37154 173027
31 1983 890767 1577368 1628346 619212 207258 156937 80563 106758
32 1984 432954 1204226 972542 275997 209046 124572 123533 225416
33 1985 1052931 1354882 996685 235554 231200 137424 40219 212844
34 1986 821188 1559763 1172319 343754 409680 166179 78931 146896
35 1987 378762 2372142 1358300 146963 50677 45487 27354 70074
36 1988 1725728 2070614 1039478 140129 33163 15686 14680 21340
37 1989 1113168 1826467 1385188 106313 41240 23941 9374 10010
38 1990 1101655 2609762 790747 212087 97017 74879 60175 63898
39 1991 1197076 2190165 588433 96016 105347 34942 32053 51821
40 1992 1367443 1895016 833741 161041 47378 69838 56897 22928
41 1993 988442 2102203 1031346 208371 83237 52766 79599 178022
42 1994 708148 2863041 696340 160490 36962 27918 40370 163956
43 1995 1327523 2302110 992772 108378 118960 122804 78394 93902
44 1996 1343761 2438753 342995 96818 55599 39962 46529 77277
45 1997 1769533 1666480 763456 96324 49881 53179 39700 27793
46 1998 1847969 1933866 546087 83660 31479 32148 32259 36206
47 1999 1852736 1612315 1087974 248920 68592 52359 43632 50509
48 -1 end of catch data
49 #-----
50 # NOW ENTER IN THE ABUNDANCE INDEX SPECIFICATIONS
51 #-----
52 # INDEX PDF (0= do not use,1=lognormal, 2=normal)
53 # | UNITS (1 = numbers, 2 = biomass)
54 # | VULNERABILITY (1=fixed, 2=frac.catches, 3=part. catches, 4=Butt. & Gero.
55 # | TIMING (-1=average, +integer = number of months elapsed)}
56 # | FIRST AGE LAST AGE TITLE (IN SINGLE QUOTES)
57 1 1 1 1 -1 2 2 'SP. TROLL 2'
58 2 1 1 4 -1 2 8 'TAIWAN LL'
59 -1 end index specifications
60 #-----
61 # NOW ENTER IN THE INDICES OF ABUNDANCE
62 #-----
63 #INDEX YEAR INDEX VALUE INDEX STD ERROR
64 1 1981 40.50319669 -1 SP Troll 2
65 1 1982 53.95664758 -1
66 1 1983 38.30118752 -1
67 1 1984 31.99824001 -1
68 1 1985 24.86051748 -1
69 1 1986 37.62169586 -1
70 1 1987 42.23633635 -1
71 1 1988 41.50778091 -1
=====

```

```

71 1 1989 22.77312019 -1
72 1 1990 38.9929516 -1
73 1 1991 57.01309062 -1
74 1 1992 49.02747727 -1
75 1 1993 42.29127929 -1
76 1 1994 66.17355432 -1
77 1 1995 51.94995761 -1
78 1 1996 61.3982235 -1
79 1 1997 38.33567411 -1
80 1 1998 34.43869895 -1
81 1 1999 28.71963116 -1
82 2 1975 14.3106 -1 Chinese-Taipe LL
83 2 1976 16.0662 -1
84 2 1977 12.3064 -1
85 2 1978 14.0685 -1
86 2 1979 16.532 -1
87 2 1980 17.3829 -1
88 2 1981 16.3676 -1
89 2 1982 20.168 -1
90 2 1983 19.0735 -1
91 2 1984 15.3925 -1
92 2 1985 13.0577 -1
93 2 1986 11.33 -1
94 2 1987 10.342 -1
95 2 1988 17.2733 -1
96 2 1989 14.2442 -1
97 2 1990 11.6289 -1
98 2 1991 9.6744 -1
99 2 1992 11.0432 -1
100 2 1993 14.2994 -1
101 2 1994 11.0544 -1
102 2 1995 17.2424 -1
103 2 1996 6.6744 -1
104 2 1997 7.9734 -1
105 2 1998 14.3053 -1
106 -1 end index data
107 #=====
108 # NOW ENTER IN THE VulnerabilitiES OR PARTIAL CATCHES FOR THE INDICES OF ABUNDANCE
109 #=====
110 #INDEX YEAR AGE1 AGE 2 AGE 3 AGE 4 AGE 5 AGE 6 AGE 7 AGE 8
111 2 1975 1 8004 117604 136701 80679 45508 53501 28105
112 2 1976 1 20625 110919 267439 206916 127664 62566 29343
113 2 1977 1 25506 130719 122264 227435 142092 60194 39084
114 2 1978 1 2358 58387 111893 122751 125723 50297 15838
115 2 1979 1 32263 71613 48715 68205 51369 30048 62593
116 2 1980 1 14023 119100 111482 56875 34060 21647 48676
117 2 1981 1 29024 62736 96319 38412 26434 27092 69689
118 2 1982 1 67783 151933 119530 58476 53898 25025 115500
119 2 1983 1 49625 162733 239222 118373 100967 52898 82696
120 2 1984 1 56542 128831 167504 151424 79661 62894 136840
121 2 1985 1 31390 106341 135704 176272 102264 29379 165136
122 2 1986 1 32052 92679 207010 348902 142385 65886 124171
123 2 1987 1 85954 104652 60162 27649 27904 19321 61656
124 2 1988 1 4083 71760 42457 6332 2291 3959 13382
125 2 1989 1 13 26034 19085 21453 11262 1522 349
126 2 1990 1 8 8887 23971 38597 11777 1697 4862
127 2 1991 1 14 94566 27532 92448 23152 7031 12421
128 2 1992 1 289 17639 22351 22613 31948 17784 6396
129 2 1993 1 19154 84338 65883 69497 24628 33747 56260
130 2 1994 1 25322 39961 26040 10477 10969 22885 121014
131 2 1995 1 18269 88299 49967 45340 33248 12944 7432
132 2 1996 1 22114 48631 34637 24666 11195 7296 48784
133 2 1997 1 2994 99172 33814 16296 20193 14837 10667
134 2 1998 1 316 89790 33267 11842 14431 15955 17393
135 2 1999 1 530 169504 62954 24445 24473 25948 33850
136 -1 end index vulnerabilities
137 #=====
138 # NOW ENTER IN THE WEIGHTS AT AGE FOR THE INDICES OF ABUNDANCE (row=year, col=age)
139 #=====
140 #Index year age 1 age 2 age 3 age 4 age 5 age 6 age 7 age 8
141 1 1975 2.59 5.88 10.55 15.19 18.75 22.92 29.64 38.99
142 -1
143 #=====
144 # NOW ENTER IN THE FECUNDITY AT AGE FOR THE SPAWNING STOCK BIOMASS (row=year, col=age)
145 #=====
146 #year age 1 age 2 age 3 age 4 age 5 age 6 age 7 age 8
147 1975 2.59 5.88 10.55 15.19 18.75 22.92 29.64 38.99

```

148	1976	2.52	5.94	10.27	15	19.17	23.57	28.9	39.01
149	1977	2.45	5.84	10.64	15.01	19.01	23.88	29.18	38.48
150	1978	2.69	6.2	10.55	15.04	19.59	23.54	28.78	39.14
151	1979	2.59	5.99	10.92	15.45	18.79	22.51	28.33	37.22
152	1980	2.65	6.03	10.57	15.81	19.06	22.93	26.91	37.07
153	1981	2.74	6.08	10.49	15.48	19.77	23.29	26.94	36.78
154	1982	2.49	5.88	10.67	15.75	18.61	21.58	26	36.37
155	1983	2.78	6.1	10.51	15.32	19.13	22.05	27.47	37.87
156	1984	2.84	6.01	10.64	15.18	19.32	21.58	26.02	37.14
157	1985	2.72	6.23	10.67	15.04	19.31	21.81	26.9	36.8
158	1986	2.64	6.1	10.66	15.21	19.06	22.83	28.87	37.45
159	1987	3.1	6.02	10.94	15.98	19.13	23.08	28.02	36.47
160	1988	2.81	6.28	10.88	15.28	19.6	23.18	28.08	37.33
161	1989	2.64	6.07	11.11	16.37	19	22.16	27.69	38.13
162	1990	2.65	6.07	10.7	15.39	19.54	22.37	27.46	38.1
163	1991	2.67	6.12	10.98	16.14	17.63	22.96	26.87	37.11
164	1992	2.68	6.08	10.7	15.56	18.64	22.22	28.49	38.84
165	1993	2.6	6.02	10.66	15.31	17.82	22.06	27.23	36.19
166	1994	2.56	6.04	10.86	15.66	19.27	22.01	27.25	36.83
167	1995	2.59	6.15	10.93	15.16	18.27	22.34	27.30	37.61
168	1996	2.62	6.37	11.09	15.62	18.87	21.98	27.60	36.84
169	1997	2.65	6.20	11.07	15.69	18.27	22.95	29.10	37.97
170	1998	2.65	6.02	10.89	15.97	18.36	22.58	27.75	37.89
171	1999	2.65	6.12	10.67	15.78	18.92	22.98	28.10	37.51
172	-1								
173	#####								
174	# BEGIN INPUT FOR Zone/STOCK 2								
175	#####								

APPENDIX 3. Sample tag-recovery data file with line numbers

```

First column of file
Line |
1 #####
2 # TAG-RECOVERY DATA FILE FOR PROGRAM VPA-2BOX, Version 3.0
3 #   The data and specifications are entered in the order indicated
4 #   by the existing comments. Additional comments must be preceded by a # symbol
5 #   in the first column, otherwise the line is perceived as free format input.
6 #####
7 #
8 #-----
9 # Release information
10 #-----
11 # release zone
12 #   release year
13 #   release age
14 #   number released
15 #   time of year released (in months)
16 #   weight given to tagging data in objective function
17 #
18 # 1 75 0 0. 0.0 1
19 # 1 75 1 0. 0.0 1
20 # 1 75 2 0. 0.0 1
21 # 1 75 3 0. 0.0 1
22 # 1 75 4 0. 0.0 1
23 # 1 75 5 0. 0.0 1
24 # 1 75 6 0. 0.0 1
25 # 1 75 7 0. 0.0 1
26 # 1 75 8 0. 0.0 1
27 # 2 75 0 5. 6.8 1
28 # 2 75 1 134. 7.1 1
29 # 2 75 2 78. 6.9 1
30 # 2 75 3 15. 7.1 1
31 # 2 75 4 38. 7.7 1
32 # 2 75 5 7. 8.1 1
33 # 2 75 6 3. 8.7 1
34 # 2 75 7 1. 7.0 1
35 # 2 75 8 1. 7.0 1
36 # 1 76 0 0. 0.0 1
37 # 1 76 1 0. 0.0 1
38 # 1 76 2 1. 9.0 1
39 # 1 76 3 0. 0.0 1
40 # 1 76 4 0. 0.0 1
41 # 1 76 5 0. 0.0 1
42 # 1 76 6 0. 0.0 1
43 # 1 76 7 0. 0.0 1
44 # 1 76 8 0. 0.0 1
45 # 2 76 0 2. 7.5 1
46 # 2 76 1 729. 7.0 1
47 # 2 76 2 939. 7.0 1
48 # 2 76 3 589. 7.0 1
49 # 2 76 4 0. 0.0 1
50 # 2 76 5 0. 0.0 1
51 # 2 76 6 0. 0.0 1
52 # 2 76 7 0. 0.0 1
53 # 2 76 8 0. 0.0 1
54 # -1 end release data
55 #-----
56 # Recapture data
57 #-----
58 # release zone
59 #   release year
60 #   release age
61 #   recapture zone
62 #   number recaptured by year (from first to last)
63 #
64 # 1 75 0 1 1975 1976 1977 1978 1979 1980
65 # 1 75 0 2 0. 0. 0. 0. 0. 0.
66 # 1 75 1 1 0. 0. 0. 0. 0. 0.
67 # 1 75 1 2 0. 0. 0. 0. 0. 0.
68 # 1 75 2 1 0. 0. 0. 0. 0. 0.
69 # 1 75 2 2 0. 0. 0. 0. 0. 0.
70 #

```

71	1	75	3	1	0.	0.	0.	0.	0.	0.
72	1	75	3	2	0.	0.	0.	0.	0.	0.
73	1	75	4	1	0.	0.	0.	0.	0.	0.
74	1	75	4	2	0.	0.	0.	0.	0.	0.
75	1	75	5	1	0.	0.	0.	0.	0.	0.
76	1	75	5	2	0.	0.	0.	0.	0.	0.
77	1	75	6	1	0.	0.	0.	0.	0.	0.
78	1	75	6	2	0.	0.	0.	0.	0.	0.
79	1	75	7	1	0.	0.	0.	0.	0.	0.
80	1	75	7	2	0.	0.	0.	0.	0.	0.
81	1	75	8	1	0.	0.	0.	0.	0.	0.
82	1	75	8	2	0.	0.	0.	0.	0.	0.
83	2	75	0	1	0.	0.	0.	0.	0.	0.
84	2	75	0	2	0.	0.	0.	0.	0.	0.
85	2	75	1	1	0.	0.	0.	0.	0.	0.
86	2	75	1	2	8.	12.	1.	1.	0.	0.
87	2	75	2	1	0.	0.	0.	0.	0.	0.
88	2	75	2	2	9.	7.	1.	0.	0.	0.
89	2	75	3	1	0.	0.	0.	0.	0.	0.
90	2	75	3	2	3.	0.	0.	0.	0.	0.
91	2	75	4	1	0.	0.	0.	0.	0.	0.
92	2	75	4	2	2.	1.	0.	0.	0.	0.
93	2	75	5	1	0.	0.	0.	0.	0.	0.
94	2	75	5	2	0.	0.	0.	0.	0.	0.
95	2	75	6	1	0.	0.	0.	0.	0.	0.
96	2	75	6	2	0.	0.	0.	0.	0.	0.
97	2	75	7	1	0.	0.	0.	0.	0.	0.
98	2	75	7	2	0.	0.	0.	0.	0.	0.
99	2	75	8	1	0.	0.	0.	0.	0.	0.
100	2	75	8	2	0.	0.	0.	0.	0.	0.
101	1	76	0	1	0.	0.	0.	0.	0.	0.
102	1	76	0	2	0.	0.	0.	0.	0.	0.
103	1	76	1	1	0.	0.	0.	0.	0.	0.
104	1	76	1	2	0.	0.	0.	0.	0.	0.
105	1	76	2	1	0.	0.	0.	0.	0.	0.
106	1	76	2	2	0.	0.	0.	0.	0.	0.
107	1	76	3	1	0.	0.	0.	0.	0.	0.
108	1	76	3	2	0.	0.	0.	0.	0.	0.
109	1	76	4	1	0.	0.	0.	0.	0.	0.
110	1	76	4	2	0.	0.	0.	0.	0.	0.
111	1	76	5	1	0.	0.	0.	0.	0.	0.
112	1	76	5	2	0.	0.	0.	0.	0.	0.
113	1	76	6	1	0.	0.	0.	0.	0.	0.
114	1	76	6	2	0.	0.	0.	0.	0.	0.
115	1	76	7	1	0.	0.	0.	0.	0.	0.
116	1	76	7	2	0.	0.	0.	0.	0.	0.
117	1	76	8	1	0.	0.	0.	0.	0.	0.
118	1	76	8	2	0.	0.	0.	0.	0.	0.
119	2	76	0	1	0.	0.	0.	0.	0.	0.
120	2	76	0	2	0.	0.	0.	0.	0.	0.
121	2	76	1	1	0.	0.	0.	0.	0.	0.
122	2	76	1	2	0.	23.	33.	41.	3.	0.
123	2	76	2	1	0.	0.	0.	0.	0.	0.
124	2	76	2	2	0.	61.	4.	20.	3.	0.
125	2	76	3	1	0.	0.	0.	0.	1.	0.
126	2	76	3	2	0.	25.	19.	5.	1.	0.
127	2	76	4	1	0.	0.	0.	0.	0.	0.
128	2	76	4	2	0.	0.	0.	0.	0.	0.
129	2	76	5	1	0.	0.	0.	0.	0.	0.
130	2	76	5	2	0.	0.	0.	0.	0.	0.
131	2	76	6	1	0.	0.	0.	0.	0.	0.
132	2	76	6	2	0.	0.	0.	0.	0.	0.
133	2	76	7	1	0.	0.	0.	0.	0.	0.
134	2	76	7	2	0.	0.	0.	0.	0.	0.
135	2	76	8	1	0.	0.	0.	0.	0.	0.
136	2	76	8	2	0.	0.	0.	0.	0.	0.
137					-1	end of	recapture	data		

APPENDIX 4. Sample parameter file with line numbers

```

=====
First column of file
Line |
1 #####
2 # PARAMETER FILE FOR PROGRAM VPA-2BOX, Version 3.0
3 # The specifications are entered in the order indicated
4 # by the existing comments. Additional comments must be preceded by a # symbol
5 # in the first column, otherwise the line is perceived as free format input.
6 #
7 # Each parameter in the model must have its own specification line unless a $
8 # symbol is placed in the first column followed by an integer value (n), which
9 # tells the program that the next n parameters abide by the same specifications.
10 #
11 # The format of each specification line is as follows
12 #
13 # column 1
14 # number of parameter to which these specifications apply
15 # lower bound
16 # best estimate (prior expectation)
17 # upper bound
18 # method of estimation
19 # standard deviation of prior
20 # $ 5 0 1.2 2.0 1 0.1
21 #
22 # The methods of estimation include:
23 # 0 set equal to the value given for the best estimate (a fixed constant)
24 # 1 estimate in the usual frequentist (non-Bayesian) sense
25 # 2(0.1) estimate as a random deviation from the previous parameter
26 # 3(0.2) estimate as a random deviation from the previous constant or type 1 parameter
27 # 4(0.3) estimate as random deviation from the best estimate.
28 # -0.1 set equal to the value of the closest previous estimated parameter
29 # -n set equal to the value of the nth parameter in the list (estimated or not)
30 #####
31 =====
32 # TERMINAL F PARAMETERS: (lower bound, best estimate, upper bound, indicator, reference age)
33 # Note 1: the method indicator for the terminal F parameters is unique in that if it is
34 # zero but the best estimate is set to a value < 9, then the 'best estimate'
35 # is taken to be the vulnerability relative to the reference age in the last
36 # (fifth) column. Otherwise these parameters are treated the same as the
37 # others below and the fifth column is the standard deviation of the prior.
38 # Note 2: the last age is represented by an F-ratio parameter (below), so the number
39 # of entries here should be 1 fewer than the number of ages
40 #-----
41 $ 1 0 .2 3 0 2 first age (here age 1)
42 $ 1 0 .4886 2 1 .1
43 $ 1 0 .5118 2 1 .1
44 $ 1 0 .1416 2 1 .1
45 $ 1 0 .2439 2 1 .1
46 $ 1 0 .1738 2 1 .1
47 $ 1 0 .9 2 0 6 next to last age
48 #-----
49 # F-RATIO PARAMETERS F{oldest}/F{oldest-1} one parameter (set of specifications) for each year
50 #-----
51 $ 25 0.1 1.0 5.0 0 .2 fixed
52 #-----
53 # NATURAL MORTALITY PARAMETERS: one parameter (set of specifications) for each age
54 #-----
55 $ 1 0 0.30 1.0 1 .1
56 $ 1 0 0.30 1.0 1 .1
57 $ 6 0 0.30 1.0 -0.1 .1
58 #-----
59 # MIXING PARAMETERS: one parameter (set of specifications) for each age
60 #-----
61 $ 8 0 0.0 1.0 0 .1
62 #-----
63 # STOCK-RECRUITMENT PARAMETERS: five parameters so 5 sets of specifications
64 #-----
65 0 0.11d+08 1.D20 0 0.4 maximum recruitment
66 0 0.85d+04 1.D20 0 0.0 spawning biomass scaling parameter
67 0 0.000 0.9 0 0.0 extra parameter (not used yet)
68 0 0 1 0 0 autocorrelation parameter
69 0 0.4 2 0 0 variance of random component (discounting the autocorrelation)
70 #=====

```

```

71 # VARIANCE SCALING PARAMETER (lower bound, best estimate, upper bound, indicator, std. dev.)
72 #   this parameter scales the input variance up or down as desired
73 #   In principal, if you estimate this you should obtain more accurate estimates of the
74 #   magnitude of the parameter variances-- all other things being equal.
75 #   (1 parameter so 1 set of specifications)
76 #-----
77 $ 1 0 0.5 1.0 1 .1
78 $ 1 0 0.5 1.0 -.1 .1
79 #-----
80 # CATCHABILITY PARAMETERS (do not try to estimate q's for indices you are not using!)#
81 #-----
82 # index 1
83 $ 1 0 .0 1.0 1 .2 estimate
84 $ 24 0. .00001 2.0 -.1 .2 set equal to above estimate
85 # index 2
86 $ 1 0 .00001 1.0 1 .2 1975 estimate
87 $ 23 0. .00001 1.0 3 .2 1976-98 random walk
88 $ 1 0 .0 1.0 0 .2 1999 ignore (don't estimate)
89 #-----
90 # FRACTION SURVIVING THE INITIAL TAGGING PROCESS (one line for each age)
91 #-----
92 $ 8 0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00
93 #-----
94 # TAG SHEDDING RATE
95 #-----
96 $ 8 0.0000D+00 0.2600D+00 0.1000D+01 0.0 0.1000D+00
97 #-----
98 # TAG REPORTING RATE
99 #-----
100 $ 1 0.0000D+00 0.2331D+00 0.1000D+01 1.0 0.1000D+00
101 $ 24 0.0000D+00 0.2331D+00 0.1000D+01 -.1 0.1000D+00
102 #-----
103 # pre-mixing adjustment first year
104 #-----
105 $ 1 0.0000D+00 1.00000000 0.5000D+01 1.0 0.1000D+00
106 $ 199 0.0000D+00 1.00000000 0.5000D+01 -.1 0.1000D+00
107 #-----
108 # pre-mixing adjustment first year
109 #-----
110 $ 200 0.0000D+00 1.00000000 0.5000D+01 0.0 0.1000D+00
111 @ end of file

```

7. INDEX

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APPENDIX 3. WORKED EXAMPLE:

Atlantic Bluefin Tuna (2 stocks with mixing)

A3.1 Input data Files

There are three input files in this example:

- a Control file,
- an Input Data file,
- a Tagging data file, and
- a Parameter specification file

A3.1.1 Control File

```
#####
###          CONTROL FILE FOR PROGRAM VPA-2BOX, Version 2.0      ###
#####
# INSTRUCTIONS: the control options are entered in the order specified.
# Additional comment lines may be inserted anywhere in this
# file provided they are preceded by a #,!, or * in the FIRST
# column, otherwise the line is perceived as free-format data.
#####
'diffusion model T5P2R2L'          TITLE OF RUN
'MIX.d01'          DATA FILE
'MIX.p01'          PARAMETER FILE
'MIX.R01'          RESULTS
'MIX.E01'          PARAMETER ESTIMATES
'MIX.spd'          spreadsheet
'tag-all.t01'     TAGGING DATA FILE
2                 NUMBER OF AREAS
1                 MODEL TYPE (0=SINGLE STOCK, 1=DIFFUSION, 2=OVERLAP)
3 1.0 1 1 0 0 0 1 1 1 1 1 1 1 1 1 pdf OF TAG DATA,DOWNWEIGHTING DIVISOR, TIME OF YEAR WHEN FISHING SEASON BEGINS, DURATION OF FISHING
SEASON-- (<=0) DO NOT USE TAGGING DATA
-911             SEED
30              maximum number of AMOEBA RESTARTS
3               CHECKFLAG
.4              PDEV
-1              SCALE (DIVIDE INDEX VALUES BY THEIR MEAN)- ANY VALUE > 0 = YES
0 1.0           INDEX WEIGHTING (999) ESTIMATE BY MLE, (0) INPUT CV's, (+) DEFAULT CV, (-) = DEFAULT STD. DEV.
0              VARIANCE OPTIONS (0) MULTIPLICATIVE or (1) ADDITIVE
0 .4           LINK THE SELECTIVITIES IN THE LAST N YEARS (0 or - = do not link)
0 .1           LINK THE RECRUITMENTS IN THE LAST N YEARS (0 or - = do not link)
0 .1 1.0       LINK THE RECRUITMENTS OF THE TWO STOCKS (0 or - = do not link) AND RATIO OF MALES TO FEMALES AND
PENALTY SIGMA
0 3            IMPOSE STOCK RECRUITMENT RELATIONSHIP {pdf-- 0=none, 1=lognormal, 2=normal (negative indicates est.
sigma by concentrated likelihood)}, {ignore last n years}
1             OPTION TO USE (1) F'S OR (2) N'S AS TERMINAL YEAR PARAMETERS
-1           ESTIMATE Q IN (+) SEARCH or (<0) by MLE's
0 `1 -20      BOOTSTRAP OPTION (0)=NONE, (N)=PERFORM N BOOTSTRAP REPLICATES, (-N)=PERFORM N MONTECARLO REPLICATES
0            RETROSPECTIVE ANALYSIS, NUMBER OF YEARS TO STEP BACK FOR
84           printer lines per page for graphics -- a negative integer means no graphics)
@EOF#####

          OUTPUT OPTIONS: 1 = print N,F,indices for area 1
                           2 = print N,F for area 1
                           3 = print N,F,indices for both
                           4 = print N,F for both areas
```

A.3.1.2 Input Data file

```
#####
###          INPUT FILE FOR PROGRAM VPA-2BOX, Version 2.0      ###
#####
# INSTRUCTIONS: the control options are entered in the order specified by
# the existing comments. The existing comment blocks may be
# expanded to as many lines as desired, however new comment
# lines may not be placed anywhere in the file other than
# immediately before or immediately after existing comments.
# All comment lines must have one of the following four symbols
# in the first column of the line: #, !, *, or - .
# Otherwise the line is perceived as free-format data input.
#####
# Bluefin Tuna 1970-97          TITLE FOR THIS RUN
70 97                          FIRST AND LAST YEAR
1 10 10                         FIRST AGE, LAST AGE AND PLUSGROUP AGE
#####
# BEGIN INPUT FOR AREA 1
#####
8                 NUMBER OF INDICES TO USE
6                 SPANNING SEASON
0 0 0 0.5 1 1 1 1 1 1 1 1 1 1 1 FECUNDITY (MATURITY) AT AGE
# TITLE                PDF OF CATCH
# |                    |          UNITS (1=no's, 2=wt)
```

```

# | | | | | | | | | |
# 'EAST' 2 1
# X
# NOW ENTER THE CATCH-AT-AGE DATA. ROW=YEAR, COLUMN=AGE
#
70 131834 73211 26994 17842 9793 6523 4501 3254 6114 25014
71 10384 88198 50413 16589 12777 4390 4529 5157 4906 21189
72 116980 137100 73231 17152 9923 7289 4363 2521 2809 16079
73 140707 68048 71707 11121 3710 3659 6740 7668 7385 17757
74 182955 125976 64125 54045 11608 5786 3665 4894 8649 42935
75 692276 272026 45944 18469 6853 4582 3240 3527 4697 54436
76 96176 195792 236722 48724 18378 6163 3649 2317 3039 39367
77 220444 256835 75831 41725 6345 4861 4180 2639 2613 35976
78 176030 179228 131623 24546 5211 1702 2569 1828 1382 26483
79 77747 48322 82586 43682 8753 2691 2378 3797 3656 22807
80 181555 138196 112676 34813 10919 4745 3159 2246 2340 24568
81 153659 308374 112260 16763 12811 6096 4418 4737 3416 17651
82 610048 255871 180005 35080 6973 3594 5132 8972 5205 38888
83 661161 183593 117908 27771 11486 4906 8530 6412 5103 38832
84 167350 593304 77856 29822 19162 9733 5548 6303 10300 41385
85 211218 329782 277272 58541 14591 9209 4330 3627 3833 33306
86 589053 279348 169783 65035 12138 6547 3553 2306 3160 27540
87 231377 403819 123350 33317 13324 8403 8448 4599 4096 24101
88 764519 194898 224722 45555 12889 10546 12087 6687 5708 33569
89 427685 374544 104582 69006 39704 7228 10436 7301 5099 24004
90 390979 318667 195899 55194 38505 8399 7470 10924 12874 25255
91 257208 399047 189996 53999 40314 8501 5384 6126 13655 40469
92 426527 496269 274484 48134 16089 7918 7096 7639 10185 42593
93 291913 761131 365258 65159 26289 14508 8127 5584 6765 42839
94 273175 505865 160218 54239 37542 25496 20047 18932 22229 85868
95 397190 298948 271217 58546 37126 23756 15577 11943 15399 88172
96 473520 660055 220479 126894 38949 18317 16240 14690 17129 81033
97 310602 476212 160888 51831 43254 28100 18335 24970 29385 68633
-1 end of catch data
# X
# NOW ENTER IN THE CPUE SPECIFICATIONS
# X
# GEAR, PDF, UNITS, SELECTIVITY (1 = fixed, 2 = fractional catches, 3 = partial catches, 4 = Butterworth)
# | | | | | TIMING (-1 = AVERAGE DURING YEAR, POSITIVE INTEGER = NUMBER OF MONTHS ELAPSED)
# | | | | | FIRST AGE, LAST AGE
# | | | | | TITLE (IN SINGLE QUOTES)
1 1 1 1 -1 2 2 'ESP BB'
2 0 1 1 -1 2 2 'FRA PS Early 2'
3 0 1 1 -1 2 2 'FRA PS Late 2'
4 1 1 1 -1 3 3 'FRA PS Early 3'
5 1 1 1 -1 3 3 'FRA PS Late 3'
6 1 1 4 -1 4 10 'ESP TRAP 4+'
7 1 1 4 -1 8 10 'JLL East&Med 8+'
8 0 1 4 -1 8 10 'JLL Cent 8+'
-1 end index specifications
# X
# NOW ENTER IN THE INDICES OF ABUNDANCE
# X
1 70 36.0200 0.2264 ESP BB 2
1 71 27.4700 0.2264
1 72 26.6600 0.2264
1 73 51.2400 0.2264
1 74 38.8000 0.2264
1 75 81.5200 0.2264
1 76 53.6400 0.2264
1 77 58.5800 0.2264
1 78 32.9900 0.2264
1 79 10.4000 0.2264
1 80 22.5600 0.2264
1 81 33.8500 0.2264
1 82 31.4600 0.2264
1 83 44.2000 0.2264
1 84 140.020 0.2264
1 85 67.8600 0.2264
1 86 48.5400 0.2264
1 87 86.0000 0.2264
1 88 59.7900 0.2264
1 89 63.1900 0.2264
1 90 33.6900 0.2264
1 91 63.8500 0.2264
1 92 64.6700 0.2264
1 93 142.970 0.2264
1 94 32.0100 0.2264
1 95 48.6200 0.2264
1 96 63.8500 0.2264
1 97 39.2000 0.2264
2 70 0.7600 1.6730 FRA PSM 2
2 71 1.1910 3.3900
2 72 1.6520 1.6820
2 73 0.9720 2.9410
2 74 1.6110 2.9460
2 75 6.3090 0.6510
2 76 1.9390 0.6920
2 77 5.6410 0.7150
2 78 2.4790 1.0350
2 79 3.1900 0.7290
2 80 1.3320 0.9440
2 81 7.5230 0.5760
3 82 3.6730 0.5270 FRA PSM Plane 2
3 83 3.3670 2.1230
3 84 4.8260 0.9570
3 85 1.7250 0.5350

```

3	86	0.7970	0.9630							
3	87	3.0620	0.6850							
3	88	1.3030	0.7120							
3	89	5.2230	0.5520							
3	90	3.5890	0.4680							
3	91	3.5320	0.4420							
3	92	5.1910	0.4420							
3	93	1.6340	0.4430							
3	94	0.2700	0.6480							
3	95	2.0520	0.4810							
3	96	3.9910	0.4880							
3	97	6.3030	0.6400							
4	70	1.0180	1.4780	FRA PSM 3						
4	71	0.9860	1.5310							
4	72	1.1130	1.8150							
4	73	3.5220	1.4300							
4	74	2.5780	2.4500							
4	75	1.4380	1.1860							
4	76	5.4630	0.6050							
4	77	4.7490	1.1580							
4	78	3.0500	1.1380							
4	79	2.0540	0.9300							
4	80	1.2550	1.2090							
4	81	1.5160	0.8140							
5	82	2.7160	0.5750	FRA PSM Plane 3						
5	83	0.6480	4.1170							
5	84	0.5220	1.8420							
5	85	9.5740	0.4880							
5	86	3.1420	0.9580							
5	87	3.3500	0.7320							
5	88	6.7800	0.6070							
5	89	1.3990	0.7030							
5	90	2.2640	0.5130							
5	91	2.0630	0.4860							
5	92	3.2030	0.4650							
5	93	2.7260	0.4660							
5	94	1.2470	0.5600							
5	95	2.8260	0.4620							
5	96	2.4400	0.5000							
5	97	0.7490	0.9710							
6	81	79.9179	0.4426	Spanish trap 4+						
6	82	81.2069	0.2565							
6	83	90.1072	0.2565							
6	84	76.0203	0.2565							
6	85	75.6411	0.2565							
6	86	39.2127	0.2235							
6	87	39.4881	0.2317							
6	88	63.2440	0.2235							
6	89	67.3565	0.2235							
6	90	66.2212	0.2235							
6	91	61.8060	0.2235							
6	92	50.9070	0.232							
6	93	42.1401	0.2313							
6	94	41.4712	0.2317							
6	95	39.9249	0.2312							
6	96	38.4362	0.2235							
6	97	94.0663	0.2235							
7	75	0.6341	0.2290	Japan LL E & Med 8+						
7	76	0.8375	0.2297							
7	77	1.2610	0.2352							
7	78	0.6077	0.2329							
7	79	0.4925	0.2502							
7	80	0.6912	0.2400							
7	81	0.5825	0.2438							
7	82	0.9978	0.2349							
7	83	0.5558	0.2307							
7	84	0.5178	0.2268							
7	85	0.5739	0.2374							
7	86	0.5237	0.2311							
7	87	0.9178	0.2389							
7	88	0.5203	0.2333							
7	89	0.3695	0.2428							
7	90	0.4469	0.2334							
7	91	0.6236	0.2346							
7	92	0.3344	0.2304							
7	93	0.3990	0.2371							
7	94	0.3557	0.2454							
7	95	0.4142	0.2300							
7	96	0.1049	0.2384							
7	97	0.1880	0.2391							
8	90	0.2179	0.3440	Japan LL Cent 8+						
8	91	0.1889	0.3472							
8	92	0.2938	0.2975							
8	93	0.1455	0.2696							
8	94	0.2607	0.3001							
8	95	0.5086	0.2748							
8	96	0.3809	0.3027							
8	97	0.3142	0.3177							
-1 end index data										
# X										
# NOW ENTER IN THE SELECTIVITIES OR PARTIAL CATCHES FOR THE INDICES OF ABUNDANCE										
# X										
6	70	0 0 0	0	27	61	259	488	1536	6482	spanish traps 4+
6	71	0 0 0	0	0	6	21	41	186	2557	
6	72	0 0 0	24	4	32	48	81	84	1068	
6	73	0 0 0	0	0	31	28	154	244	2262	
6	74	0 0 0	0	0	0	0	1	4	59	

6	75	0	0	0	8	0	0	14	52	1920
6	76	0	0	0	0	0	0	14	14	2086
6	77	0	0	0	0	0	64	110	124	1504
6	78	0	0	0	0	10	34	167	195	1786
6	79	0	0	0	81	176	226	343	556	2338
6	80	0	0	0	39	125	479	267	252	2790
6	81	0	0	0	160	761	1161	1566	520	2192
6	82	0	0	0	125	445	1656	1638	1752	6759
6	83	0	0	0	0	0	0	268	492	8620
6	84	0	0	0	97	135	490	1105	2846	9675
6	85	0	0	3	121	611	168	306	514	6128
6	86	0	0	0	0	33	114	96	160	3278
6	87	0	0	0	8	110	123	130	174	3749
6	88	0	0	0	29	358	325	369	457	9779
6	89	0	0	1	147	628	1073	1101	583	3391
6	90	0	0	28	247	473	915	2032	2329	4760
6	91	0	0	5	248	725	365	651	972	3215
6	92	0	0	26	184	624	1298	954	925	3394
6	93	0	0	0	5	57	114	290	630	4907
6	94	0	0	0	15	54	137	226	341	4184
6	95	0	0	5	75	32	72	228	739	3815
6	96	0	0	31	78	116	136	160	375	4133
6	97	0	0	80	882	1347	869	1440	1568	9108
7	72	0	0	0	0	0	0	0	0	0
7	73	0	0	0	131	240	997	Japan E & C 8+		
7	74	0	0	0	78	68	1302			
7	75	0	0	0	1454	1186	19510			
7	76	0	0	0	884	943	26817			
7	77	0	0	0	354	405	14117			
7	78	0	0	0	1224	1736	8539			
7	79	0	0	0	114	21	2968			
7	80	0	0	0	2264	1460	508			
7	81	0	0	0	539	694	2641			
7	82	0	0	0	653	522	2176			
7	83	0	0	0	4691	199	14494			
7	84	0	0	0	2327	1861	10641			
7	85	0	0	0	1924	3684	7409			
7	86	0	0	0	503	451	6042			
7	87	0	0	0	410	547	4584			
7	88	0	0	0	821	781	4688			
7	89	0	0	0	1187	1078	4556			
7	90	0	0	0	1085	890	2852			
7	91	0	0	0	1690	2280	5119			
7	92	0	0	0	2055	3856	9729			
7	93	0	0	0	1979	3244	12551			
7	94	0	0	0	1233	1228	10338			
7	95	0	0	0	2519	2467	7407			
7	96	0	0	0	2935	4191	13361			
7	97	0	0	0	3995	4396	12032			
7	98	0	0	0	3895	5659	8814			
8	70	0	0	0	0	0	0	Japan C 8+		
8	71	0	0	0	3	11	203			
8	72	0	0	0	4	0	4			
8	73	0	0	0	0	0	20			
8	74	0	0	0	32	75	2777			
8	75	0	0	0	0	16	132			
8	76	0	0	0	0	1	1357			
8	77	0	0	0	0	2	489			
8	78	0	0	0	0	0	0			
8	79	0	0	0	0	0	1			
8	80	0	0	0	33	16	18			
8	81	0	0	0	1	1	5			
8	82	0	0	0	2	0	18			
8	83	0	0	0	0	0	0			
8	84	0	0	0	7	18	37			
8	85	0	0	0	39	22	22			
8	86	0	0	0	17	45	277			
8	87	0	0	0	20	60	7			
8	88	0	0	0	12	19	50			
8	89	0	0	0	232	154	101			
8	90	0	0	0	454	706	1650			
8	91	0	0	0	927	1557	4772			
8	92	0	0	0	623	765	2160			
8	93	0	0	0	973	471	1108			
8	94	0	0	0	1114	994	1094			
8	95	0	0	0	2145	2926	1833			
8	96	0	0	0	3589	3930	6303			
8	97	0	0	0	2895	4152	4633			
-1	-1	end index selectivities								
#	X									
#	NOW ENTER IN THE WEIGHTS AT AGE FOR THE INDICES OF ABUNDANCE (row=year, col=age)									
#	X									
-1										
#	X									
#	NOW ENTER IN THE WEIGHTS AT AGE FOR THE SPAWNING STOCK BIOMASS (row=year, col=age)									
#	X									
70	4.5	10	21.7	35.1	53	72.7	95.5	117.6	146.5	219.5
71	4.6	10.1	19	35.3	54.1	72.3	96.1	119.7	144.4	265.4
72	4.5	10.6	20.1	34.6	55.4	73	94.6	117.3	147	274.9
73	4	10.2	19	32.6	54.2	73.2	97.7	121.2	141.9	268
74	4.1	11	21.2	35.7	53.7	74.1	97.1	121.9	152.4	265.1
75	4.2	10.9	21.4	36.8	52.3	72.5	94.2	122	148.7	260.9
76	4.5	11.9	19.8	35.6	53.6	74.9	94.9	120.9	152	278.8
77	4.1	10.9	22.6	35.3	56.1	74.3	94.4	116	140.7	282.6
78	5.3	10.2	21.3	36	54.6	72.7	95	121.6	145.1	278.8
79	4.6	12	21.3	35.5	52	71.6	92.2	113.7	137.9	273.1
80	4.8	10.9	18.7	31.9	51.7	72.7	93.2	116.1	143.4	257.6
81	4.8	11.1	18.6	32	52.8	72	93.5	115.6	143.6	240.6


```

# | | | | | | | | | |
# 'WEST' | | | | | | | | | |
# # NOW ENTER THE CATCH-AT-AGE DATA. ROW-YEAR, COLUMN-AGE
# #
70 64886 105064 127518 21455 3677 914 176 162 514 3673
71 62998 153364 38360 46074 672 1673 2109 1350 1133 5958
72 45402 98578 33762 3730 3857 118 569 1576 261 5519
73 5105 74311 30482 7161 2132 1451 953 1544 555 4445
74 55958 20056 21094 6506 3170 683 916 3170 1081 12507
75 43556 148027 8328 11963 821 547 317 671 1651 9473
76 5412 19781 72393 2910 2899 344 296 1168 558 14033
77 1274 22419 9717 32139 4946 3633 957 513 1109 13532
78 5133 10863 20015 6315 10530 4061 655 472 341 11982
79 2745 10552 16288 14916 3448 3494 2612 599 557 12281
80 3160 16183 11068 8881 2866 2982 5533 3454 1061 12214
81 6087 9616 16541 5244 6023 3721 2884 3211 2764 10621
82 3528 3729 1654 498 342 751 477 519 896 3077
83 4173 2438 3268 894 866 911 1402 1353 1039 5628
84 868 7504 1848 2072 2077 1671 594 759 1091 4575
85 568 5523 12310 2814 4329 4019 1024 612 696 5603
86 563 5939 7135 3442 1128 1726 931 345 520 5335
87 1513 13340 9137 5491 4385 2318 1566 1251 1014 3856
88 4850 9149 11745 3933 4144 4220 2258 1631 1600 4554
89 787 12877 1679 3815 1713 2082 2677 1864 1461 5356
90 2368 4238 17958 1947 2747 1825 1629 2388 1522 4253
91 3327 14533 10761 2924 1650 2166 2347 1946 1915 4485
92 420 5985 1997 711 1425 1870 1916 1870 1323 4383
93 329 1130 5215 3689 2089 1883 1598 2456 1479 2922
94 1990 697 1538 2283 2735 1687 2107 2408 1477 3013
95 1036 1229 3549 3476 4399 2572 904 1810 1802 3389
96 261 6753 1449 3894 2120 1643 3029 1021 1311 4006
97 185 990 6481 827 1669 1403 2238 2190 973 3973
-1 end of catch data

```

```

# # NOW ENTER IN THE CPUE SPECIFICATIONS
# #
# # GEAR, PDF, UNITS, SELECTIVITY (1 = fixed, 2 = fractional catches, 3 = partial catches)
# # TIMING (-1 = AVERAGE DURING YEAR, POSITIVE INTEGER = NUMBER OF MONTHS ELAPSED)
# # FIRST AGE, LAST AGE
# # TITLE (IN SINGLE QUOTES)
1 1 1 1 1 -1 10 10 'CAN GSI'
2 1 1 1 4 -1 7 10 'CAN SWNS'
3 1 1 1 1 0 10 10 'JLL GOM'
4 0 1 1 4 0 2 9 'DUMMY'
5 1 1 1 4 0 2 9 'JLL NW ATL'
6 1 2 1 1 -1 8 10 'LARVAL'
7 1 1 1 4 0 8 10 'US LL GOM'
8 1 1 1 4 -1 2 3 'US RR 66-114'
9 1 1 1 4 -1 4 5 'US RR 115-144'
10 1 1 1 4 -1 1 5 'US RR <145'
11 1 1 1 1 -1 6 6 'US RR 145-177'
12 0 1 1 4 -1 7 10 'US RR >178'
13 0 1 1 4 -1 8 10 'US RR >195'
14 1 1 1 1 -1 1 3 'TAGGING'
15 1 1 1 4 -1 8 10 'US RR >195 C'
-1 end index specifications

```

#	X			
#	NOW ENTER IN THE INDICES OF ABUNDANCE			
#	X			
	1	81	6.072	0.289
	1	82	5.578	0.285
	1	83	7.673	0.273
	1	84	4.414	0.29
	1	85	1.643	0.307
	1	86	1.829	0.35
	1	87	0.963	0.526
	1	88	1.805	0.407
	1	89	2.112	0.412
	1	90	1.048	0.396
	1	91	1.975	0.426
	1	92	2.874	0.357
	1	93	2.153	0.322
	1	94	0.629	0.38
	1	95	2.95	0.286
	1	96	0.767	0.287
	1	97	0.823	0.287
	2	88	2.947	0.332
	2	89	4.907	0.304
	2	90	4.05	0.304
	2	91	3.195	0.304
	2	92	2.845	0.243
	2	93	1.062	0.236
	2	94	2.177	0.249
	2	95	1.851	0.235
	2	96	0.65	0.244
	2	97	0.75	0.246
3	74	0.968	0.266	
3	75	0.534	0.205	
3	76	0.666	0.207	
3	77	0.913	0.216	
3	78	0.876	0.225	
3	79	1.287	0.283	
3	80	1.158	0.265	
3	81	0.553	0.239	
	4	70	-1	1 this index is not useful
	5	76	0.269	0.468
	5	77	0.933	0.286
	5	78	0.46	0.349
	5	79	0.318	0.373
	5	80	0.551	0.304
	5	81	0.765	0.275
	5	82	0.235	0.418
	5	83	0.109	0.67
	5	84	0.325	0.367
	5	85	0.437	0.324
	5	86	0.066	1.405
	5	87	0.301	0.419
	5	88	0.408	0.335
	5	89	0.333	0.372
	5	90	0.292	0.393
	5	91	0.26	0.421
	5	92	0.552	0.344
	5	93	0.6	0.309
	5	94	0.493	0.316
	5	95	0.402	0.381
	5	96	1.176	0.324
	5	97	0.617	0.344
	6	77	2.435	0.4333
	6	78	5.824	0.2725
	6	79	-999	-999
	6	80	-999	-999
	6	81	1.277	0.4325
	6	82	1.514	0.3112
	6	83	1.235	0.3083
	6	84	0.653	0.8016
	6	85	-999	-999
	6	86	0.261	0.6058
	6	87	0.445	0.5075
	6	88	1.946	0.3262
	6	89	0.798	0.4395
	6	90	0.474	0.2000
	6	91	0.365	0.5940
	6	92	0.614	0.3820
	6	93	0.667	0.6145
	6	94	0.72	0.4049
	6	95	0.465	0.5850
	6	96	1.458	0.6301
	6	97	0.619	0.4483
	7	87	0.88	0.29169
	7	88	0.4	0.45147
	7	89	0.7	0.31119
	7	90	0.85	0.30889
	7	91	1	0.30063
	7	92	0.24	0.52874
	7	93	0.23	0.56165
	7	94	0.1	0.90025
	7	95	0.17	0.6834
	7	96	0.18	0.69573
	7	97	0.31	0.53595
	8	93	0.4	0.472
	8	94	0.09	1.482
	8	95	0.22	0.617
	8	96	0.72	0.341

8	97	1	0.286
9	93	0.461	1.004
9	94	0.043	4.698
9	95	0.198	1.327
9	96	1	0.585
9	97	0.325	1.373
10	80	0.38	0.43
10	81	0.19	0.52
10	82	1	0.33
10	83	0.53	0.26
10	84	-999	-999
10	85	0.3	0.64
10	86	0.37	0.43
10	87	0.58	0.4
10	88	0.47	0.38
10	89	0.47	0.43
10	90	0.43	0.34
10	91	0.6	0.35
10	92	0.39	0.42
11	93	0.409	2.1704
11	94	1.0959	1.1333
11	95	1.5322	1.0936
11	96	1.632	0.9627
11	97	0.3309	4.7427
12	93	0.5967	0.553
12	94	0.6932	0.5256
12	95	0.9522	0.365
12	96	1.8196	0.2792
12	97	0.9382	0.6387
13	83	2.8049	0.2 0.0995
13	84	1.2456	0.2 0.1884
13	85	0.8571	0.2997
13	86	0.5027	1.0973
13	87	0.529	0.4761
13	88	0.9412	0.3639
13	89	0.7632	0.3636
13	90	0.626	0.3354
13	91	0.8205	0.2842
13	92	0.91	0.2763
14	70	1065132	0.2
14	71	1001624	0.2
14	72	431955	0.2
14	73	183616	0.2
14	74	341589	0.2
14	75	554596	0.2
14	76	253265	0.2
14	77	257385	0.2
14	78	121110	0.2
14	79	98815	0.2
14	80	192541	0.2
14	81	337995	0.242
15	83	1.923	0.242 0.2 0.043
15	84	1.136	0.256 0.2 0.056
15	85	0.714	0.277 0.2 0.092
15	86	0.712	0.602 0.269
15	87	0.711	0.340 0.2 0.120
15	88	0.828	0.287 0.2 0.110
15	89	0.853	0.296 0.2 0.105
15	90	0.755	0.293 0.2 0.092
15	91	0.961	0.276 0.2 0.079
15	92	0.912	0.274 0.2 0.081
15	93	0.681	0.369 0.2 0.146
15	94	0.683	0.384 0.2 0.167
15	95	1.031	0.305 0.2 0.083
15	96	1.772	0.344 0.2 0.119
15	97	1.327	0.333 0.2 0.082
-1 end index data			
# X			
# NOW ENTER IN THE SELECTIVITIES OR PARTIAL CATCHES FOR THE INDICES OF ABUNDANCE			
# X			
1	70	0 0 0 0 0 0 0 0	0.5
1	71	0 0 0 0 0 0 0 0	0.5
1	72	0 0 0 0 0 0 0 0	0.5
1	73	0 0 0 0 0 0 0 0	0.5
1	74	0 0 0 0 0 0 0 0	0.5
1	75	0 0 0 0 0 0 0 0	0.5
1	76	0 0 0 0 0 0 0 0	0.5
1	77	0 0 0 0 0 0 0 0	0.5
1	78	0 0 0 0 0 0 0 0	0.5
1	79	0 0 0 0 0 0 0 0	0.5
1	80	0 0 0 0 0 0 0 0	0.5
1	81	0 0 0 0 0 0 0 0	0.645
1	82	0 0 0 0 0 0 0 0	0.474
1	83	0 0 0 0 0 0 0 0	0.445
1	84	0 0 0 0 0 0 0 0	0.338
1	85	0 0 0 0 0 0 0 0	0.325
1	86	0 0 0 0 0 0 0 0	0.407
1	87	0 0 0 0 0 0 0 0	0.396
1	88	0 0 0 0 0 0 0 0	0.375
1	89	0 0 0 0 0 0 0 0	0.337
1	90	0 0 0 0 0 0 0 0	0.358975
1	91	0 0 0 0 0 0 0 0	0.345038
1	92	0 0 0 0 0 0 0 0	0.24217
1	93	0 0 0 0 0 0 0 0	0.483911
1	94	0 0 0 0 0 0 0 0	0.399641
1	95	0 0 0 0 0 0 0 0	0.52056
1	96	0 0 0 0 0 0 0 0	0.424635

5	82	0	87	166	240	259	564	346	204	205	0
5	83	0	120	2189	777	786	744	1204	610	359	0
5	84	0	1563	706	1701	1922	1471	454	409	350	0
5	85	0	133	6717	2653	4233	3723	842	425	283	0
5	86	0	173	1469	2688	999	1492	726	381	161	0
5	87	0	391	1687	2753	3999	2168	1319	837	534	0
5	88	0	339	4104	3325	2917	3345	1693	806	296	0
5	89	0	177	160	685	728	1058	1028	435	187	0
5	90	0	52	752	516	1725	1036	796	816	367	0
5	91	0	148	647	1265	1393	1684	1292	370	420	0
5	92	0	17	305	407	1177	617	1051	831	211	0
5	93	0	10	392	1204	1261	1591	766	711	390	0
5	94	0	72	240	1828	2064	1113	562	494	177	0
5	95	0	54	173	766	1571	2003	148	221	17	0
5	96	0	176	504	973	1024	881	903	178	144	0
5	97	0	0	64	334	756	826	682	453	85	0
6	70	0	0	0	0	0	0	1	1	1	
6	71	0	0	0	0	0	0	1	1	1	
6	72	0	0	0	0	0	0	1	1	1	
6	73	0	0	0	0	0	0	1	1	1	
6	74	0	0	0	0	0	0	1	1	1	
6	75	0	0	0	0	0	0	1	1	1	
6	76	0	0	0	0	0	0	1	1	1	
6	77	0	0	0	0	0	0	1	1	1	
6	78	0	0	0	0	0	0	1	1	1	
6	79	0	0	0	0	0	0	1	1	1	
6	80	0	0	0	0	0	0	1	1	1	
6	81	0	0	0	0	0	0	1	1	1	
6	82	0	0	0	0	0	0	1	1	1	
6	83	0	0	0	0	0	0	1	1	1	
6	84	0	0	0	0	0	0	1	1	1	
6	85	0	0	0	0	0	0	1	1	1	
6	86	0	0	0	0	0	0	1	1	1	
6	87	0	0	0	0	0	0	1	1	1	
6	88	0	0	0	0	0	0	1	1	1	
6	89	0	0	0	0	0	0	1	1	1	
6	90	0	0	0	0	0	0	1	1	1	
6	91	0	0	0	0	0	0	1	1	1	
6	92	0	0	0	0	0	0	1	1	1	
6	93	0	0	0	0	0	0	1	1	1	
6	94	0	0	0	0	0	0	1	1	1	
6	95	0	0	0	0	0	0	1	1	1	
6	96	0	0	0	0	0	0	1	1	1	
6	97	0	0	0	0	0	0	1	1	1	
7	70	0	0	0	0	0	0	0	0	0	
7	71	0	0	0	0	0	0	0	0	0	
7	72	0	0	0	0	0	0	0	0	0	
7	73	0	0	0	0	0	0	0	0	0	
7	74	0	0	0	0	0	0	0	0	0	
7	75	0	0	0	0	0	0	0	0	0	
7	76	0	0	0	0	0	0	0	0	0	
7	77	0	0	0	0	0	0	0	0	0	
7	78	0	0	0	0	0	0	0	0	0	
7	79	0	0	0	0	0	0	0	0	0	
7	80	0	0	0	0	0	0	1	7	34	
7	81	0	0	0	0	0	0	0	11	274	
7	82	0	0	0	0	0	0	14	13	83	
7	83	0	0	0	0	0	0	62	34	204	
7	84	0	0	0	0	0	0	27	39	398	
7	85	0	0	0	0	0	0	5	17	457	
7	86	0	0	0	0	0	0	3	16	2235	
7	87	0	0	0	0	0	0	20	26	1038	
7	88	0	0	0	0	0	0	143	102	934	
7	89	0	0	0	0	0	0	81	227	1086	
7	90	0	0	0	0	0	0	104	104	747	
7	91	0	0	0	0	0	0	63	142	1140	
7	92	0	0	0	0	0	0	118	96	459	
7	93	0	0	0	0	0	0	60	67	241	
7	94	0	0	0	0	0	0	167	105	346	
7	95	0	0	0	0	0	0	340	140	264	
7	96	0	0	0	0	0	0	145	79	299	
7	97	0	0	0	0	0	0	100	51	155	
8	70	0	4222	748	0	0	0	0	0	0	
8	71	0	5442	0	0	0	0	0	0	0	
8	72	0	8293	2963	0	0	0	0	0	0	
8	73	0	2889	1125	0	0	0	0	0	0	
8	74	0	1646	1176	0	0	0	0	0	0	
8	75	0	2544	104	0	0	0	0	0	0	
8	76	0	952	609	0	0	0	0	0	0	
8	77	0	3884	465	0	0	0	0	0	0	
8	78	0	3794	254	0	0	0	0	0	0	
8	79	0	3976	580	0	0	0	0	0	0	
8	80	0	5169	399	0	0	0	0	0	0	
8	81	0	1484	455	0	0	0	0	0	0	
8	82	0	3076	736	0	0	0	0	0	0	
8	83	0	2319	972	0	0	0	0	0	0	
8	84	0	5731	1139	0	0	0	0	0	0	
8	85	0	5390	5556	0	0	0	0	0	0	
8	86	0	5764	5653	0	0	0	0	0	0	
8	87	0	12932	7389	0	0	0	0	0	0	
8	88	0	8791	7434	0	0	0	0	0	0	
8	89	0	12685	1488	0	0	0	0	0	0	
8	90	0	4170	17153	0	0	0	0	0	0	
8	91	0	14382	10114	0	0	0	0	0	0	
8	92	0	5968	1669	0	0	0	0	0	0	
8	93	0	1086	4471	0	0	0	0	0	0	
8	94	0	616	1289	0	0	0	0	0	0	

8	95	0	1147	3347	0	0	0	0	0	0	0	0	0	0
8	96	0	6568	936	0	0	0	0	0	0	0	0	0	0
8	97	0	986	6407	0	0	0	0	0	0	0	0	0	0
9	70	0	0	0	30	0	0	0	0	0	0	0	0	0
9	71	0	0	0	0	53	0	0	0	0	0	0	0	0
9	72	0	0	0	372	368	0	0	0	0	0	0	0	0
9	73	0	0	0	282	93	0	0	0	0	0	0	0	0
9	74	0	0	0	0	0	0	0	0	0	0	0	0	0
9	75	0	0	0	295	10	0	0	0	0	0	0	0	0
9	76	0	0	0	27	65	0	0	0	0	0	0	0	0
9	77	0	0	0	96	5	0	0	0	0	0	0	0	0
9	78	0	0	0	31	13	0	0	0	0	0	0	0	0
9	79	0	0	0	46	13	0	0	0	0	0	0	0	0
9	80	0	0	0	207	64	0	0	0	0	0	0	0	0
9	81	0	0	0	53	33	0	0	0	0	0	0	0	0
9	82	0	0	0	134	65	0	0	0	0	0	0	0	0
9	83	0	0	0	105	42	0	0	0	0	0	0	0	0
9	84	0	0	0	367	138	0	0	0	0	0	0	0	0
9	85	0	0	0	129	95	0	0	0	0	0	0	0	0
9	86	0	0	0	684	66	0	0	0	0	0	0	0	0
9	87	0	0	0	2591	228	0	0	0	0	0	0	0	0
9	88	0	0	0	155	382	0	0	0	0	0	0	0	0
9	89	0	0	0	2910	734	0	0	0	0	0	0	0	0
9	90	0	0	0	1411	677	0	0	0	0	0	0	0	0
9	91	0	0	0	1655	194	0	0	0	0	0	0	0	0
9	92	0	0	0	269	166	0	0	0	0	0	0	0	0
9	93	0	0	0	1856	703	0	0	0	0	0	0	0	0
9	94	0	0	0	427	613	0	0	0	0	0	0	0	0
9	95	0	0	0	2624	2743	0	0	0	0	0	0	0	0
9	96	0	0	0	2889	1039	0	0	0	0	0	0	0	0
9	97	0	0	0	472	875	0	0	0	0	0	0	0	0
10	70	5121	4222	748	30	0	0	0	0	0	0	0	0	0
10	71	13023	5442	0	0	53	0	0	0	0	0	0	0	0
10	72	4421	8293	2963	372	368	0	0	0	0	0	0	0	0
10	73	228	2889	1125	282	93	0	0	0	0	0	0	0	0
10	74	34813	1646	1176	0	0	0	0	0	0	0	0	0	0
10	75	13795	2544	104	295	10	0	0	0	0	0	0	0	0
10	76	1296	952	609	27	65	0	0	0	0	0	0	0	0
10	77	493	3884	465	96	5	0	0	0	0	0	0	0	0
10	78	1200	3794	254	31	13	0	0	0	0	0	0	0	0
10	79	2661	3976	580	46	13	0	0	0	0	0	0	0	0
10	80	967	5169	399	207	64	0	0	0	0	0	0	0	0
10	81	2994	1484	455	53	33	0	0	0	0	0	0	0	0
10	82	2633	3076	736	134	65	0	0	0	0	0	0	0	0
10	83	1680	2319	972	105	42	0	0	0	0	0	0	0	0
10	84	772	5731	1139	367	138	0	0	0	0	0	0	0	0
10	85	551	5390	5556	129	95	0	0	0	0	0	0	0	0
10	86	561	5764	5653	684	66	0	0	0	0	0	0	0	0
10	87	1505	12932	7389	2591	228	0	0	0	0	0	0	0	0
10	88	4783	8791	7434	155	382	0	0	0	0	0	0	0	0
10	89	786	12685	1488	2910	734	0	0	0	0	0	0	0	0
10	90	2361	4170	17153	1411	677	0	0	0	0	0	0	0	0
10	91	3324	14382	10114	1655	194	0	0	0	0	0	0	0	0
10	92	413	5968	1669	269	166	0	0	0	0	0	0	0	0
10	93	327	1086	4471	1856	703	0	0	0	0	0	0	0	0
10	94	1990	616	1289	427	613	0	0	0	0	0	0	0	0
10	95	982	1147	3347	2624	2743	0	0	0	0	0	0	0	0
10	96	255	6568	936	2889	1039	0	0	0	0	0	0	0	0
10	97	185	986	6407	472	875	0	0	0	0	0	0	0	0
12	70	0	0	0	0	0	0	0	0	0	0	0	0	0
12	71	0	0	0	0	0	123	43	124	3129				
12	72	0	0	0	0	0	92	64	72	3765				
12	73	0	0	0	0	0	32	125	74	1738				
12	74	0	0	0	0	0	0	10	410	7616				
12	75	0	0	0	0	0	16	39	29	2323				
12	76	0	0	0	0	0	2	28	45	1118				
12	77	0	0	0	0	0	5	6	4	1423				
12	78	0	0	0	0	0	0	27	29	1814				
12	79	0	0	0	0	0	159	30	45	1827				
12	80	0	0	0	0	0	23	108	57	1466				
12	81	0	0	0	0	0	1	137	293	1295				
12	82	0	0	0	0	0	25	120	268	981				
12	83	0	0	0	0	0	85	217	162	2155				
12	84	0	0	0	0	0	90	153	221	1767				
12	85	0	0	0	0	0	143	86	133	1903				
12	86	0	0	0	0	0	95	63	68	1019				
12	87	0	0	0	0	0	102	96	121	951				
12	88	0	0	0	0	0	128	122	104	800				
12	89	0	0	0	0	0	657	296	179	1092				
12	90	0	0	0	0	0	264	261	172	1122				
12	91	0	0	0	0	0	172	225	424	1646				
12	92	0	0	0	0	0	355	261	232	1532				
12	93	0	0	0	0	0	529	335	392	949				
12	94	0	0	0	0	0	816	728	327	1142				
12	95	0	0	0	0	0	265	455	525	1279				
12	96	0	0	0	0	0	1706	367	318	1066				
12	97	0	0	0	0	0	1189	908	359	1549				
13	70	0	0	0	0	0	0	12	189	1422				
13	71	0	0	0	0	0	0	43	124	3129				
13	72	0	0	0	0	0	0	64	72	3765				
13	73	0	0	0	0	0	0	125	74	1738				
13	74	0	0	0	0	0	0	10	410	7616				
13	75	0	0	0	0	0	0	39	29	2323				
13	76	0	0	0	0	0	0	28	45	1118				
13	77	0	0	0	0	0	0	6	4	1423				
13	78	0	0	0	0	0	0	27	29	1814				
13	79	0	0	0	0	0	0	30	45	1827				

13	80	0	0	0	0	0	0	0	108	57	1466						
13	81	0	0	0	0	0	0	0	137	293	1295						
13	82	0	0	0	0	0	0	0	120	268	981						
13	83	0	0	0	0	0	0	0	217	162	2155						
13	84	0	0	0	0	0	0	0	153	221	1767						
13	85	0	0	0	0	0	0	0	86	133	1903						
13	86	0	0	0	0	0	0	0	63	68	1019						
13	87	0	0	0	0	0	0	0	96	121	951						
13	88	0	0	0	0	0	0	0	122	104	800						
13	89	0	0	0	0	0	0	0	296	179	1092						
13	90	0	0	0	0	0	0	0	261	172	1122						
13	91	0	0	0	0	0	0	0	225	424	1646						
13	92	0	0	0	0	0	0	0	261	232	1532						
13	93	0	0	0	0	0	0	0	335	392	949						
13	94	0	0	0	0	0	0	0	728	327	1142						
13	95	0	0	0	0	0	0	0	455	525	1279						
13	96	0	0	0	0	0	0	0	367	318	1066						
13	97	0	0	0	0	0	0	0	908	359	1549						
14	70	1							1	0	0	0	0	0	0	0	
14	71	1							1	0	0	0	0	0	0	0	0
14	72	1							1	0	0	0	0	0	0	0	0
14	73	1							1	0	0	0	0	0	0	0	0
14	74	1							1	0	0	0	0	0	0	0	0
14	75	1							1	0	0	0	0	0	0	0	0
14	76	1							1	0	0	0	0	0	0	0	0
14	77	1							1	0	0	0	0	0	0	0	0
14	78	1							1	0	0	0	0	0	0	0	0
14	79	1							1	0	0	0	0	0	0	0	0
14	80	1							1	0	0	0	0	0	0	0	0
14	81	1							1	0	0	0	0	0	0	0	0
14	82	1							1	0	0	0	0	0	0	0	0
14	83	1							1	0	0	0	0	0	0	0	0
14	84	1							1	0	0	0	0	0	0	0	0
14	85	1							1	0	0	0	0	0	0	0	0
14	86	1							1	0	0	0	0	0	0	0	0
14	87	1							1	0	0	0	0	0	0	0	0
14	88	1							1	0	0	0	0	0	0	0	0
14	89	1							1	0	0	0	0	0	0	0	0
14	90	1							1	0	0	0	0	0	0	0	0
14	91	1							1	0	0	0	0	0	0	0	0
14	92	1							1	0	0	0	0	0	0	0	0
14	93	1							1	0	0	0	0	0	0	0	0
14	94	1							1	0	0	0	0	0	0	0	0
14	95	1							1	0	0	0	0	0	0	0	0
14	96	1							1	0	0	0	0	0	0	0	0
14	97	1							1	0	0	0	0	0	0	0	0
15	70	0	0	0	0	0	0	0	12	189	1422						
15	71	0	0	0	0	0	0	0	43	124	3129						
15	72	0	0	0	0	0	0	0	64	72	3765						
15	73	0	0	0	0	0	0	0	125	74	1738						
15	74	0	0	0	0	0	0	0	10	410	7616						
15	75	0	0	0	0	0	0	0	39	29	2323						
15	76	0	0	0	0	0	0	0	28	45	1118						
15	77	0	0	0	0	0	0	0	6	4	1423						
15	78	0	0	0	0	0	0	0	27	29	1814						
15	79	0	0	0	0	0	0	0	30	45	1827						
15	80	0	0	0	0	0	0	0	108	57	1466						
15	81	0	0	0	0	0	0	0	137	293	1295						
15	82	0	0	0	0	0	0	0	120	268	981						
15	83	0	0	0	0	0	0	0	217	162	2155						
15	84	0	0	0	0	0	0	0	153	221	1767						
15	85	0	0	0	0	0	0	0	86	133	1903						
15	86	0	0	0	0	0	0	0	63	68	1019						
15	87	0	0	0	0	0	0	0	96	121	951						
15	88	0	0	0	0	0	0	0	122	104	800						
15	89	0	0	0	0	0	0	0	296	179	1092						
15	90	0	0	0	0	0	0	0	261	172	1122						
15	91	0	0	0	0	0	0	0	225	424	1646						
15	92	0	0	0	0	0	0	0	261	232	1532						
15	93	0	0	0	0	0	0	0	335	392	949						
15	94	0	0	0	0	0	0	0	728	327	1142						
15	95	0	0	0	0	0	0	0	455	525	1279						
15	96	0	0	0	0	0	0	0	367	318	1066						
15	97	0	0	0	0	0	0	0	908	359	1549						

-1 -1 end index selectivities

#	# NOW ENTER IN THE WEIGHTS AT AGE FOR THE INDICES OF ABUNDANCE (row=year, col=age)										
#	X	X	X	X	X	X	X	X	X	X	X
6	70	3.2	8.4	17	37.4	56.3	79.7	112.9	148.3	172	270.35
6	71	3.5	8.4	21.2	32	60.3	82	108.5	135.1	169.2	267.2
6	72	4.4	9.7	19.3	40.7	57.6	84.8	114.9	137.5	171.9	283.2
6	73	3.7	8.9	20.8	39.9	62.4	77.5	119.5	142.7	172.7	287.96
6	74	3.6	10	17.2	36.8	57.1	82.9	102.5	138.5	169.2	295.51
6	75	3.9	8.7	23.8	34.2	58.6	78.5	114.7	141.3	164.8	278.05
6	76	3.9	10.3	18.9	34.1	51.9	81.1	119.4	152.2	171.8	277.7
6	77	4.4	10.3	20.8	35.3	52.4	74.8	97.9	136.5	165.3	292.41
6	78	5	10.8	21.7	35.5	54.4	73.6	107	145.3	183	318.14
6	79	5.3	11.2	21.9	39.2	50.8	78.7	105.8	141.1	179.2	307.38
6	80	5	12.2	21.4	35.7	53.3	84.6	114.4	140.6	186.7	320.53
6	81	5.6	11	21.5	34.7	52.3	77.6	107.2	141.1	174.2	328.21
6	82	4	10.8	21.3	34.3	59.6	82	115.3	150.1	181.6	316.21
6	83	3.9	10.1	20	37.9	59	84.5	116.3	149	184.7	312.89
6	84	4.7	11.2	23.6	39.5	60	85.9	116.4	148.3	183	299.45
6	85	3.7	10.2	17.3	33.3	49	70.9	98.4	131.3	170.2	279.13
6	86	4.2	9.9	20.2	41.2	57	84.8	116.3	148.5	180.9	299.15
6	87	4.2	9.7	22.7	40.2	58.5	75.8	109.1	138.1	169.4	299.01
6	88	3.9	11.4	21.1	38.5	58	81.2	108.3	142.9	179.4	293.58
6	89	3.9	11	22.4	39.5	55.1	84.4	113.9	141.9	176.7	283.79
6	90	4.5	11.4	19	39	55.7	77.9	111.6	146.6	179.4	286.62
6	91	5.1	13.1	20.1	42	61.8	86.4	115.7	151.9	181.3	279.37
6	92	5.7	12.6	19	39.7	58.7	83	112.1	140.9	179.8	275.15
6	93	4.4	11.2	25	38.2	56.4	82.5	109.6	143.2	174.3	292.6
6	94	4.8	11.6	23.7	34.5	52.2	74.5	111.1	137.6	176.4	272.81
6	95	4.4	13.4	23.1	40.3	62.8	85.4	109.3	145.9	175	295.95
6	96	3.6	11.1	24.6	38.6	55.8	85.6	113.4	144.9	185.8	287.81
6	97	4.7	12.3	20.6	42.5	60.3	85.5	113.1	142.6	177.6	288.44

#	# NOW ENTER IN THE WEIGHTS AT AGE FOR THE SPANNING STOCK BIOMASS (row=year, col=age)										
#	X	X	X	X	X	X	X	X	X	X	X
70	3.2	8.4	17	37.4	56.3	79.7	112.9	148.3	172	270.35	
71	3.5	8.4	21.2	32	60.3	82	108.5	135.1	169.2	267.2	
72	4.4	9.7	19.3	40.7	57.6	84.8	114.9	137.5	171.9	283.2	
73	3.7	8.9	20.8	39.9	62.4	77.5	119.5	142.7	172.7	287.96	
74	3.6	10	17.2	36.8	57.1	82.9	102.5	138.5	169.2	295.51	
75	3.9	8.7	23.8	34.2	58.6	78.5	114.7	141.3	164.8	278.05	
76	3.9	10.3	18.9	34.1	51.9	81.1	119.4	152.2	171.8	277.7	
77	4.4	10.3	20.8	35.3	52.4	74.8	97.9	136.5	165.3	292.41	
78	5	10.8	21.7	35.5	54.4	73.6	107	145.3	183	318.14	
79	5.3	11.2	21.9	39.2	50.8	78.7	105.8	141.1	179.2	307.38	
80	5	12.2	21.4	35.7	53.3	84.6	114.4	140.6	186.7	320.53	
81	5.6	11	21.5	34.7	52.3	77.6	107.2	141.1	174.2	328.21	
82	4	10.8	21.3	34.3	59.6	82	115.3	150.1	181.6	316.21	
83	3.9	10.1	20	37.9	59	84.5	116.3	149	184.7	312.89	
84	4.7	11.2	23.6	39.5	60	85.9	116.4	148.3	183	299.45	
85	3.7	10.2	17.3	33.3	49	70.9	98.4	131.3	170.2	279.13	
86	4.2	9.9	20.2	41.2	57	84.8	116.3	148.5	180.9	299.15	
87	4.2	9.7	22.7	40.2	58.5	75.8	109.1	138.1	169.4	299.01	
88	3.9	11.4	21.1	38.5	58	81.2	108.3	142.9	179.4	293.58	
89	3.9	11	22.4	39.5	55.1	84.4	113.9	141.9	176.7	283.79	
90	4.5	11.4	19	39	55.7	77.9	111.6	146.6	179.4	286.62	
91	5.1	13.1	20.1	42	61.8	86.4	115.7	151.9	181.3	279.37	
92	5.7	12.6	19	39.7	58.7	83	112.1	140.9	179.8	275.15	
93	4.4	11.2	25	38.2	56.4	82.5	109.6	143.2	174.3	292.6	
94	4.8	11.6	23.7	34.5	52.2	74.5	111.1	137.6	176.4	272.81	
95	4.4	13.4	23.7	34.5	52.2	74.5	111.1	137.6	176.4	272.81	
96	4.8	11.6	23.7	34.5	52.2	74.5	111.1	137.6	176.4	272.81	
97	4.4	13.4	23.1	40.3	62.8	85.4	109.3	145.9	175	295.95	

96	3.6	11.1	24.6	38.6	55.8	85.6	113.4	144.9	185.8	287.81
97	4.7	12.3	20.6	42.5	60.3	85.5	113.1	142.6	177.6	286.44

A.3.1.3 Tagging Data file

```

#-----
# Release information
#-----
# release area
# |   release year
# | |   release age
# | | |   number released
# | | |   time of year releaed (in months)
# | | |   weight given to tagging data in objective function (acts like a standard deviation)
# | | | |
1 70 0   0. 0.0 1
1 70 1   0. 0.0 1
1 70 2   0. 0.0 1
1 70 3   0. 0.0 1
1 70 4   0. 0.0 1
1 70 5   0. 0.0 1
1 70 6   0. 0.0 1
1 70 7   0. 0.0 1
1 70 8   0. 0.0 1
1 70 9   0. 0.0 1
1 70 10  0. 0.0 1
2 70 0   6. 7.3 1
2 70 1  212. 7.8 1
2 70 2   24. 7.8 1
2 70 3   72. 8.1 1
2 70 4    2. 7.5 1
2 70 5    1. 8.0 1
2 70 6    1. 8.0 1
2 70 7    0. 0.0 1
2 70 8    3. 7.3 1
2 70 9   18. 5.6 1
2 70 10 218. 6.2 1
1 71 0    0. 0.0 1
1 71 1    0. 0.0 1
1 71 2    0. 0.0 1
1 71 3    0. 0.0 1
1 71 4    0. 0.0 1
1 71 5    0. 0.0 1
1 71 6    0. 0.0 1
1 71 7    0. 0.0 1
1 71 8    0. 0.0 1
1 71 9    0. 0.0 1
1 71 10  0. 0.0 1
2 71 0    0. 0.0 1
2 71 1  162. 8.0 1
2 71 2  170. 7.9 1
2 71 3   11. 8.0 1
2 71 4    5. 7.8 1
2 71 5    1. 7.0 1
2 71 6    1. 8.0 1
2 71 7    0. 0.0 1
2 71 8    0. 0.0 1
2 71 9    5. 5.8 1
2 71 10  77. 6.5 1
1 72 0    0. 0.0 1
1 72 1    0. 0.0 1
1 72 2    0. 0.0 1
1 72 3    0. 0.0 1
1 72 4    0. 0.0 1
1 72 5    0. 0.0 1
1 72 6    0. 0.0 1
1 72 7    0. 0.0 1
1 72 8    0. 0.0 1
1 72 9    0. 0.0 1
1 72 10  0. 0.0 1
2 72 0    1. 10.0 1
2 72 1  110. 8.4 1
2 72 2   76. 9.0 1
2 72 3    8. 8.5 1
2 72 4    0. 0.0 1
2 72 5    1. 7.0 1
2 72 6    2. 7.5 1
2 72 7    0. 0.0 1
2 72 8    1. 8.0 1
2 72 9    2. 8.5 1
2 72 10  82. 7.1 1
1 73 0    0. 0.0 1
1 73 1    0. 0.0 1
1 73 2    0. 0.0 1
1 73 3    0. 0.0 1
1 73 4    0. 0.0 1
1 73 5    0. 0.0 1
1 73 6    0. 0.0 1
1 73 7    0. 0.0 1
1 73 8    0. 0.0 1
1 73 9    0. 0.0 1
1 73 10  0. 0.0 1
2 73 0   42. 9.8 1
2 73 1   46. 7.6 1
2 73 2  187. 7.3 1
2 73 3   24. 8.0 1
2 73 4    1. 8.0 1
2 73 5    0. 0.0 1

```

2	73	6	1.	7.0	1
2	73	7	0.	0.0	1
2	73	8	0.	0.0	1
2	73	9	2.	7.5	1
2	73	10	44.	5.7	1
1	74	0	4.	12.0	1
1	74	1	0.	0.0	1
1	74	2	0.	0.0	1
1	74	3	0.	0.0	1
1	74	4	0.	0.0	1
1	74	5	0.	0.0	1
1	74	6	0.	0.0	1
1	74	7	0.	0.0	1
1	74	8	0.	0.0	1
1	74	9	0.	0.0	1
1	74	10	0.	0.0	1
2	74	0	10.	7.8	1
2	74	1	1326.	7.3	1
2	74	2	189.	7.6	1
2	74	3	137.	7.8	1
2	74	4	10.	8.0	1
2	74	5	0.	0.0	1
2	74	6	0.	0.0	1
2	74	7	0.	0.0	1
2	74	8	0.	0.0	1
2	74	9	0.	0.0	1
2	74	10	32.	6.2	1
1	75	0	0.	0.0	1
1	75	1	0.	0.0	1
1	75	2	0.	0.0	1
1	75	3	0.	0.0	1
1	75	4	0.	0.0	1
1	75	5	0.	0.0	1
1	75	6	0.	0.0	1
1	75	7	0.	0.0	1
1	75	8	0.	0.0	1
1	75	9	0.	0.0	1
1	75	10	0.	0.0	1
2	75	0	5.	6.8	1
2	75	1	134.	7.1	1
2	75	2	78.	6.9	1
2	75	3	15.	7.1	1
2	75	4	38.	7.7	1
2	75	5	7.	8.1	1
2	75	6	3.	8.7	1
2	75	7	1.	7.0	1
2	75	8	1.	7.0	1
2	75	9	3.	7.7	1
2	75	10	30.	7.0	1
1	76	0	0.	0.0	1
1	76	1	0.	0.0	1
1	76	2	1.	9.0	1
1	76	3	0.	0.0	1
1	76	4	0.	0.0	1
1	76	5	0.	0.0	1
1	76	6	0.	0.0	1
1	76	7	0.	0.0	1
1	76	8	0.	0.0	1
1	76	9	0.	0.0	1
1	76	10	0.	0.0	1
2	76	0	2.	7.5	1
2	76	1	729.	7.0	1
2	76	2	939.	7.0	1
2	76	3	589.	7.0	1
2	76	4	0.	0.0	1
2	76	5	0.	0.0	1
2	76	6	0.	0.0	1
2	76	7	0.	0.0	1
2	76	8	0.	0.0	1
2	76	9	1.	7.0	1
2	76	10	34.	7.8	1
1	77	0	0.	0.0	1
1	77	1	9.	7.4	1
1	77	2	6.	8.0	1
1	77	3	0.	0.0	1
1	77	4	0.	0.0	1
1	77	5	0.	0.0	1
1	77	6	0.	0.0	1
1	77	7	0.	0.0	1
1	77	8	0.	0.0	1
1	77	9	0.	0.0	1
1	77	10	0.	0.0	1
2	77	0	46.	8.9	1
2	77	1	177.	6.8	1
2	77	2	1629.	7.0	1
2	77	3	14.	7.0	1
2	77	4	11.	7.1	1
2	77	5	1.	8.0	1
2	77	6	0.	0.0	1
2	77	7	1.	8.0	1
2	77	8	1.	7.0	1
2	77	9	0.	0.0	1
2	77	10	207.	7.3	1
1	78	0	0.	0.0	1
1	78	1	113.	8.0	1
1	78	2	41.	8.0	1
1	78	3	6.	7.0	1

1	78	4	1.	8.0	1
1	78	5	0.	0.0	1
1	78	6	0.	0.0	1
1	78	7	0.	0.0	1
1	78	8	0.	0.0	1
1	78	9	0.	0.0	1
1	78	10	0.	0.0	1
2	78	0	19.	8.1	1
2	78	1	806.	7.9	1
2	78	2	516.	7.8	1
2	78	3	10.	6.5	1
2	78	4	1.	7.0	1
2	78	5	39.	9.0	1
2	78	6	2.	8.0	1
2	78	7	0.	0.0	1
2	78	8	25.	9.9	1
2	78	9	6.	8.0	1
2	78	10	234.	7.7	1
1	79	0	0.	0.0	1
1	79	1	9.	8.9	1
1	79	2	89.	9.0	1
1	79	3	1.	9.0	1
1	79	4	0.	0.0	1
1	79	5	0.	0.0	1
1	79	6	0.	0.0	1
1	79	7	0.	0.0	1
1	79	8	0.	0.0	1
1	79	9	0.	0.0	1
1	79	10	0.	0.0	1
2	79	0	4.	6.8	1
2	79	1	109.	6.4	1
2	79	2	54.	6.3	1
2	79	3	100.	7.0	1
2	79	4	14.	6.1	1
2	79	5	78.	7.0	1
2	79	6	174.	6.2	1
2	79	7	2.	7.5	1
2	79	8	20.	6.3	1
2	79	9	1.	8.0	1
2	79	10	562.	8.7	1
1	80	0	2.	8.0	1
1	80	1	218.	8.0	1
1	80	2	54.	8.0	1
1	80	3	9.	8.0	1
1	80	4	6.	8.0	1
1	80	5	1.	8.0	1
1	80	6	4.	8.0	1
1	80	7	0.	0.0	1
1	80	8	0.	0.0	1
1	80	9	0.	0.0	1
1	80	10	0.	0.0	1
2	80	0	7.	7.9	1
2	80	1	41.	6.5	1
2	80	2	1938.	6.0	1
2	80	3	205.	6.1	1
2	80	4	68.	6.2	1
2	80	5	0.	0.0	1
2	80	6	0.	0.0	1
2	80	7	0.	0.0	1
2	80	8	1.	9.0	1
2	80	9	0.	0.0	1
2	80	10	5.	5.8	1
1	81	0	0.	0.0	1
1	81	1	68.	8.0	1
1	81	2	229.	8.0	1
1	81	3	1.	8.0	1
1	81	4	0.	0.0	1
1	81	5	0.	0.0	1
1	81	6	0.	0.0	1
1	81	7	0.	0.0	1
1	81	8	0.	0.0	1
1	81	9	0.	0.0	1
1	81	10	0.	0.0	1
2	81	0	4.	8.3	1
2	81	1	132.	8.0	1
2	81	2	37.	7.6	1
2	81	3	12.	6.6	1
2	81	4	0.	0.0	1
2	81	5	0.	0.0	1
2	81	6	0.	0.0	1
2	81	7	0.	0.0	1
2	81	8	0.	0.0	1
2	81	9	0.	0.0	1
2	81	10	4.	6.8	1
1	82	0	0.	0.0	1
1	82	1	215.	8.0	1
1	82	2	70.	8.0	1
1	82	3	75.	8.0	1
1	82	4	28.	8.0	1
1	82	5	1.	8.0	1
1	82	6	1.	8.0	1
1	82	7	0.	0.0	1
1	82	8	0.	0.0	1
1	82	9	0.	0.0	1
1	82	10	0.	0.0	1
2	82	0	0.	0.0	1
2	82	1	90.	6.6	1

2	82	2	33.	6.5	1
2	82	3	1.	6.0	1
2	82	4	1.	6.0	1
2	82	5	7.	9.0	1
2	82	6	0.	0.0	1
2	82	7	1.	9.0	1
2	82	8	5.	9.0	1
2	82	9	8.	8.9	1
2	82	10	63.	8.5	1
1	83	0	331.	11.0	1
1	83	1	37.	7.9	1
1	83	2	332.	8.0	1
1	83	3	1.	9.0	1
1	83	4	1.	9.0	1
1	83	5	2.	9.0	1
1	83	6	0.	0.0	1
1	83	7	0.	0.0	1
1	83	8	0.	0.0	1
1	83	9	0.	0.0	1
1	83	10	0.	0.0	1
2	83	0	1.	9.0	1
2	83	1	81.	9.1	1
2	83	2	10.	8.8	1
2	83	3	3.	10.0	1
2	83	4	7.	9.1	1
2	83	5	0.	0.0	1
2	83	6	0.	0.0	1
2	83	7	0.	0.0	1
2	83	8	0.	0.0	1
2	83	9	1.	9.0	1
2	83	10	27.	9.0	1
1	84	0	52.	9.0	1
1	84	1	1.	8.0	1
1	84	2	394.	8.0	1
1	84	3	96.	8.0	1
1	84	4	8.	8.0	1
1	84	5	7.	8.0	1
1	84	6	0.	0.0	1
1	84	7	2.	8.0	1
1	84	8	0.	0.0	1
1	84	9	0.	0.0	1
1	84	10	0.	0.0	1
2	84	0	0.	0.0	1
2	84	1	15.	6.8	1
2	84	2	46.	7.0	1
2	84	3	11.	8.0	1
2	84	4	4.	9.0	1
2	84	5	4.	7.8	1
2	84	6	1.	8.0	1
2	84	7	0.	0.0	1
2	84	8	0.	0.0	1
2	84	9	0.	0.0	1
2	84	10	3.	6.7	1
1	85	0	0.	0.0	1
1	85	1	30.	8.0	1
1	85	2	227.	8.0	1
1	85	3	50.	7.9	1
1	85	4	2.	7.5	1
1	85	5	0.	0.0	1
1	85	6	0.	0.0	1
1	85	7	0.	0.0	1
1	85	8	0.	0.0	1
1	85	9	0.	0.0	1
1	85	10	0.	0.0	1
2	85	0	1.	9.0	1
2	85	1	40.	8.8	1
2	85	2	22.	8.4	1
2	85	3	34.	8.1	1
2	85	4	15.	7.7	1
2	85	5	2.	7.5	1
2	85	6	0.	0.0	1
2	85	7	1.	6.0	1
2	85	8	0.	0.0	1
2	85	9	2.	6.0	1
2	85	10	12.	4.7	1
1	86	0	0.	0.0	1
1	86	1	800.	9.6	1
1	86	2	27.	9.8	1
1	86	3	4.	9.5	1
1	86	4	1.	8.0	1
1	86	5	1.	8.0	1
1	86	6	0.	0.0	1
1	86	7	0.	0.0	1
1	86	8	0.	0.0	1
1	86	9	0.	0.0	1
1	86	10	0.	0.0	1
2	86	0	0.	0.0	1
2	86	1	4.	7.5	1
2	86	2	6.	7.5	1
2	86	3	7.	7.9	1
2	86	4	7.	7.9	1
2	86	5	0.	0.0	1
2	86	6	0.	0.0	1
2	86	7	0.	0.0	1
2	86	8	0.	0.0	1
2	86	9	1.	5.0	1
2	86	10	17.	4.6	1

1	87	0	0.	0.0	1
1	87	1	0.	0.0	1
1	87	2	0.	0.0	1
1	87	3	0.	0.0	1
1	87	4	0.	0.0	1
1	87	5	0.	0.0	1
1	87	6	0.	0.0	1
1	87	7	0.	0.0	1
1	87	8	0.	0.0	1
1	87	9	0.	0.0	1
1	87	10	0.	0.0	1
2	87	0	0.	0.0	1
2	87	1	17.	7.5	1
2	87	2	5.	7.4	1
2	87	3	6.	8.2	1
2	87	4	4.	8.3	1
2	87	5	4.	8.0	1
2	87	6	2.	8.0	1
2	87	7	0.	0.0	1
2	87	8	0.	0.0	1
2	87	9	1.	4.0	1
2	87	10	17.	4.7	1
1	88	0	0.	0.0	1
1	88	1	1121.	7.8	1
1	88	2	26.	7.0	1
1	88	3	1.	7.0	1
1	88	4	0.	0.0	1
1	88	5	0.	0.0	1
1	88	6	0.	0.0	1
1	88	7	0.	0.0	1
1	88	8	0.	0.0	1
1	88	9	0.	0.0	1
1	88	10	0.	0.0	1
2	88	0	1.	10.0	1
2	88	1	36.	8.6	1
2	88	2	26.	8.6	1
2	88	3	1.	7.0	1
2	88	4	0.	0.0	1
2	88	5	3.	8.0	1
2	88	6	3.	8.0	1
2	88	7	1.	8.0	1
2	88	8	1.	7.0	1
2	88	9	0.	0.0	1
2	88	10	8.	4.1	1
1	89	0	0.	0.0	1
1	89	1	118.	8.6	1
1	89	2	7.	8.0	1
1	89	3	0.	0.0	1
1	89	4	0.	0.0	1
1	89	5	0.	0.0	1
1	89	6	2.	7.0	1
1	89	7	0.	0.0	1
1	89	8	0.	0.0	1
1	89	9	0.	0.0	1
1	89	10	0.	0.0	1
2	89	0	0.	0.0	1
2	89	1	10.	7.4	1
2	89	2	33.	8.1	1
2	89	3	18.	8.7	1
2	89	4	22.	8.5	1
2	89	5	9.	9.6	1
2	89	6	7.	9.3	1
2	89	7	1.	10.0	1
2	89	8	0.	0.0	1
2	89	9	1.	5.0	1
2	89	10	2.	6.0	1
1	90	0	536.	10.8	1
1	90	1	841.	8.1	1
1	90	2	6.	8.2	1
1	90	3	0.	0.0	1
1	90	4	0.	0.0	1
1	90	5	0.	0.0	1
1	90	6	0.	0.0	1
1	90	7	0.	0.0	1
1	90	8	0.	0.0	1
1	90	9	0.	0.0	1
1	90	10	7.	7.7	1
2	90	0	2.	9.0	1
2	90	1	110.	8.1	1
2	90	2	64.	8.2	1
2	90	3	66.	8.9	1
2	90	4	77.	8.7	1
2	90	5	44.	8.6	1
2	90	6	19.	9.0	1
2	90	7	56.	8.8	1
2	90	8	11.	8.4	1
2	90	9	1.	9.0	1
2	90	10	2.	6.0	1
1	91	0	2101.	11.0	1
1	91	1	248.	10.5	1
1	91	2	12.	10.3	1
1	91	3	1.	11.0	1
1	91	4	0.	0.0	1
1	91	5	0.	0.0	1
1	91	6	0.	0.0	1
1	91	7	0.	0.0	1
1	91	8	1.	8.0	1

1	91	9	0.	0.0	1
1	91	10	1.	9.0	1
2	91	0	2.	9.0	1
2	91	1	324.	8.3	1
2	91	2	327.	9.1	1
2	91	3	253.	9.1	1
2	91	4	26.	8.5	1
2	91	5	23.	8.6	1
2	91	6	20.	7.6	1
2	91	7	18.	8.3	1
2	91	8	27.	8.0	1
2	91	9	24.	8.5	1
2	91	10	26.	7.8	1
1	92	0	476.	10.9	1
1	92	1	0.	0.0	1
1	92	2	1.	6.0	1
1	92	3	0.	0.0	1
1	92	4	0.	0.0	1
1	92	5	0.	0.0	1
1	92	6	0.	0.0	1
1	92	7	1.	8.0	1
1	92	8	1.	8.0	1
1	92	9	0.	0.0	1
1	92	10	0.	0.0	1
2	92	0	3.	5.3	1
2	92	1	27.	7.1	1
2	92	2	436.	8.7	1
2	92	3	361.	8.9	1
2	92	4	32.	7.5	1
2	92	5	16.	6.6	1
2	92	6	34.	6.3	1
2	92	7	20.	7.5	1
2	92	8	6.	7.5	1
2	92	9	6.	8.0	1
2	92	10	7.	6.9	1
1	93	0	3.	10.0	1
1	93	1	1.	10.0	1
1	93	2	1.	10.0	1
1	93	3	1.	5.0	1
1	93	4	1.	7.0	1
1	93	5	0.	0.0	1
1	93	6	0.	0.0	1
1	93	7	1.	7.0	1
1	93	8	1.	9.0	1
1	93	9	1.	7.0	1
1	93	10	0.	0.0	1
2	93	0	0.	0.0	1
2	93	1	29.	7.0	1
2	93	2	120.	8.9	1
2	93	3	302.	8.7	1
2	93	4	77.	8.5	1
2	93	5	33.	7.4	1
2	93	6	14.	5.2	1
2	93	7	8.	7.8	1
2	93	8	1.	4.0	1
2	93	9	2.	6.5	1
2	93	10	7.	8.6	1
1	94	0	651.	9.8	1
1	94	1	15.	11.1	1
1	94	2	2.	11.5	1
1	94	3	0.	0.0	1
1	94	4	0.	0.0	1
1	94	5	0.	0.0	1
1	94	6	0.	0.0	1
1	94	7	0.	0.0	1
1	94	8	0.	0.0	1
1	94	9	0.	0.0	1
1	94	10	0.	0.0	1
2	94	0	0.	0.0	1
2	94	1	18.	7.6	1
2	94	2	26.	8.6	1
2	94	3	48.	8.5	1
2	94	4	42.	8.6	1
2	94	5	30.	7.8	1
2	94	6	30.	5.7	1
2	94	7	29.	6.9	1
2	94	8	37.	6.9	1
2	94	9	52.	7.2	1
2	94	10	74.	7.5	1
1	95	0	5.	9.8	1
1	95	1	2.	10.0	1
1	95	2	0.	0.0	1
1	95	3	0.	0.0	1
1	95	4	0.	0.0	1
1	95	5	1.	11.0	1
1	95	6	0.	0.0	1
1	95	7	1.	9.0	1
1	95	8	1.	8.0	1
1	95	9	1.	9.0	1
1	95	10	0.	0.0	1
2	95	0	1.	12.0	1
2	95	1	606.	8.0	1
2	95	2	73.	8.6	1
2	95	3	34.	6.8	1
2	95	4	24.	7.3	1
2	95	5	11.	6.9	1
2	95	6	29.	6.1	1

2	95	7	73.	4.1	1
2	95	8	113.	3.1	1
2	95	9	208.	2.9	1
2	95	10	341.	3.6	1
1	96	0	0.	0.0	1
1	96	1	2.	7.5	1
1	96	2	1.	8.0	1
1	96	3	0.	0.0	1
1	96	4	1.	9.0	1
1	96	5	0.	0.0	1
1	96	6	0.	0.0	1
1	96	7	0.	0.0	1
1	96	8	0.	0.0	1
1	96	9	0.	0.0	1
1	96	10	0.	0.0	1
2	96	0	1.	6.0	1
2	96	1	70.	7.1	1
2	96	2	147.	6.7	1
2	96	3	19.	6.2	1
2	96	4	54.	3.3	1
2	96	5	111.	2.8	1
2	96	6	455.	2.2	1
2	96	7	651.	2.5	1
2	96	8	449.	2.8	1
2	96	9	240.	3.0	1
2	96	10	230.	3.9	1
1	97	0	0.	0.0	1
1	97	1	0.	0.0	1
1	97	2	1.	9.0	1
1	97	3	2.	8.5	1
1	97	4	0.	0.0	1
1	97	5	0.	0.0	1
1	97	6	0.	0.0	1
1	97	7	0.	0.0	1
1	97	8	0.	0.0	1
1	97	9	1.	8.0	1
1	97	10	13.	8.5	1
2	97	0	2.	9.5	1
2	97	1	170.	8.6	1
2	97	2	216.	8.2	1
2	97	3	222.	7.2	1
2	97	4	90.	4.2	1
2	97	5	262.	3.3	1

A.3.1.4 Parameter specification file

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# terminal age structure of population
0.0000D+00 0.6000D+00 0.3000D+01 0.0 0.2000D+01 1
0.1000D-01 0.6703D+00 0.5000D+01 1.0 0.1000D+00 2
0.0000D+00 0.1000D+01 0.3000D+01 0.0 0.2000D+01 3
0.1000D-01 0.2174D+00 0.5000D+01 1.0 0.1000D+00 4
0.0000D+00 0.1000D+01 0.3000D+01 0.0 0.4000D+01 5
0.1000D-01 0.1000D+01 0.5000D+01 0.0 0.4000D+01 6
0.0000D+00 0.1000D+01 0.3000D+01 0.0 0.4000D+01 7
0.1000D-01 0.6286D+00 0.5000D+01 1.0 0.1000D+00 8
0.0000D+00 0.1000D+01 0.3000D+01 0.0 0.8000D+01 9
# terminal-age f-ratios
0.1000D+00 0.1000D+01 0.5000D+01 0.0 0.2000D+00 10
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 11
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 12
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 13
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 14
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 15
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 16
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 17
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 18
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 19
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 20
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 21
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 22
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 23
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 24
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 25
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 26
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 27
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 28
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 29
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 30
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 31
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 32
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 33
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 34
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 35
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 36
-0.1000D+02 0.1000D+01 0.1001D+02 0.0 0.1000D+00 37
# natural mortality
0.0000D+00 0.4900D+00 0.1000D+01 0.0 0.1000D+00 38
0.0000D+00 0.2400D+00 0.1000D+01 0.0 0.1000D+00 39
0.0000D+00 0.2400D+00 0.1000D+01 0.0 0.1000D+00 40
0.0000D+00 0.2400D+00 0.1000D+01 0.0 0.1000D+00 41
0.0000D+00 0.2400D+00 0.1000D+01 0.0 0.1000D+00 42
0.0000D+00 0.2000D+00 0.1000D+01 0.0 0.1000D+00 43
0.0000D+00 0.1750D+00 0.1000D+01 0.0 0.1000D+00 44
0.0000D+00 0.1500D+00 0.1000D+01 0.0 0.1000D+00 45
0.0000D+00 0.1250D+00 0.1000D+01 0.0 0.1000D+00 46
0.0000D+00 0.1000D+00 0.1000D+01 0.0 0.1000D+00 47
# transfer coefficients
0.0000D+00 0.0000D+00 0.1000D+01 0.0 0.1000D+00 48
0.0000D+00 0.8968D-02 0.1000D+01 1.0 0.1000D+00 49
0.0000D+00 0.8968D-02 0.1000D+01 -0.1 0.1000D+00 50
0.0000D+00 0.3849D-01 0.1000D+01 1.0 0.1000D+00 51
0.0000D+00 0.3849D-01 0.1000D+01 -0.1 0.1000D+00 52
0.0000D+00 0.3849D-01 0.1000D+01 -0.1 0.1000D+00 53
0.0000D+00 0.3849D-01 0.1000D+01 -0.1 0.1000D+00 54
0.0000D+00 0.3849D-01 0.1000D+01 -0.1 0.1000D+00 55
0.0000D+00 0.3849D-01 0.1000D+01 -0.1 0.1000D+00 56
0.0000D+00 0.3849D-01 0.1000D+01 -0.1 0.1000D+00 57
# Stock recruitment relationship
0.0000D+00 0.2507D+06 0.1000D+21 0.0 0.4000D+00 58
0.0000D+00 0.1660D+05 0.1000D+21 0.0 0.0000D+00 59
0.0000D+00 0.1580D+00 0.9000D+00 0.0 0.0000D+00 60
0.0000D+00 0.1000D+01 0.2000D+01 0.0 0.0000D+00 61
0.0000D+00 0.1000D+01 0.2000D+01 0.0 0.0000D+00 62
# Variance scaling parameters
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 63
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 64
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 65
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 66
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 67
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 68
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 69
0.0000D+00 0.1000D+01 0.1000D+21 0.0 0.4000D+00 70
# fraction surviving the intial tagging process
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 71
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 72
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 73
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 74
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 75
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 76
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 77
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 78
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 79
0.0000D+00 0.8000D+00 0.1000D+01 0.0 0.1000D+00 80
# tag shedding rate
0.0000D+00 0.2600D+00 0.1000D+01 1.0 0.1000D+00 81
0.0000D+00 0.2600D+00 0.1000D+01 -1.0 0.1000D+00 82

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0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	668	124	10
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	669	125	1
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	670	125	2
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	671	125	3
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	672	125	4
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	673	125	5
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	674	125	6
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	675	125	7
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	676	125	8
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	677	125	9
0.0000D+00	0.1000D+01	0.5000D+01	-0.1	0.1000D+00	678	125	10
# terminal age structure of population							
0.0000D+00	0.3180D+00	0.3000D+01	0.0	0.2000D+01	679		
0.1000D-01	0.4111D-01	0.3000D+01	1.0	0.1000D+00	680		
0.0000D+00	0.1000D+01	0.3000D+01	0.0	0.2000D+01	681		
0.1000D-01	0.4193D-01	0.3000D+01	1.0	0.1000D+00	682		
0.0000D+00	0.1000D+01	0.3000D+01	0.0	0.4000D+01	683		
0.1000D-01	0.1275D+00	0.3000D+01	1.0	0.1000D+00	684		
0.0000D+00	0.1000D+01	0.3000D+01	0.0	0.6000D+01	685		
0.1000D-01	0.1629D+00	0.3000D+01	1.0	0.1000D+00	686		
0.0000D+00	0.1000D+01	0.3000D+01	0.0	0.8000D+01	687		
# terminal-age f-ratios							
0.0000D+00	0.1000D+01	0.4000D+01	0.0	0.2000D+00	688		
0.0000D+00	0.1000D+01	0.4000D+01	0.0	0.2000D+00	689		
0.0000D+00	0.1000D+01	0.4000D+01	0.0	0.2000D+00	690		
0.0000D+00	0.1000D+01	0.4000D+01	0.0	0.2000D+00	691		
0.1000D-01	0.8845D+00	0.4000D+01	1.0	0.2000D+00	692		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	693		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	694		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	695		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	696		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	697		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	698		
0.1000D-01	0.8845D+00	0.4000D+01	-0.1	0.1000D+00	699		
0.1000D-01	0.1140D+01	0.4000D+01	0.3	0.2500D+00	700		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	701		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	702		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	703		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	704		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	705		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	706		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	707		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	708		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	709		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	710		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	711		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	712		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	713		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	714		
0.1000D-01	0.1140D+01	0.4000D+01	-0.1	0.1000D+00	715		
# natural mortality							
0.0000D+00	0.4900D+00	0.1000D+01	0.0	0.1000D+00	716		
0.0000D+00	0.2400D+00	0.1000D+01	0.0	0.1000D+00	717		
0.0000D+00	0.2400D+00	0.1000D+01	0.0	0.1000D+00	718		
0.0000D+00	0.2400D+00	0.1000D+01	0.0	0.1000D+00	719		
0.0000D+00	0.2400D+00	0.1000D+01	0.0	0.1000D+00	720		
0.0000D+00	0.2000D+00	0.1000D+01	0.0	0.1000D+00	721		
0.0000D+00	0.1750D+00	0.1000D+01	0.0	0.1000D+00	722		
0.0000D+00	0.1500D+00	0.1000D+01	0.0	0.1000D+00	723		
0.0000D+00	0.1250D+00	0.1000D+01	0.0	0.1000D+00	724		
0.0000D+00	0.1000D+00	0.1000D+01	0.0	0.1000D+00	725		
# transfer coefficients							
0.0000D+00	0.0000D+00	0.1000D+01	0.0	0.1000D+00	726		
0.0000D+00	0.2427D-02	0.1000D+01	1.0	0.1000D+00	727		
0.0000D+00	0.2427D-02	0.1000D+01	-0.1	0.1000D+00	728		
0.0000D+00	0.2490D-01	0.1000D+01	1.0	0.1000D+00	729		
0.0000D+00	0.2490D-01	0.1000D+01	-0.1	0.1000D+00	730		
0.0000D+00	0.2490D-01	0.1000D+01	-0.1	0.1000D+00	731		
0.0000D+00	0.2490D-01	0.1000D+01	-0.1	0.1000D+00	732		
0.0000D+00	0.1553D-01	0.1000D+01	1.0	0.1000D+00	733		
0.0000D+00	0.1553D-01	0.1000D+01	-0.1	0.1000D+00	734		
0.0000D+00	0.1553D-01	0.1000D+01	-0.1	0.1000D+00	735		
# Stock recruitment relationship							
-0.1000D+21	0.3141D+06	0.1000D+21	0.0	0.4000D+00	736		
-0.1000D+21	0.1638D+06	0.1000D+21	0.0	0.0000D+00	737		
-0.1000D+02	0.1500D+01	0.9000D+00	0.0	0.0000D+00	738		
0.0000D+00	0.5000D+00	0.2000D+01	0.0	0.0000D+00	739		
0.0000D+00	0.3464D+00	0.2000D+01	0.0	0.0000D+00	740		
# Variance scaling parameters							
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	741		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	742		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	743		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	744		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	745		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	746		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	747		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	748		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	749		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	750		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	751		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	752		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	753		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	754		
0.0000D+00	0.1000D+01	0.1000D+21	0.0	0.4000D+00	755		

81	0.121	0.428	0.357	0.121	0.111	0.039	0.056	0.074	0.046	0.046
82	0.316	0.384	0.522	0.187	0.071	0.042	0.041	0.147	0.101	0.101
83	0.234	0.184	0.331	0.144	0.089	0.066	0.130	0.062	0.108	0.108
84	0.100	0.435	0.119	0.135	0.145	0.103	0.098	0.128	0.126	0.126
85	0.146	0.369	0.406	0.129	0.094	0.098	0.060	0.082	0.100	0.100
86	0.261	0.371	0.358	0.162	0.037	0.056	0.049	0.039	0.090	0.090
87	0.172	0.365	0.300	0.114	0.047	0.033	0.094	0.079	0.084	0.084
88	0.385	0.270	0.387	0.179	0.061	0.048	0.060	0.096	0.123	0.123
89	0.226	0.425	0.245	0.204	0.243	0.045	0.061	0.045	0.092	0.092
90	0.192	0.333	0.450	0.205	0.174	0.075	0.059	0.080	0.097	0.097
91	0.119	0.389	0.369	0.222	0.236	0.054	0.062	0.060	0.127	0.127
92	0.188	0.450	0.556	0.156	0.099	0.067	0.057	0.112	0.125	0.125
93	0.134	0.789	0.784	0.255	0.124	0.124	0.089	0.056	0.127	0.127
94	0.192	0.463	0.405	0.255	0.238	0.174	0.246	0.293	0.300	0.300
95	0.225	0.423	0.532	0.264	0.289	0.236	0.150	0.217	0.378	0.378
96	0.298	0.966	0.703	0.537	0.294	0.228	0.247	0.198	0.502	0.502
97	0.440	0.734	0.734	0.365	0.365	0.365	0.365	0.691	0.691	0.691

TABLE 2.1 ABUNDANCE AT THE BEGINNING OF THE YEAR [BY AREA] FOR EAST

	1	2	3	4	5	6	7	8	9	10
70	839440.	407538.	256252.	207707.	305586.	364638.	126228.	118275.	99400.	396483.
71	1244733.	413005.	247664.	172667.	150988.	232915.	294102.	102356.	101107.	429238.
72	933262.	754513.	238717.	145232.	123160.	109621.	187605.	243909.	83890.	465408.
73	1313402.	481718.	456478.	118423.	100363.	88710.	84861.	154173.	208845.	488368.
74	1931654.	696225.	308705.	285930.	83930.	76559.	69722.	66454.	126344.	612947.
75	2017543.	1042334.	421733.	179783.	177808.	56099.	58126.	55470.	54132.	626838.
76	1897194.	711319.	558914.	282189.	126302.	134081.	41988.	46362.	44779.	568036.
77	1402939.	1087941.	372116.	221117.	181307.	83818.	104415.	32059.	38329.	521170.
78	1045263.	690161.	606207.	217929.	140170.	138707.	64720.	83991.	25312.	475673.
79	1274454.	505248.	370351.	347887.	150997.	107302.	113271.	52296.	70766.	431971.
80	1888648.	720711.	343692.	210649.	236533.	111868.	86509.	93835.	41828.	432913.
81	1698843.	1017078.	429485.	164056.	135911.	177213.	87893.	70541.	79619.	407049.
82	2815364.	922264.	507161.	229852.	114585.	96120.	140169.	70158.	57050.	422323.
83	3976412.	1258018.	480514.	230237.	150592.	84131.	75745.	113368.	52463.	393999.
84	2212986.	1928529.	799984.	263841.	157701.	108869.	64575.	56018.	92078.	364258.
85	1957136.	1226575.	954070.	542981.	182137.	107979.	80786.	49221.	42602.	364767.
86	3211738.	1036280.	648178.	486214.	376218.	131057.	80731.	64177.	39094.	334947.
87	1840207.	1515917.	547061.	346511.	326308.	285772.	101842.	64951.	53431.	310531.
88	2976730.	949305.	804377.	309914.	244067.	245789.	226813.	78105.	52097.	303314.
89	2644878.	1240326.	554388.	417813.	204775.	181199.	192335.	179653.	61371.	285074.
90	2810752.	1291925.	619783.	331903.	268984.	126950.	142226.	152333.	148177.	286231.
91	2887311.	1421308.	707628.	302192.	213597.	178469.	97009.	112845.	121412.	355200.
92	3129725.	1570485.	736369.	374188.	191009.	133392.	139073.	77006.	91739.	378744.
93	2920158.	1589330.	765625.	322894.	252323.	136680.	102754.	110727.	59691.	374937.
94	1967060.	1563985.	552007.	267293.	197729.	175629.	79379.	70158.	96068.	346233.
95	2472383.	995020.	752369.	281478.	164062.	123281.	121078.	65452.	51404.	292391.
96	2297416.	1209645.	498429.	337954.	170573.	97566.	80163.	87602.	213530.	45656.
97	1083913.	1044910.	352331.	188726.	156441.	100406.	64258.	52938.	62024.	142323.
98		427574.	383569.	129589.	103480.	86356.	57346.	37932.	23039.	92649.

TABLE 3.1 CATCH OF EAST

	1	2	3	4	5	6	7	8	9	10
70	131834.	73211.	26994.	17842.	9793.	6523.	4501.	3254.	6114.	25014.
71	10384.	88198.	50413.	16589.	12777.	4390.	4529.	5157.	4906.	21189.
72	116980.	137100.	73231.	17152.	9923.	7289.	4363.	2521.	2809.	16079.
73	140707.	68048.	71707.	11121.	3710.	3659.	6740.	7668.	7385.	17757.
74	182955.	125976.	64125.	54045.	11608.	5786.	3665.	4894.	8649.	42935.
75	692276.	272026.	45944.	18469.	6853.	4582.	3240.	3527.	4697.	54436.
76	96176.	195792.	236722.	48724.	18378.	6163.	3649.	2317.	3039.	39367.
77	220444.	256835.	75831.	41725.	6345.	4861.	4180.	2639.	2613.	35976.
78	176030.	179228.	131623.	24546.	5211.	1702.	2569.	1828.	1382.	26483.
79	77747.	48322.	82586.	43682.	8753.	2691.	2378.	3797.	3656.	22807.
80	181555.	138196.	112676.	34813.	10919.	4745.	3159.	2246.	2340.	24568.
81	153659.	308374.	112260.	16763.	12811.	6096.	4418.	4737.	3416.	17651.
82	610048.	255871.	180005.	35080.	6973.	3594.	5132.	8972.	5205.	38888.
83	661161.	183593.	117908.	27771.	11486.	4906.	8530.	6412.	5103.	38832.
84	167350.	593304.	77856.	29822.	19162.	9733.	5548.	6303.	10300.	41385.
85	211218.	329782.	277272.	58541.	14591.	9209.	4330.	3627.	3833.	33306.
86	589053.	279348.	169783.	65035.	12138.	6547.	3553.	2306.	3160.	27540.
87	231377.	403819.	123350.	33317.	13324.	8403.	8448.	4599.	4096.	24101.
88	764519.	194898.	224722.	45555.	12889.	10546.	12087.	6687.	5708.	33569.
89	427685.	374544.	104582.	69006.	39704.	7228.	10436.	7301.	5099.	24004.
90	390979.	318667.	195899.	55194.	38505.	8399.	7470.	10924.	12874.	25255.
91	257208.	399047.	189996.	53999.	40314.	8501.	5384.	6126.	13655.	40469.
92	426527.	496269.	274484.	48134.	16089.	7918.	7096.	7639.	10185.	42593.
93	291913.	761131.	365258.	65159.	26289.	14508.	8127.	5584.	6765.	42839.
94	273175.	505865.	160218.	54239.	37542.	25496.	20047.	18932.	22229.	85868.
95	397190.	298948.	271217.	58546.	37126.	23756.	15577.	11943.	15399.	88172.
96	473520.	660055.	220479.	126894.	38949.	18317.	16240.	14690.	17129.	81033.
97	310602.	476212.	160888.	51831.	43254.	28100.	18335.	24970.	29385.	68633.

TABLE 4.1 SPAWNING STOCK FECUNDITY AND RECRUITMENT OF EAST

year	spawning biomass	recruits from VPA
70	161011.	839440.
71	183815.	1244733.
72	191700.	933262.
73	188799.	1313402.
74	194959.	1931654.
75	183303.	2017543.
76	180586.	1897194.
77	171531.	1402939.
78	161520.	1045263.
79	153023.	1274454.
80	147336.	1888648.

81 136736. 1698843.
 82 134187. 2815364.
 83 121154. 3976412.
 84 118569. 2212986.
 85 121347. 1957136.
 86 127234. 3211738.
 87 129335. 1840207.
 88 132886. 2976730.
 89 132997. 2644878.
 90 130965. 2810752.
 91 129841. 2887311.
 92 128312. 3129725.
 93 135302. 2920158.
 94 117549. 1967060.
 95 97088. 2472383.
 96 74910. 2297416.
 97 50100. 1083913.

TABLE 5.1 FITS TO INDEX DATA EAST

5.1 ESP BB

Lognormal dist.
 average numbers
 Ages 2 - 2
 log-likelihood = -9.74
 deviance = 103.37
 Chi-sq. discrepancy= 114.25

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
70	3.584	3.049	0.535	0.224	0.666E-04	36.020	21.086	9.786
71	3.313	3.039	0.274	0.224	0.666E-04	27.470	20.883	1.941
72	3.283	3.662	-0.379	0.224	0.666E-04	26.660	38.933	1.939
73	3.937	3.240	0.696	0.224	0.666E-04	51.240	25.535	19.771
74	3.658	3.582	0.076	0.224	0.666E-04	38.800	35.948	0.123
75	4.401	3.930	0.470	0.224	0.666E-04	81.520	50.925	7.042
76	3.982	3.537	0.446	0.224	0.666E-04	53.640	34.353	6.150
77	4.070	3.990	0.080	0.224	0.666E-04	58.580	54.056	0.137
78	3.496	3.518	-0.022	0.224	0.666E-04	32.990	33.713	0.009
79	2.342	3.315	-0.973	0.224	0.666E-04	10.400	27.526	7.552
80	3.116	3.609	-0.493	0.224	0.666E-04	22.560	36.924	2.952
81	3.522	3.873	-0.351	0.224	0.666E-04	33.850	48.071	1.707
82	3.449	3.794	-0.346	0.224	0.666E-04	31.460	44.452	1.667
83	3.789	4.196	-0.407	0.224	0.666E-04	44.200	66.407	2.182
84	4.942	4.509	0.433	0.224	0.666E-04	140.020	90.826	5.724
85	4.217	4.086	0.132	0.224	0.666E-04	67.860	59.495	0.386
86	3.882	3.917	-0.035	0.224	0.666E-04	48.540	50.245	0.022
87	4.454	4.300	0.155	0.224	0.666E-04	86.000	73.667	0.547
88	4.091	3.875	0.216	0.224	0.666E-04	59.790	48.185	1.132
89	4.146	4.072	0.074	0.224	0.666E-04	63.190	58.677	0.115
90	3.517	4.154	-0.637	0.224	0.666E-04	33.690	63.684	4.328
91	4.157	4.224	-0.068	0.224	0.666E-04	63.850	68.331	0.084
92	4.169	4.297	-0.128	0.224	0.666E-04	64.670	73.486	0.281
93	4.963	4.163	0.799	0.224	0.666E-04	142.970	64.290	29.221
94	3.466	4.287	-0.821	0.224	0.666E-04	32.010	72.752	6.118
95	3.884	3.853	0.031	0.224	0.666E-04	48.620	47.120	0.020
96	4.157	3.819	0.338	0.224	0.666E-04	63.850	45.552	3.148
97	3.669	3.767	-0.098	0.224	0.666E-04	39.200	43.257	0.172

Selectivities by age

Year 2

 70 1.000
 71 1.000
 72 1.000
 73 1.000
 74 1.000
 75 1.000
 76 1.000
 77 1.000
 78 1.000
 79 1.000
 80 1.000
 81 1.000
 82 1.000
 83 1.000
 84 1.000
 85 1.000
 86 1.000
 87 1.000
 88 1.000
 89 1.000
 90 1.000
 91 1.000
 92 1.000
 93 1.000
 94 1.000
 95 1.000

96 1.000
97 1.000

5.2 FRA PS Early 2

Not used

5.3 FRA PS Late 2

Not used

5.4 FRA PS Early 3

Lognormal dist.
average numbers
Ages 3 - 3
log-likelihood = -1.13
deviance = 3.67
Chi-sq. discrepancy= 3.95

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
70	0.018	0.501	-0.483	1.076	0.790E-05	1.018	1.650	0.067
71	-0.014	0.402	-0.416	1.099	0.790E-05	0.986	1.494	0.049
72	0.107	0.289	-0.182	1.207	0.790E-05	1.113	1.335	0.008
73	1.259	1.043	0.216	1.055	0.790E-05	3.522	2.838	0.028
74	0.947	0.618	0.329	1.395	0.790E-05	2.578	1.856	0.025
75	0.363	0.995	-0.632	0.937	0.790E-05	1.438	2.704	0.156
76	1.698	1.042	0.656	0.558	0.790E-05	5.463	2.834	2.352
77	1.558	0.808	0.750	0.922	0.790E-05	4.749	2.243	0.931
78	1.115	1.286	-0.171	0.911	0.790E-05	3.050	3.620	0.019
79	0.720	0.790	-0.070	0.789	0.790E-05	2.054	2.203	0.005
80	0.227	0.636	-0.409	0.949	0.790E-05	1.255	1.889	0.077
81	0.416	0.910	-0.494	0.713	0.790E-05	1.516	2.484	0.229

Selectivities by age
Year 3

70 1.000
71 1.000
72 1.000
73 1.000
74 1.000
75 1.000
76 1.000
77 1.000
78 1.000
79 1.000
80 1.000
81 1.000

5.5 FRA PS Late 3

Lognormal dist.
average numbers
Ages 3 - 3
log-likelihood = 1.58
deviance = 12.64
Chi-sq. discrepancy= 13.04

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
82	0.999	0.727	0.273	0.534	0.599E-05	2.716	2.068	0.297
83	-0.434	0.757	-1.191	1.699	0.599E-05	0.648	2.132	0.029
84	-0.650	1.365	-2.015	1.217	0.599E-05	0.522	3.915	0.221
85	2.259	1.410	0.850	0.462	0.599E-05	9.574	4.094	7.523
86	1.145	1.044	0.100	0.807	0.599E-05	3.142	2.842	0.012
87	1.209	0.901	0.308	0.655	0.599E-05	3.350	2.462	0.242
88	1.914	1.247	0.667	0.560	0.599E-05	6.780	3.481	2.437
89	0.336	0.940	-0.604	0.634	0.599E-05	1.399	2.559	0.416
90	0.817	0.959	-0.141	0.483	0.599E-05	2.264	2.608	0.066
91	0.724	1.127	-0.403	0.460	0.599E-05	2.063	3.087	0.466
92	1.164	1.084	0.080	0.442	0.599E-05	3.203	2.957	0.032
93	1.003	1.026	-0.024	0.443	0.599E-05	2.726	2.791	0.003
94	0.221	0.863	-0.642	0.522	0.599E-05	1.247	2.369	0.716
95	1.039	1.116	-0.078	0.440	0.599E-05	2.826	3.054	0.026
96	0.892	0.631	0.261	0.472	0.599E-05	2.440	1.880	0.355
97	-0.289	0.273	-0.562	0.815	0.599E-05	0.749	1.314	0.196

Selectivities by age
Year 3

82 1.000
83 1.000
84 1.000
85 1.000

86 1.000
 87 1.000
 88 1.000
 89 1.000
 90 1.000
 91 1.000
 92 1.000
 93 1.000
 94 1.000
 95 1.000
 96 1.000
 97 1.000

 5.6 ESP TRAP 4+

Lognormal dist.
 average numbers
 Ages 4 - 10
 log-likelihood = -3.27
 deviance = 55.18
 Chi-sq. discrepancy= 168.31

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
81	4.381	4.283	0.098	0.423	0.141E-03	79.918	72.462	0.054
82	4.397	4.258	0.139	0.252	0.141E-03	81.207	70.657	0.339
83	4.501	4.207	0.294	0.252	0.141E-03	90.107	67.150	1.777
84	4.331	4.136	0.195	0.252	0.141E-03	76.020	62.573	0.702
85	4.326	4.086	0.240	0.252	0.141E-03	75.641	59.516	1.116
86	3.669	4.066	-0.397	0.221	0.141E-03	39.213	58.306	2.147
87	3.676	4.091	-0.415	0.229	0.141E-03	39.488	59.827	2.153
88	4.147	4.119	0.028	0.221	0.141E-03	63.244	61.494	0.016
89	4.210	4.168	0.042	0.221	0.141E-03	67.357	64.602	0.036
90	4.193	4.216	-0.023	0.221	0.141E-03	66.221	67.730	0.010
91	4.124	4.252	-0.128	0.221	0.141E-03	61.806	70.231	0.288
92	3.930	4.230	-0.300	0.229	0.141E-03	50.907	68.746	1.251
93	3.741	4.203	-0.462	0.228	0.141E-03	42.140	66.918	2.563
94	3.725	4.082	-0.357	0.229	0.141E-03	41.471	59.254	1.678
95	3.687	3.862	-0.175	0.228	0.141E-03	39.925	47.550	0.481
96	3.649	3.594	0.055	0.221	0.141E-03	38.436	36.380	0.064
97	4.544	3.217	1.327	0.221	0.141E-03	94.066	24.950	153.634

Selectivities by age

Year	4	5	6	7	8	9	10
81	0.003	0.048	0.158	0.256	0.507	0.674	1.000
82	0.003	0.048	0.158	0.256	0.507	0.674	1.000
83	0.003	0.048	0.158	0.256	0.507	0.674	1.000
84	0.003	0.048	0.158	0.256	0.507	0.674	1.000
85	0.003	0.048	0.158	0.256	0.507	0.674	1.000
86	0.003	0.048	0.158	0.256	0.507	0.674	1.000
87	0.003	0.048	0.158	0.256	0.507	0.674	1.000
88	0.003	0.048	0.158	0.256	0.507	0.674	1.000
89	0.003	0.048	0.158	0.256	0.507	0.674	1.000
90	0.003	0.048	0.158	0.256	0.507	0.674	1.000
91	0.003	0.048	0.158	0.256	0.507	0.674	1.000
92	0.003	0.048	0.158	0.256	0.507	0.674	1.000
93	0.003	0.048	0.158	0.256	0.507	0.674	1.000
94	0.003	0.048	0.158	0.256	0.507	0.674	1.000
95	0.003	0.048	0.158	0.256	0.507	0.674	1.000
96	0.003	0.048	0.158	0.256	0.507	0.674	1.000
97	0.003	0.048	0.158	0.256	0.507	0.674	1.000

 5.7 JLL East&Med 8+

Lognormal dist.
 average numbers
 Ages 8 - 10
 log-likelihood = 1.46
 deviance = 64.17
 Chi-sq. discrepancy= 75.96

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
75	-0.456	-0.295	-0.161	0.226	0.136E-05	0.634	0.745	0.420
76	-0.177	-0.398	0.221	0.227	0.136E-05	0.838	0.672	1.156
77	0.232	-0.509	0.741	0.232	0.136E-05	1.261	0.601	21.786
78	-0.498	-0.518	0.020	0.230	0.136E-05	0.608	0.596	0.007
79	-0.708	-0.553	-0.155	0.246	0.136E-05	0.493	0.575	0.331
80	-0.369	-0.540	0.171	0.237	0.136E-05	0.691	0.582	0.605
81	-0.540	-0.542	0.001	0.240	0.136E-05	0.583	0.582	0.000
82	-0.002	-0.594	0.592	0.232	0.136E-05	0.998	0.552	11.806
83	-0.587	-0.575	-0.012	0.228	0.136E-05	0.556	0.563	0.003
84	-0.658	-0.656	-0.002	0.224	0.136E-05	0.518	0.519	0.000
85	-0.555	-0.779	0.224	0.234	0.136E-05	0.574	0.459	1.116
86	-0.647	-0.814	0.167	0.228	0.136E-05	0.524	0.443	0.618
87	-0.086	-0.827	0.741	0.236	0.136E-05	0.918	0.437	21.154
88	-0.653	-0.835	0.181	0.230	0.136E-05	0.520	0.434	0.725

89	-0.996	-0.623	-0.372	0.239	0.136E-05	0.370	0.536	1.640
90	-0.805	-0.490	-0.315	0.230	0.136E-05	0.447	0.612	1.341
91	-0.472	-0.508	0.035	0.231	0.136E-05	0.624	0.602	0.023
92	-1.095	-0.594	-0.501	0.227	0.136E-05	0.334	0.552	2.925
93	-0.919	-0.607	-0.312	0.234	0.136E-05	0.399	0.545	1.275
94	-1.034	-0.734	-0.300	0.242	0.136E-05	0.356	0.480	1.115
95	-0.881	-1.001	0.120	0.227	0.136E-05	0.414	0.367	0.307
96	-2.255	-1.198	-1.057	0.235	0.136E-05	0.105	0.302	7.493
97	-1.671	-1.587	-0.084	0.236	0.136E-05	0.188	0.204	0.113

Selectivities by age

Year	8	9	10
75	0.810	1.000	0.791
76	0.810	1.000	0.791
77	0.810	1.000	0.791
78	0.810	1.000	0.791
79	0.810	1.000	0.791
80	0.810	1.000	0.791
81	0.810	1.000	0.791
82	0.810	1.000	0.791
83	0.810	1.000	0.791
84	0.810	1.000	0.791
85	0.810	1.000	0.791
86	0.810	1.000	0.791
87	0.810	1.000	0.791
88	0.810	1.000	0.791
89	0.810	1.000	0.791
90	0.810	1.000	0.791
91	0.810	1.000	0.791
92	0.810	1.000	0.791
93	0.810	1.000	0.791
94	0.810	1.000	0.791
95	0.810	1.000	0.791
96	0.810	1.000	0.791
97	0.810	1.000	0.791

96	261.	6753.	1449.	3894.	2120.	1643.	3029.	1021.	1311.	4006.
97	185.	990.	6481.	827.	1669.	1403.	2238.	2190.	973.	3973.

TABLE 4.2 SPAWNING STOCK FECUNDITY AND RECRUITMENT OF WEST

year	spawning biomass	recruits from VPA
70	97540.	481531.
71	89370.	346503.
72	91477.	352324.
73	85297.	289394.
74	83064.	789532.
75	69274.	218637.
76	62860.	201043.
77	55108.	126081.
78	50871.	60310.
79	41317.	114563.
80	38265.	94108.
81	34363.	78593.
82	31236.	42830.
83	29556.	82588.
84	25401.	67334.
85	20705.	112275.
86	19874.	101694.
87	18162.	107106.
88	16841.	103546.
89	15384.	15257.
90	14887.	79147.
91	13657.	111061.
92	13174.	3636.
93	13770.	116448.
94	13699.	12828.
95	14352.	437397.
96	13290.	12148.
97	12726.	23933.

TABLE 5.2 FITS TO INDEX DATA WEST

5.1 CAN GSL

Lognormal dist.
average numbers
Ages 10 - 10
log-likelihood = -8.60
deviance = 17.19
Chi-sq. discrepancy= 72.80

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
81	1.804	1.767	0.037	0.283	0.105E-03	6.072	5.853	0.017
82	1.719	1.441	0.278	0.279	0.105E-03	5.578	4.226	1.260
83	2.038	1.351	0.687	0.268	0.105E-03	7.673	3.862	13.069
84	1.485	0.980	0.505	0.284	0.105E-03	4.414	2.664	5.130
85	0.497	0.867	-0.371	0.300	0.105E-03	1.643	2.381	1.019
86	0.604	0.944	-0.340	0.340	0.105E-03	1.829	2.571	0.680
87	-0.038	0.738	-0.775	0.494	0.105E-03	0.963	2.091	1.052
88	0.591	0.606	-0.016	0.392	0.105E-03	1.805	1.833	0.001
89	0.748	0.442	0.305	0.396	0.105E-03	2.112	1.556	0.751
90	0.047	0.404	-0.357	0.382	0.105E-03	1.048	1.498	0.575
91	0.681	0.309	0.372	0.408	0.105E-03	1.975	1.362	1.116
92	1.056	-0.075	1.130	0.346	0.105E-03	2.874	0.928	34.499
93	0.767	0.545	0.222	0.314	0.105E-03	2.153	1.725	0.594
94	-0.464	0.397	-0.860	0.367	0.105E-03	0.629	1.487	2.305
95	1.082	0.692	0.390	0.280	0.105E-03	2.950	1.997	2.785
96	-0.265	0.524	-0.790	0.281	0.105E-03	0.767	1.689	3.619
97	-0.195	0.714	-0.909	0.281	0.105E-03	0.823	2.042	4.326

Selectivities by age

Year	10
81	0.645
82	0.474
83	0.445
84	0.338
85	0.325
86	0.407
87	0.396
88	0.375
89	0.337
90	0.359
91	0.345
92	0.242
93	0.484
94	0.400
95	0.521
96	0.425

 5.2 CAN SWNS

Lognormal dist.
 average numbers
 Ages 7 - 10
 log-likelihood = -15.71
 deviance = 31.42
 Chi-sq. discrepancy= 72.36

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
88	1.081	0.683	0.398	0.323	0.492E-04	2.947	1.979	2.168
89	1.591	0.635	0.956	0.297	0.492E-04	4.907	1.886	27.740
90	1.399	0.618	0.780	0.297	0.492E-04	4.050	1.856	15.129
91	1.162	0.588	0.574	0.297	0.492E-04	3.195	1.800	6.492
92	1.046	0.580	0.466	0.240	0.492E-04	2.845	1.786	5.960
93	0.060	0.670	-0.610	0.233	0.492E-04	1.062	1.954	3.740
94	0.778	0.673	0.105	0.245	0.492E-04	2.177	1.960	0.198
95	0.616	0.584	0.032	0.232	0.492E-04	1.851	1.793	0.019
96	-0.431	0.465	-0.895	0.240	0.492E-04	0.650	1.591	5.877
97	-0.288	0.515	-0.803	0.242	0.492E-04	0.750	1.674	5.037

Selectivities by age

Year	7	8	9	10
88	0.249	0.672	1.000	0.415
89	0.249	0.672	1.000	0.415
90	0.249	0.672	1.000	0.415
91	0.249	0.672	1.000	0.415
92	0.249	0.672	1.000	0.415
93	0.249	0.672	1.000	0.415
94	0.249	0.672	1.000	0.415
95	0.249	0.672	1.000	0.415
96	0.249	0.672	1.000	0.415
97	0.249	0.672	1.000	0.415

 5.3 JLL GOM

Lognormal dist.
 month 0 numbers
 Ages 10 - 10
 log-likelihood = -6.02
 deviance = 12.05
 Chi-sq. discrepancy= 48.51

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
74	-0.033	0.183	-0.216	0.261	0.444E-05	0.968	1.201	0.532
75	-0.627	0.068	-0.695	0.203	0.444E-05	0.534	1.070	5.973
76	-0.406	0.027	-0.433	0.205	0.444E-05	0.666	1.027	2.886
77	-0.091	-0.142	0.051	0.214	0.444E-05	0.913	0.868	0.058
78	-0.132	-0.286	0.154	0.222	0.444E-05	0.876	0.751	0.548
79	0.252	-0.475	0.728	0.278	0.444E-05	1.287	0.622	14.310
80	0.147	-0.670	0.816	0.261	0.444E-05	1.158	0.512	22.677
81	-0.592	-0.851	0.259	0.236	0.444E-05	0.553	0.427	1.531

Selectivities by age

Year	10
74	1.000
75	1.000
76	1.000
77	1.000
78	1.000
79	1.000
80	1.000
81	1.000

 5.4 DUMMY

Not used

 5.5 JLL NW ATL

Lognormal dist.
 month 0 numbers
 Ages 2 - 9
 log-likelihood = 2.76
 deviance = -5.52
 Chi-sq. discrepancy= 46.81

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
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76	-1.313	-0.425	-0.888	0.445	0.278E-05	0.269	0.653	1.581
77	-0.069	-0.446	0.377	0.280	0.278E-05	0.933	0.640	2.563
78	-0.777	-0.487	-0.290	0.339	0.278E-05	0.460	0.615	0.520
79	-1.146	-0.577	-0.569	0.361	0.278E-05	0.318	0.562	1.353
80	-0.596	-0.783	0.187	0.297	0.278E-05	0.551	0.457	0.460
81	-0.268	-0.950	0.682	0.270	0.278E-05	0.765	0.387	12.669
82	-1.448	-1.140	-0.308	0.401	0.278E-05	0.235	0.320	0.403
83	-2.216	-1.101	-1.115	0.609	0.278E-05	0.109	0.332	1.006
84	-1.124	-1.007	-0.117	0.355	0.278E-05	0.325	0.365	0.091
85	-0.828	-0.870	0.042	0.316	0.278E-05	0.437	0.419	0.018
86	-2.718	-0.851	-1.867	1.044	0.278E-05	0.066	0.427	0.362
87	-1.201	-0.772	-0.428	0.402	0.278E-05	0.301	0.462	0.691
88	-0.896	-0.749	-0.148	0.326	0.278E-05	0.408	0.473	0.168
89	-1.100	-0.782	-0.318	0.360	0.278E-05	0.333	0.458	0.536
90	-1.231	-0.765	-0.466	0.379	0.278E-05	0.292	0.465	0.898
91	-1.347	-0.845	-0.502	0.404	0.278E-05	0.260	0.429	0.878
92	-0.594	-0.876	0.282	0.334	0.278E-05	0.552	0.416	0.895
93	-0.511	-0.801	0.290	0.302	0.278E-05	0.600	0.449	1.183
94	-0.707	-0.833	0.126	0.309	0.278E-05	0.493	0.435	0.180
95	-0.911	-0.764	-0.147	0.368	0.278E-05	0.402	0.466	0.129
96	0.162	-0.737	0.899	0.316	0.278E-05	1.176	0.479	20.227
97	-0.483	-0.494	0.011	0.334	0.278E-05	0.617	0.610	0.001

Selectivities by age

Year	2	3	4	5	6	7	8	9
76	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
77	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
78	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
79	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
80	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
81	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
82	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
83	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
84	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
85	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
86	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
87	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
88	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
89	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
90	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
91	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
92	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
93	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
94	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
95	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
96	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555
97	0.058	0.398	0.630	0.789	1.000	0.878	0.704	0.555

5.6 LARVAL

Lognormal dist.

average biomass

Ages 8 - 10

log-likelihood = -1.64

deviance = 3.28

Chi-sq. discrepancy= 57.08

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
77	0.890	0.963	-0.073	0.415	0.475E-07	2.435	2.618	0.026
78	1.762	0.883	0.879	0.268	0.475E-07	5.824	2.417	26.756
81	0.245	0.491	-0.247	0.414	0.475E-07	1.277	1.634	0.256
82	0.415	0.394	0.020	0.304	0.475E-07	1.514	1.483	0.004
83	0.211	0.340	-0.128	0.301	0.475E-07	1.235	1.404	0.153
84	-0.426	0.188	-0.614	0.704	0.475E-07	0.653	1.207	0.328
86	-1.343	-0.057	-1.286	0.559	0.475E-07	0.261	0.944	1.427
87	-0.810	-0.147	-0.662	0.479	0.475E-07	0.445	0.863	0.911
88	0.666	-0.222	0.888	0.318	0.475E-07	1.946	0.801	19.226
89	-0.226	-0.312	0.087	0.420	0.475E-07	0.798	0.732	0.042
90	-0.747	-0.345	-0.401	0.198	0.475E-07	0.474	0.708	2.732
91	-1.008	-0.431	-0.577	0.550	0.475E-07	0.365	0.650	0.544
92	-0.488	-0.467	-0.020	0.369	0.475E-07	0.614	0.627	0.003
93	-0.405	-0.424	0.019	0.566	0.475E-07	0.667	0.655	0.001
94	-0.329	-0.429	0.100	0.390	0.475E-07	0.720	0.651	0.068
95	-0.766	-0.382	-0.384	0.543	0.475E-07	0.465	0.682	0.297
96	0.377	-0.459	0.836	0.578	0.475E-07	1.458	0.632	4.303
97	-0.480	-0.502	0.022	0.428	0.475E-07	0.619	0.605	0.003

Selectivities by age

Year	8	9	10
77	1.000	1.000	1.000
78	1.000	1.000	1.000
81	1.000	1.000	1.000
82	1.000	1.000	1.000
83	1.000	1.000	1.000
84	1.000	1.000	1.000
86	1.000	1.000	1.000
87	1.000	1.000	1.000


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88 1.000 1.000 1.000
89 1.000 1.000 1.000
90 1.000 1.000 1.000
91 1.000 1.000 1.000
92 1.000 1.000 1.000
93 1.000 1.000 1.000
94 1.000 1.000 1.000
95 1.000 1.000 1.000
96 1.000 1.000 1.000
97 1.000 1.000 1.000

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5.7 US LL GOM

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Lognormal dist.
month 0 numbers
Ages 8 - 10
log-likelihood = -3.83
deviance = 7.67
Chi-sq. discrepancy= 20.13

```

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
87	-0.128	-0.448	0.321	0.286	0.874E-05	0.880	0.639	1.679
88	-0.916	-0.503	-0.414	0.431	0.874E-05	0.400	0.605	0.563
89	-0.357	-0.551	0.194	0.304	0.874E-05	0.700	0.577	0.473
90	-0.163	-0.584	0.422	0.302	0.874E-05	0.850	0.558	2.882
91	0.000	-0.656	0.656	0.294	0.874E-05	1.000	0.519	9.512
92	-1.427	-0.666	-0.761	0.497	0.874E-05	0.240	0.514	1.015
93	-1.470	-0.659	-0.810	0.524	0.874E-05	0.230	0.517	0.978
94	-2.303	-0.610	-1.693	0.770	0.874E-05	0.100	0.544	0.822
95	-1.772	-0.644	-1.128	0.619	0.874E-05	0.170	0.525	0.980
96	-1.715	-0.732	-0.982	0.628	0.874E-05	0.180	0.481	0.809
97	-1.171	-0.748	-0.423	0.502	0.874E-05	0.310	0.473	0.414

Selectivities by age

Year	8	9	10
87	0.729	0.820	1.000
88	0.729	0.820	1.000
89	0.729	0.820	1.000
90	0.729	0.820	1.000
91	0.729	0.820	1.000
92	0.729	0.820	1.000
93	0.729	0.820	1.000
94	0.729	0.820	1.000
95	0.729	0.820	1.000
96	0.729	0.820	1.000
97	0.729	0.820	1.000

5.8 US RR 66-114

```

Lognormal dist.
average numbers
Ages 2 - 3
log-likelihood = 1.77
deviance = -3.53
Chi-sq. discrepancy= 1.90

```

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
93	-0.916	-0.943	0.026	0.448	0.329E-05	0.400	0.390	0.003
94	-2.408	-0.931	-1.477	1.078	0.329E-05	0.090	0.394	0.271
95	-1.514	-0.940	-0.574	0.568	0.329E-05	0.220	0.391	0.501
96	-0.329	-0.281	-0.047	0.332	0.329E-05	0.720	0.755	0.018
97	0.000	-0.263	0.263	0.280	0.329E-05	1.000	0.769	1.109

Selectivities by age

Year	2	3
93	0.738	1.000
94	0.738	1.000
95	0.738	1.000
96	0.738	1.000
97	0.738	1.000

5.9 US RR 115-144

```

Lognormal dist.
average numbers
Ages 4 - 5
log-likelihood = -1.90
deviance = 3.81
Chi-sq. discrepancy= 1.92

```

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
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93	-0.774	-0.877	0.103	0.835	0.623E-05	0.461	0.416	0.012
94	-3.147	-0.503	-2.644	1.772	0.623E-05	0.043	0.605	0.039
95	-1.619	-0.747	-0.872	1.008	0.623E-05	0.198	0.474	0.192
96	0.000	-0.558	0.558	0.543	0.623E-05	1.000	0.572	1.631
97	-1.124	-0.761	-0.363	1.029	0.623E-05	0.325	0.467	0.049

Selectivities by age

Year	4	5
93	1.000	0.952
94	1.000	0.952
95	1.000	0.952
96	1.000	0.952
97	1.000	0.952

5.10 US RR <145

Lognormal dist.

average numbers

Ages 1 - 5

log-likelihood = 4.08

deviance = -8.17

Chi-sq. discrepancy= 21.17

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
80	-0.968	-0.836	-0.132	0.412	0.312E-05	0.380	0.434	0.082
81	-1.661	-0.782	-0.879	0.489	0.312E-05	0.190	0.457	1.264
82	0.000	-0.856	0.856	0.322	0.312E-05	1.000	0.425	16.819
83	-0.635	-0.822	0.187	0.256	0.312E-05	0.530	0.439	0.629
85	-1.204	-0.532	-0.672	0.586	0.312E-05	0.300	0.587	0.584
86	-0.994	-0.533	-0.462	0.412	0.312E-05	0.370	0.587	0.739
87	-0.545	-0.471	-0.074	0.385	0.312E-05	0.580	0.624	0.031
88	-0.755	-0.509	-0.246	0.367	0.312E-05	0.470	0.601	0.329
89	-0.755	-0.722	-0.033	0.412	0.312E-05	0.470	0.486	0.006
90	-0.844	-0.871	0.027	0.331	0.312E-05	0.430	0.419	0.006
91	-0.511	-0.714	0.203	0.340	0.312E-05	0.600	0.490	0.415
92	-0.942	-0.696	-0.246	0.403	0.312E-05	0.390	0.499	0.269

Selectivities by age

Year	1	2	3	4	5
80	0.487	1.000	0.854	0.201	0.075
81	0.487	1.000	0.854	0.201	0.075
82	0.487	1.000	0.854	0.201	0.075
83	0.487	1.000	0.854	0.201	0.075
85	0.487	1.000	0.854	0.201	0.075
86	0.487	1.000	0.854	0.201	0.075
87	0.487	1.000	0.854	0.201	0.075
88	0.487	1.000	0.854	0.201	0.075
89	0.487	1.000	0.854	0.201	0.075
90	0.487	1.000	0.854	0.201	0.075
91	0.487	1.000	0.854	0.201	0.075
92	0.487	1.000	0.854	0.201	0.075

5.11 US RR 145-177

Lognormal dist.

average numbers

Ages 6 - 6

log-likelihood = -0.97

deviance = 1.94

Chi-sq. discrepancy= 0.44

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
93	-0.894	0.044	-0.938	1.320	0.501E-04	0.409	1.045	0.079
94	0.092	-0.387	0.479	0.909	0.501E-04	1.096	0.679	0.294
95	0.427	0.204	0.222	0.887	0.501E-04	1.532	1.227	0.052
96	0.490	0.520	-0.030	0.810	0.501E-04	1.632	1.682	0.001
97	-1.106	-0.230	-0.875	1.777	0.501E-04	0.331	0.794	0.015

Selectivities by age

Year	6
93	1.000
94	1.000
95	1.000
96	1.000
97	1.000

5.12 US RR >178

Not used

 5.13 US RR >195

Not used

 5.14 TAGGING

Lognormal dist.
 average numbers
 Ages 1 - 3
 log-likelihood = -22.16
 deviance = 44.32
 Chi-sq. discrepancy= 124.13

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
70	13.879	13.273	0.606	0.198	0.849E+00	1065132.000	581137.415	17.341
71	13.817	12.899	0.918	0.198	0.849E+00	1001624.000	399998.902	56.555
72	12.976	12.776	0.200	0.198	0.849E+00	431955.000	353701.493	1.224
73	12.121	12.756	-0.636	0.198	0.849E+00	183616.000	346760.891	5.534
74	12.741	13.471	-0.729	0.198	0.849E+00	341589.000	708295.890	6.701
75	13.226	13.170	0.056	0.198	0.849E+00	554596.000	524600.989	0.082
76	12.442	12.836	-0.394	0.198	0.849E+00	253265.000	375625.122	2.653
77	12.458	12.427	0.032	0.198	0.849E+00	257385.000	249344.558	0.026
78	11.704	12.122	-0.418	0.198	0.849E+00	121110.000	183883.266	2.913
79	11.501	11.965	-0.464	0.198	0.849E+00	98815.000	157127.131	3.443
80	12.168	11.885	0.283	0.198	0.849E+00	192541.000	145037.130	2.682
81	12.731	11.938	0.793	0.239	0.849E+00	337995.000	152978.877	24.976

Selectivities by age

Year	1	2	3
70	1.000	1.000	1.000
71	1.000	1.000	1.000
72	1.000	1.000	1.000
73	1.000	1.000	1.000
74	1.000	1.000	1.000
75	1.000	1.000	1.000
76	1.000	1.000	1.000
77	1.000	1.000	1.000
78	1.000	1.000	1.000
79	1.000	1.000	1.000
80	1.000	1.000	1.000
81	1.000	1.000	1.000

 5.15 US RR >195 C

Lognormal dist.
 average numbers
 Ages 8 - 10
 log-likelihood = 8.66
 deviance = -17.33
 Chi-sq. discrepancy= 26.54

Year	Observed	Predicted	Residuals (Obs-pred)	Standard Deviation	Q Catchabil.	Untransfrmd Observed	Untransfrmd Predicted	Chi-square Discrepancy
83	0.654	0.428	0.226	0.239	0.155E-04	1.923	1.534	1.096
84	0.128	0.301	-0.173	0.252	0.155E-04	1.136	1.351	0.387
85	-0.337	0.128	-0.465	0.272	0.155E-04	0.714	1.137	1.803
86	-0.340	0.049	-0.388	0.556	0.155E-04	0.712	1.050	0.286
87	-0.341	0.035	-0.376	0.331	0.155E-04	0.711	1.035	0.849
88	-0.189	-0.032	-0.157	0.281	0.155E-04	0.828	0.969	0.256
89	-0.159	-0.091	-0.068	0.290	0.155E-04	0.853	0.913	0.050
90	-0.281	-0.108	-0.173	0.287	0.155E-04	0.755	0.898	0.295
91	-0.040	-0.190	0.150	0.271	0.155E-04	0.961	0.827	0.346
92	-0.092	-0.191	0.099	0.269	0.155E-04	0.912	0.826	0.144
93	-0.384	-0.160	-0.224	0.357	0.155E-04	0.681	0.852	0.296
94	-0.381	-0.107	-0.274	0.371	0.155E-04	0.683	0.899	0.390
95	0.031	-0.155	0.186	0.298	0.155E-04	1.031	0.856	0.447
96	0.572	-0.268	0.841	0.334	0.155E-04	1.772	0.765	14.669
97	0.283	-0.283	0.566	0.324	0.155E-04	1.327	0.754	5.220

Selectivities by age

Year	8	9	10
83	0.887	1.000	0.940
84	0.887	1.000	0.940
85	0.887	1.000	0.940
86	0.887	1.000	0.940
87	0.887	1.000	0.940
88	0.887	1.000	0.940
89	0.887	1.000	0.940
90	0.887	1.000	0.940
91	0.887	1.000	0.940
92	0.887	1.000	0.940
93	0.887	1.000	0.940
94	0.887	1.000	0.940
95	0.887	1.000	0.940
96	0.887	1.000	0.940

97 0.887 1.000 0.940

=====

95	10	2	obsd	9.00	4.00	3.00
			pred	3.48	3.34	4.00
96	10	2	obsd	2.00	2.00	
			pred	2.57	2.40	
97	10	2	obsd	1.00		
			pred	1.53		

TOTAL NUMBER OF FUNCTION EVALUATIONS = 28145

APPENDIX 4. SOURCE CODE

A copy of the entire source code has been filed with the ICCAT Secretariat and the full source code is available from the author (Clay.Porch@noaa.gov) on request.