APPLICATION OF AN AGE-STRUCTURED PRODUCTION MODEL (ASPM) TO THE INDIAN OCEAN BIGEYE TUNA (*THUNNUS OBESUS*) RESOURCE

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ABSTRACT

Two implementations of age-structured stock production models (ASPM) were used to further explore the assessment of bigeye tuna (Thunus obesus). The ASPM97 software that was used in WPTT 2001 was again considered and the lack of convergence of some runs was explored and resolved. Limited sensitivity analyses were also performed, particularly with regard to the deterministic versus stochastic assumption about recruitment, and the choice of input parameters governing the recruitment deviations. A new in-house ASPM implementation in AD Model Builder was also applied to the data combined with different assumptions and input parameters. Results show a wide range of possible outcomes depending on the input parameters and assumptions. Estimates of steepness suggest that there is very little information about the stock-recruit relationship in the data.

INTRODUCTION

Assessments of bigeye tuna (*Thunus obesus*) were done at the 2001 IOTC WP meeting using an age-structured production model as implemented in software by Restrepo (1996) (called aspm97.exe; also see Nishida *et al.* (2001)). Some of the runs, notably the ones based on a more recent growth curve (Lehodey *et al.*, 1999), did not converge, and it is not clear why. In order to make progress it is usually valuable to explore why runs are not converging, and at meetings there is clearly only limited time for this. In addition to exploring convergence or lack thereof, there are also some parameters which are fixed (not estimated), and we have explored a little further the sensitivity of results to these parameters using the Restrepo software. In particular, the constraints on the recruitment deviations from the recruitment at virign biomass (*R*0) as defined by an auto-correlation and variance parameter are explored. The main part of this document presents results from an alternative implementation of the age-structured production model. This is in-house software developed in AD Model Builder[1]. One major advantage is that the source code is readily available and interpretable. We have included a detailed section on the methodology so that the equations and assumptions used are transparent.

ASSESSMENTS USING RESTREPO SOFTWARE (ASPM97)

The input data used at the third session of the IOTC WPTT (Anonymous, 2001) were obtained from the IOTC Secretariat so that we could explore reasons for non-convergence. A few relatively minor discrepancies between the input data (in the files) and the summary of runs in Appendix V of the WPTT report (Anonymous, 2001) were noted. There was a minor discrepancy in natural mortality, in that vectors had mortality at age 1, M_1=0.8 for all 4 runs, whereas the Table suggests that M_1=04. Discrepancies were also found in the selectivity for purse seiners (surface fishery) which differs between runs 1 and 2 for age 0 (0.188 for run 1, 0.151 in run 2), though the Table suggests they should be identical. Finally, selectivities for purse seiners, at all ages, differ between runs 3 and 4, though the Table suggests they should be identical. Values in the files are:

Run 3 1960-1999: 1.0 0.795 0.502 0.468 0.439 0.368 0.258 0.197 0.126

Run 4 1960-1999: 1.0 0.956 0.6 0.553 0.51 0.418 0.284 0.21 0.13

Given the differences in mortality between runs 1&2 and between runs 3&4, one would expect differences in the selectivities, though probably less so than for the different sets of growth parameters. All runs done with the Restrepo software were based on the input files provided by the IOTC unless stated otherwise (see e.g. run 4 below). The detailed inputs used with the AD Model Builder implementation differ from these in several ways, and are described in the appropriate sections.

Convergence Issues

To ensure that the software was performing properly, runs 1 and 2 were repeated. Results were identical to those given in Table V.3 of last year's WPTT Report (Anonymous, 2001). The two runs which had not converged at the meeting were further explored. Nonconvergence appears to have different causes in these 2 runs.

Non-convergence of Run 3

With regard to run 3, it appears that the non-convergence simply had to do with the starting values. For example, when

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[1] c 2000 Otter Research Ltd., Sydney, B.C., Canada

run with a higher starting value for virgin biomass (*B*0), the run appears to converge properly. The original run was done with *B*0=2*106. Two alternative starting values for *B*0 were tried: 5*106 and 7*106. These both converged to the same solution. The unconverged run may simply have reached the maximum number of iterations before getting to the fully converged state and enabling it to calculate the variance-covariance matrix. Unfortunately, the software does not appear to allow the user to change the maximum number of iterations. A closer look at results shows that even the unconverged run got very close to the converged, final solution (Table 1). Note that values for the unconverged run are from the LAST CENTROID of simplex before the"Run Summary".

***Table 1**: Comparison of results from converged and unconverged versions of WPTT 2001 run 3.*

	unconverged run	converged run
LLHD	-104.19	-104.20
indices component	-93.862	-93.845
s-r fit component	-9.5286	-9.5449
virg-b0 component	-0.80468	-0.80469
PARAMETERS		
B0 param	0.60676	0.60995
Steepness	0.9900	0.9900

To conclude, run3 appears simply to have suffered from a starting value and possibly a maximum iteration limit problem. The converged solution is given in Table 2 below.

Non-convergence of run 4

Run 4 was also rerun with different starting values for *B*0 (5*106 and 7*106), as well as a higher starting value for steepness (0.9 instead of 0.5, note that the upper bound was set to 0.99). In all these cases the minimum appears to have been reached, in the sense that the minimum from the simplex algorithm and that from the quadratic surface fitting about the supposed minimum were pretty much identical. The matrix of estimated second derivatives was not, however, positive definite (so no CV's could be obtained), indicating a problem with the minimization.

Two minor changes seemed to resolve this. A change in M_1 from 0.8 to 0.4 (still using the original selectivities of [1, 0.956, 0.6, 0.553, 0.51, 0.418, 0.284, 0.21, 0.13] for the surface fishery) lead to a properly converged solution with positive definite matrix of second derivatives (run 4a in Table 2 below). Alternatively, a change in the selectivities for the purse seine to the values used in run 3, with either of the mortality vectors (M_1= 0.8 or 0.4) provided properly converged solutions (only results for M_1 08, run 4b in Table 2 are shown, results for M_1= 0.8 were similar). Although it is not quite clear why the original run 4 did not converge properly, there may be an incompatibility between the mortality vector and the selectivity vector.

Stochastic and deterministic runs

Restrepo and Legault (1998) compare stochastic and deterministic runs for Atlantic bluefin tuna (*Thunnus thynnus*). A plot of the deterministic- and stochastic-based estimates of biomass show that they are at a similar level, with the deterministic-based estimates a smooth curve running through the stochastic-based estimates. In the case of the bigeye data, very different results are obtained from deterministic and stochastic runs, particularly when the initial spawning biomass is allowed to be different from the unfished spawning biomass. Note that this behaviour was also seen when the AD Model Builder software was used with the data.

***Table 2**: Results of bigeye assessments from Restrepo software (aspm97.exe) with input files as used in WPTT meeting 2001, except for runs 4a (M_1 =0.4) and 4b (selectivities for PS as in run3)*

	Run 1	Run 2	Run 3	Run 4a M_1=0.4	Run 4b M_1=0.8 and PS sel. as in run 3
MSY(t)	89,090	89,267	71,199	73,059	70,749
Virgin Biomass (million t)	0.794 (CV=0.48)	0.787 (CV=0.49)	0.610 (CV=0.40)	0.644 (CV=0.40)	0.596 (CV=0.43)
-loge(L)	-92.63	-92.65	-104.20	-105.35	-104.19
Steepness	0.99	0.99	0.99	0.99	0.99
F(ratio) =F1999/Fmsy	0.85	0.83	1.32 =0.57/0.43	1.25 =0.52/0.42	1.32 =0.59/0.45
Bratio(SSB) =B1999/Bmsy	2.11	2.15	1.45 =0.17/0.12	1.54 =0.2/0.13	1.45 =0.16/0.11
B1ratio =B1999/B1960	0.48 =0.37/0.78	0.48 =0.37/0.77	0.28 =0.17/0.61	0.31 =0.2/0.64	0.31 =0.16/0.59

This outcome strongly supports the notion that there is very little information content in the abundance index, and certainly very little information about the stock-recruitment relationship. A summary of the main differences is given below.

Attempts were made to fix some of the parameters (by narrowing the bounds and/or setting stepsize to zero), but the Restrepo software always seemed to estimate those parameters too. For example, for a step size of 0 on the steepness parameter, the output suggests that is is a ”fixed” parameter at the start of the output file, but where the optimal solution is reported, it seems that the steepness is in fact estimated.

***Table 3**: Comparison between stochastic and deterministic runs (WPTT 2001 run 3 as an example).*

Deterministic	Stochastic
high virgin biomass (2MT)	lower virgin biomass (0.6 MT)
low *MSY* (37 KT)	high *MSY* (71 KT)
BMSY=0.45**B*0	*BMSY*=0.17**B*0
high mean *R*	lower mean *R*
low steepness (0.3)	high steepness (0.99)
high *B*1999	lower *B*1999
Less depletion (0.73)	more depleted (0.28)
current catch>>MSY	Current catch>MSY
current *B* above *BMSY*	current *B* close to *BMSY*

***Table 4**: Results of limited sensitivity runs based on WPTT 2001 run 1 data. The first row is for the deterministic run for comparison. The input values for r and s_f^2 are given in the second and third columns. The calculated first (r1) and second (r2) order autocorrelations of the recruitment deviations are shown. The CV of recruitment is calculated as the square root of (s^2/ (1-r^2)). (na=not applicable)*

Run	ρ	σ_ϕ^2	r1	r2	*Bvirgin*	steepness	*B*1/*Bvirgin*	MSY	*loge(L)*	CV(R)
1.Det	0	0	na	na	1.511	0.314	0.75	42.7	-44.3	na
a	0	0.05	0.93	0.74	1.168	0.99	1.02	119.3	-118.3	0.224
b	0	0.4	0.71	0.25	0.959	0.99	1.03	100	-91.3	0.632
c	0.1	0.05	0.93	0.73	1.125	0.99	1.02	122.2	-120.3	0.225
d	0.1	0.4	0.72	0.25	0.876	0.99	1.01	97.2	-91.9	0.636
e	0.4	0.05	0.92	0.71	1.137	0.99	1.03	116.9	-126.2	0.244
f	0.4	0.4	0.77	0.36	0.716	0.99	0.94	77.9	-93.1	0.690

Sensitivity to input parameters for stochastic recruitment

Two input parameters which define the first order autoregressive process (AR (1)) for the recruitment deviations are the first order correlation coefficient (ρ), and the variance of the error term in the AR (1) series (σϕ). The interpretation of these two results is identical to that in Equation 27 (Appendix A.5). We explored the sensitivity of results to these two parameters using Run 1 as an example. Results are summarised in Table 4. Runs with a low CV(R) are probably rather unrealistic, but serve to show sensitivity in a general sense. It is interesting to note that the resulting series of recruitment deviations have much higher first order autocorrelations than the input value, and in some cases have very high second order autocorrelation too. Results turn out to be quite similar for the runs with low σ^2 (a,c,e), irrespective of the value of ρ, and the runs with higher σ^2 (b,d,f), irrespective of ρ.

METHODS

We implemented an age-aggregated surplus production model (ASPM) similar to that of Punt *et al.* (1995) and applied it to the Indian Ocean bigeye tuna resource. Complete details of the ASPM can be found in Appendix A. The ASPM was implemented using AD Model Builder.

Index of abundance

The index of abundance time-series used to estimate the model parameters is the CPUE from the Japanese longline fishery and was supplied to us by the IOTC. It is the index that was calculated at the third session of the IOTC working party on tropical tuna (WPTT) (Anonymous, 2001) and can be found in Table 10.

Catch data

The catch data by gear type were obtained from the IOTC and is available for two types of fisheries:

1. surface fishery (mainly purse seine)

2. midwater fishery (mainly longline)

The longline catch data spans the period 1960-1999 and the purse seine catch data spans the period 1970-1999. The catch data used is shown on Figure 5 and in Table 9.

Biological parameters

We used one maturity vector and two natural mortality vectors (see Table 11).

Weight-at-age

The weight of a fish is calculated from its age in two steps. First, the fish’s length is calculated from its age using the von Bertalanffy growth function (VBGF) (von Bertalanffy, 1938):

$$L_t = L_\infty(1-e^{-k[t-t_0]}) \qquad (1)$$

where,

L_t is the predicted mean length of a fish at age *t* (cm)

L_∞ is the mean asymptotic length (cm)

k is a factor of dimension *time*

t_0 is the theoretical (and generally negative) “age” the fish would have at length zero had

they always grown as described by their VBGF

Second, the weight of a fish is calculated from its length using a length-weight relationship of the form:

$$W_L = aL^b \qquad (2)$$

where,

W_L is the weight of a fish of length L (kg)

α **and** β are the lenght-weight relationship parameters.

We evaluated two differents weight-at-age vectors. The first one used VBGF (Equation 1) parameters from Tankevich (1982). We followed the methods of Nishida *et al.* (2001) and used the female VBGF for fish of age < 3.5 and the male VBGF for fish age $\geq$ 3.5 (see Table 12). The second weight-at-age vector was calculated using VBGF parameters from Lehodey *et al.* (1999). Parameters for the length-weight relationship (Equation 2) were obtained from Nakamura and Uchiyama (1966) and Poreeyanond (1994) (see Table 13). The two resulting weight-at-age vectors can be found in Table 14.

Fleet-specific selectivities

The fleet-specific selectivities were obtained from Anonymous (2001) and can be found in Tables 15 and 16.

Details of the different runs

We performed a variety of runs in order to get a better grasp on the benefits and limitations of the ASPM. Table 5 provides the details of the different runs. Only one CPUE index was used (see Table 10) and the parameters not shown in Table 5 were the same for all runs. Each run was done using the deterministic and stochastic ASPM. Moreover, we evaluated two different initial conditions for each run, one assumes that the stock is at unfished equilibirium at the onset of fishing (“virgin”) and the other allows the stock to diverge from the unfished equilibrium at onset of fishing (“non-virgin”). Refer to Section A.3 for a description of this procedure. We therefore evaluate a total of 16 models (4 runs X stochastic/deterministic X virgin/non-virgin = 16).

***Table 5**: Details of the different runs using the AD Model Builder implementation of the ASPM.*

Run #	Growth curve/weight-at-age	Mortality vector (see Table 11)
1	Tankevich (1982)	v1
2	Tankevich (1982)	v2
3	Lehodey *et al.* (1999)	v1
4	Lehodey *et al.* (1999)	v2

***Table 6**: Comparison of deterministic base case*

	ASPM97	AD Model Builder virgin	AD Model Builder non-virgin
h	0.313	0.99	0.30
Ksp	1470200	892375	1286350
$B1/Bvirgin$	0.7448	1.0	0.71
$-loge(L)$	-44.330	-43.521	-45.053

***Table 7**: Comparison of stochastic base case*

	ASPM97	AD Model Builder virgin	AD Model Builder non-virgin
h	0.99	0.99	0.99
Ksp	797070	615295	580868
$B1/Bvirgin$	0.98	1.0	0.95
$-loge(L)$	-92.626	-73.391	-73.416

BASE CASE COMPARISONS OF SOFTWARE

A base case run was chosen for comparisons between the Restrepo software (ASPM97) and the AD Model Builder implementation. The base case evaluated here uses the same input parameters as Run 1 in Table 5. The deterministic cases are summarized in Table 6 and the stochastic cases in Table 7. Note that the calculations of the log-likelihoods are not identical in the two implementations, so the values are not directly comparable. In ASPM97, a third component is added to the *loge L* and pertains to *Bvirgin*. It is not clear to us how this third component can be differentiated from the component pertaining to the CPUE fit (see Equation 22) since changing the initial conditions of the model has an effect on the predicted CPUE, and hence on the fit to the CPUE. It is not clear either if the third component added to the *loge L* in ASPM97 corresponds to Equation 22 in Restrepo and Legault (1998). The predicted values of the index of abundance are very similar, as are the recruitment deviations (see Figure 1 and 2). Nonetheless, the level of recruitment is different and so are the biomass estimates.

There are differences between results from the two pieces of software, and this is due to difference in implementation, of which the main ones are:

1. Different minimization routines (ASPM97 uses a simplex algorithm while AD Model Builder uses automatic differentiation)

2. ASPM97 seems to use $R0$ for age 0 in year 1 even though $B1960$ could be much smaller than *Bvirgin*. The AD Model Builder implementation either uses $R0$ or scales its value to reflect non-virign biomass situations at the onset of fishing (see Equation 20 in Appendix A.3).

3. Stochastic recruitment is handled slightly differently. ASPM97 considers recruit deviations around $R0$, whereas our implementation considers recruit deviations around a mean R which is estimated (see Section A.5).

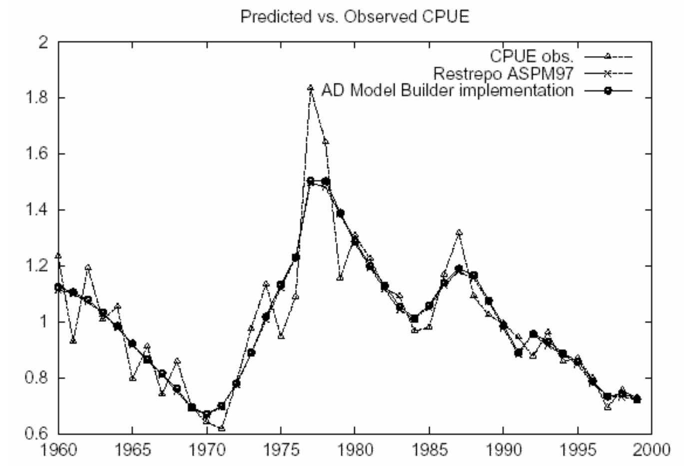

***Figure 1**: Predicted vs. observed CPUE for Restrepo's ASPM97 and the AD Model Builder implementation of the ASPM.*

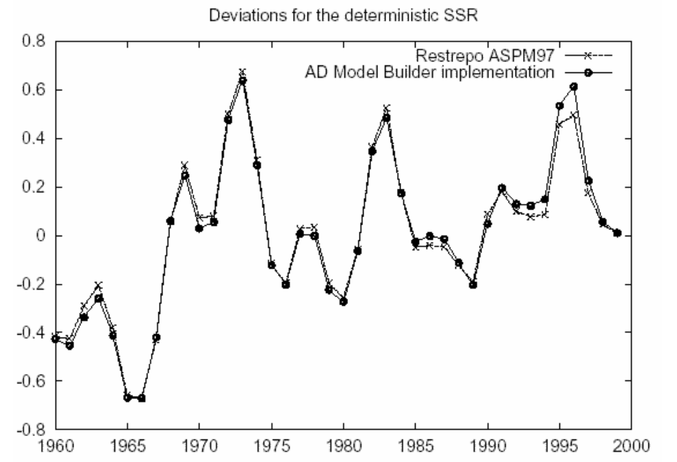

***Figure 2**: Estimated recruitment deviations from the two software implementations.*

Note that no attempts were made to get the two programs to give identical results. This is because we only have a compiled version of ASPM97, with relatively limited documentation. Even with good documentation there are often small details which are omitted, and which can make a difference to calculations and hence estimation.

RESULTS USING AD MODEL BUILDER IMPLEMENTATION OF THE ASPM

The results for the AD Model Builder implementation of the ASPM can be found in Appendix B.3. We present the value of the estimated parameters as well as some management indicators such as Maximum Sustainable Yield and Replacement Yield.

DISCUSSION AND CONCLUSION

The runs using ASPM97 underline the importance of trying different starting values for estimated parameters. Exploratory runs on the bigeye datasets showed convergence to the same solution when the minimization converged properly, but this is not always the case. Some datasets can lead to quite different results depending on starting values. It also appears that convergence may be sensitive to compatibility between selectivities and the natural mortality vector. This would not be entirely surprising, though it highlights another area worth double-checking when not obtaining convergence.

While we used the same parameter values for the VBGF and length-weight relationship our resulting weight-at-age (Table 14) is different from the one presented on page 2 of Nishida *et al.* (2001). We noted discrepancies between the catch data presented on Table 2 of Nishida *et al.* (2001) and the catch data used by the accompanying ASPMS application (Restrepo, 1997).

When the steepness parameter approaches its theoretical maximum value of 1.0 the stock-recruitment curve can yield recruits at very low spawning biomass. This situation leads to MSY values that are rather high. The standard deviations of the virgin biomass parameter imply coefficients of variation (CV) of around 30% to 40% for the stochastic runs. This large variability will have a knock-on effect on MSY-estimates, and should be borne in mind in the absence of bootstrap runs or variance estimates for MSY values.

The replacement yield values that we report have to be interpreted carefully. Since the model is age-structured the replacement yield will not necessarily lead to an equilibrium situation. On the contrary, it is possible for the spawning stock biomass to be the same in 2000 and 2001 but to further decline in subsequent years if the level of catch is maintained at *RY*00. It is also possible that *RY*00 will lead to a positive trend in spawning stock biomass if the steepness parameter *h* is large. Such a situation arises because the fisheries have selectivities that target a variety of age classes. Recall that *RY*00 is calculated by assuming that the catch split in 1999 will be maintained. The catch split in 1999 was 73% longline and 27% purse seine. Since the purse seine fishery targets younger age classes it will have virtually effect on the spawning stock biomass. Only a couple of years later will the effects of fishing younger age classes be felt and the spawning stock biomass will further decline if the catch level is maintained at *RY*00. To exemplify this point we present Figures 3 and 4 that show the spawning stock biomass time trends under a variety of constant future catch scenarios. Note that in Figure 3 constant catch level at *RY*00 eventually leads to a stock crash whereas it yields a positive biomass time trend in Figure 4. The catch level that leads to a stable spawning biomass is smaller than *RY*00.

Relaxing the assumption that the stock was at unfished equilibrium at the onset of fishing has dramatic effects on the results for the deterministic models. Estimating parameter γ (see Equation 20) changes the value of parameter *h* from 0.99 (its theoretical maximum value) to 0.3 (its theoretical minimum value). Since the value of parameter *h* was bounded to [0.3,1.0] we evaluated if the solution changed when relaxing the lower bound of the interval to 0.201 (*h* is undefined at 0.2).

***Table 8**: Results obtained for Run 1 - deterministic - non-virgin when constraining the productivity parameter h to [0.201,1.0]*

Parameter	deterministic non-virgin
h	0.220
Ksp	7504630
γ	-1.99
*Bsp*1960/*Ksp*	0.14
-logeL	-45.3387

Table 8 shows the results obtained for Run 1 -deterministic - non-virgin when the interval of the *h* parameter was relaxed. The minimizer did not reach the lower bound but the answer was very close to 0.2, an unlikely low level of productivity for the bigeye stock.

This paper does not attempt to present a definitive assessment for bigeye, but rather a range of assessments based on different assumptions and input parameters to show the sensitivity of results to assumptions. One rather worrying characteristic of all the stochastic runs is the fact that the steepness estimate (0.99 or greater) is on or close to the upper bound. It is also worrying that for the deterministic case a simple switch from assuming *Bsp*1960/*Ksp*= 1.0 to estimating that ratio leads to a change in the steepness estimate from 0.99 to a very low value (around 0.3). This clearly shows a lack of information about stock and recruitment. Productivity for the bigeye stock is unlikely to be at such extremes (very high productivity *h*=0.99 or very low productivity *h*=0.3). It would also be dangerous to assume that recruitment would be unaffected until spawning biomass reaches extremely low levels. The fact that the estimate of steepness is on the upper bound also calls into question some aspects of the validity of the results in general. There are strong implications of such a high steepness for projections, estimates of MSY and replacement yield. Regarding the variance estimate of the steepness parameter (*h*), the ASPM97 software show a variance of 0.000 when h is estimated to be at the boundary (set to 0.99 in ASPM97). This is almost certainly meaningless, since it is highly likely that the first derivative with respect to *h* will not be zero there. Covariances involving *h* are also likely to be meaningless, though variance estimates of other parameters may be unaffected. This can be checked by bootstrapping.

The AD Model Builder implementation indicates a non-zero but very low variance, though in this implementation the bound was set to 1.0. The reliability of the variance estimate is still questionable when the result is so close to the bound, and should also be checked by bootstrapping. We currently assume that the variance estimate of unexploited biomass (*Ksp*) is unaffected, or not strongly affected, but this can also be validated by bootstrap. Note, however, that ideally a calibrated bootstrap should be used.

It is interesting to note that in all cases, projections based on current catch levels lead to rapid stock decline. Between runs, there is however large differences in estimates of catch levels that would maintain the stock at its current biomass, or lead to biomass increases. Ideally, the projections for stochastic recruitment runs should again be stochastic, but we did not have enough time to do that. Although the software (AD.ModelBuilder implementation) has been tested, more work needs to be done on the behaviour of the stochastic recruitment version. It may, for example, be feasible to estimate one more parameter describing the recruitment deviations (e.g. the autocorrelation or variance parameter). This should obviously be tested with simulated data.

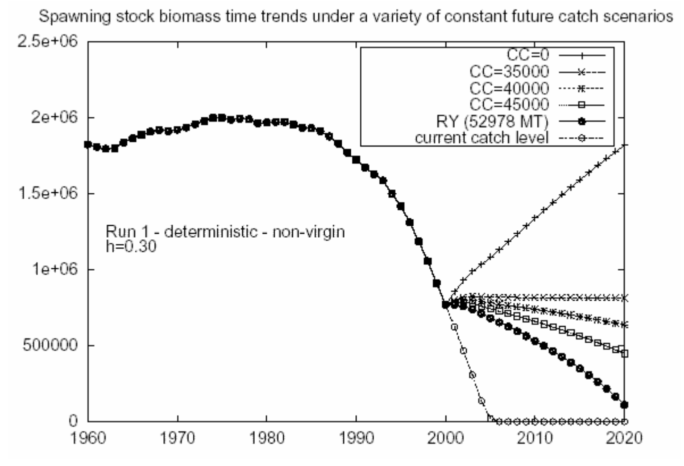

***Figure 3**: Stock projections under a variety of future constant catch scenario for run 1 -deterministic - non-virgin.*

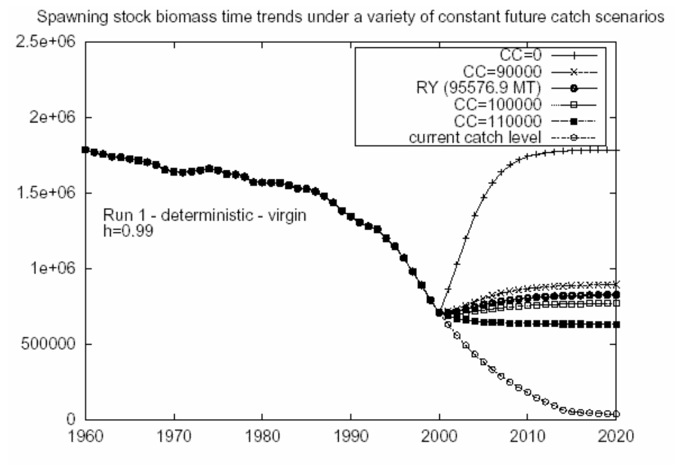

***Figure 4**: Stock projections under a variety of future constant catch scenario for run 1 -deterministic - virgin.*

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APPENDIX A. ASPM IMPLEMENTATION DETAILS

A.1 Dynamics

The dynamics of the fish population are described by three equations:

$$N_{y+1,0} = R(B^{sp}_{y+1}) \qquad (3)$$

$$N_{y+1,a+1} = (N_{y,a}e^{-M_a/2} - C_{y,a})e^{-M_a/2} \qquad (4)$$

$$N_{y+1,m} = (N_{y,m}e^{-M_m/2} - C_{y,m})e^{-M_m/2} + (N_{y,m-1}e^{-M_{m-1}/2} - C_{y,m-1})e^{-M_{m-1}/2} \qquad (5)$$

where,

$N_{y,a}$ is the number of tuna age a at the start of year y

$R(B^{sp})$ is the spawners-recruits biomass relationship assumed (see section A.2)

$C_{y,a}$ is the total number of tuna age a taken by the fishery in year y M_a is the natural mortality rate for fish age a (see Table 11) m is the largest age considered (the ”plus group”)

The fishery is assumed to occur as a pulse catch in the middle of the year. The total number of tuna of age a caught each year ($C^f y,a$) is given by:

$$C_{y,a} = \sum_f C^f_{y,a} \qquad (6)$$

where, f is fishery/fleet concerned.

The mass of the fleet-specific annual catch (C^f_y) is given by:

$$C^f_y = \sum_{a=0}^{m} w_{a+1/2}C^f_{y,a} \qquad (7)$$

$$= \sum_{a=0}^{m} w_{a+1/2}S^f_{a,y}F^f_y N_{y,a}e^{-M_a/2} \qquad (8)$$

where,

$S^f a,y$ is the fleet-specific selectivity for tuna of age a in year y (values in Table 15 and16)

$F^f y$ is the fleet-specific fishing mortality for year y (see Equation 11) $wa{+}1/2$ is the weight at mid-year (values in Table 14)

The fleet-specific exploitable biomass is calculated as:

$$B^f_y = \sum_{a=0}^{m} w_{a+1/2}S^f_a N_{y,a}e^{-M_a/2} \qquad (9)$$

or in numbers

$$N^f_y = \sum_{a=0}^{m} S^f_a N_{y,a}e^{-M_a/2} \qquad (10)$$

The proportion of the resource harvested each year ($F^f y$) by fleet f is given by:

$$F^f_y = C^f_y / B^f_y \qquad (11)$$

and

$$C^f_{y,a} = S^f_a F^f_y N_{y,a}e^{-M_a/2} \qquad (12)$$

A.2 Spawning biomass-recruitment relationship

The spawning biomass in year y is:

$$B^{sp}_y = \sum_{a=0}^{m} f_a w_a N_{y,a} \qquad (13)$$

where:

fa is the proportion of sexually mature tuna at age a (values in Table 11)

The number of recruits is calculated using a Beverton-Holt relationship:

$$R(B^{sp}_y) = \frac{aB^{sp}_y}{b + B^{sp}_y} \qquad (14)$$

To ease the biological interpretation of the stock-recruitment parameters we reparameterize equation 14 in terms of the pre-exploitation equilibrium spawning biomass (Ksp) and the ”steepness” of the stock-recruitment relationship. The ”steepness” h of the stockrecruitment curve is defined as the fraction of the pristine recruitment ($R0$) that results when the spawning biomass drops to 20% of its pristine level:

$$hR_0 = R(0.2K^{sp}) \qquad (15)$$

from which it follows that:

$$h = 0.2[b + K^{sp}]/[b + 0.2K^{sp}] \qquad (16)$$

and hence:

$$a = \frac{4hR_0}{5h-1} \qquad (17)$$

and

$$b = \frac{K^{sp}(1-h)}{5h-1} \qquad (18)$$

We constrained the value of h to [0.3,1.0] as it is very unlikely that the bigeye stock has a level of productivity below 0.3.

A.3 Biomass trajectories

Given a value for the pre-exploitation equilibrium spawning biomass Ksp and assuming that the initial age structure is at equilibrium, the initial recruitment $R0$ can be calculated as:

$$R_0 = K^{sp}/[\sum_{a=1}^{m-1} f_a w_a e^{-\sum_{a=0}^{m-1} M_a} + (f_m w_m e^{-\sum_{a=0}^{m-1} M_a}/(1-e^{-M_m}))] \qquad (19)$$

An additional parameter (γ) can be estimated to allow the stock to be at a state other than the unfished equilibrium at the onset of fishing. Note that the population structure, as represented by the proportion of fish in each age class, will be similar to that of the unfished equilibrium. The extra parameter simply scales the initial population:

$$N_{0,0} = R_0 e^g \qquad (20)$$

The notation $N_{0,0}$ means the number of recruits at the onset of fishing. Initial abundance of older age classes are calculated as:

$$N_{a,0} = N_{a-1,0}e^{-M_{a-1}}$$

Once the numbers-at-age of the population at the oset of fishing have been calculated the population dynamics can be obtained through equations 3 through 14.

A.4 Objective function

To estimate the stock recruitment parameters *r* and *Ksp*, the model is fitted to an index of abundance by maximizing an associated likelihood function. The likelihood is calculated assuming that the observed index of abundance is lognormally distributed about its expected value:

$$I_y^l = \hat{I}_y^l e^{e_y^l} \qquad \text{or} \qquad e_y^l = \ln(I_y^l) - \ln(\hat{I}_y^l) \qquad (21)$$

where,

I_y^l is the longline fleet abundance index for year *y*

$\hat{I}_y^l = q^l N_y^l$ is the corresponding model estimated value, where N_y^l is the model value for the longline exploitable resource abundance (equation 10) q^l is the constant longline catchability coefficient ε_y^l is from $N(0,(\sigma_y^l)^2)$)

The simplified log-likelihood function for the indices of abundance is given

by:

$$\log_e(L_1) = -\sum_y \left[\log_e s_y^l + \left(\frac{(e_y^l)^2}{2(s_y^l)^2} \right) \right] (22)$$

Independent estimates of $N(0,(\sigma_y^l)^2)$ are not available so they are assumed not to be dependent on year (σ_y^l is simplified to σ^l). σ^l is estimated in the likelihood maximization process as:

$$s^l = \sqrt{\frac{\sum_y (e_y^l)^2}{n}} \qquad (23)$$

where *n* is the number of data points in the abundance time series. The indices of abundance component of the log-likelihood can be further simplified to:

$$\log_e(L_l) = -n.\log_e(s^l) - \frac{n}{2} \qquad (24)$$

Under this assumption, the maximum likelihood estimate of q^l is given by:

$$\hat{q}^l = \exp\left[\sum_y \left(\log_e(I_y^l) - \log_e(N_y^l) \right) \right] \qquad (25)$$

A.5 Stochastic recruitment

The stochastic version of the ASPM requires the estimation of additional parameters. We estimate recruitment as deviations from an estimated mean recruitment and cast the recruitment deviations into a first-order autoregressive process (AR(1)):

$$R_y^* = \overline{R}.e^{n_y} \qquad (26)$$

subject to

$$n_{y+1} = rn_y + f_{y+1} \qquad (27)$$

where

R^*_y is the estimated recruitment in year *y*

$\overline{R}$ is the estimated mean recruitment

ν is a vector of recruitment deviation ($\sum_y \nu_y = 0$)

ρ is the lag-1 autocorrelation ($|r| < 1$)

ϕ is an i.i.d variable with $\phi_t \sim N(0,\sigma_\phi^2)$

The AR(1) process is incorporated by adding the following component to the log likelihood:

$$\log_e(L_2) = -\sum_y \frac{(w_y)^2}{2s_f^2} \qquad (28)$$

where

$$w_y = \frac{t_y - rt_{y-1}}{\sqrt{1-r^2}}$$

and

$$t_y = \log_e(R_y^*) - \log_e(R_y)$$

It is important to distinguish between recruitment that is estimated (R^*y, equation 26) and recruitment that is calculated using the stock-recruitment relationship (*Ry*, equation 14). The AR(1) parameters ρ and σϕ could be estimated but it is unlikely that the data will contain information about the relative contribution from recruitment variability with respect to the variability in the index of abundance. For this reason, the values of ρ and σϕ have to be set by the analyst. For all runs performed we used ρ=0.25 and σ^2_ϕ=0.4.

We estimate recruitment as deviations from an estimated mean recruitment, an approach that differs from that of Restrepo (1996) which estimated recruitment as deviations from recruitment at virgin level. We prefer our approach since it allows for the sum of deviations to equal 0 ($\sum_y \nu_y = 0$).

A.6 Summary

The deterministic version of the ASPM estimates parameters *h* and *Ksp* by maximizing *loge (L*1) (equation 24). The stochastic version of the ASPM estimates parameters *h*, *Ksp*, *R*, and ν by maximizing

$\log_e(L) = \log_e(L_1) + \log_e(L_2)$ (sum of equations 24 and 28).

In either case, parameter γ is estimated if the stock is assumed to be at a state other the unfished equilibirum at the onset of fishing. Note that minimization on the negative log likelihood is in fact used in the software (ie minimise: $-\log_e$ (L))

A.7 Other considerations

The replacement yield for 2000 is defined as the 2000 catch necessary to maintain the spawning biomass in 2001 at the same level as in 2000:

$$RY_{00} = C_{2000} \,|\, (B^{sp}_{2001} = B^{sp}_{2000}) \qquad (29)$$

The proportion of the catch taken by the longline fishery is calculated as:

$$p^{l} = \frac{C^{l}_{1999}}{C^{l}_{1999} + C^{ps}_{1999}}$$

and the proportion of the catch taken by the purse seine fishery is

$$p^{ps} = 1 - p^{l} = \frac{C^{ps}_{1999}}{C^{l}_{1999} + C^{ps}_{1999}}$$

The total catch is split accordingly between the two fisheries:

$$C^{l}_{y} = p^{l}.C_{y}$$

$$C^{ps}_{y} = p^{ps}.C_{y}$$

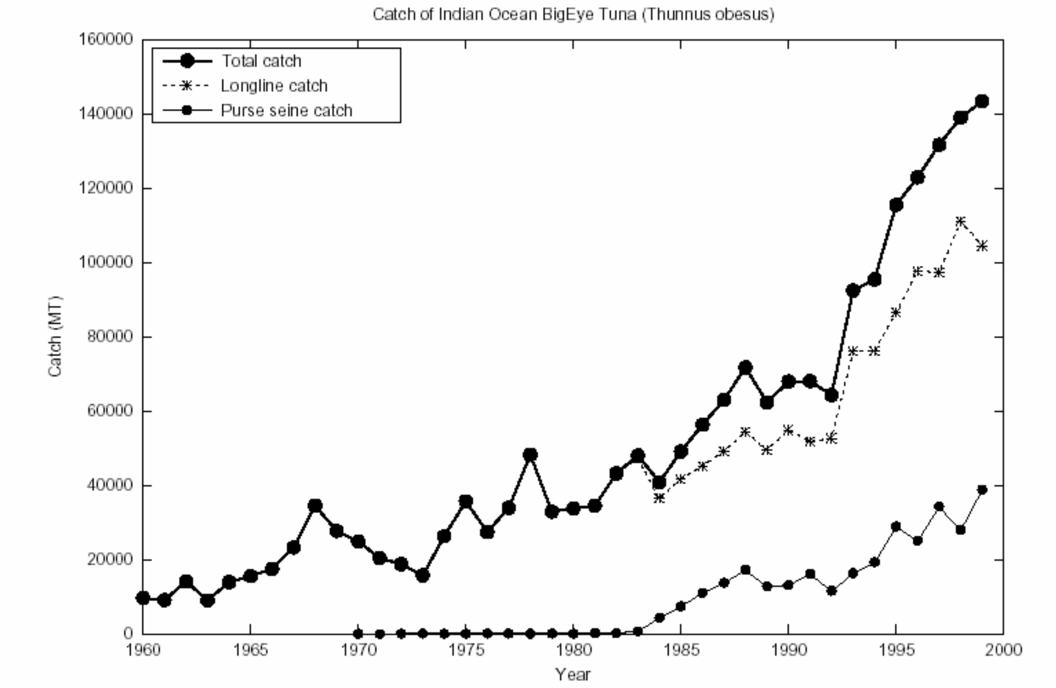
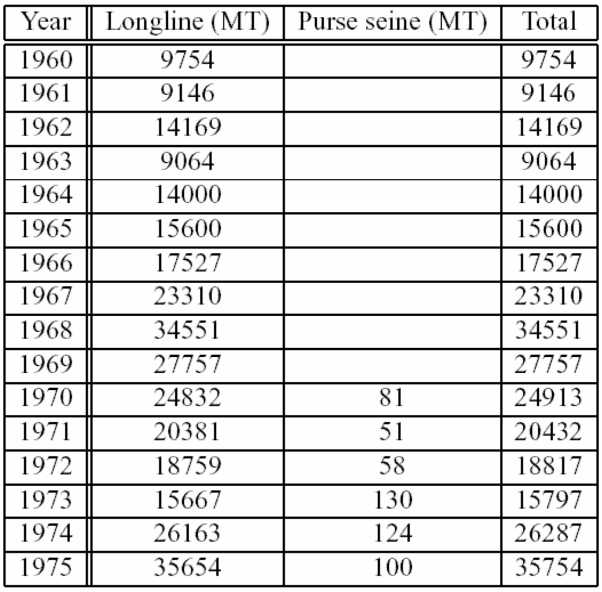


Figure 5: Catch data used. Refer to Table 9 for the data used to generate this graph.

APPENDIX B. TABLES AND FIGURES

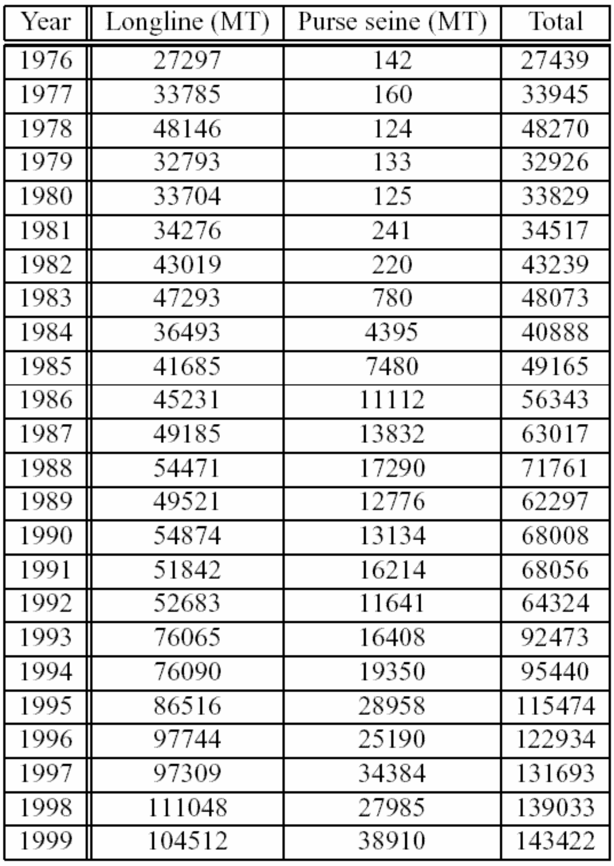
B.1 Catch data and index of abundance

Table 9: Catch data used. Refer to Figure 5 for a graph of this data.



Year	Longline (MT)	Purse seine (MT)	Total
1960	9754		9754
1961	9146		9146
1962	14169		14169
1963	9064		9064
1964	14000		14000
1965	15600		15600
1966	17527		17527
1967	23310		23310
1968	34551		34551
1969	27757		27757
1970	24832	81	24913
1971	20381	51	20432
1972	18759	58	18817
1973	15667	130	15797
1974	26163	124	26287
1975	35654	100	35754

Table 9 Continued

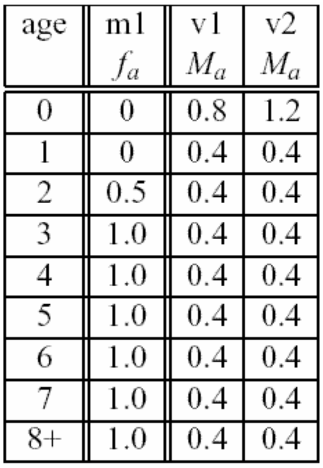


Year	Longline (MT)	Purse seine (MT)	Total
1976	27297	142	27439
1977	33785	160	33945
1978	48146	124	48270
1979	32793	133	32926
1980	33704	125	33829
1981	34276	241	34517
1982	43019	220	43239
1983	47293	780	48073
1984	36493	4395	40888
1985	41685	7480	49165
1986	45231	11112	56343
1987	49185	13832	63017
1988	54471	17290	71761
1989	49521	12776	62297
1990	54874	13134	68008
1991	51842	16214	68056
1992	52683	11641	64324
1993	76065	16408	92473
1994	76090	19350	95440
1995	86516	28958	115474
1996	97744	25190	122934
1997	97309	34384	131693
1998	111048	27985	139033
1999	104512	38910	143422

Table 10: CPUE index used.

Year	CPUE	Year	CPUE
1960	4.9856	1980	5.2869
1961	3.7597	1981	4.9582
1962	4.8213	1982	4.5332
1963	4.0728	1983	4.4082
1964	4.2588	1984	3.9103
1965	3.2196	1985	3.9628
1966	3.6846	1986	4.7259
1967	2.9918	1987	5.3255
1968	3.47	1988	4.4126
1969	2.8123	1989	4.1398
1970	2.5884	1990	4.0172
1971	2.4941	1991	3.8177
1972	3.1635	1992	3.5432
1973	3.941	1993	3.8858
1974	4.5837	1994	3.4661
1975	3.8284	1995	3.5141
1976	4.4053	1996	3.2251
1977	7.4138	1997	2.8021
1978	6.6414	1998	3.0569
1979	4.6715	1999	2.9367

Table 11: Value of the maturity vector (m1) and of the two mortality vectors (v1 and v2)used.



age	m1 f_a	v1 M_a	v2 M_a
0	0	0.8	1.2
1	0	0.4	0.4
2	0.5	0.4	0.4
3	1.0	0.4	0.4
4	1.0	0.4	0.4
5	1.0	0.4	0.4
6	1.0	0.4	0.4
7	1.0	0.4	0.4
8+	1.0	0.4	0.4

Table 12: VBGF parameters used.

	L_∞	k	t_0
From Tankevich (1982) Females	209.8	0.171	-0.86
Males	423	0.058	-1.773
From Lehodey *et al.* (1999)	166.3	0.349	-0.389

B.2 Model parameters

Table 13: Length-weight relationship parameters used

	α	β
Fork length $<$ 80cm	$2.74*10^{-5}$	2.908
Fork length $\geq$ 80cm	$3.661*10^{-5}$	2.90182

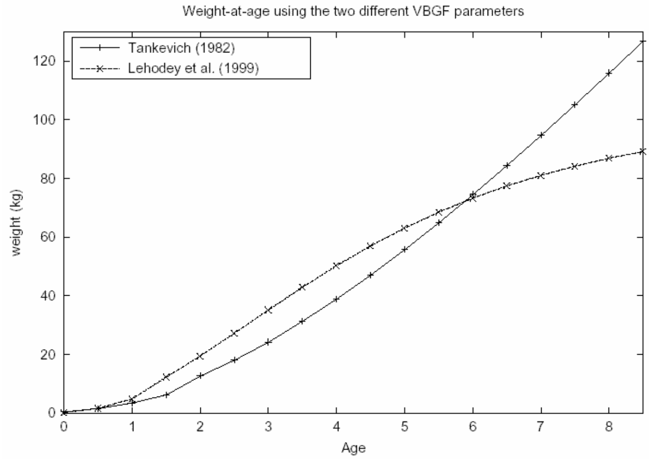


Figure 6: Resulting weight-at-age from the two growth curves used. The data used to produce this graph is in Table 14.

age	weight - (Tankevich, 1982) w_a(kg)	weight - (Lehodey *et al.*, 1999) w_a(kg)
0	0.475	0.195
0.5	1.597	1.687
1	3.526	4.874
1.5	6.270	12.317
2	12.706	19.500
2.5	18.111	27.303
3	24.233	35.245
3.5	31.417	42.978
4	38.962	50.270
4.5	47.116	56.985
5	55.808	63.058
5.5	64.973	68.475
6	74.551	73.253
6.5	84.485	77.431
7	94.727	81.058
7.5	105.232	84.189
8	115.959	86.879
8.5	126.874	89.181

Table 14: Weight-at-age vectors used.

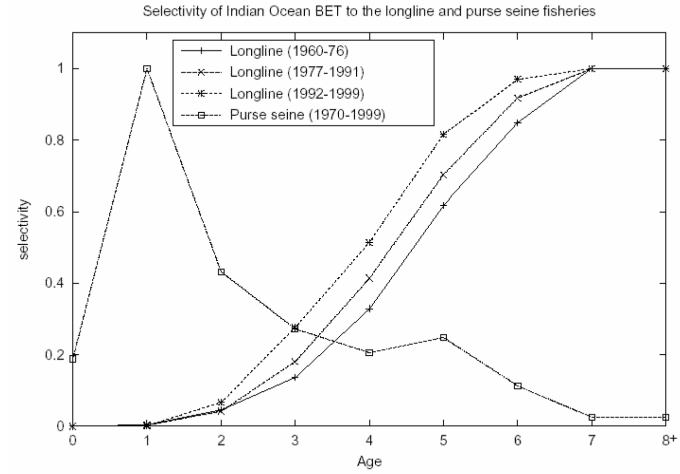


Figure 7: Selectivity of Indian Ocean BET to the longline and purse seine fisheries when using the growth parameters from Tankevich (1982). The data used to produce this graph is in Table 15.

age	S_l (1960-1976)	S_l (1977-1991)	S_l (1992-1999)	S_{ps} (1970-1999)
0	0	0	0	0.188
1	0.004	0.003	0.001	1
2	0.046	0.042	0.067	0.432
3	0.137	0.181	0.276	0.272
4	0.329	0.414	0.514	0.206
5	0.618	0.703	0.816	0.248
6	0.848	0.918	0.97	0.113
7	1	1	1	0.025
8+	1	1	1	0.025

Table 15: Value of the different selectivity vectors evaluated when using the growth parameters from Tankevich (1982). Sl is the selectivity to the longline fishery and Sps is the selectivity to the purse seine fishery. Refer to Figure 7 for a graph of this data.

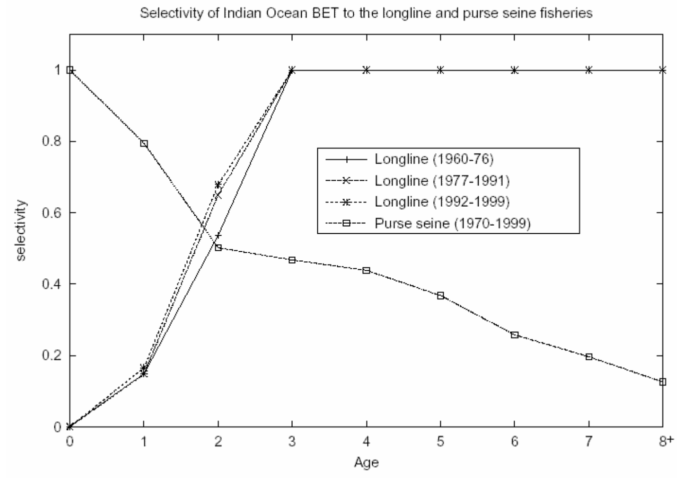


Figure 8: Selectivity of Indian Ocean BET to thelongline and purse seine fisheries when using the growth parameters from Lehodey et al. (1999). The data used toproduce this graph is in Table 16.

age	S_l (1960-1976)	S_l (1977-1991)	S_l (1992-1999)	S_{ps} (1970-1999)
0	0.001	0.001	0	1
1	0.148	0.148	0.166	0.795
2	0.536	0.65	0.679	0.502
3	0.999	1	1	0.468
4	1	1	1	0.439
5	1	1	1	0.368
6	1	1	1	0.258
7	1	1	1	0.197
8+	1	1	1	0.126

Table 16: Value of the different selectivity vectors evaluated when using the growth parameters from Lehodey et al. (1999). Sl is the selectivity to the longline fishery and Sps is the selectivity to the purse seine fishery. Refer to Figure 8 for a graph of this data.

B.3 Results

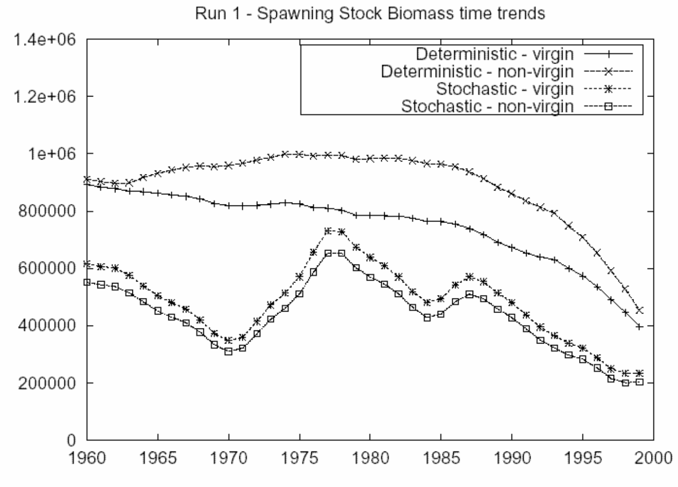


Figure 9: Spawning stock biomass time trends for Run 1.

Parameter	deterministic virgin	deterministic non-virgin	stochastic virgin	stochastic non-virgin
h	0.999	0.300	0.999	0.999
K^{sp}	892375	1286350	615295	580868
$\sigma_{K^{sp}}$	121710	114010	232740	250030
γ	0.0	-0.345	0.0	-0.052
B^{sp}_{1960}/K^{sp}	1.0	0.71	1.0	0.95
$-log_e(L)$	-43.5207	-45.0533	-73.3912	-73.4162
MSY_{total}	123862	37336.3	85414.2	80634.3
MSY_{ll}	90335.4	27214	62263.1	58775.8
MSY_{ps}	33526.4	10122.3	23151.1	21858.4
B_{MSY}	141815	570093	97531.8	92092.9
RY_{total}	95576.9	52978	85351.6	82835.6
RY_{ll}	69647.2	38605.2	62196	60362.5
RY_{ps}	25929.8	14372.8	23155.7	22473.1

Table 17: Run 1 result

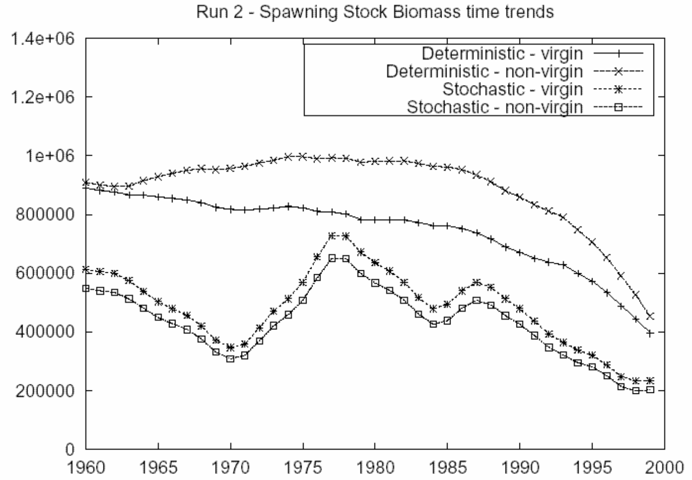


Figure 10: Spawning stock biomass time trends for Run 2.

Parameter	deterministic virgin	deterministic non-virgin	stochastic virgin	stochastic non-virgin
h	0.999	0.300	0.999	0.999
K^{sp}	890290	1284020	613623	578742
$\sigma_{K^{sp}}$	121470	113670	231970	248810
γ	0.0	-0.345	0.0	-0.053
B^{sp}_{1960}/K^{sp}	1.0	0.71	1.0	0.95
$-log_e(L)$	-43.5157	-45.0517	-73.3957	-73.4215
MSY_{total}	123945	37364.1	85445.3	80590.7
MSY_{ll}	90352.5	27234.3	62280.7	58741
MSY_{ps}	33592.4	10129.8	23164.6	21849.6
B_{MSY}	141716	569001	98015.6	92352
RY_{total}	95725.8	53103.4	85391.7	82826.4
RY_{ll}	69755.6	38696.6	62225.1	60355.8
RY_{ps}	25970.1	14406.8	23166.5	22470.6

Table 18: Run 2 results.

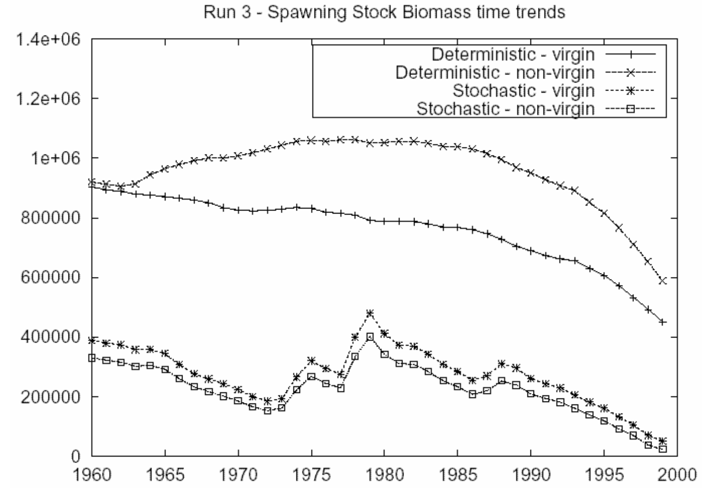


Figure 11: Spawning stock biomass time trends for Run 3.

Parameter	deterministic virgin	deterministic non-virgin	stochastic virgin	stochastic non-virgin
h	0.999	0.300	0.999	0.999
K^{sp}	902917	1394870	388467	366174
$\sigma_{K^{sp}}$	228280	200590	121870	102670
γ	0.0	-0.415	0.0	-0.102
B^{sp}_{1960}/K^{sp}	1.0	0.66	1.0	0.90
$-log_e(L)$	-42.273	-43.7981	-86.5544	-86.6792
MSY_{total}	151909	45298.4	65392.3	61643.9
MSY_{ll}	110792	33015.4	47669.3	44935.8
MSY_{ps}	41116.9	12283	17723	16708.1
B_{MSY}	81349.4	617310	34619	32596.2
RY_{total}	100775	57761.2	86629.4	80753.1
RY_{ll}	73435.1	42090.7	63127.1	58845
RY_{ps}	27340	15670.5	23502.3	21908.1

Table 19: Run 3 results.

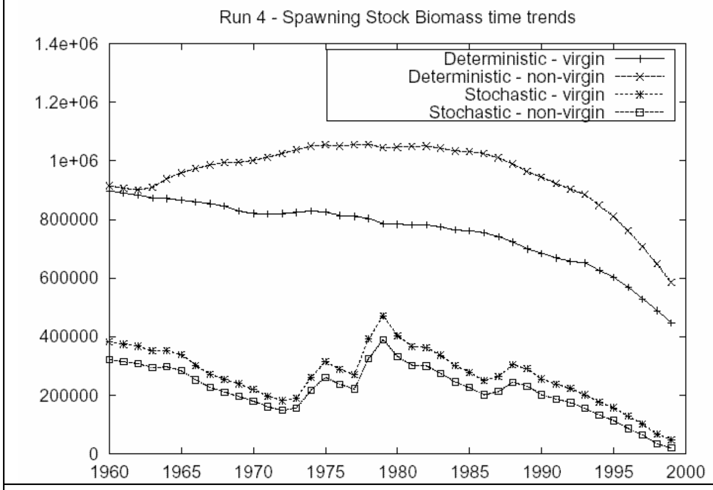


Figure 12: Spawning stock biomass time trends for Run 4.

Parameter	deterministic virgin	deterministic non-virgin	stochastic virgin	stochastic non-virgin
h	0.999	0.300	0.999	0.999
K^{sp}	897681	1388810	382492	359684
$\sigma_{K^{sp}}$	227700	199480	119430	98918
γ	0.0	-0.417	0.0	-0.109
B^{sp}_{1960}/K^{sp}	1.0	0.66	1.0	0.90
$-log_e(L)$	-42.2673	-43.7952	-86.5821	-86.7239
MSY_{total}	153055	45373.1	65255.5	61368.9
MSY_{ll}	111623	33069.6	47568.5	44734.4
MSY_{ps}	41432	12303.5	17687	16634.5
B_{MSY}	77164.6	614360	32467.8	30493
RY_{total}	101136	58028.6	85966.9	79658.7
RY_{ll}	73697.9	42285.6	62644.3	58047.5
RY_{ps}	27437.9	15743	23322.6	21611.2

Table 20: Run 4 results.