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blue shark (*Prionace glauca*) in the North Pacific¹**

Shelley Clarke² and Murdoch McAllister³

²Joint Institute for Marine and Atmospheric Research, University of
Hawaii and National Research Institute of Far Seas Fisheries, 5-7-1
Shimizu-Orido, Shizuoka 424-8633 JAPAN

³Division of Biology, Faculty of Life Sciences, Imperial College, Prince
Consort Road, London SW7 2BP, United Kingdom

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Abstract

A Bayesian surplus production model was applied to blue shark (*Prionace glauca*) in the North Pacific and used to estimate current and future values of stock assessment reference points. Several of the issues faced when selecting an assessment methodology for this species are expected to be encountered when assessing other non-target highly migratory species. This model's main strengths lie in the simplicity of its data requirements (catch data and at least one annual catch rate series) and its ability to incorporate existing information in the form of prior probability distributions for estimated parameters. This function facilitates fitting to times series that are less informative or have incomplete catch histories. The model was successfully fit to one series of blue shark catch rate data, resulting in model parameter and stock reference point estimates which are consistent with previous findings for this species.

Introduction

Biomass dynamic models describe a fish stock's behavior over time as a function of its biomass, production and mortality. Although such models are highly simplified representations of complex population dynamics, they are commonly relied upon because of their minimal data requirements, and ease of use and interpretation (Hilborn and Walters, 1992). A Bayesian implementation of the classic Schaefer surplus production model (McAllister and Babcock, 2002) combines the simplicity of the biomass dynamic approach with the ability to specify prior probability distributions for all estimated parameters. The usual model outputs and reference points, namely the intrinsic rate of increase (r), carrying capacity (K), current biomass relative to carrying capacity (B_{cur}/K) and maximum sustainable yield (MSY), are produced as posterior probability distributions allowing a formal, quantitative interpretation of uncertainty. Applying the techniques of decision analysis, the model can also be used to project stock conditions into the future given various management strategies (McAllister et al. 2001).

An assessment of blue shark (*Prionace glauca*) stocks in the North Pacific (Kleiber et al., 2001; Clarke et al., in prep) has been conducted using logbook records from the Japanese longline fleet as a measure of catch per unit effort (CPUE), and total catch estimates

compiled from both longline and drift net fleets from all fishing entities. Several special considerations were required when selecting an assessment methodology for this species. First, historical catch records for blue shark may suffer from lack of species identification, under-reporting or both (Walsh et al., 2002; Nakano and Clarke, submitted). In addition, although blue shark is not generally a target species for these fleets, incidental catches may be considerable and may be retained rather than being released alive. This situation results in considerable uncertainty in catch records. Finally, blue shark population age structure is not particularly well understood, and while age-structured models can be applied there may be considerable uncertainty surrounding age-specific parameters. Many of these issues are expected to arise when selecting assessment methods for other non-target highly migratory species.

This paper describes the application of the Bayesian Surplus Production (BSP) model in the ICCAT assessment software catalog (ICCAT, 2003) to the North Pacific blue shark stock. This model has not to our knowledge been applied to any Pacific fish stocks although it has been applied in the Atlantic to swordfish (McAllister et al. 2000), large coastal sharks (McAllister et al. 2001), white marlin (Babcock and McAllister, 2003), and most recently to blue and mako sharks in the ICCAT shark stock assessment (ICCAT, in press). In addition to exploring the usefulness of the BSP model for blue shark, this paper seeks to explore the possibilities for applying this model to other assessments of highly migratory species by highlighting key model features.

Materials and Methods

Description of the Model

The Bayesian surplus production (BSP) application software (ICCAT, 2003) is based on the Schaefer model parameterized as:

$$B_{t+1} = rB_t - \frac{r}{K}B_t^2 - C_t \quad (1)$$

where B is the biomass at each time step t , r is the intrinsic rate of increase, K is the carrying capacity and C is the catch at time t . The required inputs are a continuous catch series and at least one catch rate series with coefficients of variation, if available. The model allows specification of priors for K , r , the biomass in the first modeled time step as a ratio of K ($B_{t=1}/K$), and the average catch (C_0) for missing catch data (if any) at the beginning of the time series. The constant of proportionality between each abundance index and the biomass trend (i.e. catchability, or q) was treated as having a non-informative prior and calculated using the numerical shortcut of Walters and Ludwig (1994). Under this method, in each draw from the importance function of the model-estimated parameters (e.g. r and K) the maximum likelihood estimate for q is computed and this in turn is used to compute the likelihood of the data given r , K and the other parameters. This is equivalent to specifying a prior for q and drawing samples of q from the importance function.

Although based on the principles of biomass dynamics, this model can also operate using fish number instead of weight as the unit of interest. The model time step is fixed as years. There is no explicit spatial component, but if the existence of separate stocks is suspected, the model may be run with separate catch and CPUE series within delineated boundaries.

It is preferable to run the uncompiled version of the source code as it provides greater flexibility in modifying the model and tracing the source of parameter specification and other errors. However, the uncompiled code must be loaded within the Visual Basic 5.0 or 6.0 platforms and will not run within more recent versions of Visual Basic. For most scenarios, the number of iterations was set to one million which on a Pentium(R) 4, 3.20 GHz CPU required approximately 10 minutes to compute.

Catch and Catch per Unit Effort (CPUE) Data

A CPUE series was obtained by standardizing logbook catch and effort data from the Japanese longline fleet from 1971-2002. Prior to standardization the data were filtered using a reporting rate of 80% (see Nakano and Clarke, submitted) to remove records from vessels which appeared to be under-reporting blue shark catches. The standardization utilized a generalized linear model (GLM) with a Poisson distribution and factors for year, quarter, area (the North Pacific was divided into 16 roughly equivalently sized areas) and set depth (two categories: shallow considered to be < 7 hooks between floats (hbf) and deep considered to be ≥ 7 hbf). A habitat standardization model (Bigelow et al., 2004) was also applied but did not predict substantially different results. The resulting year coefficients for the deep and shallow series from the Poisson-based GLM are shown alongside results for a nominal (year effects only) model in Figure 1.

Catches were estimated as the product of the CPUE and the effort for the Japanese fleet, the Chinese Taipei fleet, and other fleets as calculated from Secretariat for the Pacific Community public domain databases. Catches for drift net fisheries were compiled from available Japanese statistics and estimated for other fleets during the period of operation of the small mesh squid drift net fishery. Catches from the Japanese *Kogata* (or inshore) longline fleet were estimated using effort statistics as a proportion of the offshore Japanese longline fleet. Hawaiian longline fleet catches were tallied from logbook databases (Clarke et al., in prep). Total catches in number of blue sharks are shown in Figure 2.

Model Initialization

Parameter specification for the base case of the model is described in Table 1. Based on data availability, the initial year in the model is 1971 and the current year is assumed to be 2002. All informative priors were assigned a log normal distribution, and units of 10,000 fish were used for K (carrying capacity) and $B_{t=1}/K$ (biomass in the first year of the model as a proportion of K). A non-informative prior was specified for K using a uniform distribution on $\log(K)$ which allowed the value to range between the specified minimum and maximum values while weakly favoring smaller values. The population

was assumed to be at carrying capacity at the beginning of the model ($B_{t=1}/K=1$) and the specified standard deviation allowed this parameter ($B_{t=1}/K$) to range between 67 and 148% over the 95% prior probability of K . The prior for the intrinsic rate of increase (r) was set with reference to demographic analysis which indicated that the mean of r for blue shark is 0.34 (95% confidence interval (C.I.) of 0.25-0.43; Cortés, 2002), however we assigned a less informative variance of 0.3 thus allowing r to take values between 0.19 and 0.63. This range encompasses the range of posterior predictions of r resulting from the ICCAT blue shark stock assessment (0.20-0.25), as well as most of the range of prior values used in that assessment (95% probability intervals (P.I.) of 0.10 to 0.37 for the North Atlantic and 0.19-0.31 for the South Atlantic; ICCAT, in press).

For each CPUE series, the method of estimating σ (the standard deviation in the natural logarithm of the difference between observed and model predicted values) for each time step in the series (i.e. the weighting method) was specified by the maximum likelihood estimate (MLE) of σ for each series (i.e. weighting method #2) (McAllister and Babcock, 2002). The marginal posterior distributions for model parameters were calculated using the sampling-importance resampling algorithm (SIR), with the importance function defined as a multivariate t distribution (McAllister et al., 2001).

Sensitivity analyses were conducted to examine the impact of the priors on the results and selection of the weighting method. These tests included:

- Specifying the prior for K as uniform on K rather than uniform on $\log(K)$;
- Specifying a less informative prior for r , i.e. a variance of 0.81 gives a 95% P.I. on r of 0.06 to 2.0;
- Assuming the starting biomass ($B_{t=1}/K$) is well below K , i.e. $B_{t=1}/K=0.6$;
- Specifying an alternative weighting method consisting of equal weighting of each data point using a default coefficient of variation (CV) set at 0.2. This was implemented through specification of weighting method #6.

Available diagnostic statistics for model runs were checked to verify low posterior correlations; a low number of discarded simulations (i.e. simulations are discarded if any of the parameters' values exceed the specified minimum or maximum); a low percentage value for the weight of the maximally weighted draw (i.e. a measure of the relative influence of the draw with the highest weight); and that the CV of the weights of the importance draws is less than the CV of the likelihood times the priors for the same draws (McAllister et al., 2004)

The decision analysis component of the model was used to project population parameters into the future based on a number of policy scenarios. Since there are currently no quotas or other management measures implemented for blue sharks in the North Pacific (aside from the prohibition of finning in United States waters), policies based on fishing mortality (F) were selected. Six F levels (0.05 to 0.30) were modeled over a 15-year time horizon.

Results

Simple spreadsheet surplus production models were executed to derive reasonable starting values for the Bayesian parameter estimation. Since shallow and deep sets are likely to represent different types of operations with different blue shark catchability coefficients, initially shallow and deep series were examined separately. As suspected, each series on its own produced substantially different parameter estimates for K and r . For the shallow series K was less than half of the deep series' K (2,433 versus 5,654), and the estimated r values were near 0.60 for the shallow series but only 0.24 for the deep series. The variance between the observed and estimated biomass (σ) suggests some problems with the estimation in the shallow series ($\sigma = 0.154$) with autocorrelation apparent at lags greater than 10. No such problems were apparent with the estimation based on the deep CPUE series ($\sigma = 0.077$ and no apparent autocorrelation).

Based on these preliminary results, base and sensitivity trials of the BSP model were conducted for the shallow and deep CPUE series separately. The evaluation of diagnostics for each run indicated convergence and reliable estimation for the deep series but, as expected, some problems with estimation based on the shallow series. Specifically, the CV of the weights (167) was considerably larger than the CV of the prior times the likelihood (28) for the shallow series. This suggests that the importance function may not be appropriately sampling the posterior distribution. Although increasing the number of iterations may be able to overcome this problem, there may be mis-specification such that coding of an alternative importance function may be required. Due to this indicated unreliability of the importance sampling function, the posterior parameter estimates for the shallow runs are likely to be unreliable (McAllister et al., 2002). In addition, examination of the Hessian matrix revealed a high (-0.972) correlation between K and r in both shallow and deep estimations. While potentially problematic, the influence of this correlation on parameter estimation is minimized when an informative prior for r can be specified as was the case in this assessment. The fit of the base case estimates of the parameters to the data for the deep and shallow CPUE series by the BSP model is shown in Figure 3.

The numeric results of base case and sensitivity runs for both shallow and deep series are presented in Table 2. Given the observed problems with model diagnostics for the shallow-based estimates, the shallow results must be treated with caution. Results for the deep series show little variation among the scenarios with estimates of K near 5,000 (50 million sharks) and MSY estimates near 350 (3.5 million sharks). The current biomass is estimated as being approximately 70-75% of K and the values of r (0.27-0.32) are in the range of previously estimated values for this species. For the shallow CPUE the estimates of MSY and B_{cur}/K are similar to those from the deep series. This is expected given the use of the same catch series for both deep and shallow model runs, and the high observed correlation between r and K . In contrast to the catch estimates, however, the estimates of K in the shallow runs are approximately half (2,463 to 3,351), and the estimates of r are nearly double (0.52-0.62), those for the deep runs.

The remainder of the results are based on the estimates for the deep CPUE series only under the base case scenario. Posterior probability distributions are shown for the parameters of interest in Figure 4. The 95% P.I.s for the distributions of K and r from the deep series do not encompass the expected values for these parameters as estimated using the shallow series, further reinforcing the differences in information signals from the two series. Other model parameters estimated from the deep series (but not graphically presented) indicate that the current catch is 74% of the MSY catch level ($CV=0.05$), the current biomass is 102% of the biomass at the beginning of the time series (1971; $CV=6.44$), and the current fishing mortality is 51% of the fishing mortality at MSY ($CV=0.11$). Since under the Schaefer model the harvest rate at MSY closely approximates the fishing mortality at MSY and can be calculated as $r/2$ (Hilborn and Walters, 1992), the harvest rate at MSY is approximately $0.296/2=0.145$.

In addition to these key parameters, a variety of stock assessment reference points were produced by decision analysis for various levels of fishing mortality (Table 3). These results indicate the blue shark population will drop below its MSY levels (i.e. $B_{fin}/B_{MSY}<1.0$) once fishing mortality (F) exceeds 0.15. If fishing mortality remains near 0.15, however, the population will be maintained at half of its carrying capacity and above MSY levels over a 15-year horizon (Figure 5).

Discussion

The findings of this assessment, while preliminary and based on a limited range of sensitivity tests, suggest that the blue shark population in the North Pacific is being fished at harvest rates below MSY levels and that the current population levels are similar to those at the beginning of the 1970s. As for all stock assessments, there are a number of data and model shortcomings which should be highlighted as directions for future research. For blue shark in the North Pacific, a long time series of catch rates is lacking for most fleets, therefore a heavy reliance is placed on data from the Japanese offshore longline fleet. Any biases in these data, arising either from compilation, filtering or standardization will strongly affect the assessment results. Inaccuracies in historical catches for both the longline and drift net fleets are also inevitable given the past lack of attention to recording shark catches. Similar issues are expected to arise when compiling data for other non-target highly migratory species.

The BSP model proved adequate in this application to fit parameters for at least one of the available time series, and the parameter estimates were similar to those found in previous studies. The estimated intrinsic rate of increase ($r=0.30$) was similar to that calculated from demographic methods (0.34) and from application of this model to Atlantic blue shark stocks (0.20 – 0.25) (Cortés, 2002; ICCAT, in press). A previous assessment of the North Pacific blue shark stock using an age-structured model (Multifan-CL) estimated that MSY catch levels were 170 to 300% of current catch levels, and fishing mortality at MSY was 2 to 8 times current levels of fishing mortality (Kleiber et al. 2001). Analogous estimates from the present study are more pessimistic with estimates of current catches at 74% of MSY and current F at 50% of F_{msy} , but both studies concur that the stock is in no danger of collapse. Finally, we contrast the results

of this assessment with a recent yield analysis of blue shark which suggests that only 4% of the total biomass, or 6% of the fishable biomass, can be sustainably harvested (West et al., 2004). Our median estimate of MSY (3.58 million sharks) represents 7% of our median estimate of K (49.15 million sharks) which is larger than but reasonably consistent with the results of the yield analysis. As a further check, under the Schaefer model we can compute the MSY catch as fraction of unfished abundance (K) as $r/4$, or given our results, as 7.4%.

One of the strengths of the BSP model is the simplicity of its data requirements. Unlike some biomass dynamic-based models it can operate with number of individuals and thereby avoid additional uncertainty arising from length-weight conversions necessary when the species of interest is recorded in number. Perhaps the greatest advantage with this model is its ability to allow specification of priors for all estimated parameters thereby facilitating fitting to times series that are less informative or have incomplete catch histories. Output is produced in the form of posterior probability densities for estimated parameters, thereby explicitly accounting for uncertainty.

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Table 1. Parameter specification for the deep and shallow base cases of the BSP model.

Parameter	Distribution	Mean	Standard Deviation	Range (Input Minimum and Maximum)
K	Uniform	-	-	400 to 1,000,000
$B_{t=1}/K$	Log normal	1.0	0.2 (gives a 95% P.I. of 0.67 to 1.48)	0.3 to 3.5
r	Log normal	0.34	0.3 (input as variance =0.09; gives a 95% P.I. of 0.19 to 0.63)	0.001 to 2

Table 2. BSP model results for various scenarios based on deep and shallow CPUE series separately. The results are presented as the expected value from posterior probability distributions for each parameter. Figures in parentheses, where shown, represent standard deviations.

	K	r	MSY	B_{cur}/K	σ (MLE)	q
Deep						
Base	4,915 (1,103)	0.30 (0.045)	358 (79)	0.73 (0.042)	0.075	3.13E-4
K prior not log normal	5,202 (7,783)	0.28 (0.038)	358 (664)	0.70 (0.041)	0.075	3.10E-4
Less informative r	5,109 (1,623)	0.28 (0.049)	355 (142)	0.72 (0.044)	0.075	3.08E-4
Starting biomass well below K	5,187 (684)	0.27 (0.040)	344 (13)	0.68 (0.051)	0.074	3.23E-4
Alternative weighting method	5,233 (8,947)	0.32 (0.067)	405 (733)	0.77 (0.051)	0.074	3.12E-4
Shallow						
Base	2,798 (1,191)	0.54 (0.083)	366 (99)	0.77 (0.020)	0.159	5.80E-4
K prior not log normal	3,351 (19,030)	0.57 (0.141)	423 (1,695)	0.78 (0.025)	0.160	5.71E-4
Less informative r	2,463 (1,097)	0.62 (0.118)	373 (114)	0.78 (0.016)	0.158	6.36E-4
Starting biomass well below K	2,831 (431)	0.52 (0.080)	361 (17)	0.75 (0.024)	0.156	6.00E-4
Alternative weighting method	2,636 (284)	0.56 (0.067)	366 (8)	0.77 (0.015)	0.158	5.94E-4

Table 3. Expected values of biomass as a proportion of carrying capacity (B_{fin}/K) and biomass as a proportion of MSY (B_{fin}/B_{msy}) as estimated by decision analysis for the deep catch series over a 15-year time frame.

Horizon	Policy	E(B_{fin}/K)	E(B_{fin}/B_{msy})
5-year	F=0.05	0.79	1.58
	F=0.10	0.68	1.37
	F=0.15	0.58	1.17
	F=0.20	0.49	0.98
	F=0.25	0.41	0.82
	F=0.30	0.33	0.67
	10-year	F=0.05	0.82
F=0.10		0.67	1.33
F=0.15		0.53	1.05
F=0.20		0.4	0.81
F=0.25		0.3	0.59
F=0.30		0.21	0.41
15-year		F=0.05	0.82
	F=0.10	0.66	1.32
	F=0.15	0.5	1.01
	F=0.20	0.36	0.73
	F=0.25	0.25	0.49
	F=0.30	0.15	0.3

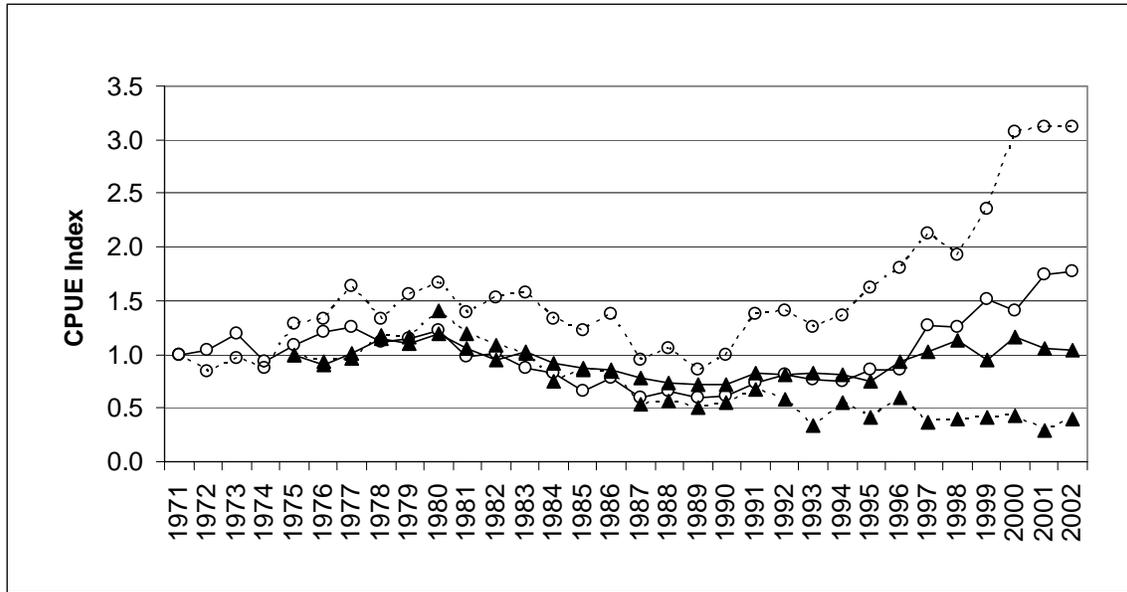


Figure 1. CPUE of blue shark caught by the Japanese longline fleet 1971-2002 standardized using nominal (year effects only; dashed lines) and Poisson-based full effects (year, quarter, area and depth effects; solid lines) models. Series for shallow (\circ) and deep (\blacktriangle) sets are shown separately. There were no deep set catch records prior to 1975.

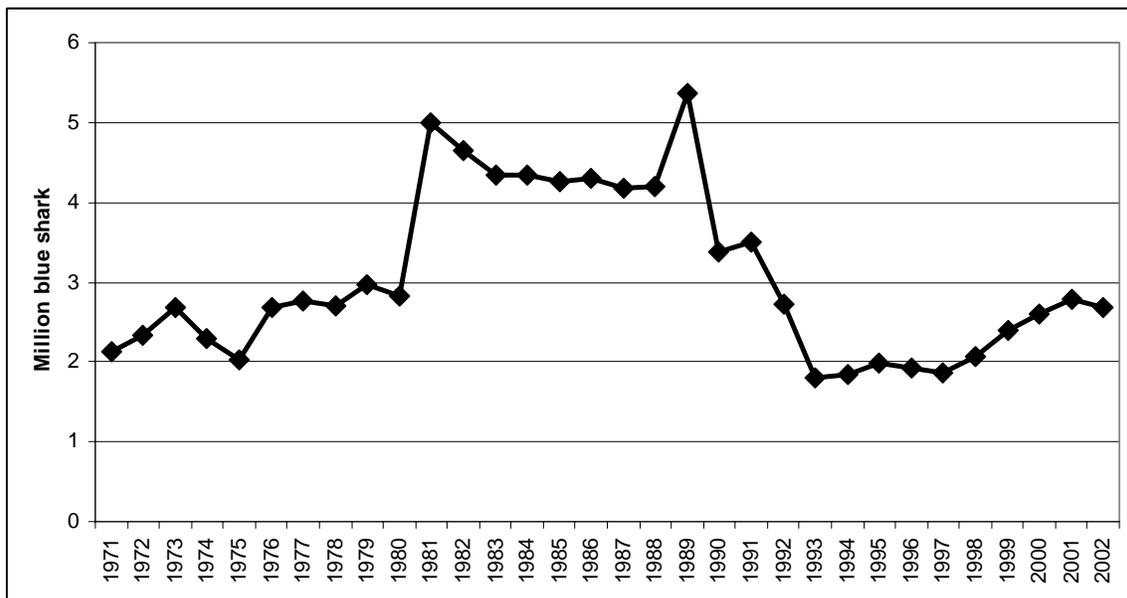


Figure 2. Estimate of total catches of blue shark in the North Pacific by all fleets, 1971-2002 (see Clarke et al., in prep. for details of the estimation methods).

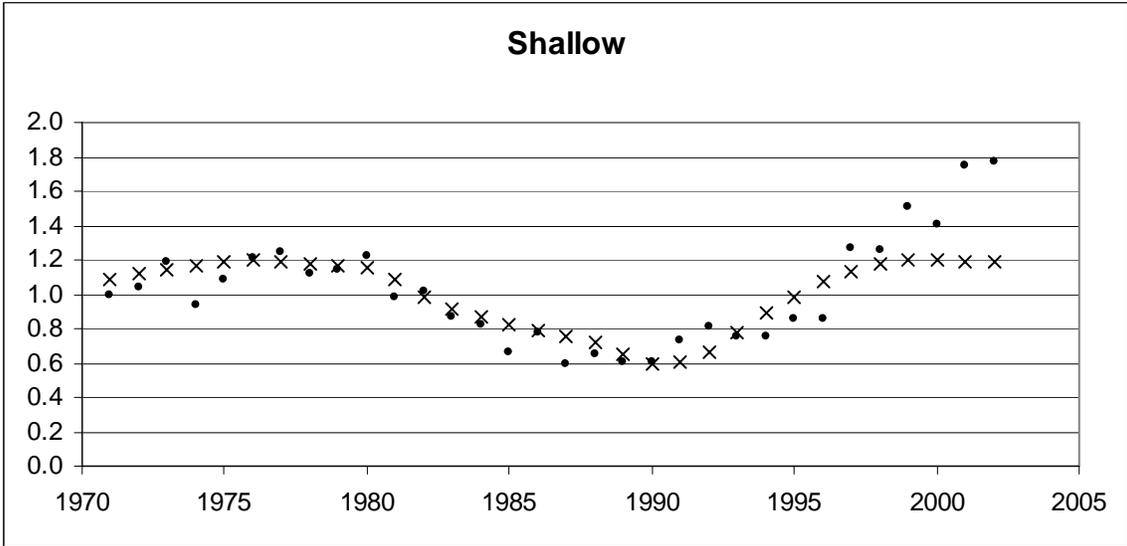
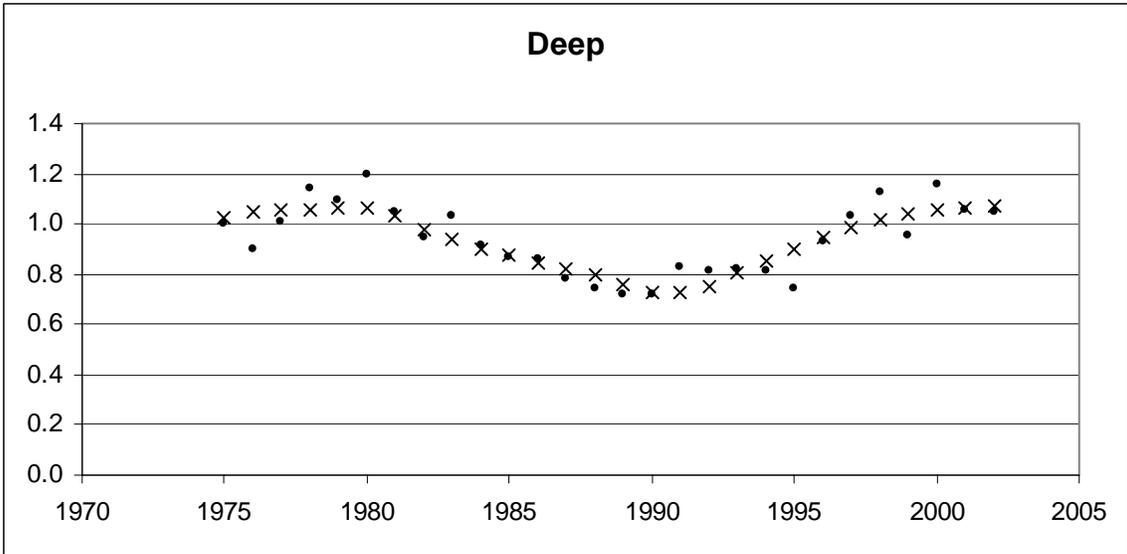


Figure 3. Fit of the BSP model predicted (×) CPUE for deep (1975-2002) and shallow (1971-2002) sets to the observed (•) deep and shallow CPUE indices.

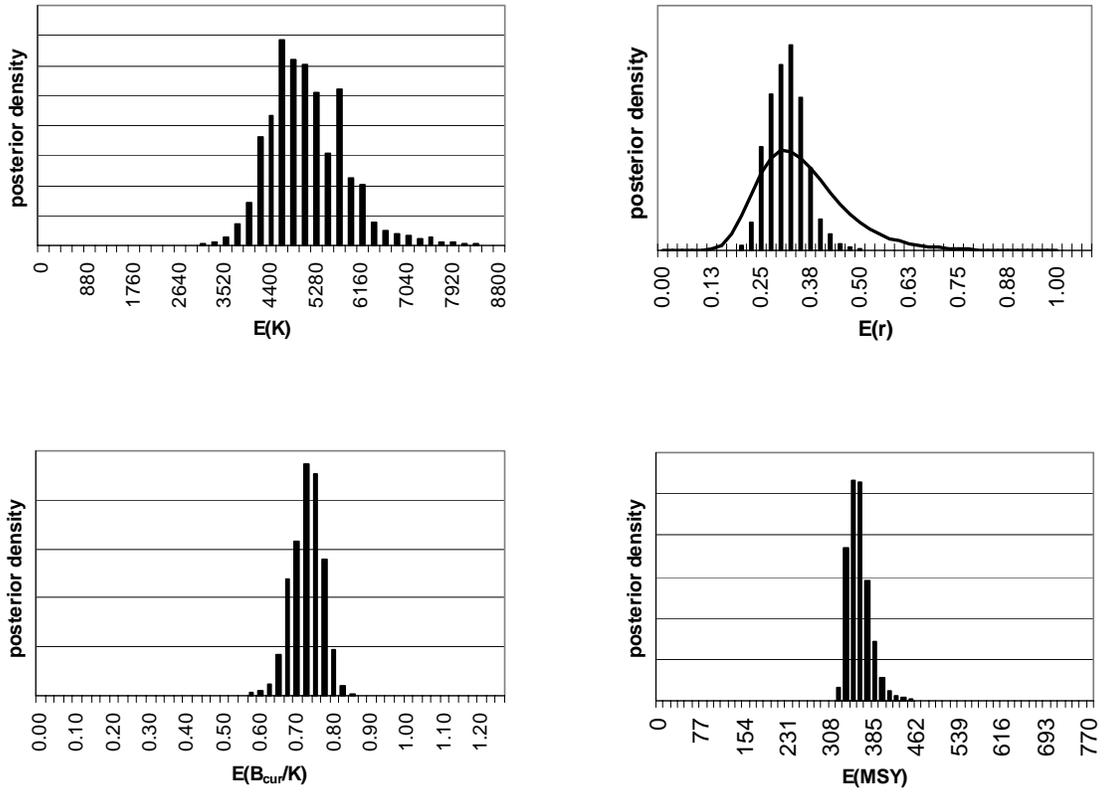


Figure 4. Posterior probability density functions estimated by the BSP model for key parameters based on the base case for the deep CPUE series. In the graph showing the intrinsic rate of increase (r), both the posterior probability density function (columns) and the prior probability density function (line) are shown.



Figure 5. Median values (annotated thick lines) and 90% probability intervals (thin lines) for stock size as a proportion of maximum sustainable yield under various scenarios for F , fishing mortality, projected for 15 years. These projections are based on the base case for the deep catch rate series only.