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Exploratory stock assessment of the striped marlin (*Tetrapturus audax*) caught in the Indian Ocean as calculated using a state-space biomass dynamic model

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Abstract

Although white marlin is not a target large commercial longline tuna boats, it is often a bycacth. There is little information on stock structure but it is assumed that the one unique stock in the Indic Ocean is the most probable hypothesis. The available data is limited to catch and catch rates. Usually the quality of the data concerning bycatch species is not high, hence it is difficult to achieve success running stock assessment models. In this paper a potentially useful Bayesian version of state-space biomass dynamic models (Fox and Schaefer types) are used in an attempt to assess the status of the white marlin stock of the Indic Ocean. Results are compared to conventional versions in which only the observational error is considered. Calculations were based on estimations of total catch and on standardized catch rates as estimated based on Japan database. In this and in his companion paper (IOTC2013-WPB11-25) the likelihood function was based on log-normal density distributions. Monte Carlo Markov Chains are used to calculate the posterior sample. Three chains starting with different parameters estimations were calculated. The first 50000 samples of each chain were discarded (burnin), and the next 50000 samples were sliced resulting in a final sample with size equal to 1000. Convergence of the chains was assessed using Gelman-Rubin diagnostics. Most of state-space models have converged, but not the observational error models. The exception among the observational error models was the Fox type as calculated with a non-informative prior. The state-space models are not biased, but the observational error are. The striped marlin database is not very informative, hence the uncertainties on the estimations were very high. The state-space model estimations were also very sensitive to choices about priors. More investigation is needed on the behavior of state-space models when the data is not that informative.

Key words: striped marlin, stock assessment, production model, Bayesian model, MCMC, biomass.

1. Introduction

In the Indic Ocean the majority of the tuna and tuna-like species are caught by longline and gillnet fleets. Most of the information available concerns longline fleet of Japan and Taiwan, China. Although the fishermen of those countries aim at species of genera *Thunnus* several other species are caught. Billfishes are among the bycatch species. The catches of the striped marlin have been higher than 2,000 in the very last years.

Striped marlin is a highly migratory species and is more oceanic than other billfishes like black and blue marlins. The Indic Ocean Tuna Commission (IOTC) assumes that unique striped marlin stock in the Indic Ocean is the more probable hypothesis. Preliminary stock assessments were attempted during the 10st Working Party on Billfishes (WPB) held in 2012 but the status of the stock is still unknown.

Available data is limited to total catch estimated for the whole Indic Ocean and standardized catch rates as calculated based on Japan and Taiwan, China. In this working paper it is considered as exercise the catch rates based on Japan database from 1977 until the end of the time series. The WPB group has decided to discard the catch rates of the very beginning cause they have shown an unreliable sharp increasing trend. Production models are alternatives to assess the stock status in such poor data scenario when only catches and catch rates are available. In this paper the blue marlin is assessed by using Bayesian state-space versions of both, Schaefer and Fox models. Both observational and process errors were considered.

In the Bayesian approach all the relevant and available information on the parameters as described in a *prior* distribution, which is combined with the likelihood function calculated based in the data. The results are the posterior distributions. In this paper Monte Carlo Markov Chains (MCMC) is used to calculate the posterior estimations of the parameters. The convergence of the models was assessed and a statistical summary of the estimations were calculated. Those estimations were also used to calculate benchmarks (e.g. biomass at "Maximum Sustainable Yield"). Finally the stock status is evaluated based on comparisons between the estimated biomass and fishery mortality time trends to the benchmarks.

2. Materials and Methods

The catch data of the aggregated Indic Ocean was extracted from the IOTC site. Estimations of catch are available for year between 1950 and 2011. The whole catch time series was used in the analysis. Standardized catch rate used in this paper are the ones calculated based on Japan database. Details on those calculations can be found in the paper IOTC–2013–WPB11–23. Here those standardized catch rates are assumed to be reasonable relative abundance indices.

The models used in this paper are well known and they has been described elsewhere (e.g. Meyer and Millar, 1999). Both observational only and state-space (observational plus process errors) models were used. Formulations and details on the structure and parameters of the models can be found in the companion paper IOTC-2013-WPB11-25.

In the Bayesian approach informative or non-informative priors can be used, depending on the availability of information and knowledge on the species and the stock being analyzed, or even similar species or stocks (McAllister and Kirkwood,1998, McAllister et al.,1994, Punt and Hilborn, 1997). Non-informative inverse gamma $\mathrm{IG}(1E-1,1E-7)$ were used for q. For r and k, wide uniform priors that convey little information on the parameters were used. The uniform prior for k with lower and upper limits defined in tons was $U(8500,50000)$. The lower limit is just a little over the maximum annual yield recorded for the species in the study area. The prior for r was $U(0,2)$, and those for $\sigma^2$and τ^2were the inverse gamma $IG(3,2)$and $IG(2,1)$, respectively. As no relevant data were found on these parameters in the literature for the Indic Ocean, the informative prior used for analysis was built based on the informative prior similar to that used in the last stock assessment of Atlantic ocean stock of blue marlin, which is lognormal with mean $\log(0.4)$ and standard deviation equal to 0.3.

In order to gather the sample from the posterior distribution the Markov Chain Monte Carlo (MCMC) algorithm was used, and the Gibbs sampler was implemented in the JAGS program (Plummer, 2005) available in the R program (R Core Team 2012) with the *runjags* package (Denwood, 2009). Three chains were initiated with different initial values for the parameters. The first 50,000 values of each chain were eliminated as burnin, and values were retrieved at every 50 steps (slice sampling) of the subsequent 50000 steps of the chain, providing a set of 1000 values of the posterior distribution for each chain. Graphs and diagnostic tests were used to determine whether a stationary distribution had been reached. These analyses were run in the CODA library (Plummer et al., 2006). Gelman and Rubin's (1992) statistic was used for diagnosis. Convergence was assumed when the 97.5% quantile of the Potential Scale Reduction Factor (PSRF) was equal to or lower than 1.05. Autocorrelations were also used to evaluate the mixing degree of the samples of the posterior distribution.

3. Results

3.1 Catch, and Standardize Catch Rates

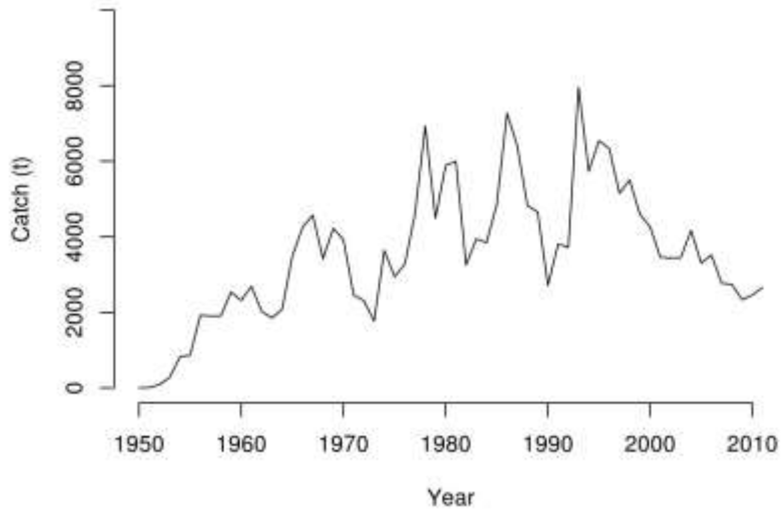


Figura1 – Catch of striped marlin (*Tetrapturus audax*) in the Indic Ocean.

Catches increased quick until the end of 1960's. Several peaks and plunges appear in from the beginning of 1970's until the beginning of 1990's. Catch rates have been decreasing quick from mid 1990's until 2012.

3.2 Convergence

If we rely in the Potential Scale Reduction Factor as criterion of convergence the conclusion is that all state-space (observational + process errors) have converged. In opposition only one of the observational models (Schaeffer with informative prior) has converged.

Table 1 – Calculations of the Potential Scale Reduction Factor (PSRF). Errors: Observational (Obs) and Process (Proc). Priors: Non-Informative (NI) and Informative (I).

Model	Error	Prior	PSRF
Fox	Obs	NI	---
Fox	Obs + Proc	NI	1.02
Fox	Obs	I	---
Fox	Obs + Proc	I	1.02
Schaeffer	Obs	NI	---
Schaeffer	Obs + Proc	NI	1.02

Schaeffer	Obs	I	1.03
Schaeffer	Obs + State	I	1.02

Autocorrelations as calculated for the models that converged do not indicate bad mixing. In this sense the posterior samples gathered were considered satisfactory.

3.3 Model fits and Residuals Diagnostics

Model fittings and residual diagnostics for all models that converged are shown in Figures 2 to 6. The observational model is clearly biased. It is not flexible enough to cope with the catch rates that show high variability, especially in the beginning and in the end of the time series. On the other hand, the state-space models that are more complex are flexible enough and fits well.

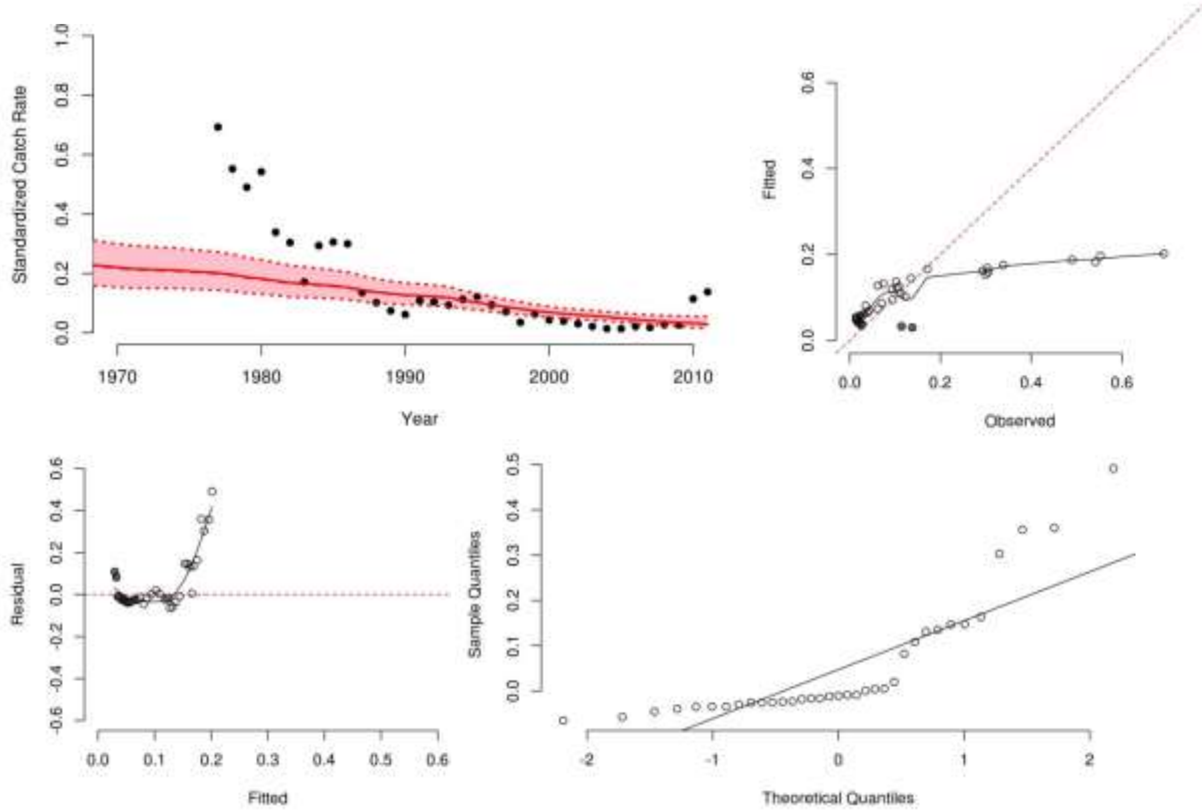


Figure 2 - Fitting of the Schaeffer observational model with informative prior and residual diagnostics.

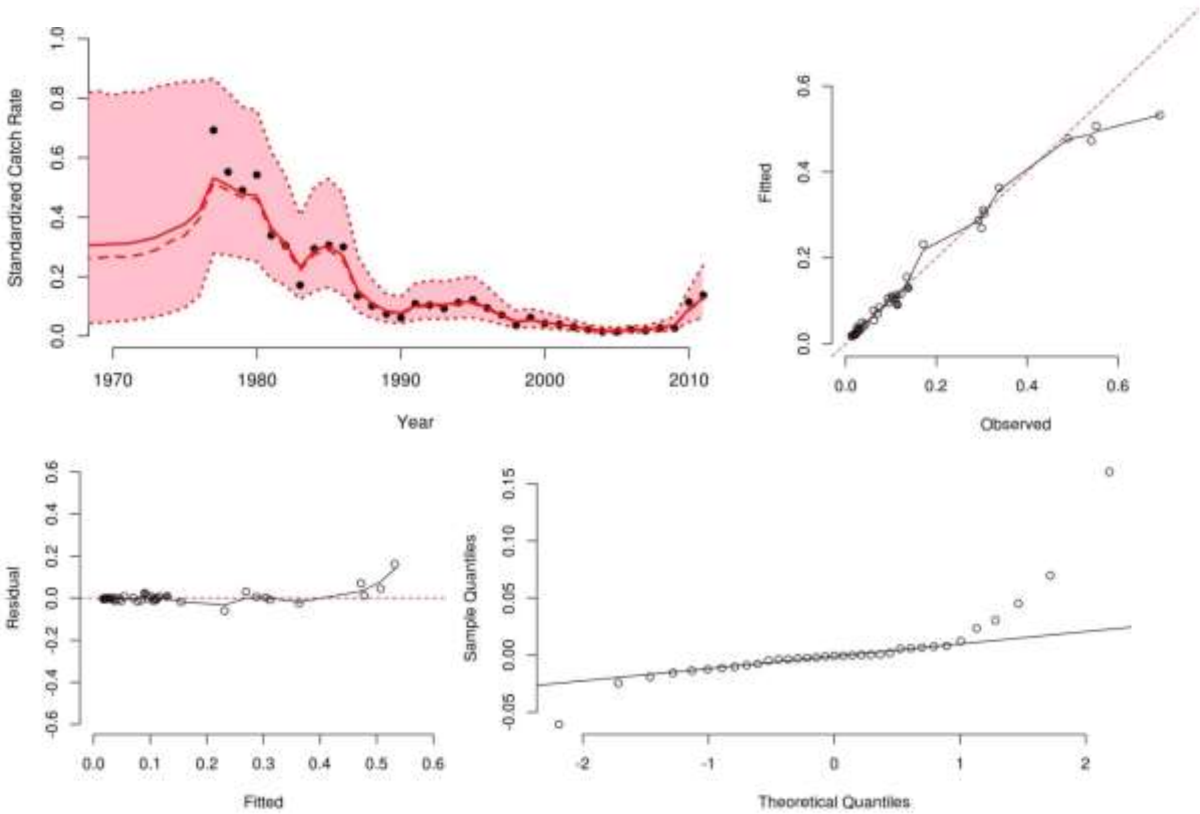


Figure 3 - Fitting of the Schaeffer state-space model with non-informative prior and residual diagnostics.

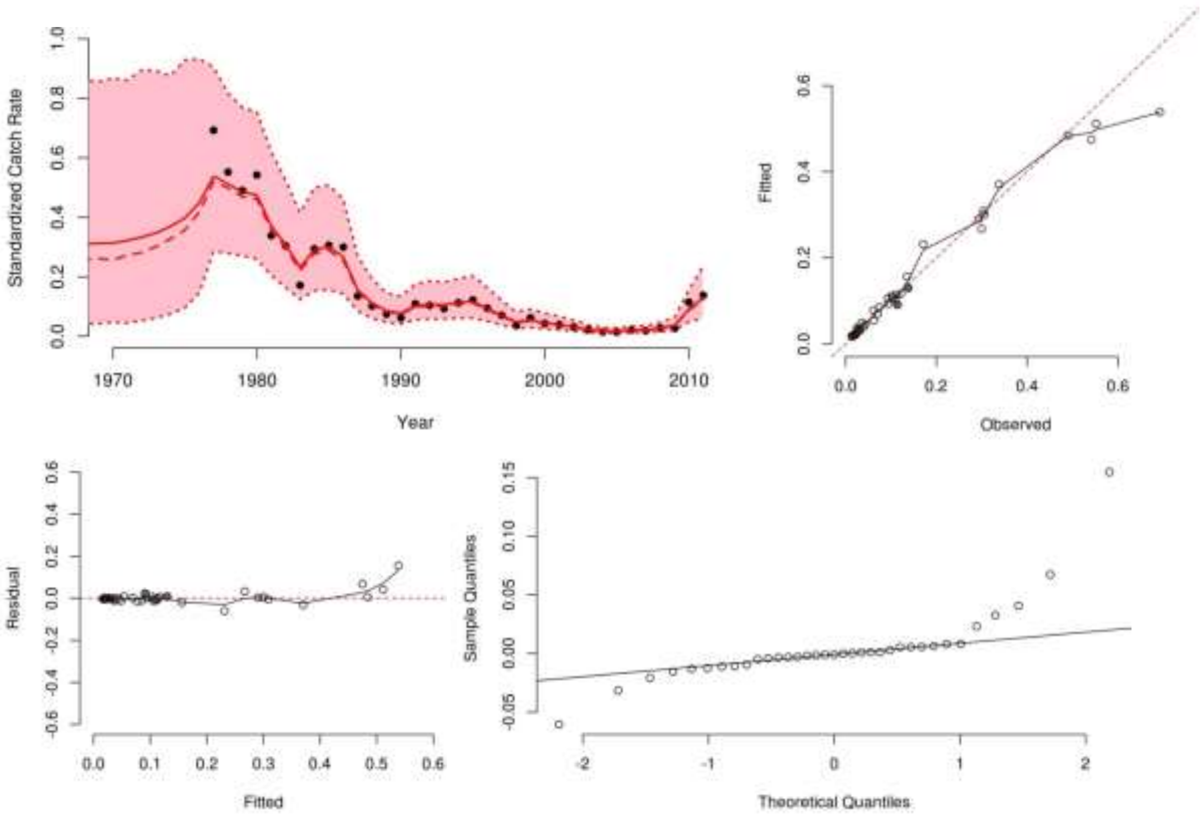


Figure 4 - Fitting of the Fox state-space model with non-informative prior and residual diagnostics.

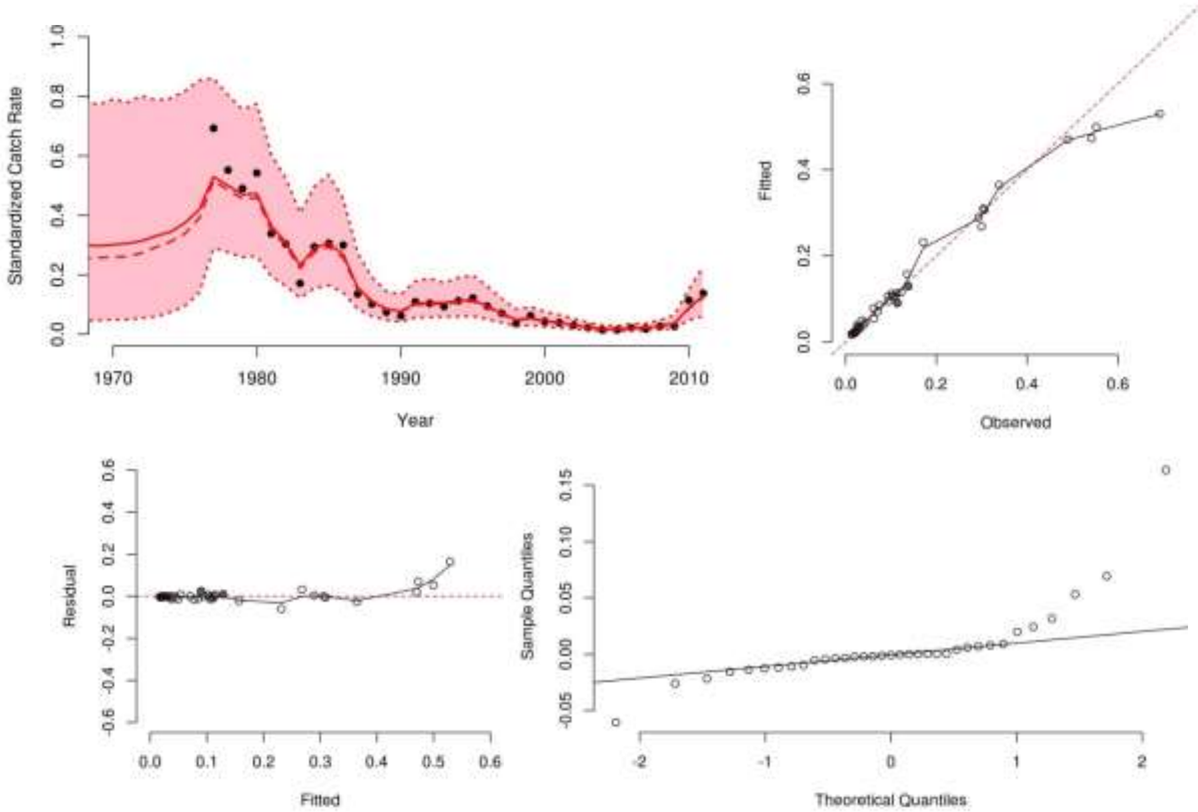


Figure 5 - Fitting of the Schaeffer state-space model with informative prior and residual diagnostics.

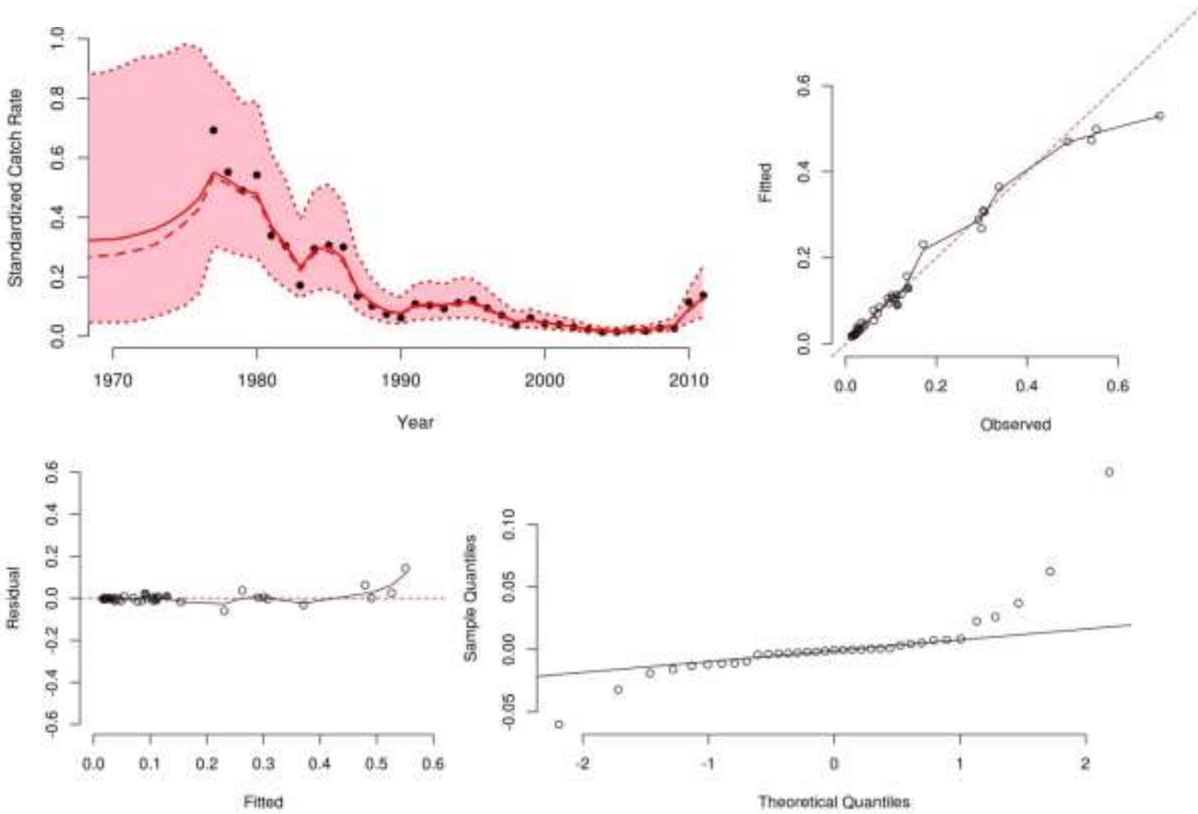


Figure 6 - Fitting of the Fox state-space model with informative prior and residual diagnostics.

3.4 Marginal Posterior distributions

All the marginal posteriors are not symmetrical (Figures 7 to 11). In spite the priors used for *k* were wide the posterior distributions as calculated for all the models showed to be bounded by the upper limits of priors. When using the Schaeffer with informative prior and observational error the posterior of *r* is very narrow and give weights to very low values. The posterior of *r* as calculated for state-space models gives high weight to values from 0.2 to 0.3if the non-informative prior is use, while the calculations with informative prior give high weights to values from 0.1 to 0.2. All the marginal posteriors of *q* give high weights to values between 1E-6 and 3E-6.

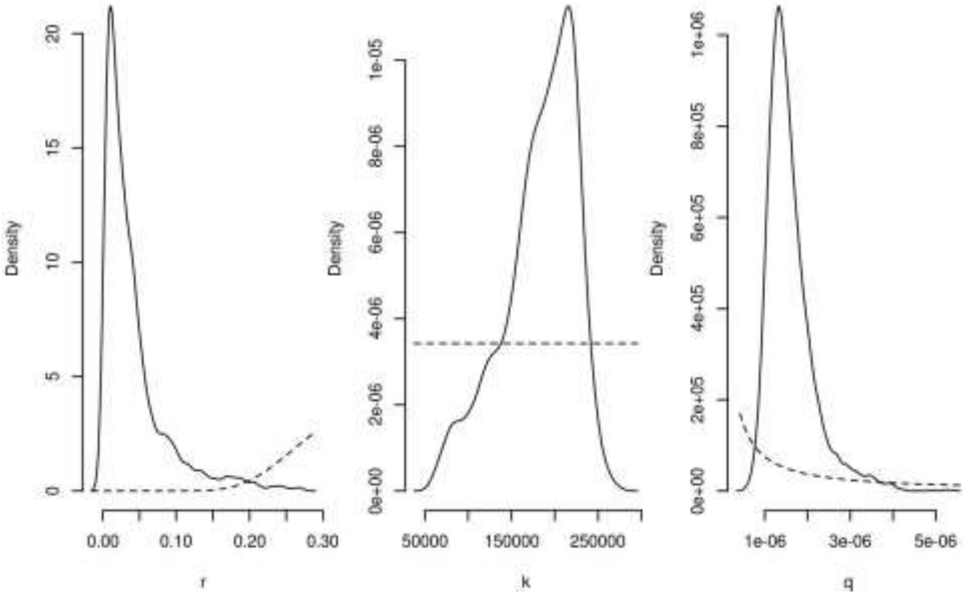


Figure 7 – Marginal posterior distributions calculated for the Schaeffer model with observational error only and with the informative priors.

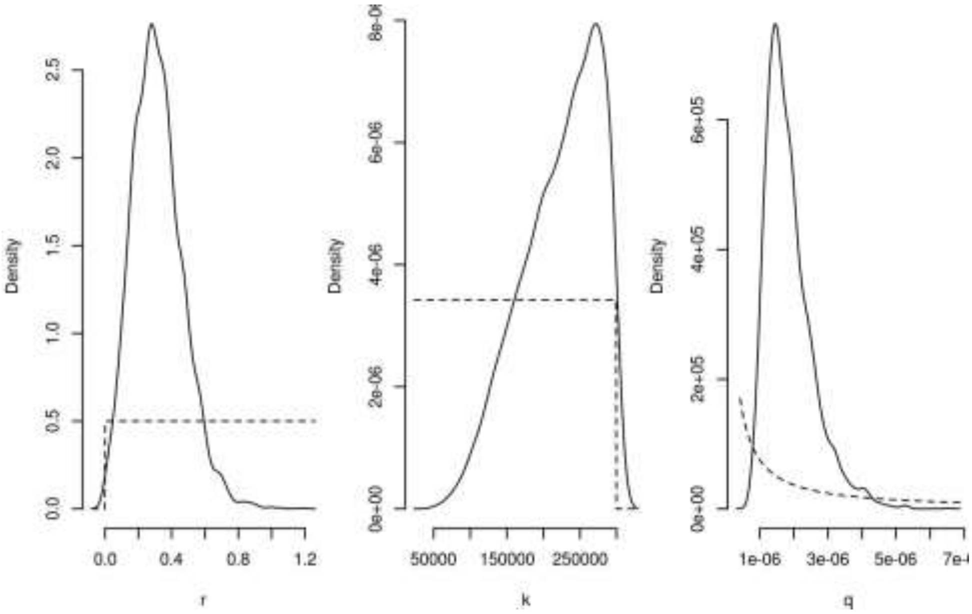


Figure 8 – Marginal posterior distributions calculated for the state-space Schaeffer model and with the non-informative priors.

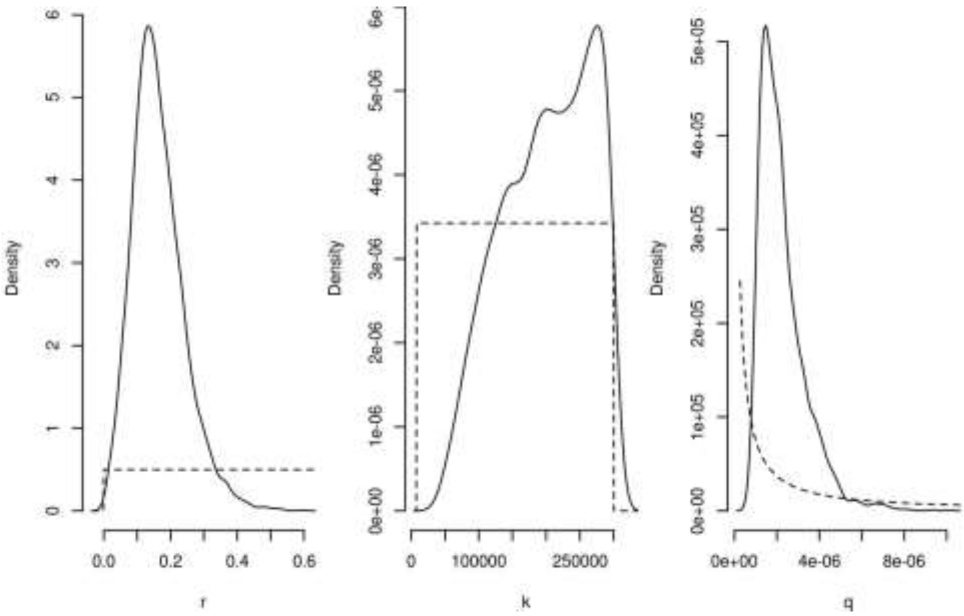


Figure 9 – Marginal posterior distributions calculated for the state-space Fox model and with the non-informative priors.

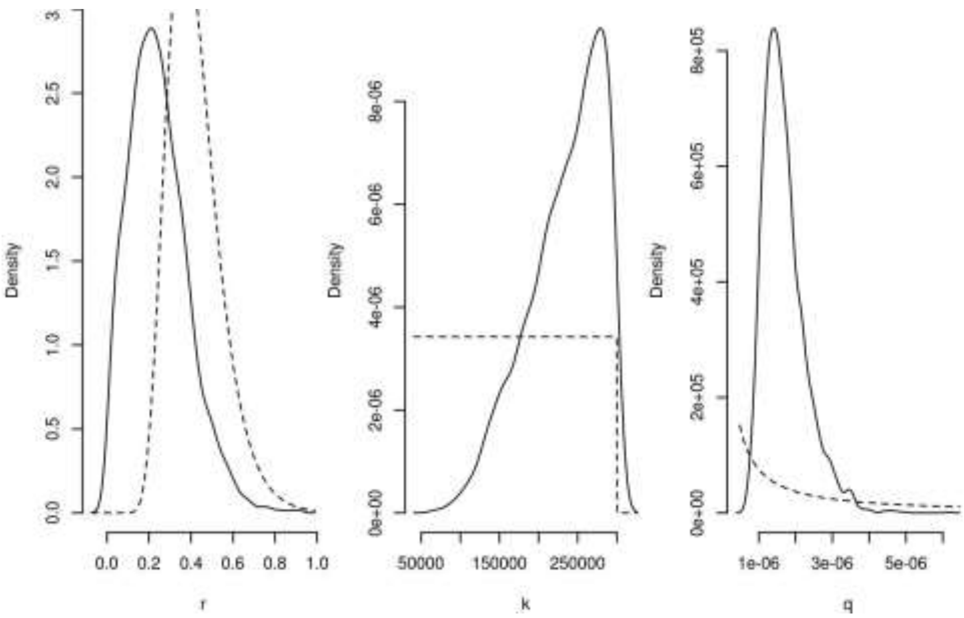


Figure 10 – Marginal posterior distributions calculated for the state-space Schaeffer model with informative priors.

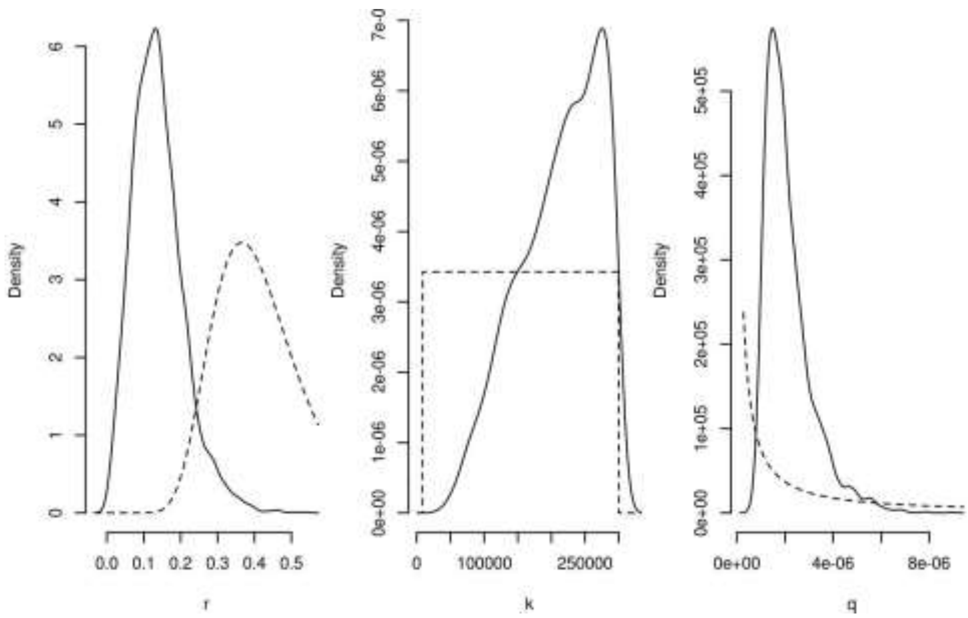


Figure 11 – Marginal posterior distributions calculated for the state-space Fox model with informative priors.

3.4 Joint Posterior distributions

All the joint marginal posteriors clearly showed to be bounded by the upper limit of the prior for *k* (Figure 12). Joint marginal posteriors for *k* and *r* show the typical "banana" shape and high correlation when used observational error only. The correlations are not so strong in the posteriors calculated with state-space Schaeffer type models. Notice that the informative prior for *r* resulted in posteriors that gives little weight to values higher than 0.1 when used Schaeffer type model with observational error only. Overall posteriors as calculated for Schaeffer type state-space models gives high weight for *r* values close to 0.2, while the posteriors for Fox gives higher weights to values close to 0.1.

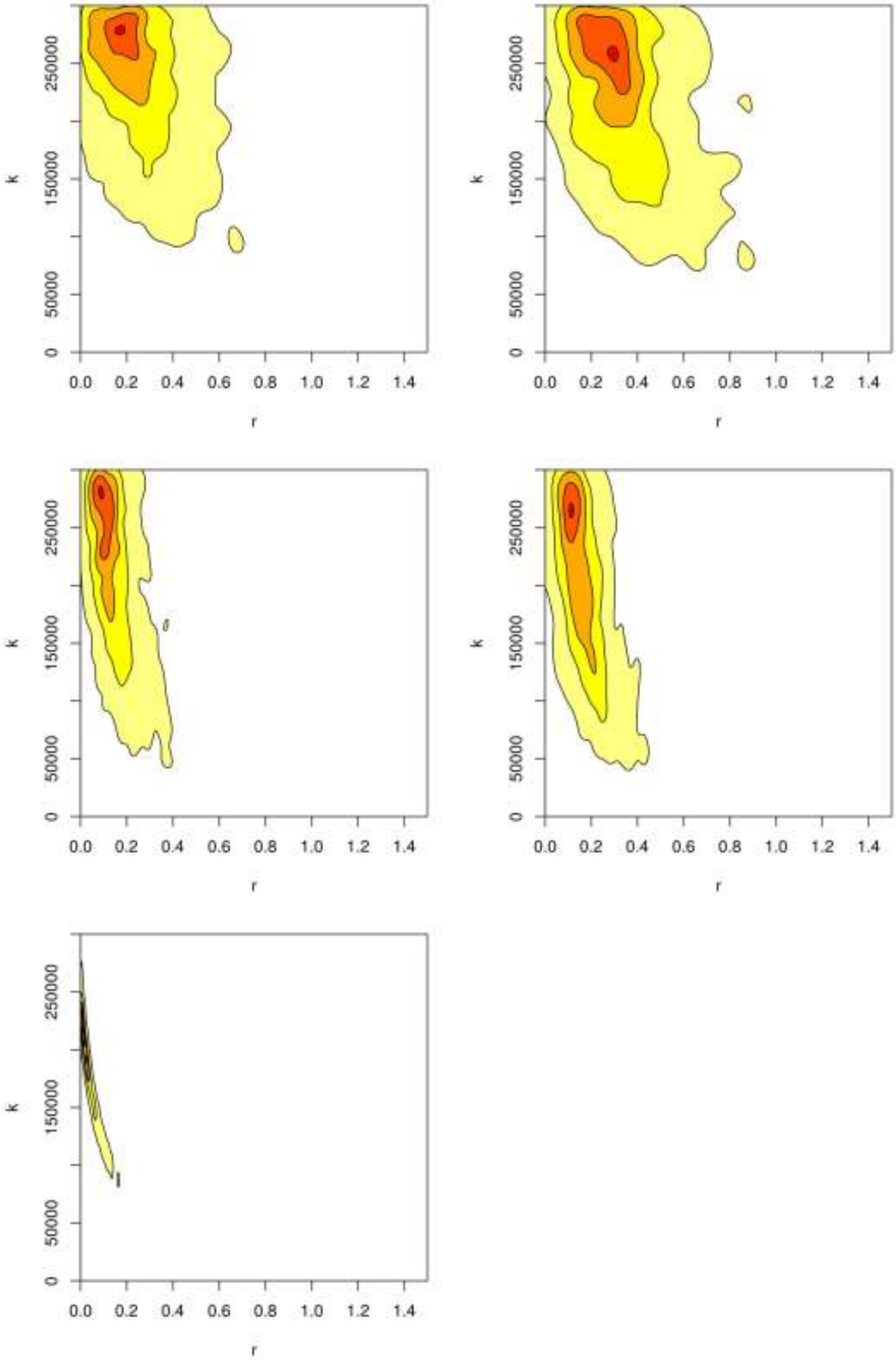
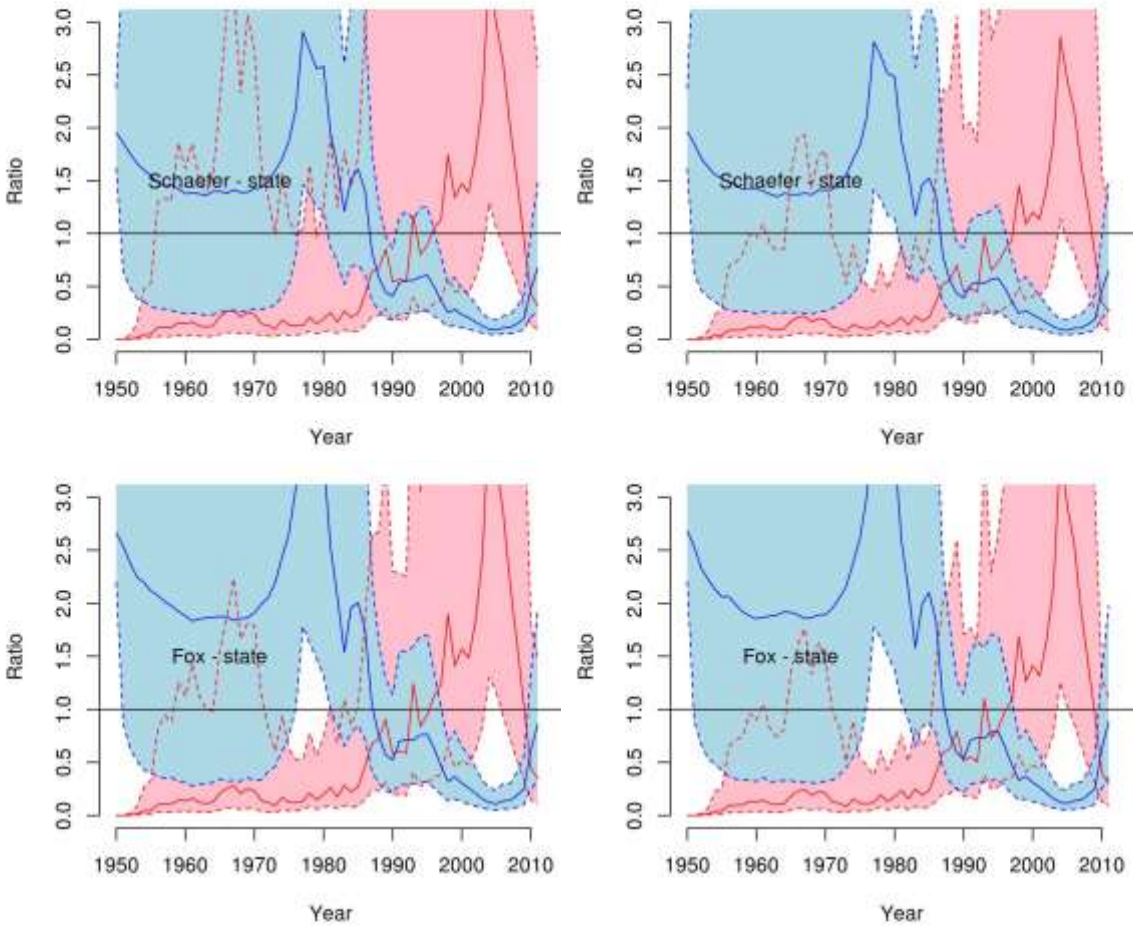


Figure 12 – Joint marginal posteriors of *r* and *k* as calculated using Schaeffer type model with observational error only (bottom panel), state-space Schaeffer model (top panels) and state-space Fox models (intermediate panels). Results gathered with informative priors are in the left panels, while the right panels stand for calculations with non-informative priors. Contour lines stand for 0.025, 0.25, 0.50, 0.75 and 0.975 of the maximum density.

3.5 F and B Ratios at MSY

Credibility intervals of ratios between biomass and biomass at MSY as calculated with Schaeffer type model with observational error only are much narrow than those calculated with the state-space models (Figure 13). All credibility intervals calculated for F ratios are wide, especially for Schaeffer type model with observation error only.

The mean of F ratio surpass 1 close to the beginning of fisheries if one relies in the results gathered when using Schaeffer type and observation error only. On the other hand the F ratio surpass 1 only in the mid 1990's if we rely in the state-space models. The uncertainties on the biomass ratio as calculated for the state-space models are particularly high in beginning of the time series because there are not estimations of catch rate for that period. The mean of the biomass ratio drop to values below to 1 in the end of 1990's for both, observational and state-space models. However, a recovery trend appears in the very end of the time series if we rely in the state-space models. The results calculated with Schaeffer type and observation error only are more pessimistic because they do not indicate that the biomass is recovering in the beginning of the 2010's. The WPB group considered that those recovery trends could be due to a decrease of effort in some areas of the Indic Ocean due to the piracy.



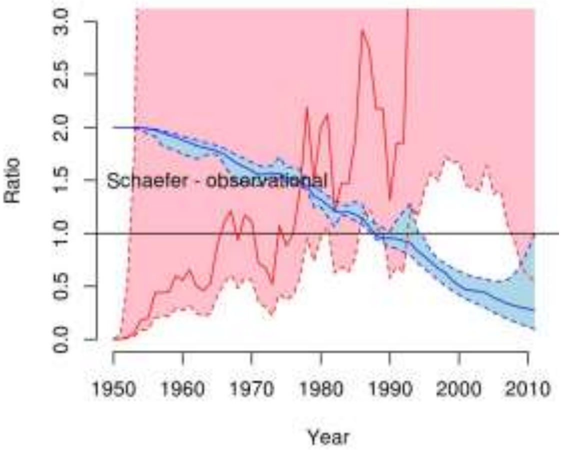


Figure 11 – Credibility intervals (95%) of the ratios between the current F and the F at MSY (pink), and between biomass and biomass at MSY (blue/green). Solid lines stand for the means. Calculations using Schaeffer type model with observational error only (bottom panel), state-space Schaeffer model (top panels) and state-space Fox models (intermediate panels). Results gathered with informative priors are in the left panels, while the right panels stand for calculations with non-informative priors.

4. Remarks

Overall the production models fitted with observational error did not converged or proved to be biased. The state-space models are not biased but the confidence intervals of the estimations are wide because the data on striped marlin are not that informative. The estimations were sensitive to the choices concerning the priors. The estimations are very dependent of the modeler skills and of the prior knowledge available on the parameters. State-space models are potentially very useful but further investigations and tests are necessary before using them to guide management decisions for striped marlin.

5. Acknowledgements

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