Received: 21 September 2013



# Exploratory stock assessment of the blue marlin (*Makaira mazara*) caught in the Indic Ocean using a State-Space Biomass Dynamic Model

Andrade, H. A.


## Abstract

Blue marlin is one the bycatch species caught by tuna longline and gillnet fleets in the Indic Ocean. Unique stock in the Indic Ocean is assumed to the most probable hypothesis. The status of the blue marlin stock is unknown and the available data is limited to catch and catch rates. Biomass dynamic models are one of the alternatives to assess the stock status in such poor data scenario. In this paper the blue marlin is assessed by using Bayesian state-space models (Fox and Schaefer types) calculated based on estimated total catches and standardized catch rates of Japan. Informative and non-informative priors were used. 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 30000 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. Schaeffer type models converged, but all Fox models did not converge. Overall the production models fitted with observational error only are biased, while the state-space models are not. Nevertheless, because there are many parameters, and because the data on blue marlin are not that informative, the uncertain on the estimations were very high and the solutions were sensitive to the choices concerning the priors. State-space model needs to be further tested before using it in situations that the data is not informative as is the blue marlin case.

Resume the results and conclude.


Key words: blue 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 fisherman aims at species of genera *Thunnus* and at swordifish (*Xiphias gladius*) several other species are caught. Billfishes are among the bycatch species. The catches of the blue marlin (*Makaira nigricans*) is the largest among billfish catches.

Blue marlin is a highly migratory species and the Indic Ocean Tuna Commission (IOTC) assumes that unique stock in the Indic Ocean is the most probable hypothesis. Preliminary stock assessments were attempted during the 11st Working Party on Billfishes (WPB) held in 2012 but the status of the stock is still unknown. Data limitations makes difficult to accomplish the stock assessment.

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 (IOTC working paper XXX). During the 10$^{th}$ WPB the group decided to consider only the Japanese catch rates, hence this database is the one used in this paper. Biomass dynamic models are one of the alternatives to assess the stock status in such poor data scenario. Schaefer and Fox production models are the most often biomass dynamics models used in the last decades. 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 are considered in those models.

In the Bayesian approach all the relevant and available information on the parameters as described in a *prior* distribution, is combined with the likelihood function calculated based in the data, to calculate the posterior distribution which conveys all the knowledge on the parameters estimations. Analytical solutions may be cumbersome or even impossible in some of the Bayesian analyses, hence numerical solutions are the usual alternative.
In this paper Monte Carlo Markov Chains (MCMC) numerical approach 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

### 2.1 Database

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 as calculated based on the Japanese longline database. Details on the calculations of the catch rate can be found in the paper IOTC2013-WPB11-23. Here those standardized catch rates is assumed to be reasonable relative abundance indices.

### 2.2 Bayesian state-space stock assessment model

The model used here is the one of Meyer and Millar (1999). The observed data are represented by vectors with values for yields and abundance indices denoted by $Y_t$and $I_t$, respectively, where $t = 1, \ldots, N$ is the index for the year. The general biomass dynamic equation is:

$$B_t = B_{t-1} + g(B_{t-1}) - Y_{t-1} \qquad (1)$$

Where $B_t$ is the biomass at the beginning of year $t$, $Y_t$ is the yield obtained during this year, and $g(\quad)$is the "surplus production" function. The formulae of Schaefer (1954) – $g(B_{t-1}) = rB_{t-1}(1 - B_{t-1}/k)$ – and Fox (1970) – $g(B_{t-1}) = rB_{t-1}[-\log(B_{t-1}/k)]$– are usually used here, where $k$ is the carrying capacity and $r$ is the intrinsic growth rate of the population.

It is assumed the link between the unobserved state ($B_t$) and the observed abundance indices in the $t^{th}$ year ($I_t$) can be represented by the equation:

$$I_t = qB_t \qquad (2)$$

where $q$ is the catchability coefficient. Management reference points may be calculated based on the estimations of the parameters $r$, $k$ and $q$.

These calculations can be considered in the context of a state-space model which includes process and observational uncertainties. In this case, the observed series of data ($I_t$) is linked to the unobserved states ($B_t$) through a stochastic model. The version of the state-space model used here was developed by Meyer and Millar (1999). This version of the model is reparametrized by the calculation of the proportion of the annual biomass in relation to the carrying capacity ($P_t = B_t/k$), which results in an improvement in the performance of the Gibbs sampler used in the Bayesian approach to generate the sample of the posterior distribution. The state equations may thus be written in the stochastic form, as:

$$P_1 \,|\sigma^2 = e^{u_1} \qquad (3)$$
$$P_t|P_{t-1}, k, r, \sigma^2 = [P_{t-1} + g(P_{t-1}) - Y_{t-1}/k]e^{u_t} t = 2, \dots, N$$

while the equation for the observations would be:

$$I_t|P_t, q, \tau^2 = qkP_t e^{v_t} t = 2, \dots, N \qquad (4)$$

Where $u_t$is an independent and identically distributed (*iid*) normal random variable with mean 0 and variance $\sigma^2$, while $v_t$ is a normal *iid* with mean 0 and variance $\tau^2$. Lognormal models were thus used for both observational and process equations. In the present case $N = 62$, given that the catch data series begins in 1950 and ends in 2009. State-space models (observational plus process error) as well as a simple observational model were used in the analyses.

If independent priors are assumed for the three parameters ($k$, $r$, $q$) of the biomass dynamic model and those that describe the errors ($\sigma^2$, $\tau^2$), the prior distribution of these parameters and of the states ($P_1, \dots, P_N$) is:

$$p(k, r, q, \sigma^2, \tau^2, P_1, \dots, P_n) = p(k)p(r)p(q)p(\sigma^2)p(\tau^2)p(P_1|\sigma^2) \prod_{i=2}^{N} p(P_t|P_{t-1}, k, r, \sigma^2) \quad (5)$$

Informative or non-informative priors can be used here, 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). Jeffrey’s non-informative reference prior for $q$is independent of $r$ and $k$, and is equivalent to a uniform prior on a logarithmic scale (Millar, 2002). Therefore, the uniform prior $U(-20, -5)$ on the logarithmic scale was used in the present study 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 $\tau^2$were 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 in this exploratory analysis was built based on some discussions of the experts of the WPB, which is lognormal with mean $\log(0.4)$ and standard deviation equal to 0.3.

The joint sample distribution for the abundance indices is given by:

$$p(I_1, \dots, I_N|k, r, q, \sigma^2, \tau^2, P_1, \dots, P_N) = \prod_{t=1}^{N} p(I_t|P_t, q, \tau^2) \qquad (6)$$

and finally, the posterior distribution for the parameters, states, and observations is:

$$p(k, r, q, \sigma^2, \tau^2, P_1, \dots, P_N, I_1, \dots, I_N) =$$
$$p(k)p(r)p(q)p(\sigma^2)p(\tau^2)p(P_1|\sigma^2) \prod_{t=2}^{N} p(P_t|P_{t-1}, k, r, \sigma^2) \prod_{t=1}^{N} p(I_t|P_t, q, \tau^2) \qquad (7)$$

Numerical Monte Carlo procedures can be used to obtain a sample of the joint posterior distribution. In the present study, a 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 30,000 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

Catches increased fast in mid 1950's but did not show time trends in 1960's and 1970's (Figure 1). There was an increasing from the beginning of 1980's until the end of 1990's, which was followed by a plunge and a peak. In the very end of the time series the catches were all close to 10000 t.

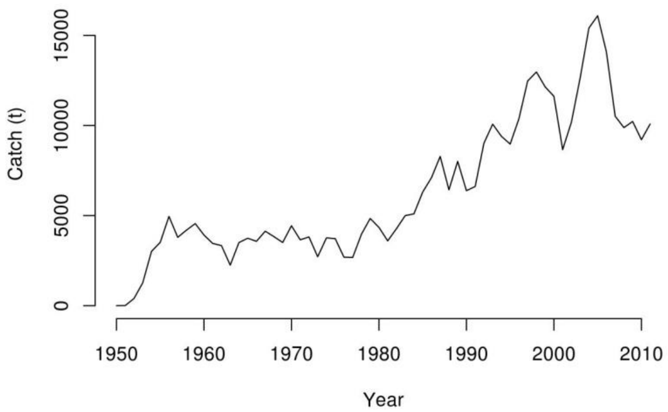



Figura1 – Catch of blue marlin (*Makaira mazara*) in the Indic Ocean.

Calculations of the catch rates used are fully described in the IOTC2013-WPB11-23 paper. In summary they show no clear time trend until the end of 1980's, drop fast until the early 1990's and continue to decrease slightly until the mid 2000's. An increasing trend appears in the end of the time series.

### 3.2 Convergence

The Potential Scale Reduction Factor as calculated for Fox and Schaeffer models shows that the Fox models did not converge, while Schaeffer models have converged when using both priors (non-informative and informative) and both errors, observational and observational plus process errors (state-space model).

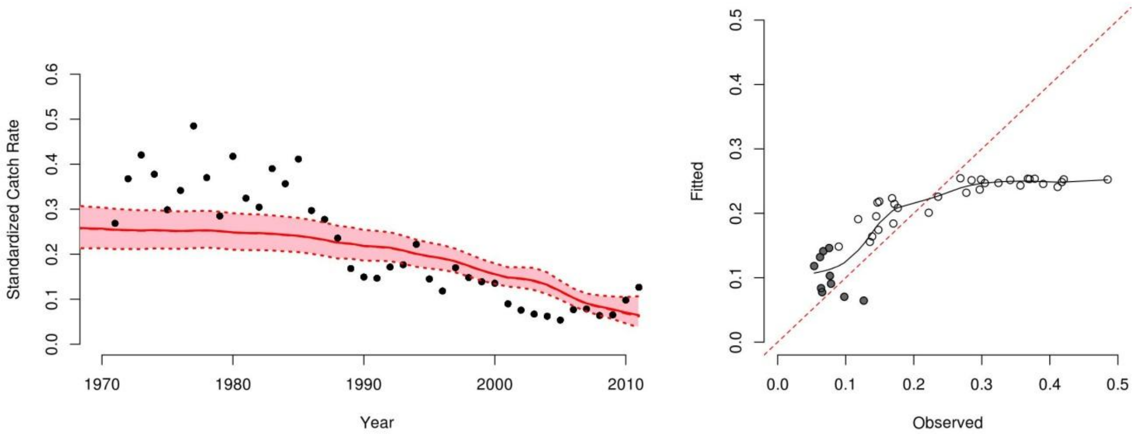
Table 1 – Calculations of the Potential Scale Reduction Factor (PSRF). Errors: Observational (Obs) and Process (Proc). Priors: Non-Informative (NI) and Informative (I).

| Model | Error | Prior | PSRF |
|---|---|---|---|
| Fox | Obs | NI | --- |
| Fox | Obs + Proc | NI | 6.25 |
| Fox | Obs | I | --- |
| Fox | Obs + Proc | I | 6.54 |
| Schaeffer | Obs | NI | 1.07 |
| Schaeffer | Obs + Proc | NI | 1.02 |
| Schaeffer | Obs | I | 1.01 |
| Schaeffer | Obs + State | I | 1.02 |

The autocorrelations were also calculated to assess the degree of mixing of the chains. There were not results pointing for bad mixing in the calculations carried out with Schaeffer models.

### 3.3 Model fits and Residuals Diagnostics

Model fittings and residual diagnostics for all models that converged are shown in Figures 2 to 5. Overall the observational models are biased. They are not flexible enough to cope with the catch rates that show high variability, especially in the beginning of the time series. The state-space models are more complex and have more parameters, hence they are more flexible and fits well the catch rate time series.



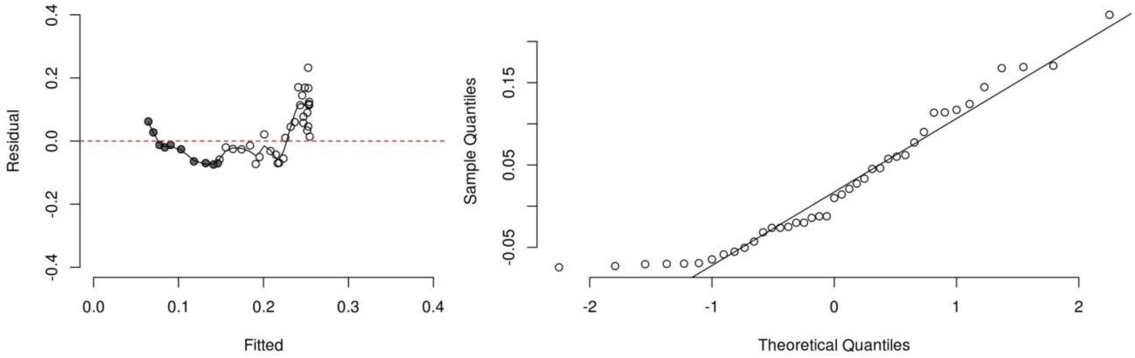



Figure 2 - Fitting of the schaeffer observational model with non-informative prior and residual diagnostics.

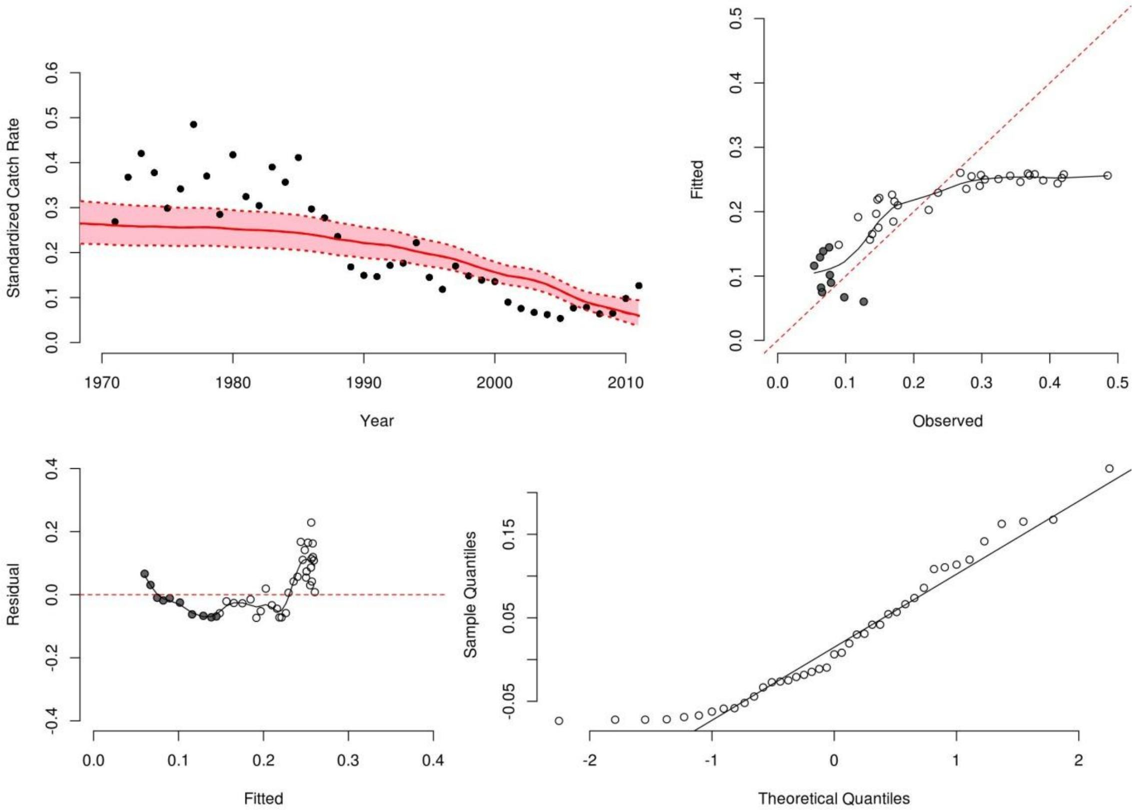



Figure 3 - Fitting of the schaeffer observational model with informative prior and residual diagnostics.

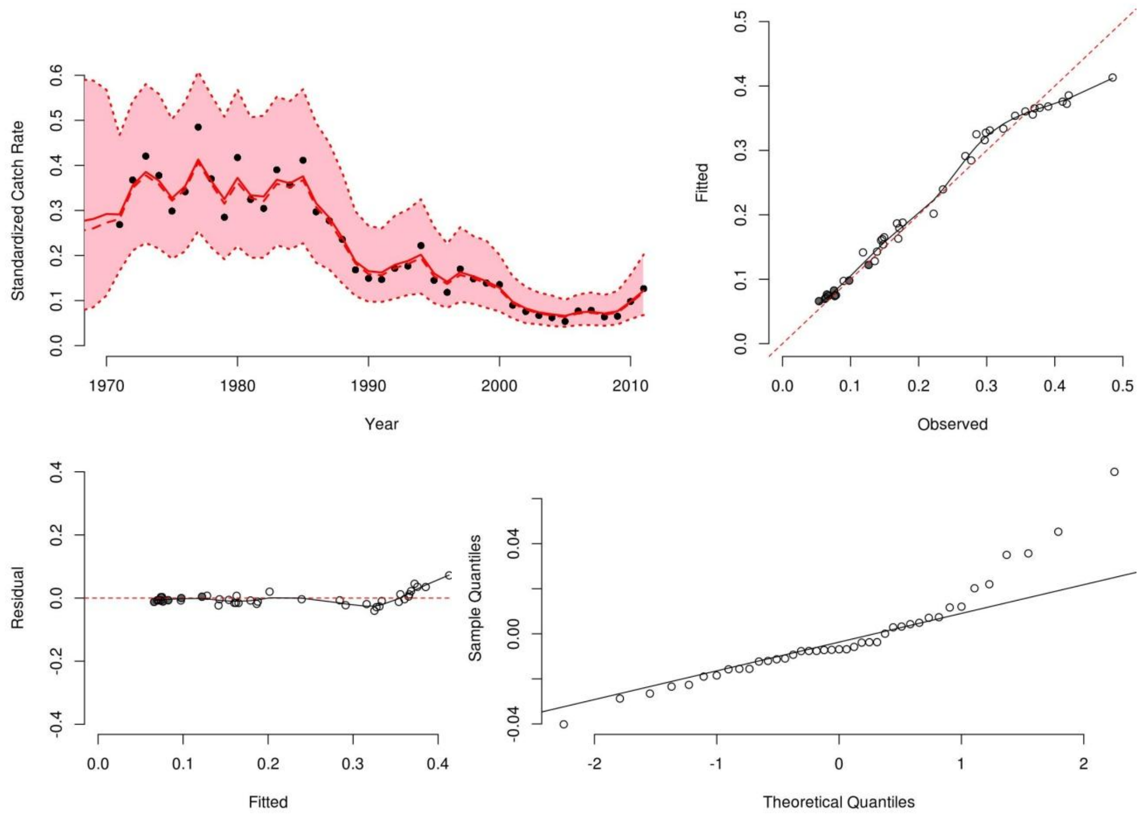



Figure 4 – Fitting of the schaeffer state-space model with non-informative prior and residual diagnostics.

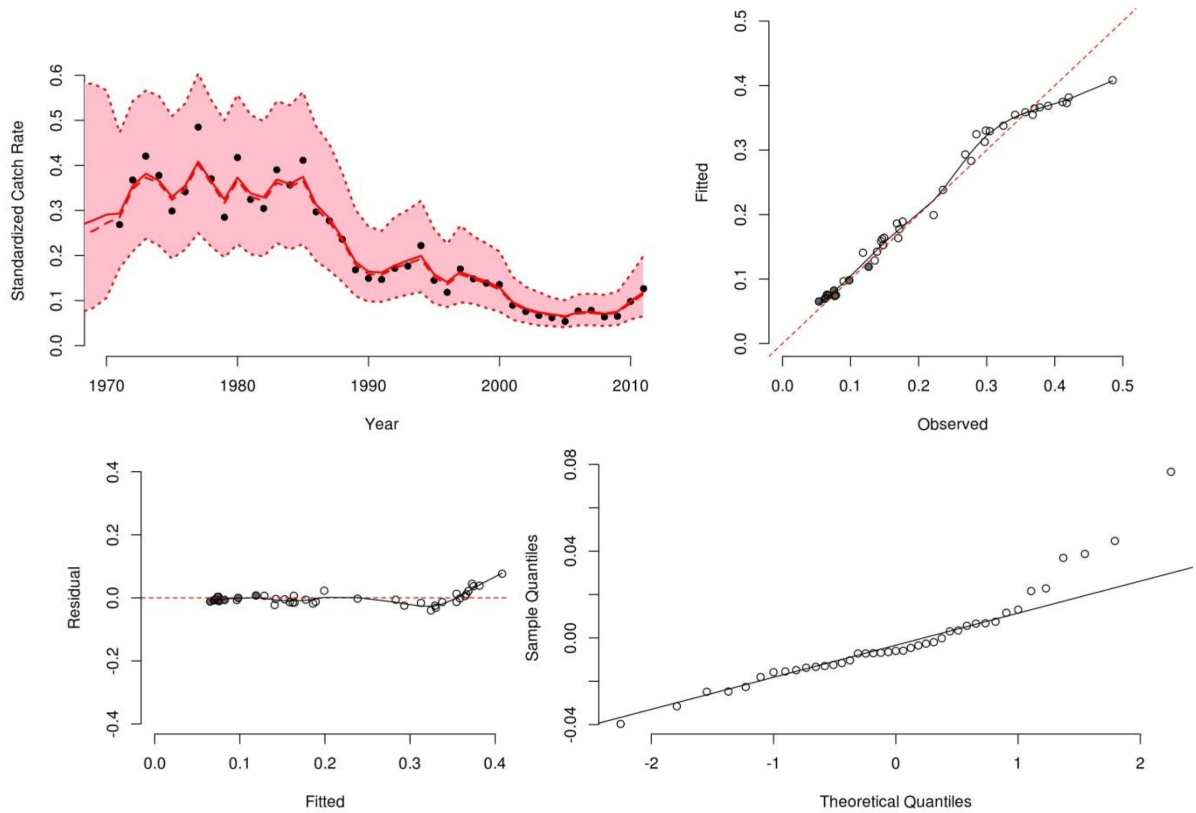



Figure 5 – Fitting of the schaeffer state-space model with informative prior and residual diagnostics.

3.4 Marginal Posterior Distributions

All the marginal posteriors are not symmetrical (Figures 6 to 9). 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 (Figures 6 to 9). When using observational error only the posteriors of *r* are very narrow and give weights to very low values, especially when using the informative prior. The posterior of *r* as calculated for state-space models gives high weight to values close to 0.4 if used the non-informative prior, while the calculations with informative prior give high weights to values close to 0.25. All the marginal posteriors of *q* give high weights to values between 1E-6 and 2E-6.

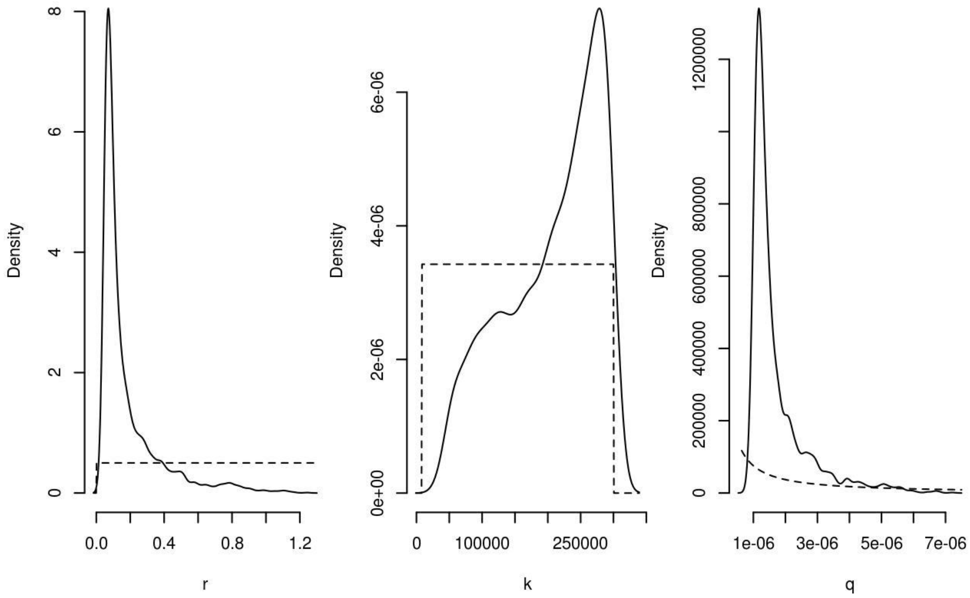



Figure 6 – Marginal posterior distributions calculated for the Schaeffer model with observational error only and with the non-informative priors.

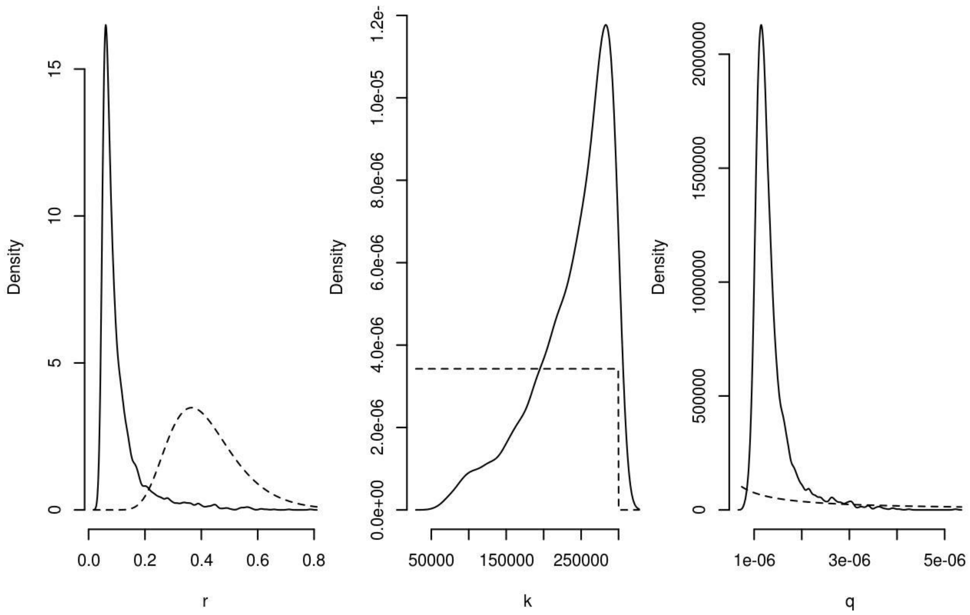



Figure 7 – Marginal posterior distributions calculated for the Schaeffer model with observational error only and with the informative priors.

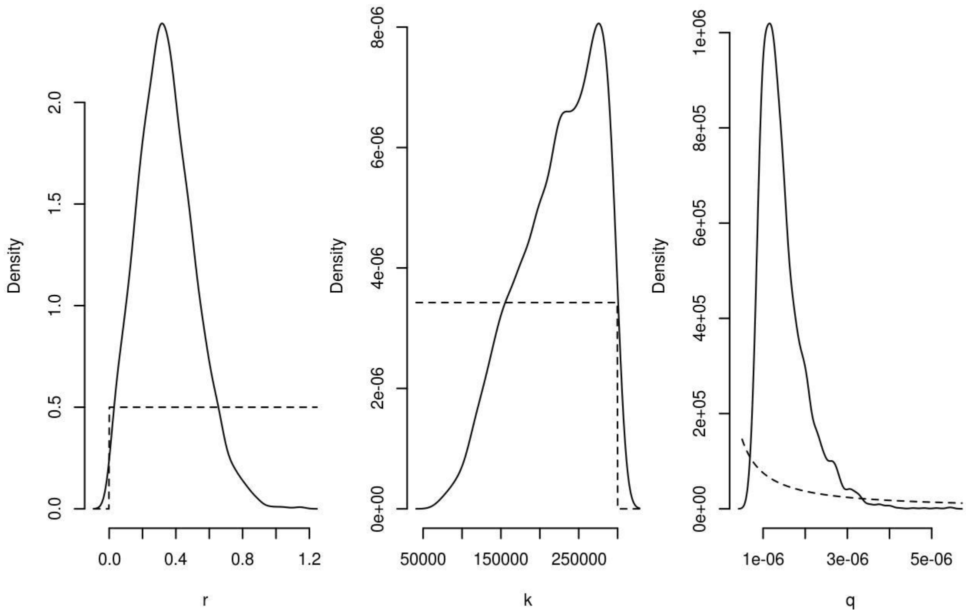



Figure 8 – Marginal posterior distributions calculated for the state-space Schaeffer model with non-informative priors.

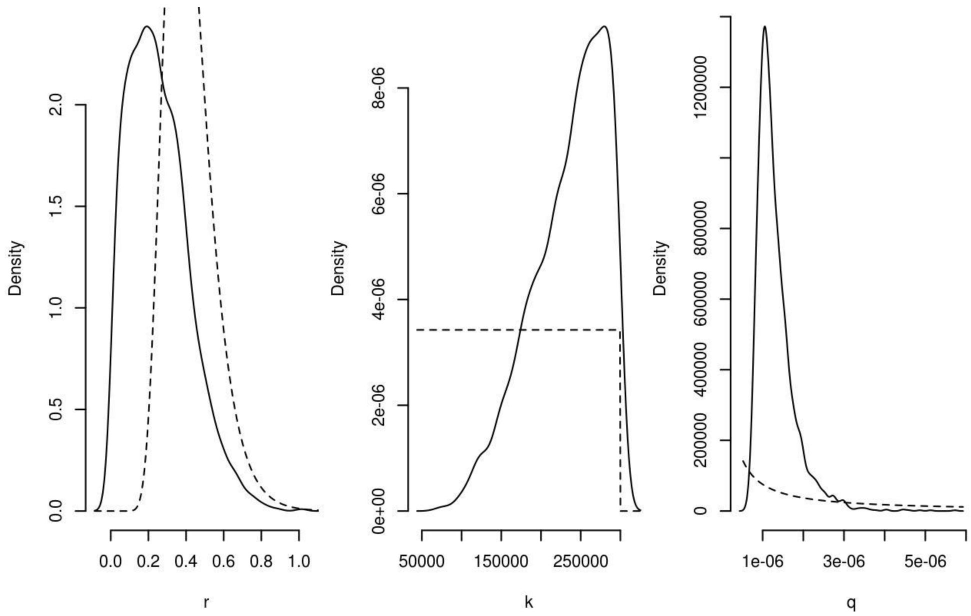



Figure 9 – Marginal posterior distributions calculated for the state-space Schaeffer model with informative priors.

## 3.4 Joint Marginal Posterior for *k* and *r*

All the joint marginal posteriors clearly showed to be bounded by the upper limit of the prior for *k* (Figure 10). Joint marginal posteriors for *k* and *r* show the typical “banana” shape and high correlation when used observational error only. That high correlations are not apparent in the posteriors calculated using the state-space model. Notice that the informative prior for *r* resulted in a posterior that gives little weight to values higher than 0.4 when used observational error only. Nevertheless posterior gives weight even to values higher than 0.6 when using the state-space model and the informative prior.

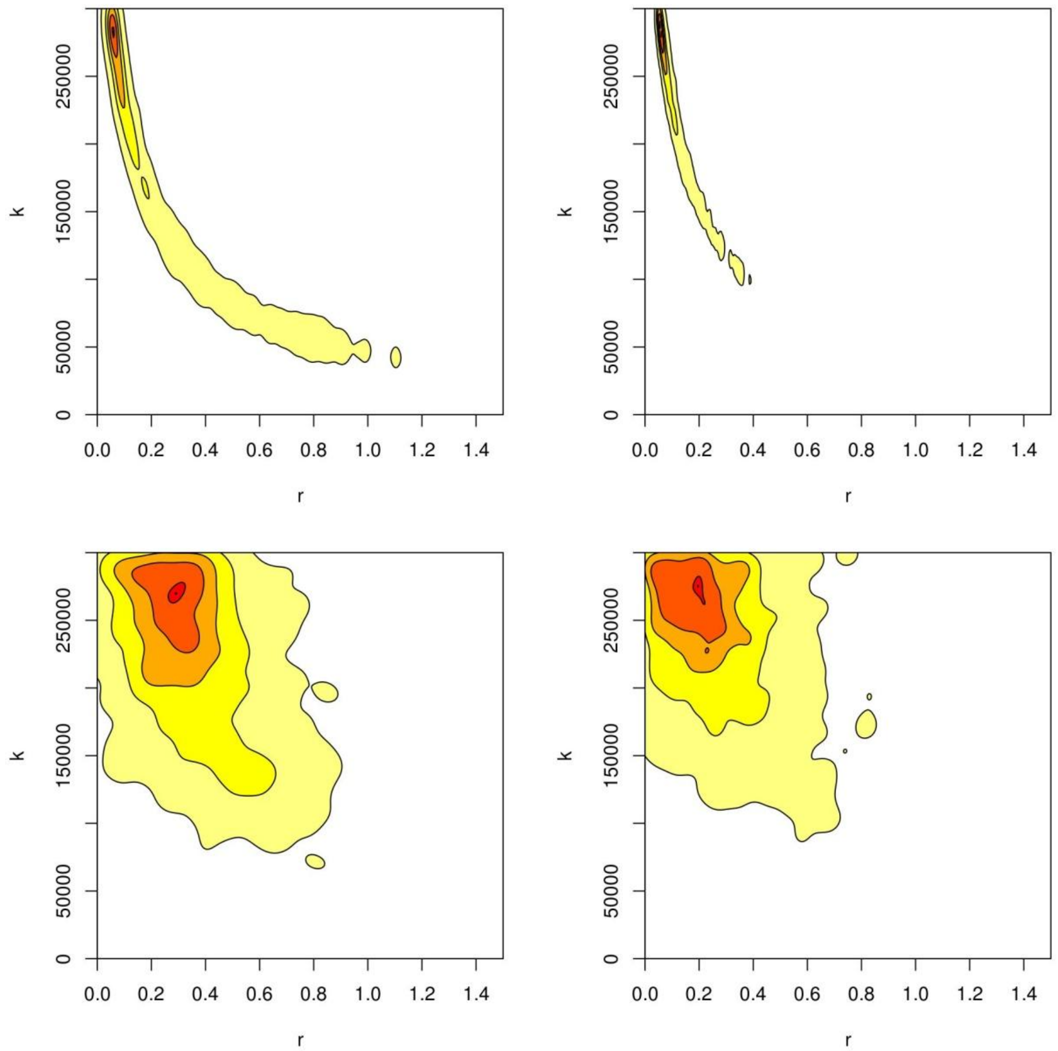



Figure 10 – Joint marginal posteriors of *r* and *k* as calculated using observational error only (top panels) and the state-space models (bottow panels), with the non-informative (left panels) and informative priors (panels at right). Contour lines stand for 0.025, 0.25, 0.50, 0.75 and 0.975 of the maximum density.

## 3.5 F and B Ratios at MSY

The credibility intervals of ratios between F and F at MSY and between biomass and biomass at MSY as calculated with observational error only are much narrow than those calculated with the state-space model (Figure 11). In the calculations with observation error only the mean of F ratio surpass 1 close to the beginning of 1990's and continue to increase until the end of the time series. On the other hand the biomass ratio cross down the level 1 in the beginning of 2000' s and continue to decrease until 2011. In summary the results gathered with the observational model are pessimistic.

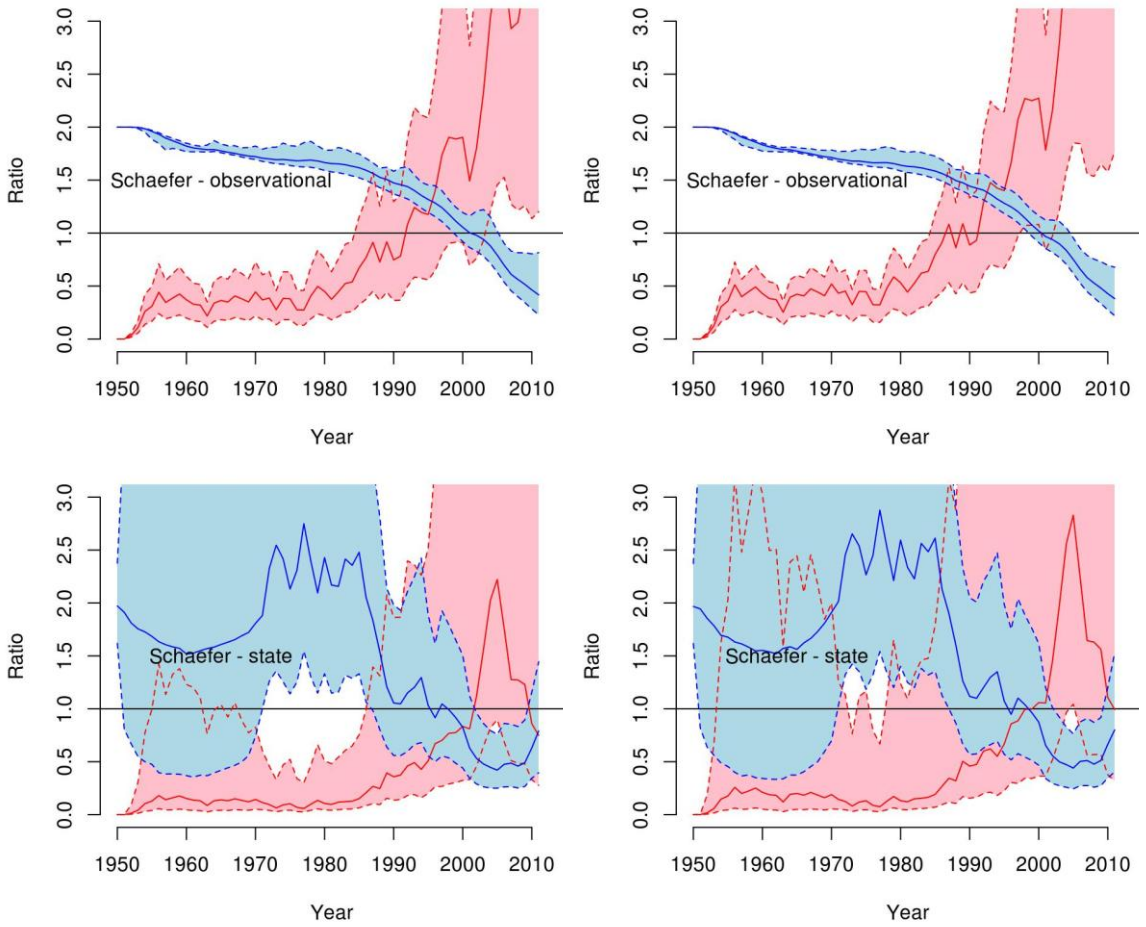



Figure 11 – Ninety five credibility intervals of the ratios between the current F and the F at MSY (pink), and between biomass and biomass at MSY (green). Solid lines stand for the means. Calculations with observational error only are in the top panels white state-space results are in the bottom. Calculations with non-informative prior are in the left, while the two panels at right stand for calculations with informative prior.

Credibility intervals are wide for both F ratio and biomass ratio when using the state-space model. The uncertain on the biomass ratio is particularly high in beginning of the time series because there are not estimations of catch rate for that period. Credibility intervals of F ratio calculations based on state-space models are wide in the beginning and in the end of the time series, especially when using the informative prior. The biomass ratio as calculated with state-space model begin to decrease in the mid 1980’s, cross the level 1 in mid of 1990’s and continue to decrease until mid of 2000’s. Nevertheless there is an increasing trend in the end of the time series, but the ratio does not surpass the level 1. The F ratio increase slightly until the end of 1970’ s, increase quick until the beginning of 2000’s, surpass the level 1, peaked in the mid of 2000’s and finally cross the level 1. Overall the results gathered with the state-space model are not as pessimistic as those gathered with the observational only error.

Remarks

Overall the production models fitted with observational error only are biased. The variability of the catch is high and erratic during some periods, and that conventional models are not flexible enough to cope with such variability. In this sense the state-space model is potentially advantageous. Nevertheless, because there are many parameters, and because the data on blue marlin are not that informative, the uncertain on the estimations were very high and the solutions were sensitive to the choices concerning the priors. So the reliability of the estimations is very dependent of the modeler skills and of the prior knowledge available on the parameters. State-space model is potentially very useful but it is necessary to test it further before using it in situations that the data is not informative as is the blue marlin case.

5. References

Denwood, M. J., 2009. runjags: Run Bayesian MCMC Models in the BUGS syntax from within R -manual. http://cran.r-project.org/web/packages/runjags/.

Fox, W. W., 1970. An exponential yield model for optimizing exploited fish populations.Trans. Amer. Fish. Soc. 99, 80-88.

McAllister, M.K., Pikitch, E.K., Punt, A.E., Hilborn, R., 1994. A bayesian approach to stock assessmentand harvest decisions using the sampling/importance resampling algorithm. Can. J. Fish. Aquat. Sci. 51, 2673-2687.

McAllister, M.K., Kirkwood, G.P., 1998. Bayesian stock assessment: a review and example application using the logistic model. ICES J. Mar. Sci. 55: 1031-1060.

Meyer, R., Millar, R. B., 1999. BUGS in bayesian stock assessment. Can. J. Fish. Aquat. Sci. 56, 1078-1086.

Millar, R. B., 2002. Reference priors for Bayesian fishery models. Can. J. Fish. Aquat. Sci. 59, 1492-1502.

Plummer, M., Best, N., Cowles, K., Vines, K., 2006. CODA: Convergence diagnosis and output analysisfor MCMC. R News. 6(1), 7-11.

Plummer, M., 2005. JAGS: Just Another Gibbs Sampler. Version 1.0.3 manual. http://www-ice.iarc.fr/˜martyn/software/jags/.

Punt, A.E., Hilborn, R., 1997, Fisheries stock assessment and decision analysis: the Bayesian approach. Rev. Fish Biol. Fish. 7, 35–63.

R Core Team., 2012. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Schaefer, M. B., 1954. Some aspects of the dynamics of populations important to the management ofcommercial marine fisheries. Inter-Am. Trop. Tuna Comm. Bull. 1, 27-56.