Preliminary stock assessment of blue marlin (*Makaira nigricans*) caught in the Indian Ocean using a Bayesian state-space production model

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Abstract

Blue marlin (*Makaira nigricans*) is a bycatch species of tuna longline and gillnet fleets operating in the Indian Ocean. Unitary stock in the Indian Ocean is assumed as the most probable hypothesis in this analysis. Indian Ocean blue marlin stock was classified as not overfished and not subject to overfishing in the last stock assessment meeting in 2013. However relative abundance indices and catch time series were updated and revised, hence new stock assessment is warranted. Bayesian state-space models (Fox and Schaefer types) were used to assess the status of blue marlin Indian Ocean stock based on estimations of total catch and standardized catch rates of Japan and Taiwan. Informative and non-informative priors were used. Likelihood function was based on log-normal density distributions. Posterior samples were calculated using Monte Carlo Markov Chains. Three chains starting on different locations of the space of parameters were calculated. The first 30000 samples of each chain were discarded (burnin), and the next 90000 samples were sliced (thin of 30) in order to gather a final sample with 3000 for each of the three chains. All the models converged. Overall the production models fitted well the data as the time trends of predicted expectations and of catch rate data were similar. However models were biased in the sense relative abundance indices of Japan were underestimated from 1970 to 1995 and overestimated in the recent decades, while indices of Taiwan were overestimated until 1995 and underestimated after that mid 1990's. Biases were partially expected because the time series of Japan and Taiwan are conflictive in some periods. Results of Schaefer and Fox type calculations were are conflictive. If we rely in calculations based on Fox model the blue marlin stock is currently not overfished but close to cross the threshold to be classified as subject to overfishing. However, calculations based on Schaefer type model indicate that currently is already subject to overfishing and it is not far from overfishing red zone.

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

1. Introduction

Longline and gillnet fleets caught most of tuna and tuna-like landed in harbors of Indian Ocean. Data are limited but most of available information concerns longline fleet. Although fisherman aims at fish of genera *Thunnus* and at swordfish (*Xiphias gladius*) several other species are caught. Billfishes are among the bycatch species. Catches of the blue marlin (*Makaira nigricans*) was the largest among marlin catches in the last years (Anon, 2013 a).

Blue marlin is a highly migratory species and unique stock have been assumed as the main hypothesis by Indian Ocean Tuna Commission (IOTC) in last stock assessment meetings (e.g. Anon, 2013 a). In the 11th Working Party on Billfishes (WPB) held in 2013 production models (ASPIC and state-space BSP) and Stock Reduction Analysis (SRA) were used to assess blue marlin stock of Indian Ocean. Data limitations made difficult to accomplish the stock assessment, but results have supported the conclusion that the stock was not overfished.

Data is still limited currently. However total catch time series (Anon, 2016) and standardized catch rates of Japan (Yokoi et al., 2016) and Taiwan (Wang, 2016) were updated. Production models can be used in stock assessment when catch and catch rates (or effort) are available. Often data are not informative to estimate shape parameter together with intrinsic growth (r), carrying capacity (k), coefficient of catchability (q) and parameters concerning errors. Hence shape is usually fixed in advance when fitting the models. Schaefer and Fox types of production models have been often used by Regional Fisheries Management Organizations (RFMOs) during the last decades. In this paper the blue marlin is assessed by using Bayesian state-space versions of Schaefer and Fox models. Both observational and process errors are when fitting the models to the available datasets.

In the Bayesian approach all available information gathered before the analysis are used to build *prior* distributions, which are combined with likelihood function calculated based in the new data, to calculate posterior distributions which conveys all the knowledge on the parameters estimations. Numerical approaches like Monte Carlo Markov Chains (MCMC) are practical to extract samples of parameters from posterior distributions. In this working paper MCMC was used to estimate parameters of production models and posterior distributions of benchmarks (e.g. “Maximum Sustainable Yield” – MSY). Posterior distributions are used to assess the status of blue marlin of Indian Ocean in the light of unitary stock hypothesis.

2. Materials and Methods

2.1 Database

The catch data of the aggregated Indic Ocean was provided by IOTC secretariat. Time series of catch available for the stock assessment in this meeting (Anon, 2016) and in the last stock assessment meeting (Anon, 2013 b) are shown in Figure 1. Estimations provided in the former meeting ends up in 2011, while currently there are estimations from 1950 to 2015. Catches in mid 1990’s were revised and the estimations of updated database (Anon, 2016) are lower than those of the former catch time series. Notice also that the estimations of catches after 2011 were higher than in previous years. Catches in the recent years have been close to or higher than 15,000 t.

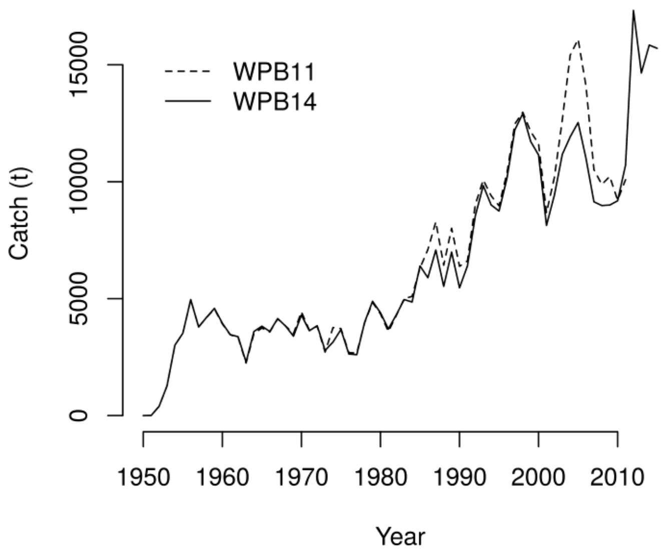

Figure 1 – Estimations of total catch of Indian Ocean blue marlin.

Standardized catch rates as calculated based on the Japanese longline and on Taiwanese longline datasets were provided as input data for stock assessment models (Figure 2). Details on the calculations of the standardized catch rate of Japan and of Taiwan can be found in Yokoi et al. (2016) and Wang (2016), respectively. Here those standardized catch rates were assumed to be valid relative abundance indices. Notice that standardized catch rates of Japan decrease from 1970 to 2005, but there was a slight increasing trend after mid 2000's. In opposition standardized catch rates of Taiwan decrease from 1980 until the beginning of 1990's. There were oscillations since then but in general there catch rates showed an increasing time trend. Overall the two estimations of standardized catch rates showed similar time trends in the beginning and in the end of the time series, but they were conflictive from 1992 to 2005.

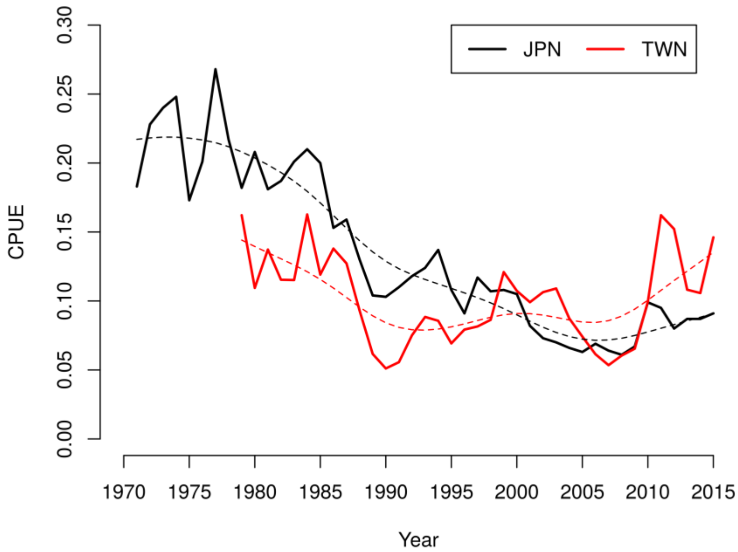

Figure 2 – Standardized catch rates of Japan (JPN) and Taiwan (TWN) are represented by solid lines. Dashed lines stand for smooth calculations.

2.2 Model

The model used here is described in Meyer and Millar (1999). Model structure used in this paper is similar to that model used before during WPB11 held in 2013. However, in WPB11 the model was fitted to one time series separated, but in the present paper multiple standardized catch rates were included in the calculations by assigning weights to them. In this preliminary approach equal weights were assigned to Japan and Taiwan time series, as an example. Follow the description of the equations. The observed data are represented by vectors with values for yields and abundance indices denoted by $Y_t$and I_t, respectively, where $t = 1, \dots, N$ is the index for the year. The general biomass dynamic equation is:

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

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) – $g(B_{t-1}) = rB_{t-1}[-\log(B_{t-1}/k)]$– were used in this work, where k is the carrying capacity and r is the intrinsic growth rate of the population. I have assumed that the relationship between unobserved state (B_t) and the observed abundance indices in the t^{th} year as calculated based on j^{th} fleet ($I_{t,j}$) are represented by the equation:

$$I_{t,j} = q_j B_t \quad (2)$$

where q_j is the catchability coefficient of the j^{th} fleet. Management reference points may be calculated based on the estimations of the parameters, especially r and k.

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 ($I_{t,j}$) are linked to the unobserved states (B_t) through a stochastic model. The version of the state-space model used here 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 (Meyer and Millar, 1999). The state equations may thus be written in the stochastic form, as:

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

while the equation for the observations would be:

$$I_{t,j}|P_t, q_j, \tau^2 = q_j k P_t e^{v_t} t = 2, \dots, N \quad (4)$$

Where $u_t$is an independent and identically distributed (*iid*) normal random variable with mean 0 and variance σ^2, while v_t is a normal *iid* with mean 0 and variance τ^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 parameters k, r, and the vector q which are the core of the biomass dynamic model, and for those parameters that describe the errors (σ^2, τ^2), the joint prior distribution of these parameters and of the states ($P_1, \dots, P_N$) is:

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

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

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

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

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

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 2016) 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.

2.3 Priors

Informative or non-informative priors can be used in the Bayesian approach depending on the information available concerning the species and the stock being analyzed, or even similar species or stocks (McAllister et al.,1994, Punt and Hilborn, 1997, McAllister and Kirkwood,1998). 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, in this work the uniform prior $U(-45,-1)$ on the logarithmic scale was used for q of both fleets (JPN and TWN). For r and k, wide uniform priors that convey little information on the parameters were used. The uniform prior for k in tons was $U(18{,}000; 20 \times 18{,}000)$. Lower and upper limits of the prior of k are based on the value 18,000 which higher but close to maximum estimation of catch that was 17,324.121 in 2012 (Anon, 2016). The non-informative prior for r was $U(0;2)$. Priors of $\sigma^2$and τ^2 were inverse gamma $IG(0.8;0.01)$and $IG(0.8,0.01)$, respectively. These priors for the errors were selected because they convey little information and because those density distributions and the posterior distributions were not conflictive. Overall the priors described above convey little information about the parameters hence they are denominated as the non-informative priors hereafter.

Production models have been used to assess the stock of blue marlin (*Makaira nigricans*) caught in the Atlantic Ocean in recent year. Uncertain was high but after some assumptions concerning k, estimations of r ranging from 0.11 and 0.65 were calculated in the last stock assessment meeting (Anon, 2011). There are not estimations of r for blue marlin of Pacific, where the stock has been assessed using Stock Synthesis models (Anon. 2013 c). In the last stock assessment of blue marlin of Indian Ocean experts of the WPB decided to use a lognormal with mean $\log(0.4)$ and standard deviation equal to 0.3 (Andrade, 2013). That prior used in the last stock assessment gives more weight to values of r between 0.1 and 0.7. That same informative prior was used in this paper because it represents the continuous case with respect to the last stock assessment of Indian Ocean blue marlin, and because it is not conflictive with the information available for Atlantic and Pacific Oceans.

2.4 Diagnostics and Convergence

Graphs (e.g. traceplots) 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 1.01. Autocorrelations were also calculated to evaluate the mixing degree of the samples of the posterior distribution. Estimations of the some parameters are usually correlated hence coefficients of correlations were calculated and the joint posterior were examined. Residuals were also investigated to assess the quality of the fittings to each time series.

3. Results

3.1 Relationships among Catch and Standardize Catch Rates

Histograms of distributions, scatterplots of relationships and coefficients of correlations of available estimations of catch and standardized catch rates are showed in Figure 3. In spite of the oscillatory pattern of the time series, overall catches have been increasing during the last decades. Hence the correlation between catches and years was positive and high.

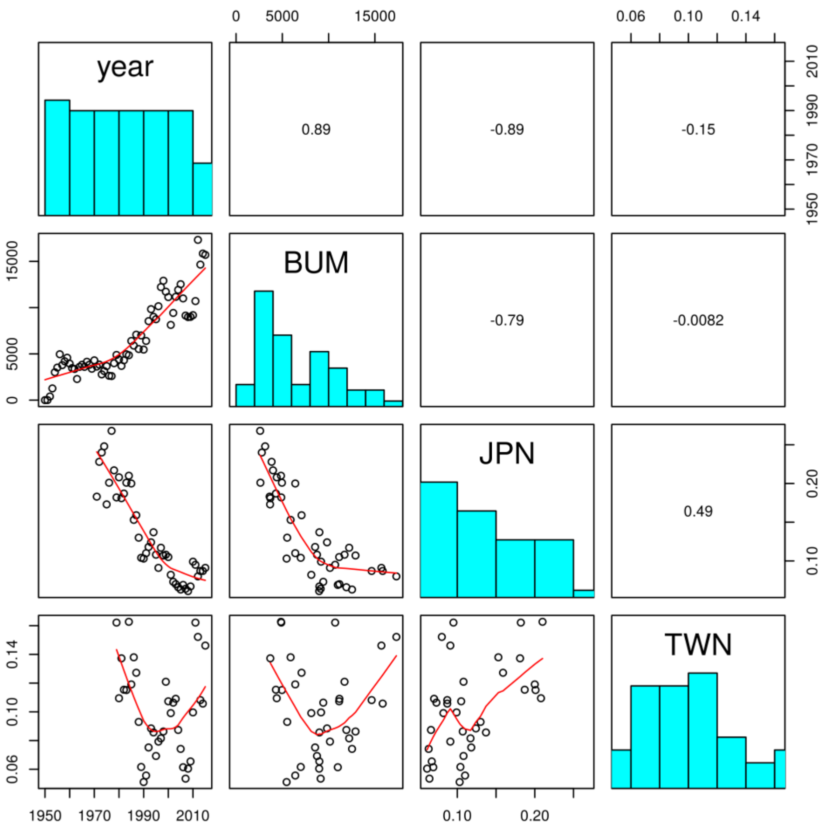

Figure 2 – Estimations of catch (t) of blue marlin (*Makaira nigricans*) (BUM), and standardized catch rates of Japan (JPN) and Taiwan (TWN) considered in the analyses.

Coefficient of correlation between year and catch rates of Japan (JPN) was strong and negative. However the correlation between year and catch rates of Taiwan (TWN) was weak because the TWN time series was not monotonous. Catch rates of TWN have decreased until mid 1990's but they have increased in the last decades. Correlation between catch and catch rates of JPN was negative and strong. In opposition the correlation between standardized catch rates of TWN and the nominal catch was weak. Finally, the correlation between standardized catch rates of Japan and of Taiwan was positive but not strong. This indicates that in some periods the two time series are in agreement, but they are conflictive in other periods.

3.2 Convergence and autocorrelations

All the calculations of 97.5% quantile of PSRF (Gelman and Rubin, 1992) were below 1.01 hence all the models (Fox or Schaefer types with non-informative or informative priors) have converged if we relay in that criterion. In addition the autocorrelation analyzes indicates a fairly acceptable mixing degree of the samples of the posterior distribution for the Schaefer type with non-informative (Figure 3), Schaefer type with informative (Figure 4), Fox type with non-informative (Figure 5) and Fox type with informative (Figure 6) models. Performance of MCMC algorithm with informative prior was superior especially when calculating the sample of r, as indicated by the quick decrease of correlation along with the increase of the lag.

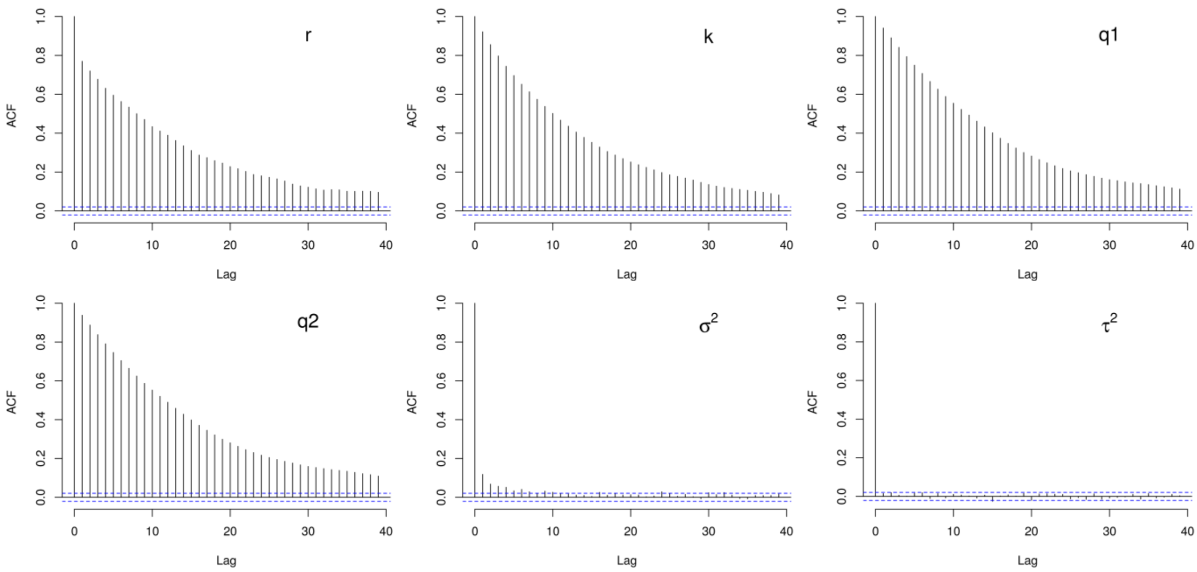

Figure 3 – Autocorrelation of samples of posteriors as calculated using Fox type and non-informative prior. r – intrinsic growth rate; k – carrying capacity; q1 – catchability coefficient of Japan; q2 – catchability coefficient of Taiwan; σ^2 variance of the process error; τ^2 variance of the observational error.

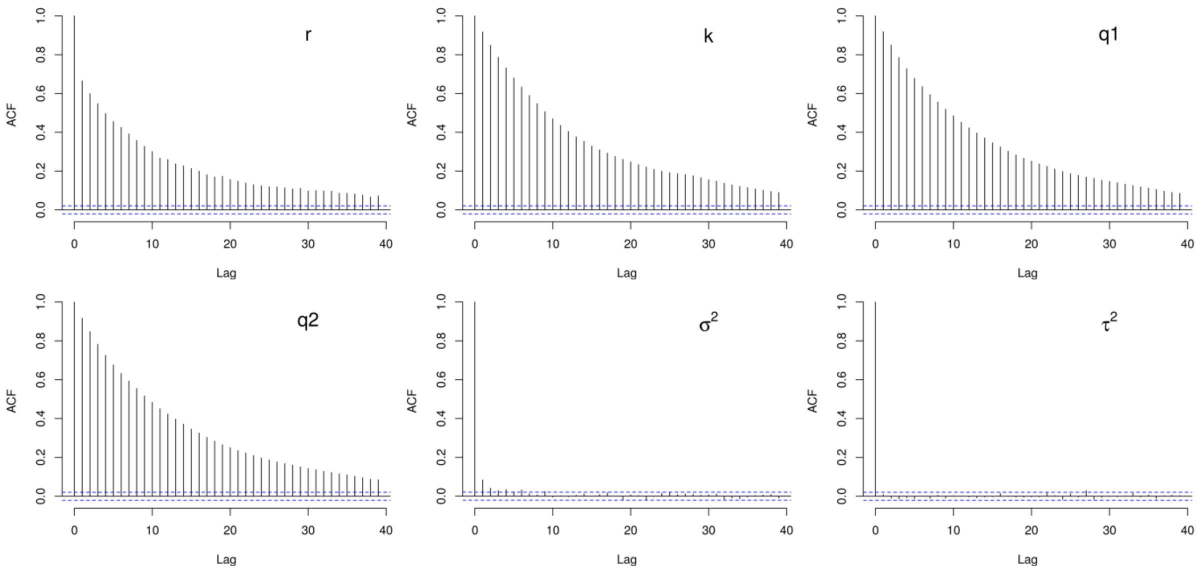

Figure 4 – Autocorrelation of samples of posteriors as calculated using Fox type and informative prior. r – intrinsic growth rate; k – carrying capacity; q1 – catchability coefficient of Japan; q2 – catchability coefficient of Taiwan; σ^2 variance of the process error; τ^2 variance of the observational error.

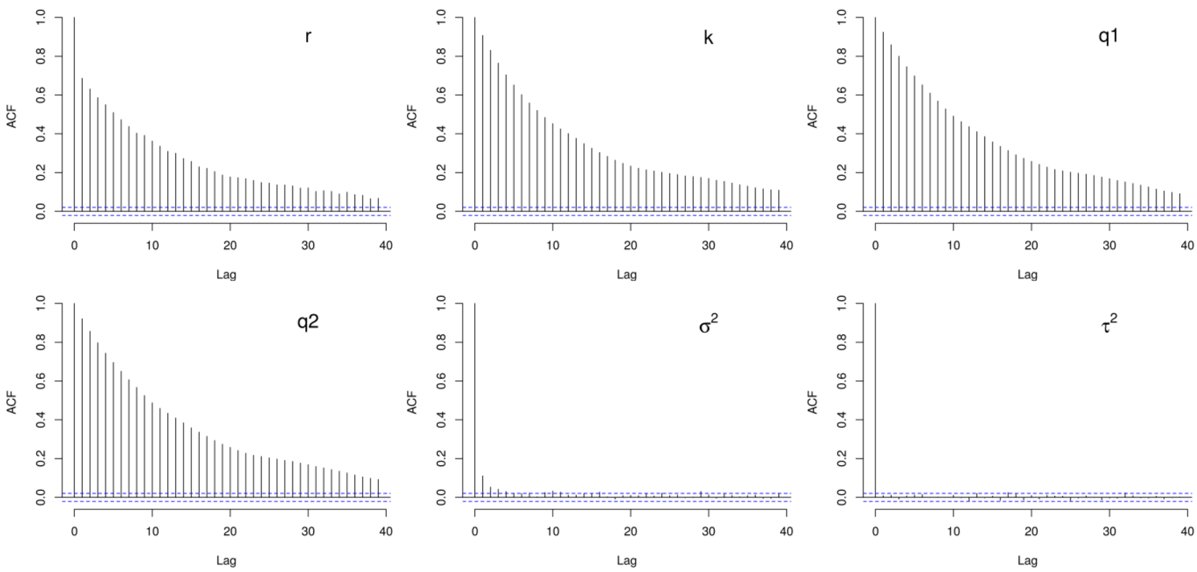

Figure 5 – Autocorrelation of samples of posteriors as calculated using Schaefer type and non-informative prior. r – intrinsic growth rate; k – carrying capacity; q1 – catchability coefficient of Japan; q2 – catchability coefficient of Taiwan; σ^2 variance of the process error; τ^2 variance of the observational error.

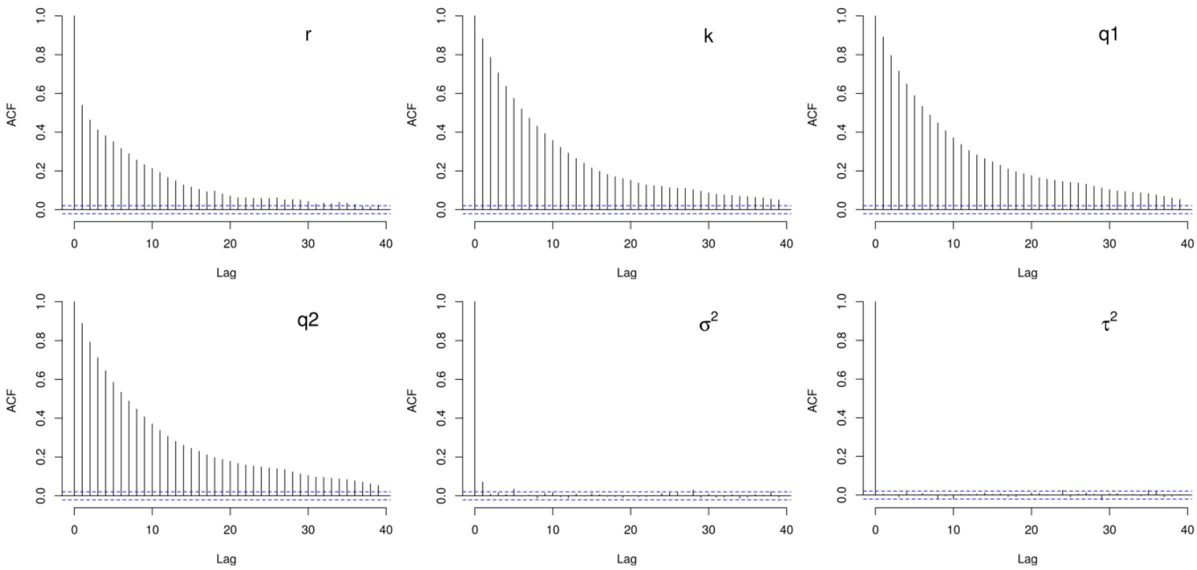

Figure 6 – Autocorrelation of samples of posteriors as calculated using Schaefer type and informative prior. r – intrinsic growth rate; k – carrying capacity; q1 – catchability coefficient of Japan; q2 – catchability coefficient of Taiwan; σ^2 variance of the process error; τ^2 variance of the observational error.

3.3 Model fittings and Residuals

Fox type models fitted to data using non-informative and informative priors are shown in Figure 7. Credibility intervals in the beginning of the time series were wide, which was expected due to the limited data. Model fittings as calculated using and non-informative and informative priors were very similar. Expectations and medians of the posterior calculations did not change much until the end of 1970's, but they decreased in 1980's. There were oscillations in the 1990's followed by a slight decreasing trend in 2000's, and an increasing trend in the beginning of 2010's. However, expectations of catch rates did no change much after 2011. Models fittings as calculated using Schaefer formulae (Figure 8) were very similar to those calculated using Fox type (Figure 7).

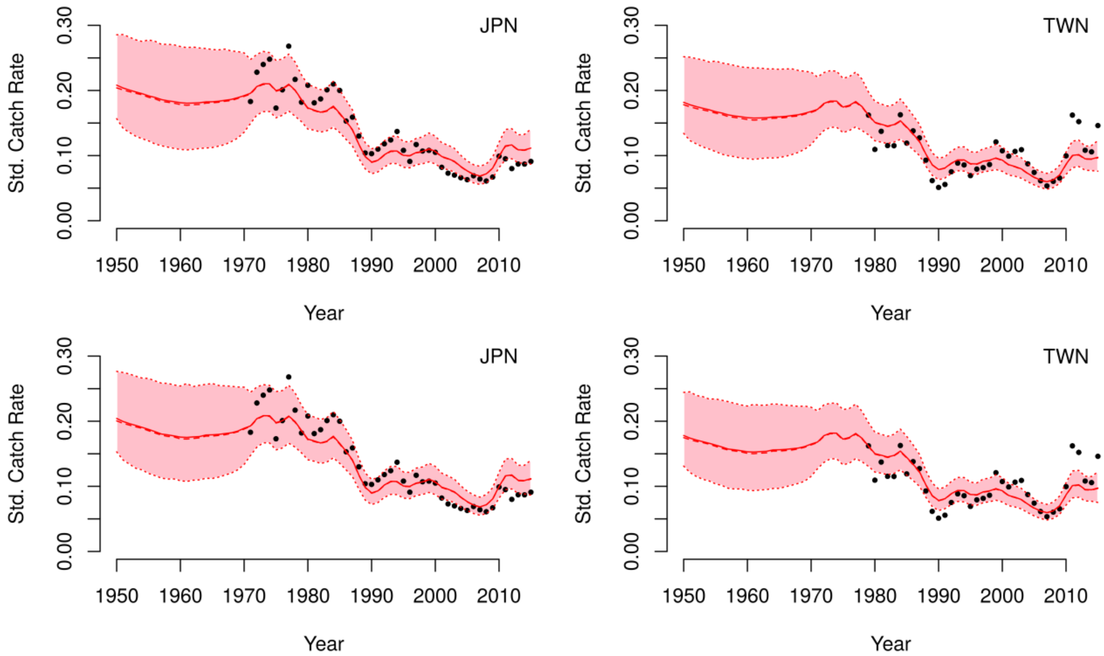

Figure 7 – Fox type models fitted to available catch rate series as calculated using non-informative (top panels) and informative priors (bottom panels). Standardized catch rate time series: Japan (JPN) and Taiwan (TWN).

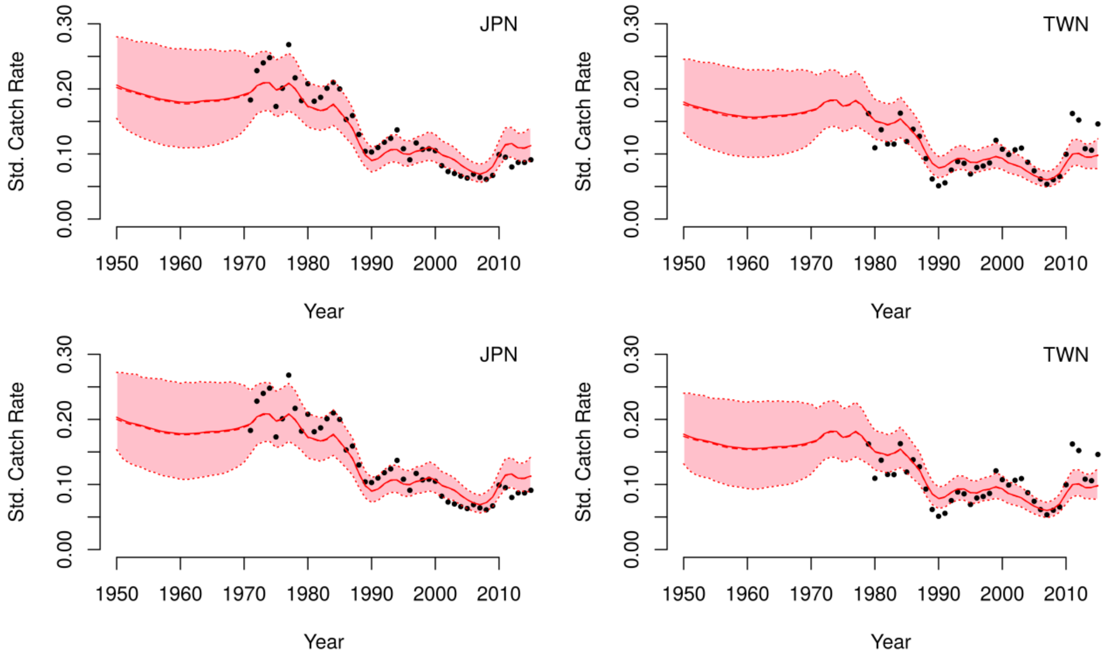

Figure 8 – Schaefer type models fitted to available catch rate series as calculated using non-informative (top panels) and informative priors (bottom panels). Standardized catch rate time series: Japan (JPN) and Taiwan (TWN).

Models with observational and process errors are flexible due to the large number of parameters. In spite of the dimension of models the fittings were not very good. Notice that the expectations calculated using the models underestimate most of the Japan standardized catch rates in the beginning of the time series, but the observed values were overestimated in the end of the time series (Figures 7 and 8 – panels at left). In opposition the expectations overestimated most of catch rates of Taiwan until the end of 1990's, but most of the observed values were underestimated from 2000 onwards (Figures 7 and 8 – panels at right). Biases were very evident in the scatterplots calculated for Fox (Figure 9) and Schaefer model's residuals (Figure 10). Biases of models fitted Japan and Taiwan times are in some sense similar to each other but with opposite signs. The moments of transition of biases from overestimation to underestimation (negative to positive residuals) were close to mid 1990's for Japan and for Taiwan time series.

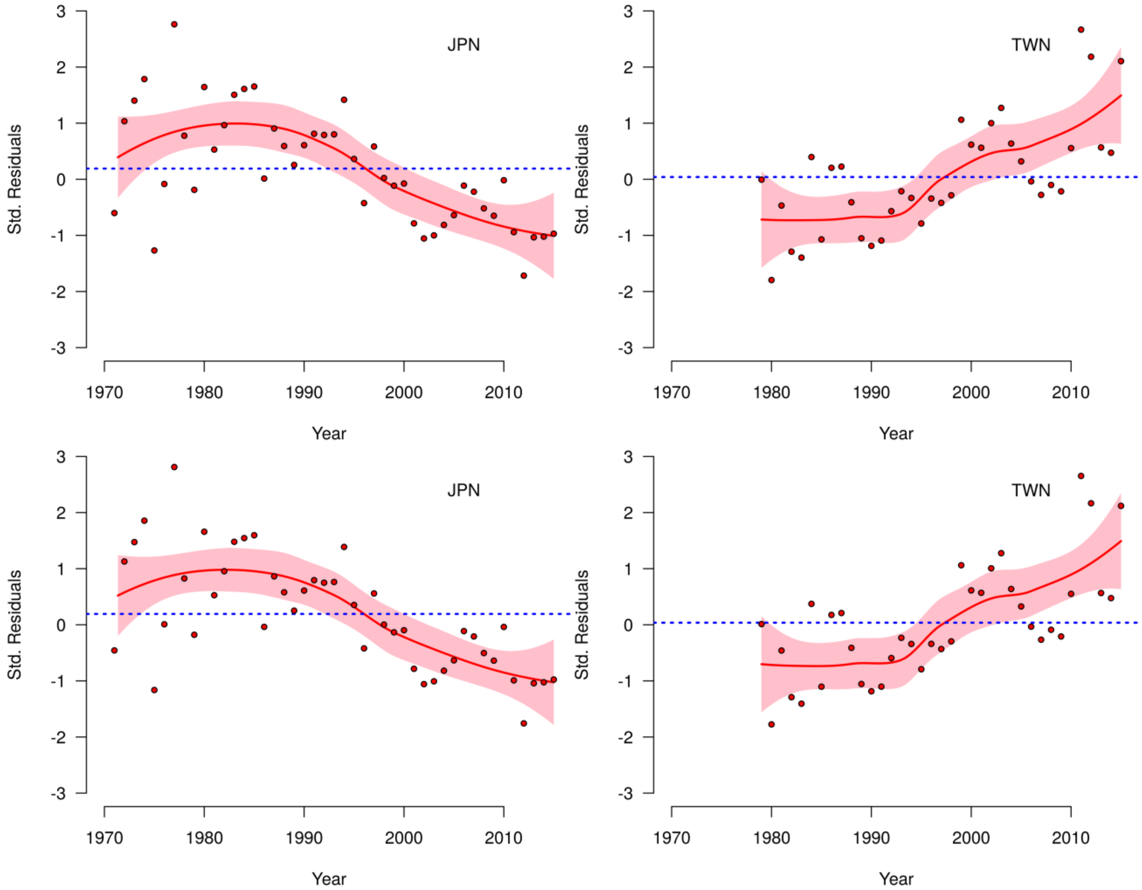

Figure 9 – Residuals of Fox type models fitted to available catch rate time series using non-informative (top panels) and informative priors (bottom panel). Catch rates: Japan (JPN) and Taiwan (TWN).

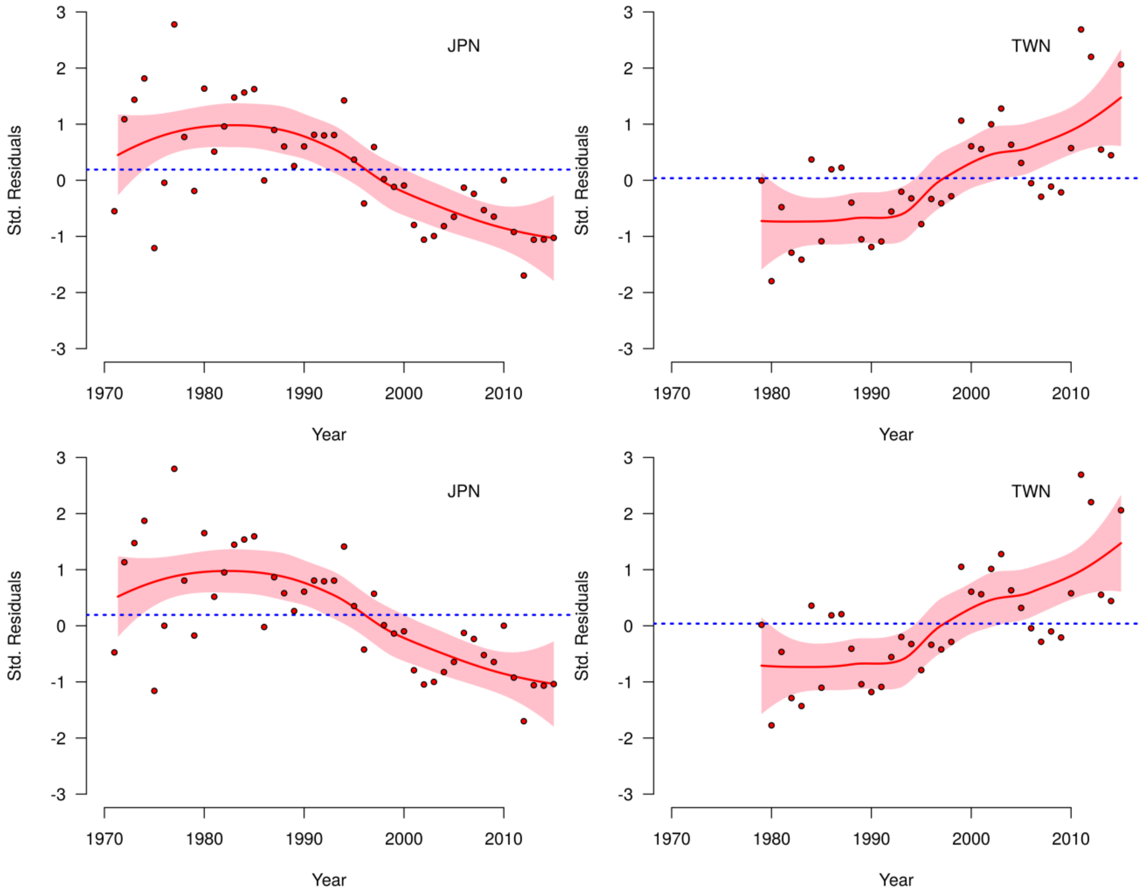

Figure 10 – Residuals of Schaefer type models fitted to available catch rate time series using non-informative (top panels) and informative priors (bottom panel). Catch rates: Japan (JPN) and Taiwan (TWN).

3.4 Marginal Posterior Distributions of Parameters

Posteriors of the parameters r, k, q, σ^2 and τ^2 as calculated using Fox type model are showed in Figure 11. Posteriors of numerous proportions ($P_t = B_t/k$) (one for each year) were not showed to not clutter. Posterior of r calculated with Fox type model and the non-informative is not symmetric and it conveys information about the parameter (Figure 11). The posterior gives more weight to values between 0.05 and 0.3. Notice that the precision of the posteriors of r calculated with non-informative and informative priors were similar. However, the prior was influential in the sense the posterior calculated with the informative prior shifted to right. Notice also that informative prior and the posterior largely overlap, which indicate they are not conflictive. Posteriors of k calculated with non-informative an informative priors were different (Figure 11). Posterior calculated with non-informative prior was flat and it was bounded at the upper limit. This result indicates that data do not convey much information about k. Informative prior on r was also informative about k, because they are correlated. Posterior of k calculated with the set of priors which included the informative prior for r gave more weight for values between 100,000 t and 250,000 t. Notice also that the posterior of k calculated with the informative prior was barely bounded at the upper limit.

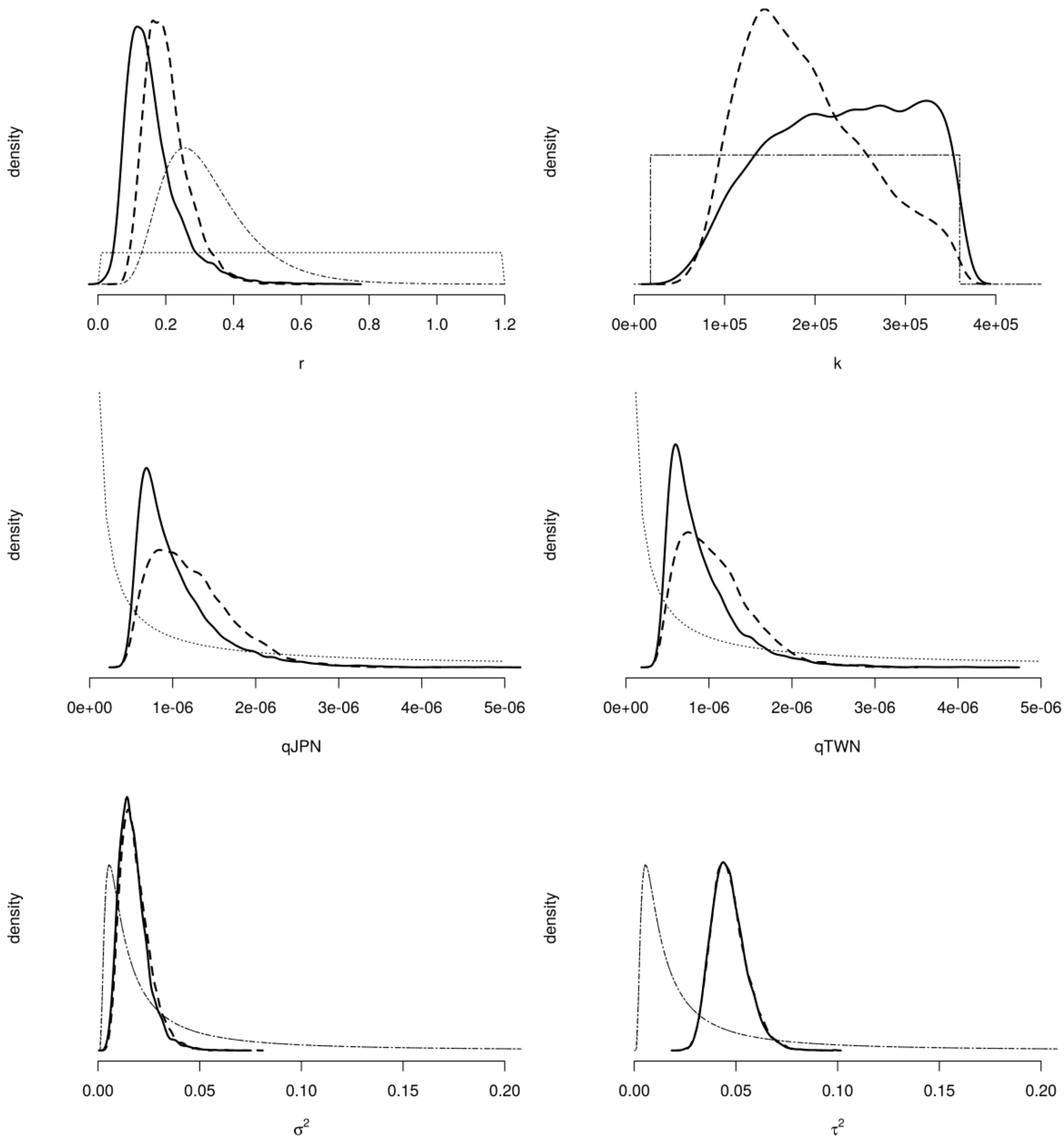

Figure 11 – Priors and posteriors of parameters of Fox type models fitted to catch rates of Japan (JPN) and of Taiwan (TWN). Non-informative prior is indicated by thin dotted line, while the informative was represented by the dotted and dashed thin line. Thick lines stand for the posteriors calculated using the non-informative (solid line) and the informative (dashed line) priors.

Expectations of posteriors of q calculated for Japan and Taiwan using Fox model and the two sets of priors (non-informative and informative) (Figure 11) were all similar. The difference was the precision. The variance of the posterior calculated with informative prior was higher than that calculated for the non-informative prior. Similarly, posteriors of q calculated for both JPN and TWN times series gave weight to values between 5E-7 and 1E-6. The scale of q values were similar because the scale of standardized catch rates were also similar.

Posteriors of variances of observational (σ^2) error calculated using non-informative and informative priors were similar (Figure 11). Similar pattern showed up for the calculations of process error parameter (τ^2). However, the modes of posteriors of σ^2 and of

τ^2 were different. If we rely in the posteriors calculations most of data noise are related to the observational model, while the variance of the process error is relatively low ($\sigma^2 \sim 0.5\tau^2$).

Posteriors calculated using the Schaefer type model (Figure 12) were in general similar to those calculated using the Fox type model (Figure 11). However it is important to highlight that the precision of posterior of k as calculated using Fox type model was higher than that calculated with Schaefer type model, and the mode of the posterior of k calculated using Fox model gives weight to values close to 150,000 t which are well bellow the modal value of the posterior calculated with Schaefer type model (200,000 t). It is also important to stress the informative posterior of r as calculated using Schaefer type model largely overlaps with the posterior calculated with the non-informative prior (Figure 12), while there are a clear difference between the modes of non-informative and informative posteriors calculated using Fox type (Figure 11). Notice also that the precisions of non-informative and informative posteriors of q using Fox are different, but they are not different when using Schaefer type model. In summary, there are important differences between informative and non-informative posteriors calculated using Fox type model. However, both posteriors (non-informative and informative) are not that different when using Schaefer model.

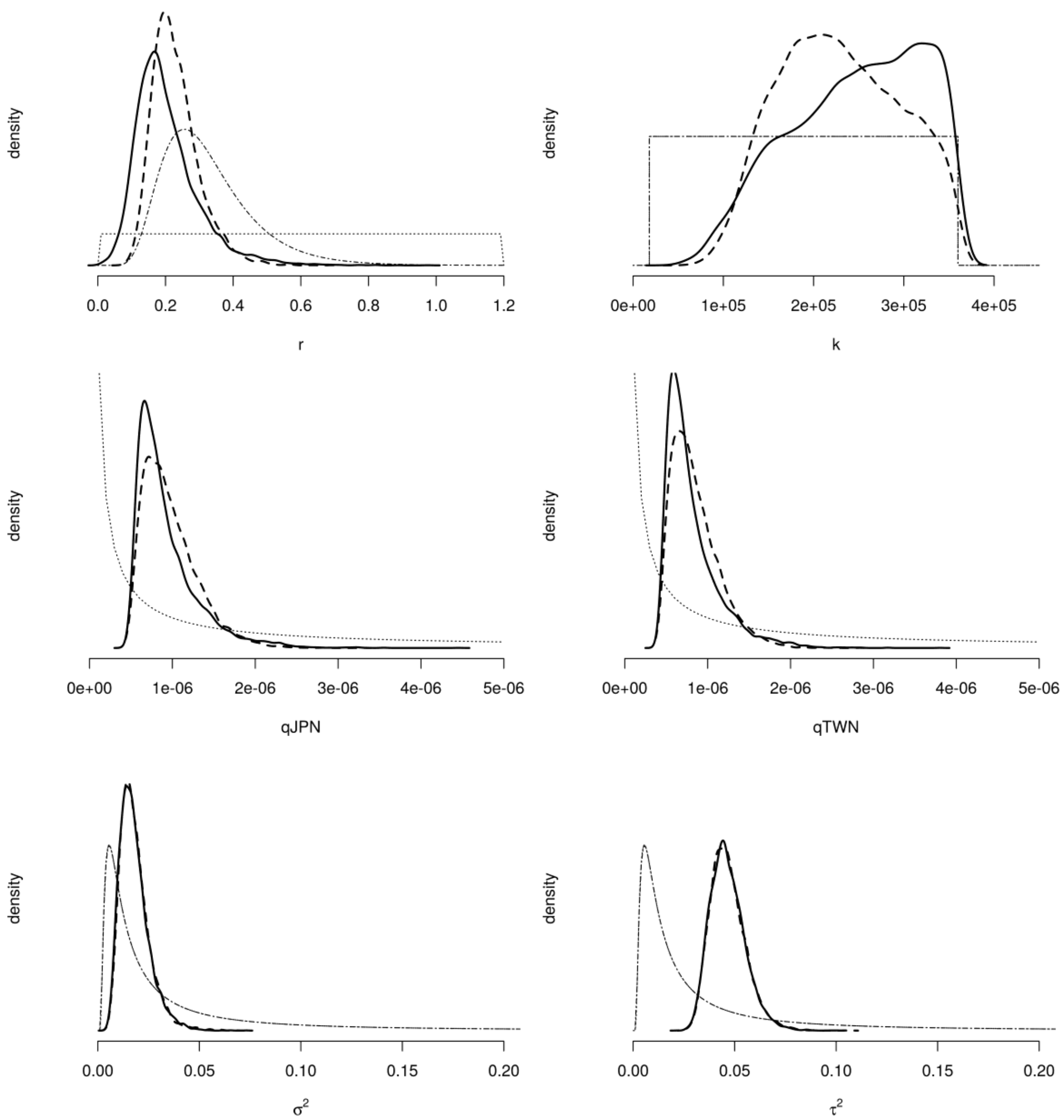

Figure 12 – Priors and posteriors of parameters of Schaefer type models fitted to catch rates of Japan (JPN) and of Taiwan (TWN). Non-informative prior is indicated by thin dotted line, while the informative was represented by the dotted and dashed thin line. Thick lines stand for the posteriors calculated using the non-informative (solid line) and the informative (dashed line) priors.

3.5 Posteriors of Ymsy

Posteriors of Y_{MSY} calculated using Fox and Schaefer type models are in Figure 13. Posteriors calculated with informative priors were more asymmetrical (positive skew) than those estimated with non-informative priors. However the modes of all four posterior samples are between 11,000-12,000 t. Variance of all posteriors were similar, all of them give more weight to values of Y_{MSY} between 5,000 and 20,000 t.

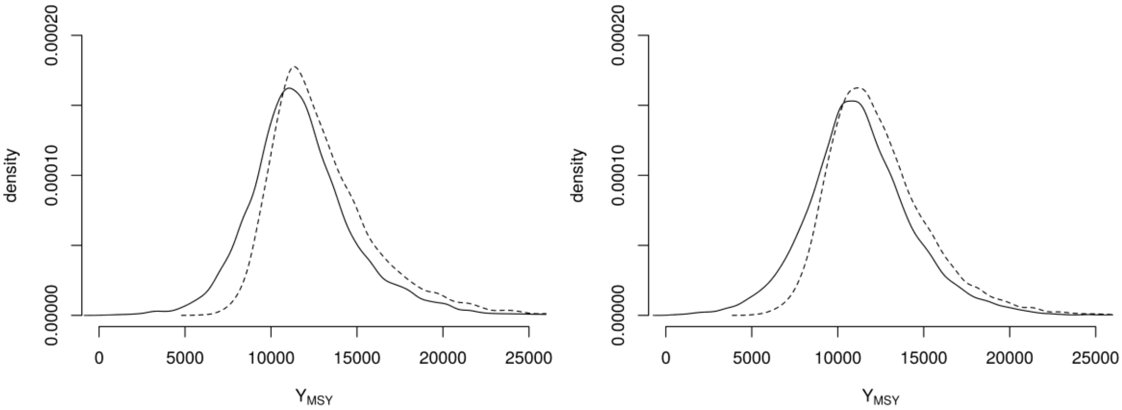

Figure 13 – Posteriors of yield at "maximum sustainable yield" as calculated using Fox (left panel) and Schaefer (right panel) type models. Priors: Non-informative (solid line) and Informative (dashed line).

3.6 Ratios H/HMSY and B/BMSY

Time series of ratios H/HMSY and B/BMSY calculated using Fox type model are in Figure 14. Credibility intervals of B/BMSY were wider in the beginning of time series due to limitation of catch rate data in that period. In opposition, credibility intervals of H/HMSY were wide in the end of time series, probably due to the variance of catches in the recent decades. Overall the posteriors calculated with the non-informative and informative priors were similar. The B/BMSY ratio did not change much in 1970, but has decreased quickly in 1980's. There were oscillations from the beginning of 1990's until recent years. In this period the credibility interval of B/BMSY includes the value one, which indicates that it is unclear if biomass were above or below the BMSY during the last decades. However the expectation of B/BMSY was below 1 only in the mid 2000's hence the posterior give more weight to the hypothesis that the biomass in the last 25 years was above the BMSY.

Harvest ratio H/HMSY was low until the end of 1970's, but the ratio increased from the beginning of 1980's until the end of 1990's (Figure 14). Expectations of H/HMSY showed oscillations since then, but it was probably close but below 1 over the recent years, except in the mid 2000's. However, it is important to highly that the credibility intervals of H/HMSY were wide and include the reference value 1 since mid 1990's. Therefore it is unclear if the harvest hate during the last decades was above or below the HMSY.

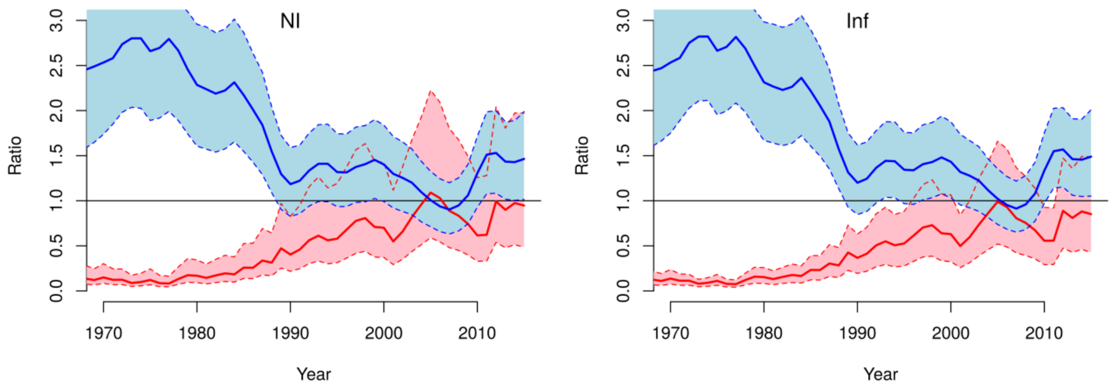

Figure 14 – Time trends of ratios between harvest rate and harvest rate at MSY (H/HMSY) (green/blue), and between biomass and biomass at MSY (B/BMSY) (pink/red), as calculated using Fox type model. Solid lines stand for the means. Calculations with non-informative (NI) prior are in the left, while the panel at right stand for calculations with informative (Inf) prior.

Overall time trends of H/HMSY and B/BMSY calculated using Schaefer model (Figure 15) were similar to those calculated with Fox model (Figure 14). However the posteriors gathered with Schaefer type formulae were more pessimistic in the sense the expectations of B/BMSY were lower that those calculated with Fox. If we rely in Schaefer calculation the expectation of biomass was below 1 in several years during the last decades. In addition, posteriors calculated with Schaefer type indicate that harvest was well above harvest at MSY in mid 2000's, and that the ration H/HMSY has been higher than 1 over the recent years (Figure 15). However, remind that the credibility intervals were wide, hence the uncertain is large.

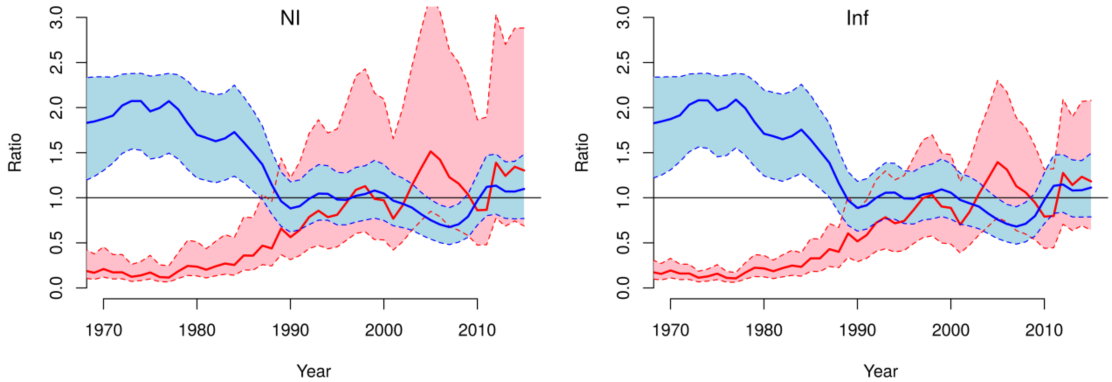

Figure 15 – Time trends of ratios between harvest rate and harvest rate at MSY (H/HMSY) (green/blue), and between biomass and biomass at MSY (B/BMSY) (pink/red), as calculated using Fox type model. Solid lines stand for the means. Calculations with non-informative (NI) prior are in the left, while the panel at right stand for calculations with informative (Inf) prior.

3.7 Kobe plots

Calculations with Fox type model indicate that the blue marlin stock was not overfished during most years in since the beginning of the fishery (Figure 16). However, the stock was subject to overfishing or even overfished once or twice in the past. In the very recent years the marginal medians and expectations of posteriors indicate that the stock was not overfished but it is close the "subject to overfishing" zone because the harvest ratio have been high over the last three or four years.

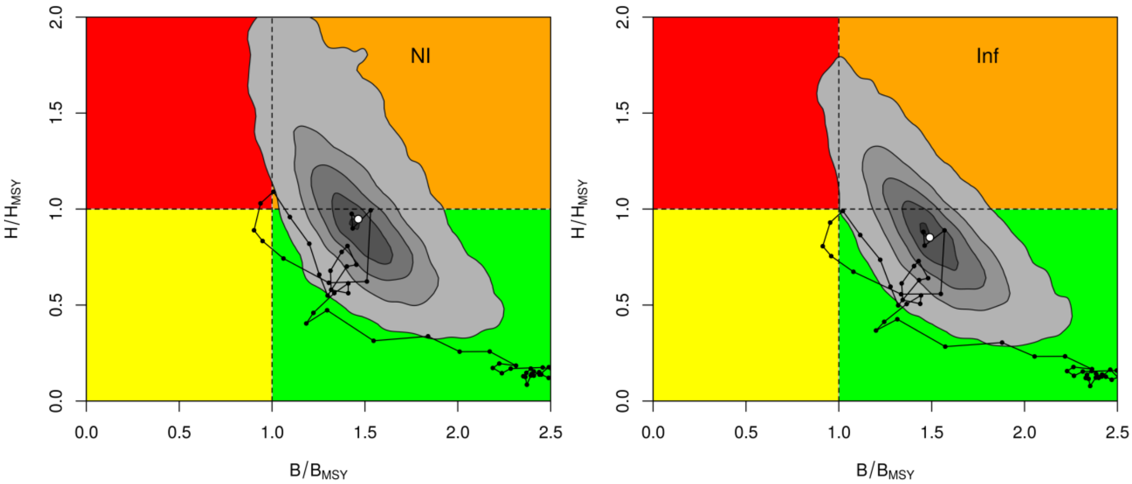

Figure 16 – Contour plots of posteriors of H/H_{MSY} and B/B_{MSY} calculated based on Fox type model. Solid lines and filled circles stand for the trajectories of marginal medians. NI – non-informative prior; Inf – Informative prior.

Calculations with Schaefer type model indicate that the blue marlin stock was not overfished in the beginning of the fishery, but it was overfished during 5-6 years in the mid of the time series (Figure 17). Harvest ratio (H/HMSY) has decreased in the mid of time series and the stock has recovered some decades ago. However harvest has increased in the recent years and the stock is no more with status of “not overfished”. It is currently subject to overfishing due to the quick increase of harvest in the very recent years.

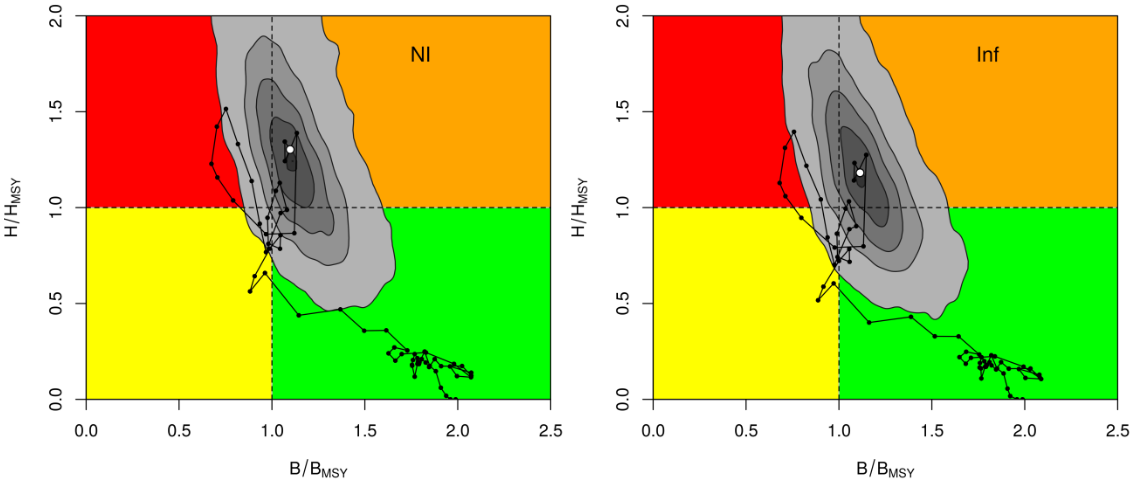

Figure 17 – Contour plots of posteriors of H/H_{MSY} and B/B_{MSY} calculated based on Schaefer type model. Solid lines and filled circles stand for the trajectories of marginal medians. NI – non-informative prior; Inf – Informative prior.

Remarks

All the models were satisfactory concerning criteria to assess convergence of MCMC algorithm. However, the fittings were biased probably because the two catch rate time series are conflictive. Data convey information about r parameters. However data do not convey much information about k. Posteriors calculated using non-informative and informative priors were not quite different. Current status of the stock is “not overfished” if we rely on calculations using Fox type model. However, posteriors estimated using Schaefer type model indicate that the stock was overfished in the past and that currently it is “subject to overfishing”. At this stage, based on technical issues (e.g. residuals, information criterion) there are not motivations to select one of the two types of models.

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