Stock assessment of swordfish (*Xiphias gladius*) caught in the Indian Ocean using a Bayesian state-space production model

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Abstract

Bayesian state-space models were used to assess the swordfish (Xiphias gladius) caught in the Indian Ocean assuming that there is a single stock. Estimations of catches as reported in the IOTC database were used and the models were fitted to standardized catch-per-unit-effort (CPUE) available for the stock assessment. Catches and standardized CPUEs were conflictive in some periods. There are periods in which the CPUE increased but the catches increased as well. Different runs were conducted with several combinations of CPUE. Uncertain is high as indicated by the wide posteriors of parameters. Data do not convey much information about parameters r and k. Estimations indicate that swordfish is probably not overfished, but it is subject to overfishing. However the results might be carefully considered given the conflict between catch and CPUE time series which drives the results of such simple models.

1. Introduction

Swordfish (*Xiphias gladius*) (SWO) been caught in Indian Ocean mainly by fleets which operate with longline. Actually SWO is the target of longline fleets of some countries (e.g. Portugal and Spain). Accumulated catches of Indonesia, Taiwan and Sri Lanka were the largest one, but in recent years the proportion of catches of other countries increased. Status of swordfish in Indian Ocean (all areas aggregated) was always “not overfished” and not “subject to overfishing” since the first stock assessment. There are detailed data concerning SWO stock hence in 2015 an complex Stock Synthesis (SS3) model was used for status stock advice. However, comparisons of results gathered with different models (simple and complex) allow for better understanding of the stock status taking into account different assumptions and structures of models. In this sense the working group requested to run a simple production model which demands only catch and relative abundance indices (or effort). Estimations of standardized CPUE of Indonesia, Japan, Portugal, South Africa, Spain and Taiwan were available. All available CPUEs and the official catch time series reported in the IOTC database were considered in this working paper to assess swordfish stock of Indian Ocean using a state-space Bayesian production model (SBPM).

2. Data

Catches increased slowly from 1950 to 1991, but jumped to more than 30,000 t in mid 1990’s (Figure 1 A). There were oscillations of catches in the last decades, with a peak in 2004 (40,257.9 t) followed by a plunge. In the very end of the time series catches increased fast and the estimation for 2015 was close to 40,000 t. Estimations of standardized CPUE are in Figure 1 B. The CPUE time series of Japan considered to run the production model are the ones of the northwest area. The series were split into two shorter series, and the values after 2010 were discarded following the recommendation of Ijima (2017). All the other CPUE series were considered as they appear in the working papers of the authors that provided them (Coelho et al., 2017; Fernández-Costa et al., 2017; Ijima, 2017; Setyadji et al, 2017; Wang 2017). The exception was the South African CPUE series which was provided by the secretariat of the IOTC. Time series of CPUE of Portugal and South Africa were rescaled by diving it to 1000 because they were estimated in quilos and the values were much higher than the ones of the other CPUE series. To deal with CPUE values of similar scale is convenient because it allow to use the same prior for the coefficient of catchability (see below).

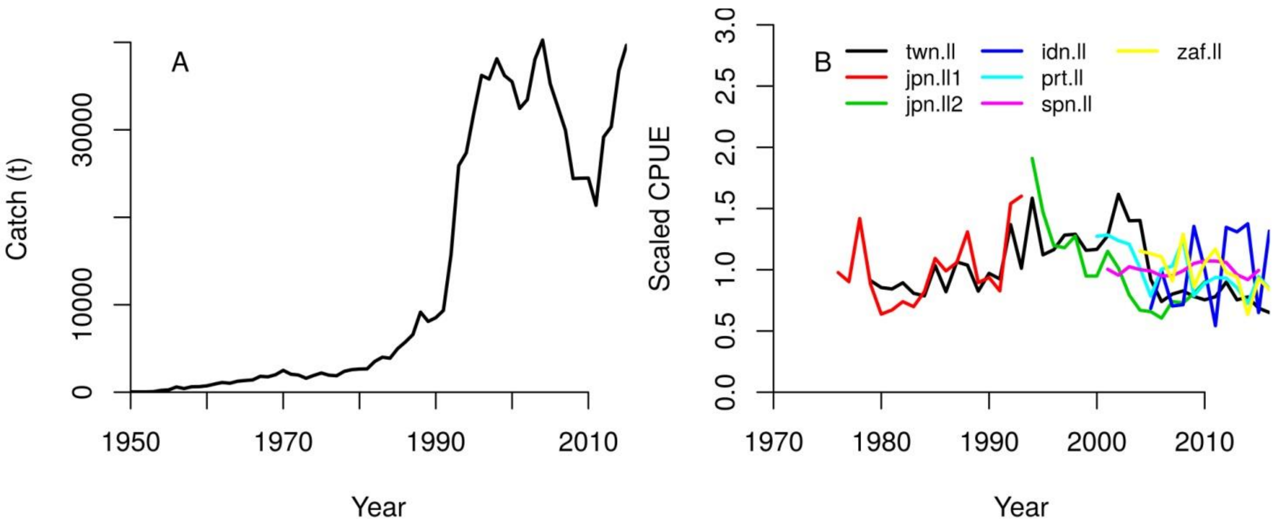


Figure 1 – Catches (A) and catch-per-unit-effort (CPUE) (B) of swordfish of the Indian Ocean. TWN.LL – standardized CPUE of longline fleet of Taiwan; JPN.LL1 – first part of the standardized CPUE of longline fleet of Japan; JPN.LL2 – second part of the standardized CPUE of longline fleet of Japan; IDN.LL – standardized CPUE of longline fleet of Indonesia; PRT.LL – standardized CPUE of longline fleet of Portugal; SPN.LL – standardized CPUE of longline fleet of Spain; ZAF.LL – standardized CPUE of longline fleet of South Africa. Values of CPUE were scaled by dividing them by the mean.

Standardized CPUE JPN.LL1 (1976-1993) oscillated from the end of 1970's to the beginning of 1990's, but in general, there was an increasing trend. JPN.LL1 CPUEs in the end (1992-1993) were higher than in the beginning of the time series (1976). Second part of Japanese series (JPN.LL2) spans from 1994 to 2010. JPN.LL2 CPUEs decreased from 1994 to 2006, but increased slightly in the end of the time series. CPUEs of Taiwan (TWN.LL) increased in the beginning of the time series throughout 2004, but it decreased fast in the following two years. Overall the TWN.LL CPUE was flat in the end of time series from 2006 to 2015. CPUEs of Spain (SPN.LL) spans from 2001 to 2015. Time series of Spain is mostly flat. Time series of Indonesian fleet (IDN.LL) largely oscillated with peaks and plunges, but there was not a clear increasing (or decreasing) time trend. CPUEs of Portugal (PRT.LL) (2000-2015) and of South Africa (ZAF.LL) (2004-2015) decreased all over the years.

3. Model

The model used here is fully described in the paper of Meyer and Millar (1999). The model was already used before in the some the previous IOTC meetings. Applications in stock assessment of species caught in longline fisheries targeting tuna and tuna like species in Indian Ocean can be found in Andrade (2013 and 2014). Here follows a summary of the model version used in this paper, and also the description of the calculation procedures. 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:

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

where B_t is the biomass at the beginning of year t, Y_t is the yield obtained during this year (all fleets aggregated), and $g(\ )$is the "surplus production" function. The formulae of Schaefer $g(B_{t-1}) = rB_{t-1}(1 - B_{t-1}/k)$ or Fox type $g(B_{t-1}) = rB_{t-1}(-\log(B_{t-1}/k))$ are often used here, where k is the carrying capacity and r is the intrinsic growth rate of the population. Both formulations Schaefer type (SCH) and Fox (FOX) where used in this analyses.

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

$$I_{tm} = q_m B_t \tag{2}$$

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

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. 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 (MCMC) 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:

$$P_1\ |\sigma^2 = e^{u_1} \tag{3}$$

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

while the equations for the observations would be:

$$I_{tm}|P_t, q_m, \tau^2 = q_m k P_t e^{v_t} t = 2, \dots, N \tag{4}$$

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.

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

$$p(k, r, q_1, \dots, q_m, \sigma^2, \tau^2, P_1, \dots, P_n) = \\ p(k)p(r)p(q_1) \dots p(q_m)p(\sigma^2)p(\tau^2)p(P_1|\sigma^2) \prod_{i=2}^{N} p(P_t|P_{t-1}, k, r, \sigma^2) \tag{5}$$

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

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

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

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

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, 2017) 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 30 steps (slice sampling) of the subsequent 30000 steps of the chain, providing a set of 1000 values of the posterior distribution for each chain.

4. Priors

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). Both non-informative and informative prior models were fitted in order to assess the effect of the prior assumptions. 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 wide uniform prior $U(-45, -1)$ on the logarithmic scale was used in the present study for the catchabilities of all fleets $q_1, \ldots, q_m$. 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 $U(42000, 20 \times 42000)$. The lower limit is close to the maximum annual yield as reported in IOTC database. The prior for r was $U(0,1)$, and those for $\sigma^2$and τ_m^2 were the inverse gamma $IG(0.3, 0.03)$and $IG(0.3, 0.03)$, respectively. The parameters of priors for the observational and process errors were selected after some exploratory analysis. The above set of priors is hereafter denominated "non-informative" (NI). In the informative set (INF), priors for most of the parameters are to the non-informative ones mentioned above, but the uniform prior of r is replaced by a lognormal distribution with mean 0.4 and standard deviation of 0.4 in the logarithm scale. This informative prior of r is similar to the one used in the last stock assessment of swordfish held in 2014 (Andrade, 2014). In addition it is also similar to that in the last stock assessment of Atlantic swordfish (Anon., 2017).

5. 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 used to evaluate the mixing degree of the samples of the posterior distribution. Estimations of 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. Deviance Information Criteria (DIC) (Spiegelhalter et al., 2002) of different models was also assessed.

6. Results

Data and Model Selection

Distributions of frequencies, relationships and coefficients of correlations of available estimations of CPUE time series available for the stock assessment are showed in Figure 2. Nine out of the sixteen correlations calculated were positive, which indicate agreement among the time series. Among the negative correlations notice the ones calculated between Indonesia and Portugal time series, and between Indonesia and South Africa time series.

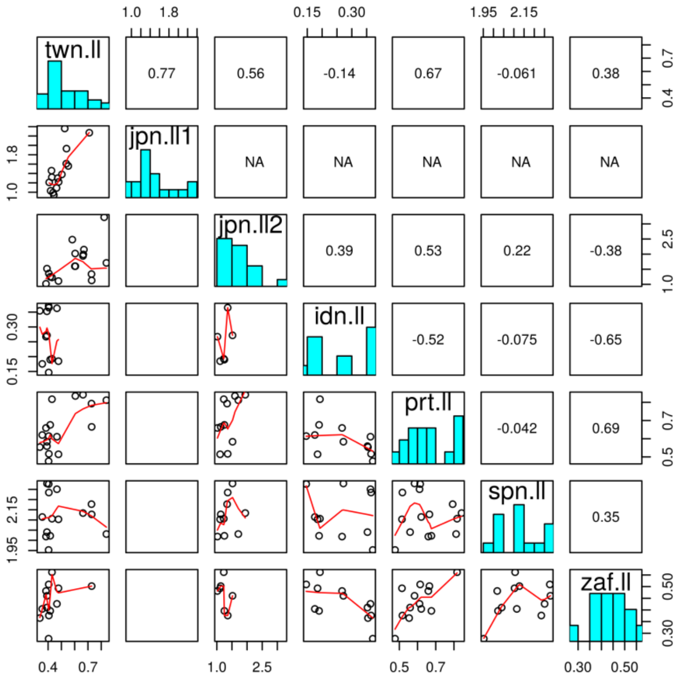


Figure 2 – Estimations of catch-per-unit-effort (CPUE). TWN.LL – standardized CPUE of longline fleet of Taiwan; JPN.LL1 – first part of the standardized CPUE of longline fleet of Japan; JPN.LL2 – second part of the standardized CPUE of longline fleet of Japan; IDN.LL – standardized CPUE of longline fleet of Indonesia; PRT.LL – standardized CPUE of longline fleet of Portugal; SPN.LL – standardized CPUE of longline fleet of Spain; ZAF.LL – standardized CPUE of longline fleet of South Africa.

An exploratory analysis taking into account different combinations of the CPUE series was conducted using the Bayesian production model mentioned above (section 3) and the JABBA (see INFO paper). In this working paper are showed the results calculated taking into account all the available CPUE time series. Four models were fitted to the CPUEs selected for the analyses, Schaefer type (SCH) with non-informative priors (NI) and with informative prior (INF), and Fox type (FOX) with non-informative priors and with informative prior. All the calculations of 97.5% quantile of PSRF (Gelman and Rubin, 1992) were lower than 1.01, which indicates that convergence is not of much concern. In addition the autocorrelation analyzes indicate a fairly acceptable mixing degree of the samples of the posterior distribution. Calculations of DIC were -101.54, -99.46, -102.06 and -98.31 for the SCH-NI, SCH-INF, FOX-NI and FOX-INF models respectively. The expectations of the standardized residuals were 0.0124 (SCH-NI), 0.0126 (SCH-INF), 0.0126 (FOX-NI) and 0.0125 (FOX-INF). The working group decided to use the informative prior which reflect biological information. If the informative prior is used the Schaefer model performs slightly better if we rely on DIC, hence hereafter only results of calculations of the run SCH-INF are showed. A summary of the fittings of the other three models (SCH-NI, FOX-NI and FOX-INF) are in Appendix I.

Fittings

Fittings of the Schaefer model with informative prior to the IOTC catch time series and to the seven longline CPUE series are in Figure 3. State-space models are very flexible because there are many parameters (i.e. $r, k, q_1, \dots, q_m, p_1, \dots, p_N, \tau^2, \sigma^2$). Usually the longer time series with clear increasing (or decreasing) trends are more influence. Hence, in spite of the flexibility of the model, if some of the CPUE datasets are conflictive, the fittings are not good for the less influential or shorter time series. The model fittings were particularly poor for the Spanish CPUE series which is flat and is not influential. Fittings were also poor for the beginning of the second part of the Japanese time series which showed a sharp decreasing trend, for the values of 2003-2005 years of Taiwan which were high and is the start of a sharp decreasing trend. Overall model fittings showed a decreasing trend from 1976 to the beginning of 1980's, followed by an increasing trend until mid 1990's, and finally a slightly decreasing trend from 1994 to 2015.

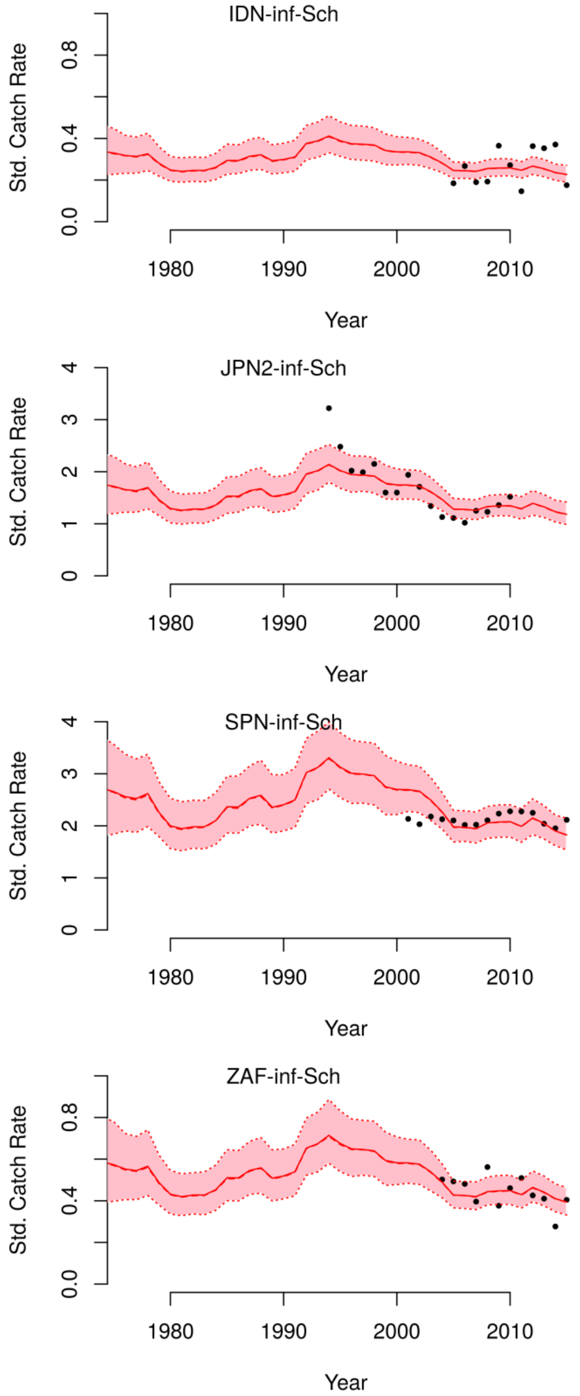
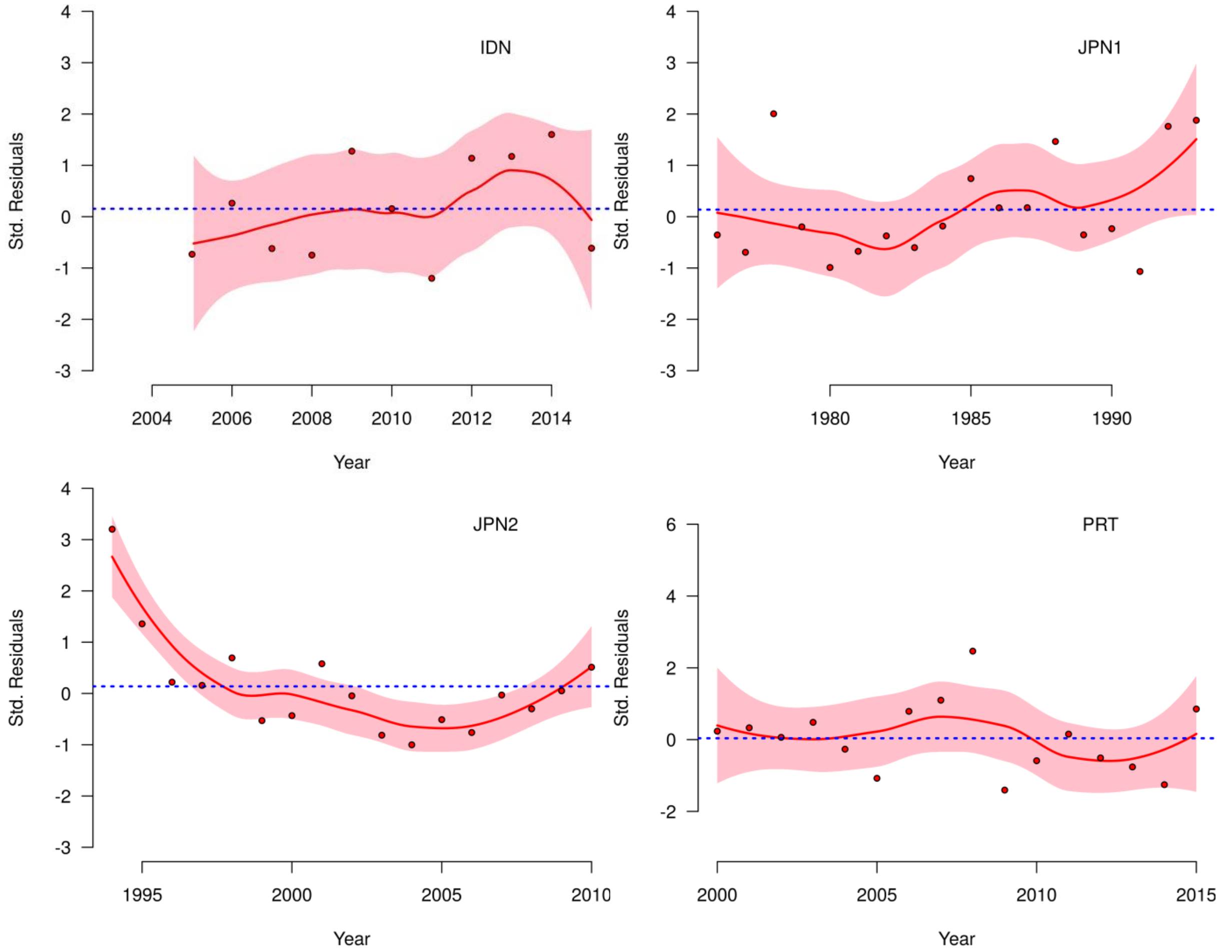


Figure 3 - Fittings of Schaefer type model with informative prior to the seven CPUE time series available for stock assessment: TWN – standardized CPUE of longline fleet of Taiwan; JPN1 – first part of the standardized CPUE of longline fleet of Japan; JPN2 – second part of the standardized CPUE of longline fleet of Japan; IDN – standardized CPUE of longline fleet of Indonesia; PRT – standardized CPUE of longline fleet of Portugal; SPN – standardized CPUE of longline fleet of Spain; ZAF – standardized CPUE of longline fleet of South Africa.

Residuals are shown in Figure 4. Overall there were no biases in the fittings for IDN, JPN1, PRT, and ZAF CPUE time series. However, the model underestimated the values of the beginning of the time series JPN2 and underestimated them in mid 2000's. The fittings to the time series of Spain were largely biased all over the years, while the models underestimated the values of the TWN series in the beginning of 2000's. In summary, the flat Spanish time series is not influential at all, hence the fittings are largely biased. In addition the sharp decreasing trends of CPUEs in the beginning of JPN2 series, and of TWN series in the beginning of 2000s can not be fit by a simple production model which does not account for detailed information concerning age, length, selectivity and sex structure of catches.



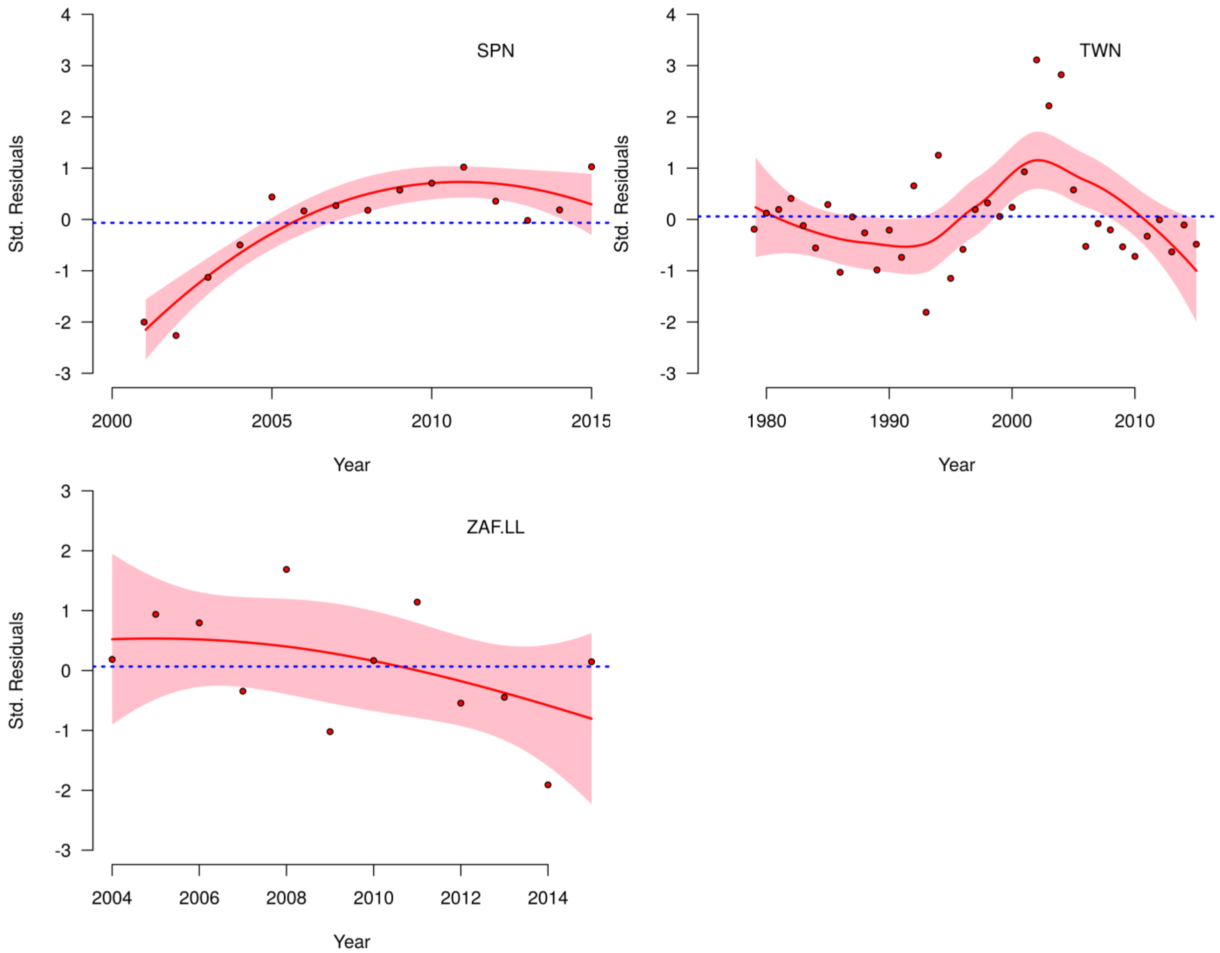


Figure 4 – Standardized residuals of the model fittings to the seven CPUE time series available for stock assessment: TWN – standardized CPUE of longline fleet of Taiwan; JPN1 – first part of the standardized CPUE of longline fleet of Japan; JPN2 – second part of the standardized CPUE of longline fleet of Japan; IDN – standardized CPUE of longline fleet of Indonesia; PRT – standardized CPUE of longline fleet of Portugal; SPN – standardized CPUE of longline fleet of Spain; ZAF – standardized CPUE of longline fleet of South Africa..

Overall residuals (all CPUE time series) are shown in Figure 5. In general the model fits well the data in the sense the there is not a time trend in the residuals.

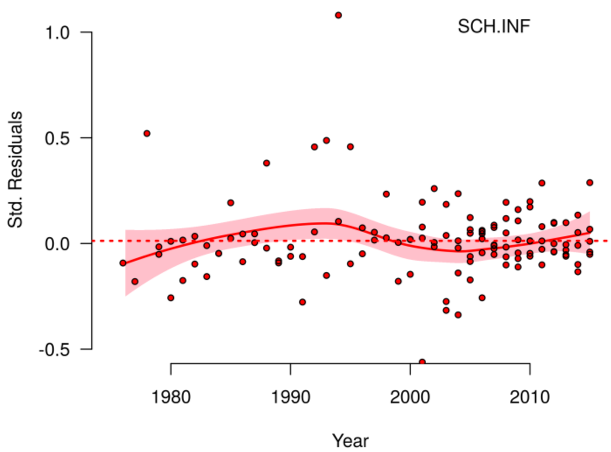


Figure 5 – Standardized residuals of the model fitting.

Posteriors of parameters and of Y_{MSY}

Priors and posteriors of r and k parameters are showed in Figure 6.The prior of r strongly influences the results. Notice that the posterior of r calculated with the informative prior give more weight to higher values than the posterior calculated with the non-informative prior. Precision of the posterior of r with informative prior is similar to that of the non-informative prior. Data are not informative about k and the posteriors were bounded by the upper limit of the uniform prior which was approximately 20 x max(catch). Some additional runs were conducted with higher values for the upper limit of the prior (e.g. 40 x max(catch)). However the right tail of the posteriors of k are heavy and were still bounded by the upper limit.

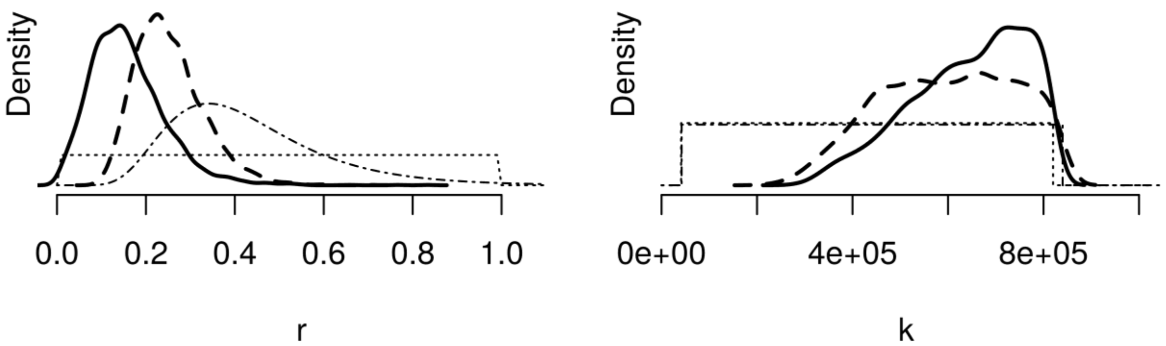


Figure 6 – Priors (thin lines) and posteriors (thick) lines of the parameters calculated with the informative and non informative priors for r. The thick solid lines stand for the posterior calculated with the non-informative prior, while the thick dashed lines stand for the posterior calculated with the informative prior.

Densities distributions of Ymsy as calculated based on the posteriors of r and k is showed in Figure 7. The shape of densities distributions of Ymsy as calculated using non-informative and informative priors were similar, but the scales were very different. The posterior calculated based on the informative prior shifted to the right and gave more weights to values between 20,000 t and 55,000 t with mode approximately equal to 30,000 t. However, the posterior calculated with the non-informative prior gave more weight to values between 5,000 t and 45,000 t with mode close to 20,000 t.

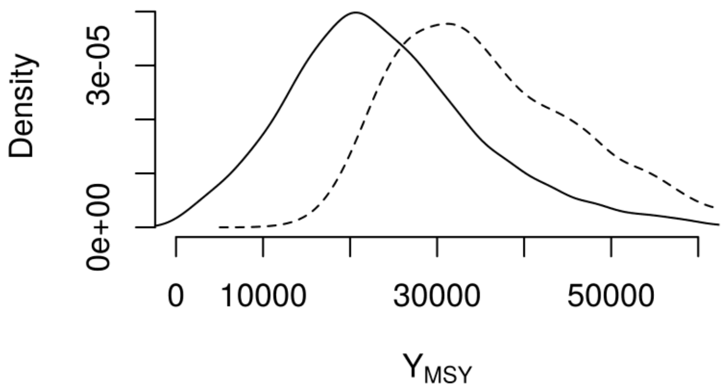


Figure 7 – Densities distributions of Y_{MSY}. Solid lines stand for results calculated using non-informative prior of r, while the dashed lines stand for the calculations using informative prior.

Joint posteriors and correlations

Contour plots, marginal distributions and correlations of posteriors of parameters and of Y_{MSY} as calculated using Schaefer type model and informative prior are in Figure 8. Correlation between r and k was negative, which is a typical result when fitting such kind of production model. Correlations among q_s were high and positive which is probably due to the similar scales of the available standardized CPUE series. Overall the correlations found among r, k, q, and Y_{MSY}, were moderate or high, while correlations with and among τ^2 and σ^2 were low.

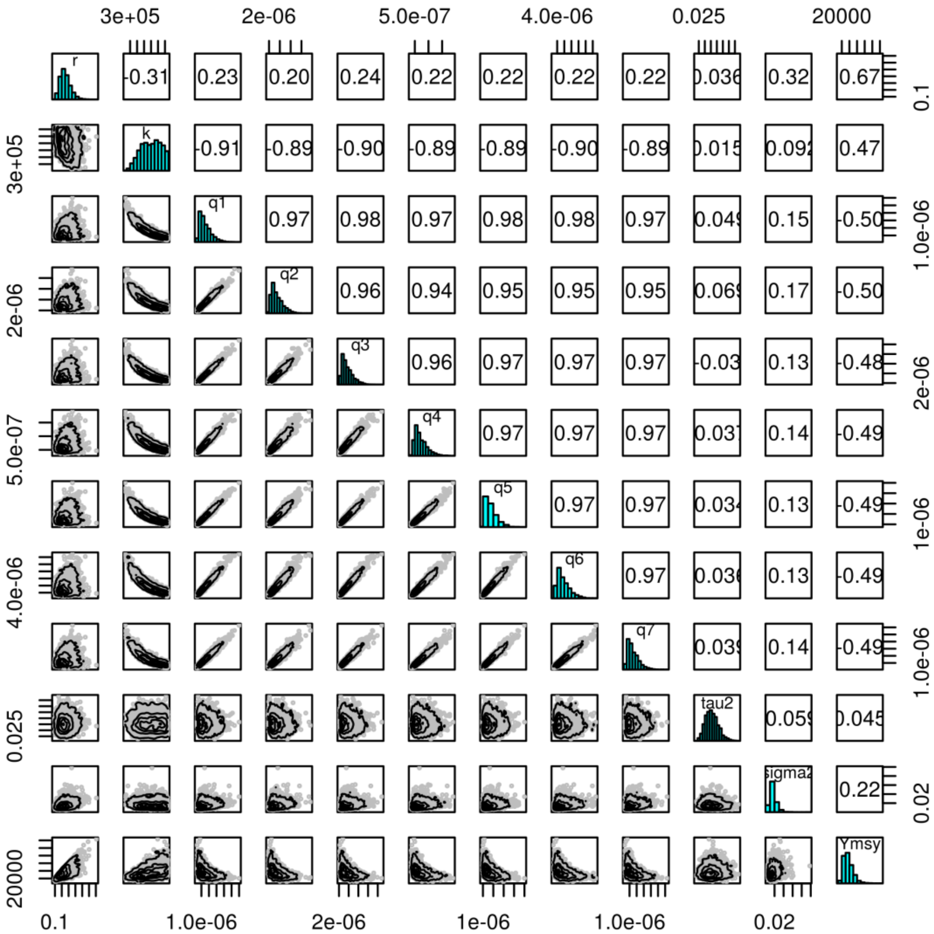


Figure 8 – Marginal and joint posterior distributions of parameters and of yield at MSY as calculated using informative prior and Schaefer type production model.

Time trends of ratios between harvests in each year and harvest at MSY (H/H_{MSY}), and between biomass in each year and biomass at MSY (B/B_{MSY}) are showed in Figure 9. Notice that credibility intervals of B/B_{MSY} were wide all over the years, while the credibility interval of H/H_{MSY} was low in the beginning of the time series, but it was wide after mid 1990's. The ratio B/B_{MSY} decreased in the end of 1970's but increased from 1980 to 1994. After 1994 the median of the ratio B/B_{MSY} decreased in a regular pace until 2015 when it was close to 1.1. The ratio H/H_{MSY} increased slowly until 1992, but fast from the beginning of 1990's until mid 2000's. The harvest ratio decreased from 2005 to 2011, but it increased in the end of the time series. In 2015 the median of H/H_{MSY} was slightly higher than 1. The concurrent increasing trend of catches, of H/H_{MSY} and of B/B_{MSY} is not a common result as the B/B_{MSY} is expected to decrease as the catch increases. This uncommon pattern was due to the increasing trends of the CPUEs of Taiwan and of the first part of the Japan time series, along with the increasing trend of catches.

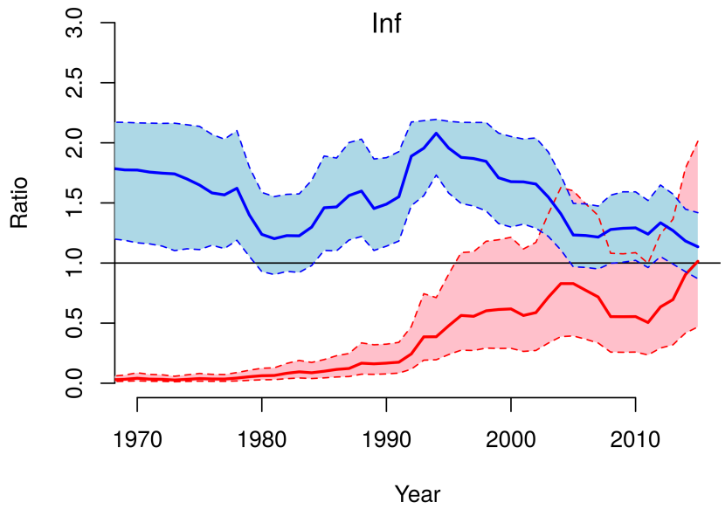


Figure 9 – Ratios between biomass in each year and harvest at MSY (B/B_{MSY}) (bluish colors) and between harvest and harvest at MSY (H/H_{MSY}) (reddish colors), as calculated using Fox type model and informative prior for r. Shaded polygons and dotted lines stand for the credibility intervals (95%), while thick solid lines stand for the medians.

Kobe plot calculated using Fox model and informative prior is showed in Figure 10. Joint posterior sample of B/B_{MSY} and H/H_{MSY} for 2015 were spread out mostly over green (not overfished and not subject to overfishing) and orange zones (not overfished but subject to overfishing). The mode of the joint posterior is close to the threshold between green and orange zones.

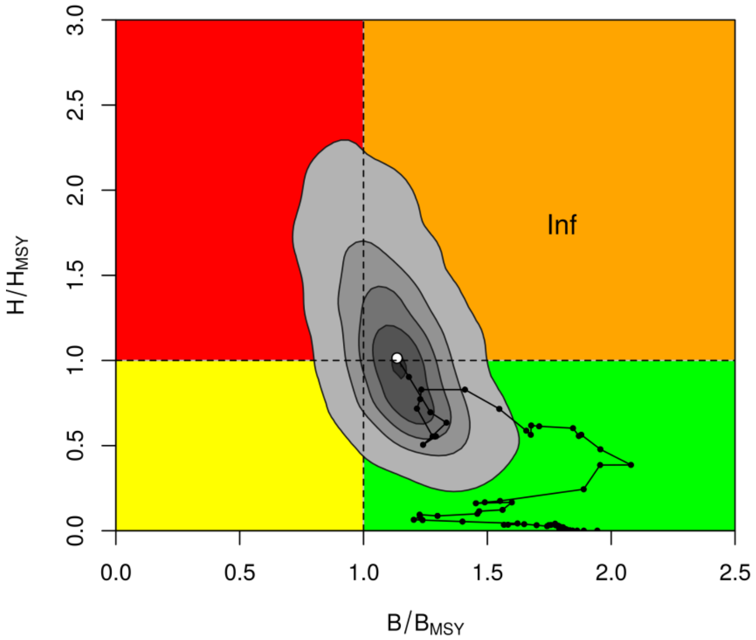


Figure 10 – Contour plots of posteriors of H/H_{MSY} and B/B_{MSY} as calculated using Fox type model and informative prior. Solid line and filled circles stand for the trajectories of marginal medians.

A summary of the estimations of quantities of interest for management is in Table 1. The catch of the last year of the time series (2015) was higher than MSY, while the median of F/F_{MSY} ratio was higher than 1, which indicate that in the recent years the fishery is driving to stock to a “subject to overfishing” scenario. However the biomass in 2015 was probably still higher than the biomass at MSY.

Table 1 – Summary of quantities of interest for management.

Management.Quantity	Aggregate.Indian.Ocean
2015 catch estimate	39668.83
Mean catch from 2011-2015	31469.22
MSY (80% CI)	34460.21(23473.95;53309.8)
Data period used in assessment	1950--2015
FMSY	0.12(0.08;0.18)
BMSY	302955.6(204604.58;394014.22)
Fcurrent/FMSY (80% CI)	1.01(0.61;1.64)
Bcurrent/BMSY (80% CI)	1.14(0.96;1.32)
Bcurrent/B0 (80% CI)	0.59(0.48;0.7)
BMSY/B0 (80% CI)	0.52(0.50;0.54)

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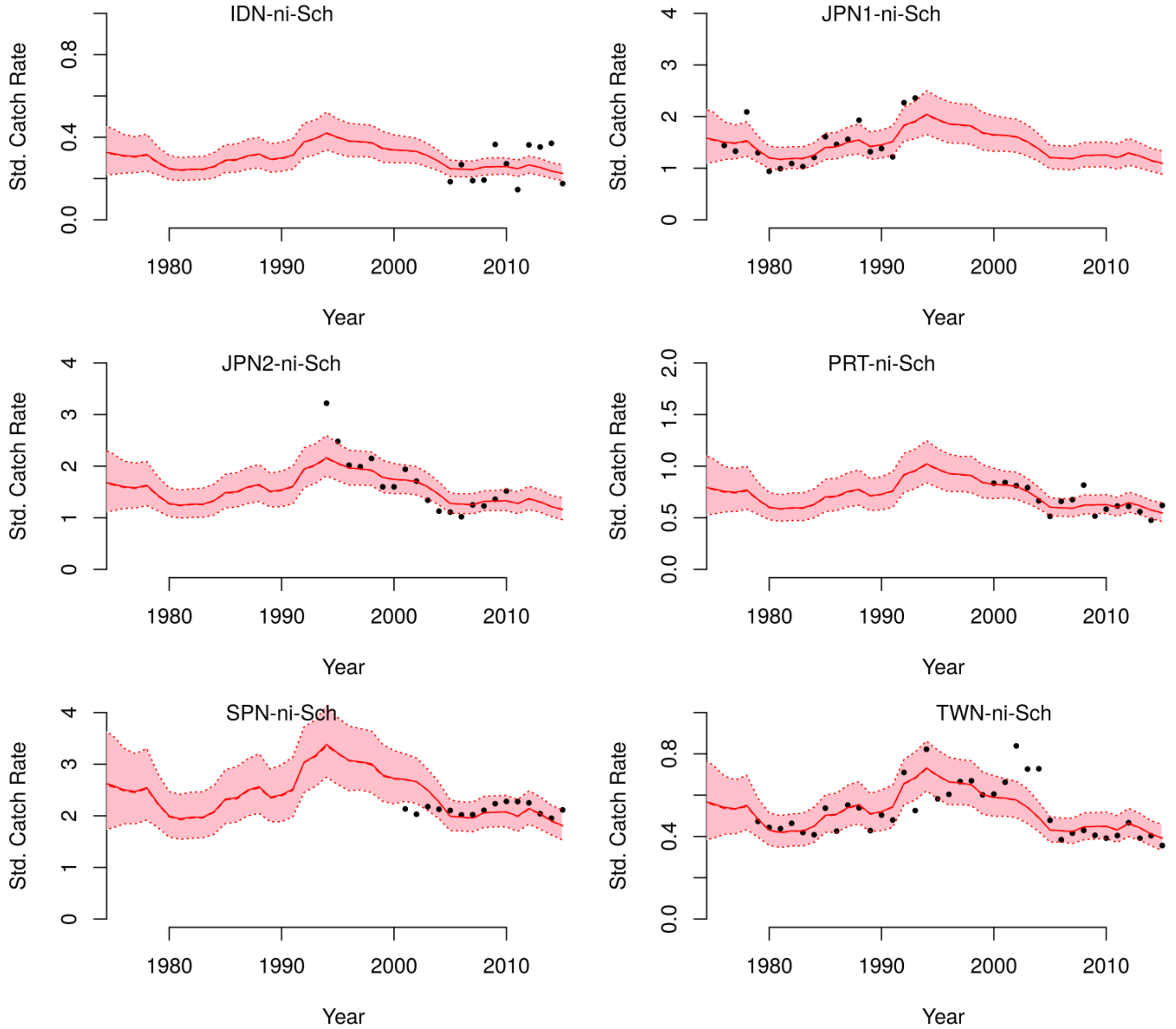
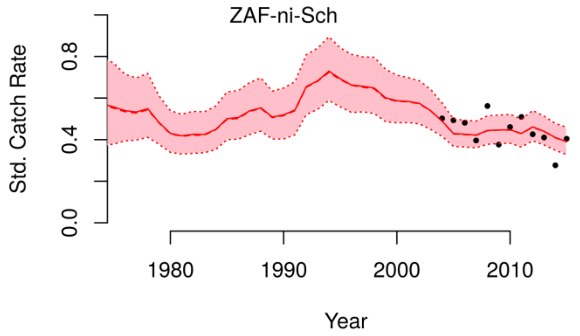
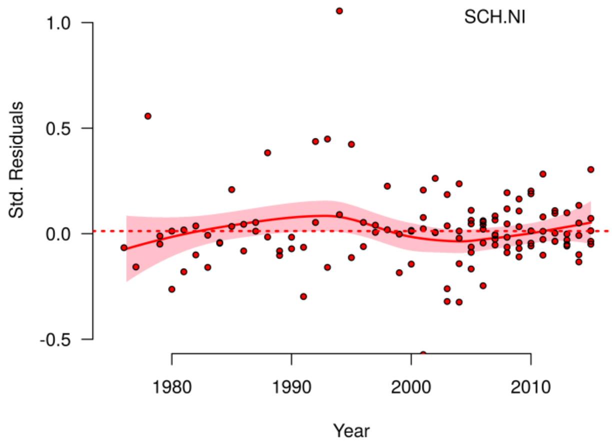
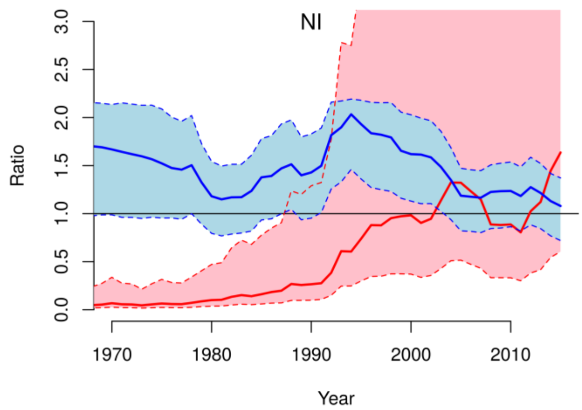
APPENDIX I

Schaefer Type – Non-Informative

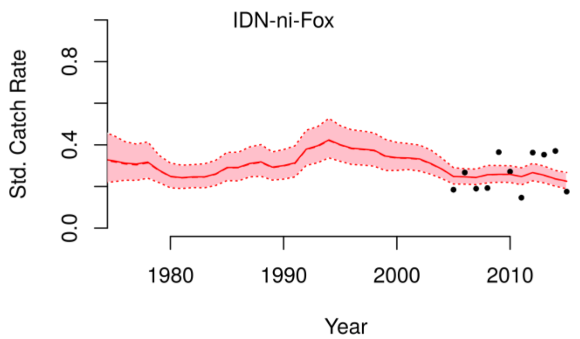


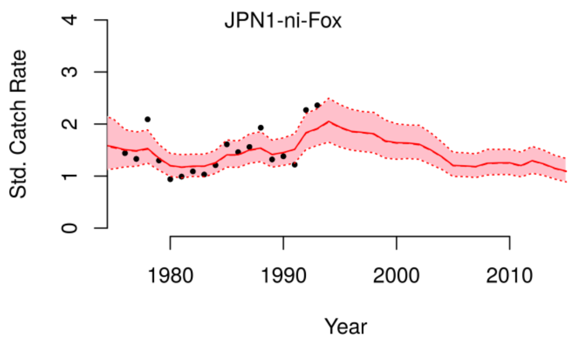


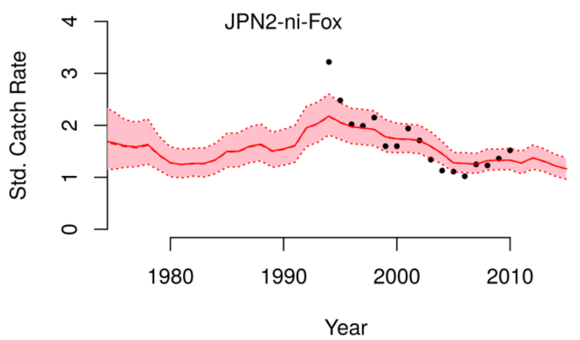


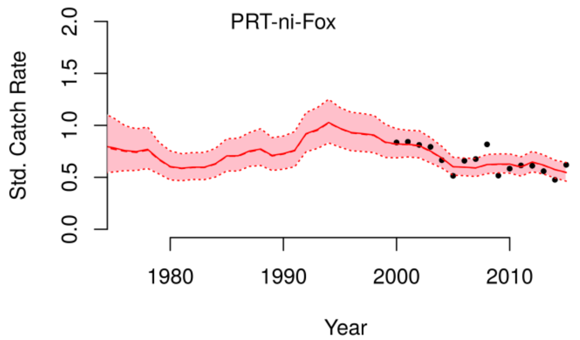


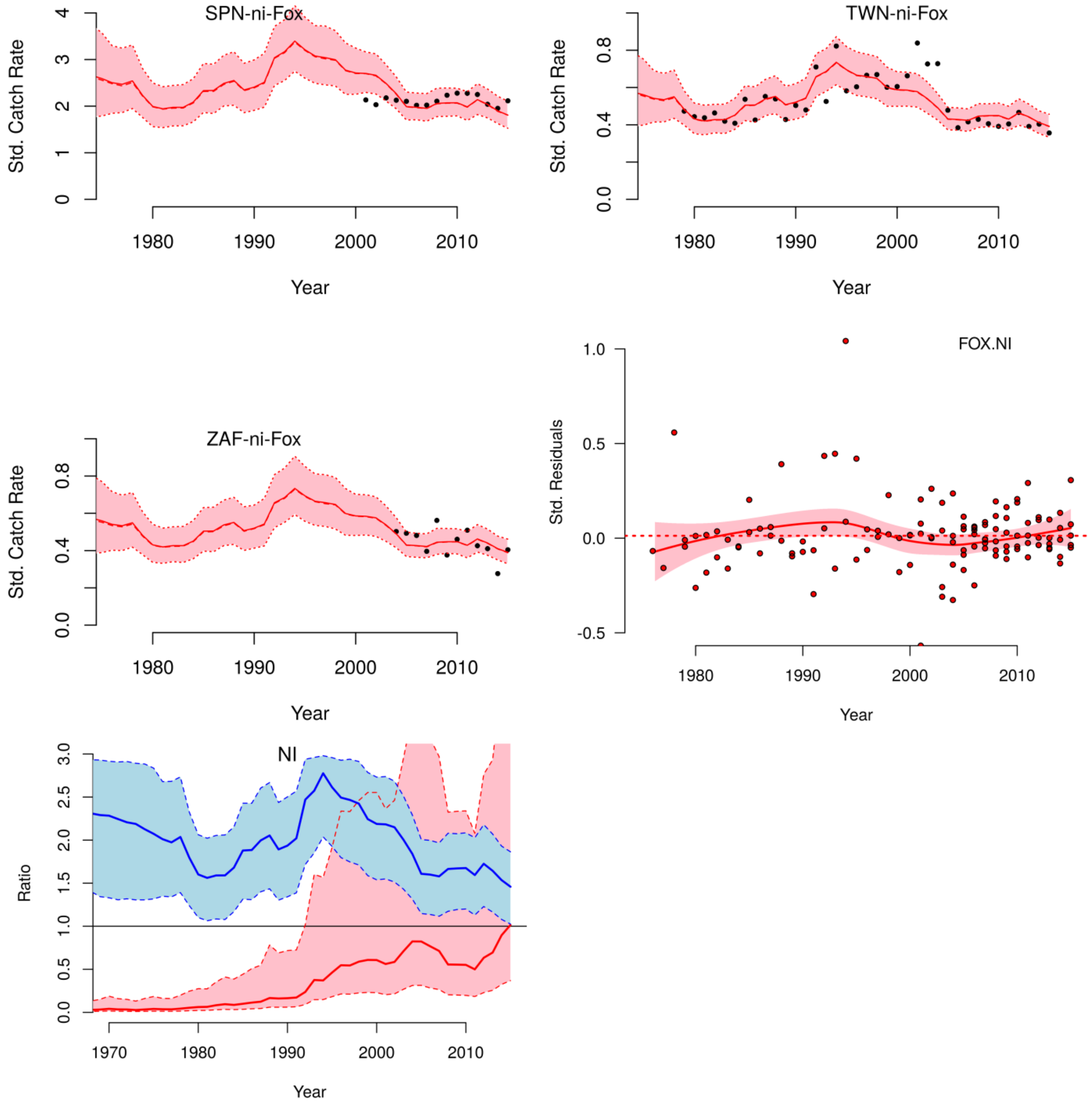
Fox Type – Non Informative Prior



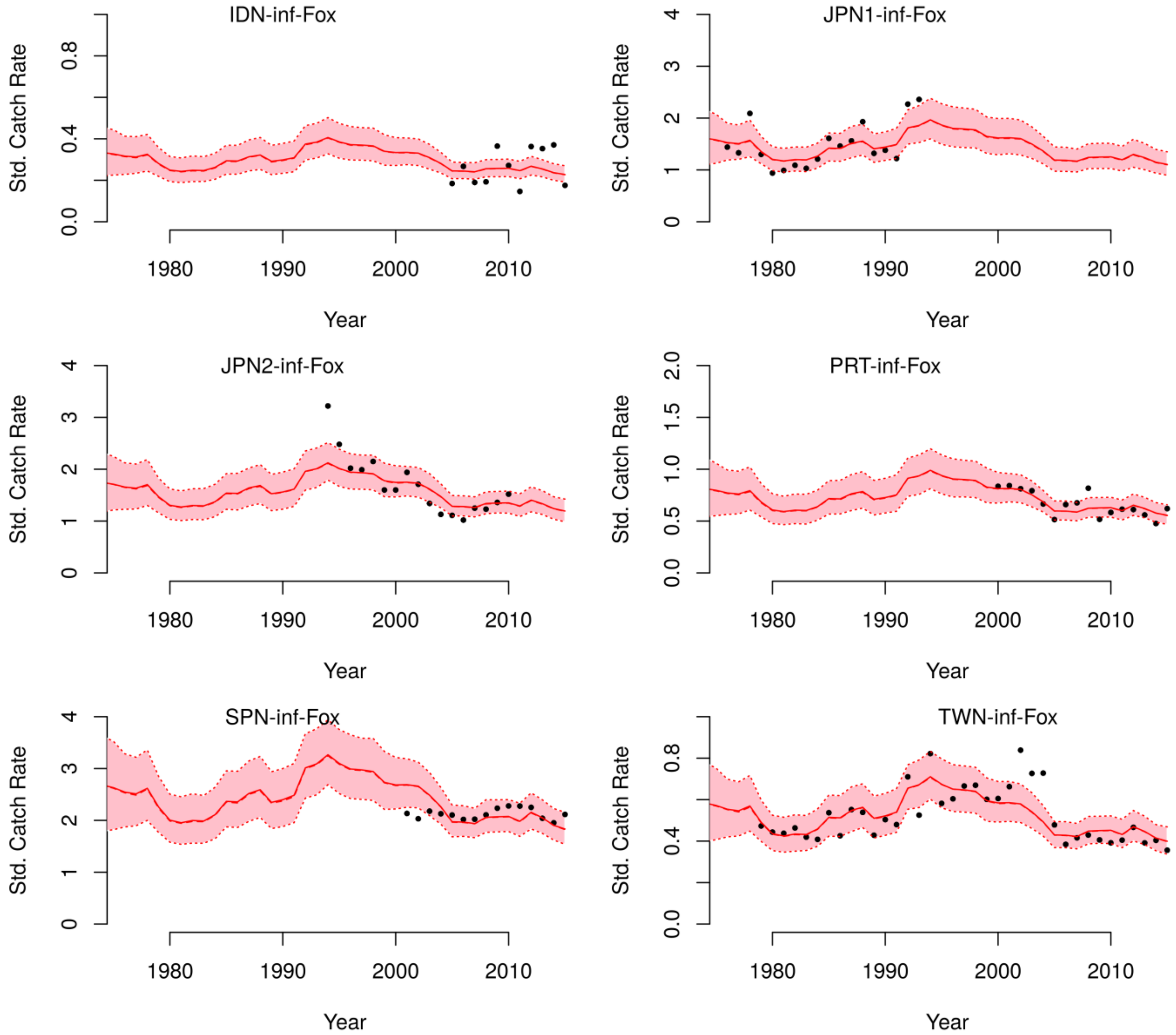


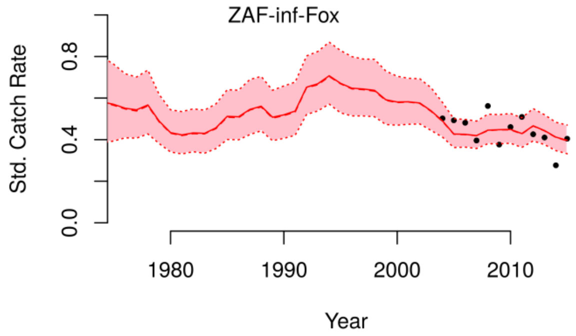


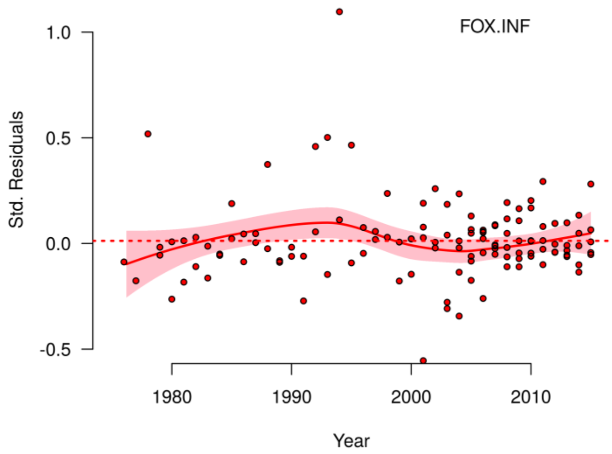


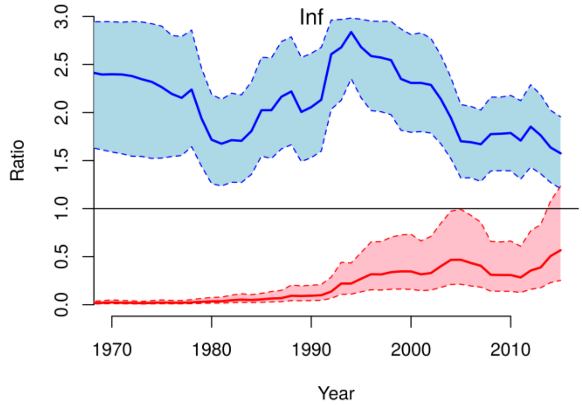


Fox – Informative Prior


IDN-inf-Fox
JPN1-inf-Fox
JPN2-inf-Fox
PRT-inf-Fox
SPN-inf-Fox
TWN-inf-Fox
Std. Catch Rate
Year
1980
1990
2000
2010


ZAF-inf-Fox
Std. Catch Rate
0.0
0.4
0.8
1980
1990
2000
2010
Year


FOX.INF
Std. Residuals
1.0
0.5
0.0
-0.5
1980
1990
2000
2010
Year


Inf
Ratio
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1970
1980
1990
2000
2010
Year