Stock assessment of striped marlin (*Tetrapturus audax*) 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 striped marlin (*Tetrapturus audax*) 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) of striped marlin caught by longline fleets in the Indian Ocean. Nominal catch rates of gillnet were also considered in exploratory runs. Catches and standardized CPUEs were conflictive in some parts of the time series. There are periods in which the CPUE indicated that there was a sharp decrease of biomass but the catches were not particularly high and was not showing an increasing trend. Uncertain is high as indicated by the wide posteriors of parameters. Data does not convey information about k. The preliminary estimations indicate that striped marlin stock has been overfished since 1990’s. Estimations of recent catches were lower than MSY but are still higher than the recent surplus production, hence the results concerning the status of the stock are pessimistic.

Introduction

Striped marlin (MLS) (*Tetrapturus audax*) been caught all in Indian Ocean by fleets which operate different types of gears. Catches of longline boats (fresh and ordinary longlines) were historically much higher than the catches of boats which operated with other gears. However, catches of gillnet boats have increased and in the recent the contribution of gillnet, fresh longline and ordinary longline were all similar.

Status of striped marlin has been “overfished” during recent years as indicated by analyses conducted in the past in the stock assessment meetings. Data and biological information concerning striped marlin are limited, hence simple models are one alternative for the stock assessment. Surplus production models demand only catch and relative abundance indices (or effort). Estimations of standardized CPUE of Japan and Taiwan longline fleets are available (Ijima, 2017; Wang 2017). In addition, estimations of nominal CPUE of the Iran, Pakistan and Taiwan were also available (Andrade, 2017 a). All the available catch and CPUE time series were considered in this paper to assess the striped marlin population of Indian Ocean using a state-space Bayesian production model (SBPM).

2. Data

Catches increased continuously from 1950 to the end of 1960’s, but oscillated very much since 1970’s (Figure 1 A). There were peaks and plunges across the years until 1993, followed by a decreasing trend until 2009. In the end of the time series catches increased and were similar to those of 1970’s. Estimations of nominal and standardized CPUE are in Figure 1 B. The CPUE time series of Japan 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). Only the second part of the CPUE series of Iran was considered following the suggestion of Andrade (2017 a). Only the second and the third part of Pakistan CPUE series which appear in Andrade (2017 a) were considered, like suggested by that author.

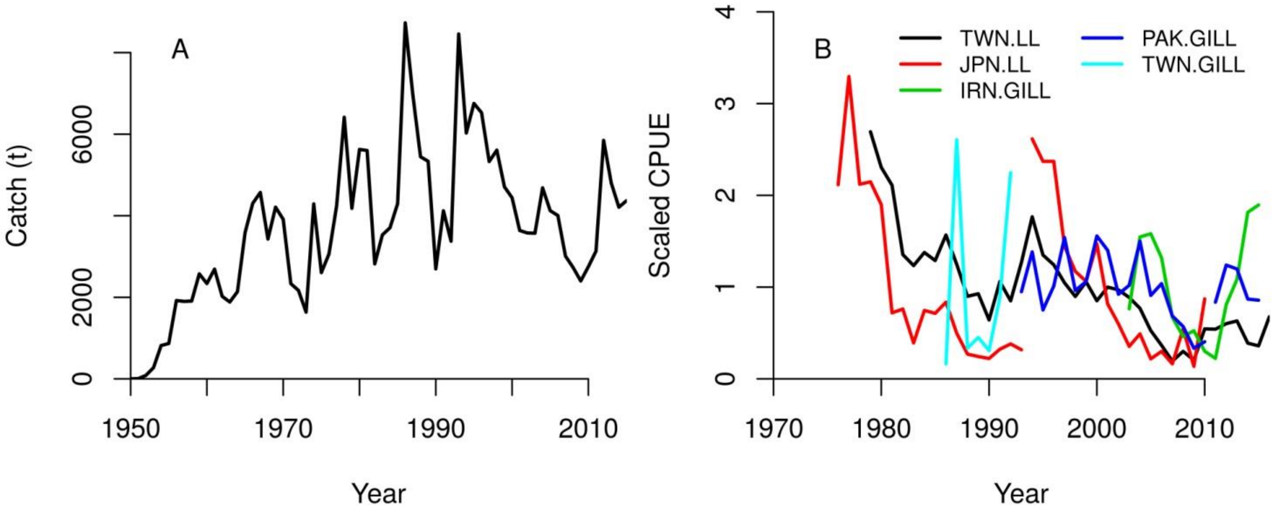

Figure 1 – Catches (A) and catch-per-unit-effort (CPUE) (B) of striped marlin of the Indian Ocean. TWN.LL – standardized CPUE of longline fleet of Taiwan; JPN.LL – standardized CPUE of longline fleet of Japan; IRN.GILL – nominal CPUE of gillnet fleet of Iran; PAK.GILL – nominal CPUE gillnet fleet of Pakistan; TWN.GILL – nominal CPUE of gillnet fleet of Taiwan. Values of CPUE were scaled by dividing them by the mean.

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 bycatch species caught in longline fisheries targeting tuna and tuna like species in Indian Ocean can be found in (Andrade, 2013 and 2014). However the model was adapted to allow using multiple CPUE time series as calculated based on different fleets. 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 $t = 1, \dots, N$ is the index for the year. The general biomass dynamic equation is:

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

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:

$$I_{tm} = q_m B_t \qquad (2)$$

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:

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

while the equations for the observations would be:

$$I_{tm}|P_t, q_m, \tau_m^2 = q_m k P_t e^{v_t} t = 2, \dots, N \quad (4)$$

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_m^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_m^2), the prior distribution of these parameters and of the states ($P_1, \dots, P_N$) is:

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

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:

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

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, 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 $q_1, \dots, q_m$. 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 $U(9000,20 \times$

9000). 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 $IG(3,0.003)$and $IG(0.3,0.03)$, respectively. The parameters of priors for the observational and process errors were selected after some exploratory analysis. Available information concerning r and also biological information were considered by Andrade (2017 b) to build a prior, which can be represented by a lognomal distribution with mean log(0.2) and 0.4 (CV~0.25). That was the informative prior used in this analysis for r. The priors for the other parameters in all the runs were the non-informative ones mentioned above. The set of priors which include the informative lognomal prior for r is denominated the "informative" (INF) prior hereafter. The set of priors which include the uniform density for r is denominated as the "non-informative" prior (NI).

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 were also assessed.

6. Results

Data and Model Selection

Distributions of frequencies, relationships and coefficients of correlations of available estimations of catches and catch rates available are showed in Figure 2. In general the correlations were low or positive. The exceptions were the correlations between the CPUE of Iran and the later series of Japan, and between CPUE of Iran and the later part of the CPUE of Pakistan.

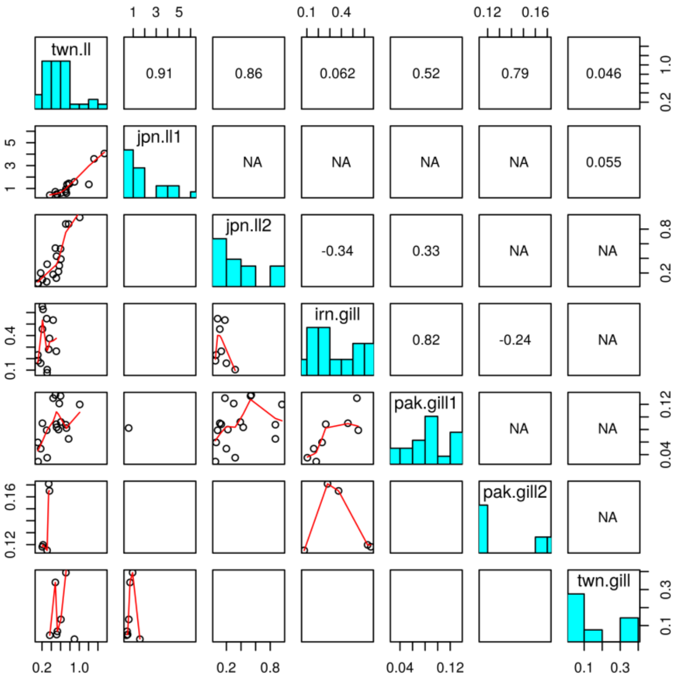

Figure 2 – Estimations of catch-per-unit-effort (CPUE). TWN.LL – standardized CPUE of longline fleet of Taiwan; JPN.LL – standardized CPUE of longline fleet of Japan; IRN.GILL – nominal CPUE of gillnet fleet of Iran; PAK.GILL – nominal CPUE gillnet fleet of Pakistan; TWN.GILL – nominal CPUE of gillnet fleet of Taiwan. Time series of Japan and of Pakistan were split into two parts.

An exploratory analysis was conducted taking into account all the CPUE series. A summary of the fittings, residuals, ratios between fishing mortality and fishing mortality at MSY (F/Fmsy) and between the biomass and the biomass at MSY (B/Bmsy) calculated in are in Appendix I. However, after the discussions the group decided to use only standardized CPUEs of longline fisheries in the stock assessment, hence hereafter, only these results are showed.

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.

Four models were fitted to the CPUEs selected for the analyses (TWN.LL, JPN.LL1, JPN.LL2) data, 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. Calculations of DIC were -40.993, -40.343, -42.487 and -42.870 for the SCH-NI, SCH-INF, FOX-NI and FOX-INF models respectively. The expectations of the standardized residuals were 0.1013311 (SCH-NI), 0.1000425 (SCH-INF), 0.09876091 (FOX-NI) and 0.09814457 (FOX-INF). Fox perfomed better than Schaeffer type model. In addition the group decided to use the informative prior which reflect biological information. Therefore hereafter only the results of the FOX-INF model runs are showed. A summary of the fittings of the other three models (SCH-NI, SCH-INF and FOX-NI) are in Appendix II.

Fittings

Fittings of the Fox model with informative prior to the IOTC catch time series and to the three longline CPUE series are in Figure 3. State-space models are very flexible because there are many parameters (i.e. $r, k, q_1, \dots, q_m, p_1, \dots, p_N, \tau^2, \sigma^2$). However, if the catch rates are conflictive, some of them may have more influence. Hence, in spite of the flexibility of the model, quality of the fittings may be not that good for the less influential and/or the shorter time series. In this sense the model fits better to the Taiwan time series than to the two series of Japan. Model fittings showed a sharp decreasing trend in the end of 1970's and in the beginning of 1980's, which was driven by the values of the beginnings of the Taiwan and of the first part of the Japan series. In the end of 1980's there was another decrease in the fittings, followed by and increasing trend until 1994. The fittings showed another decreasing trend from the mid 1990's until the end of 2000's. There was some fluctuatins from 2009 to 2015, but the fittings do not show a clear time trend (decrease or increase).

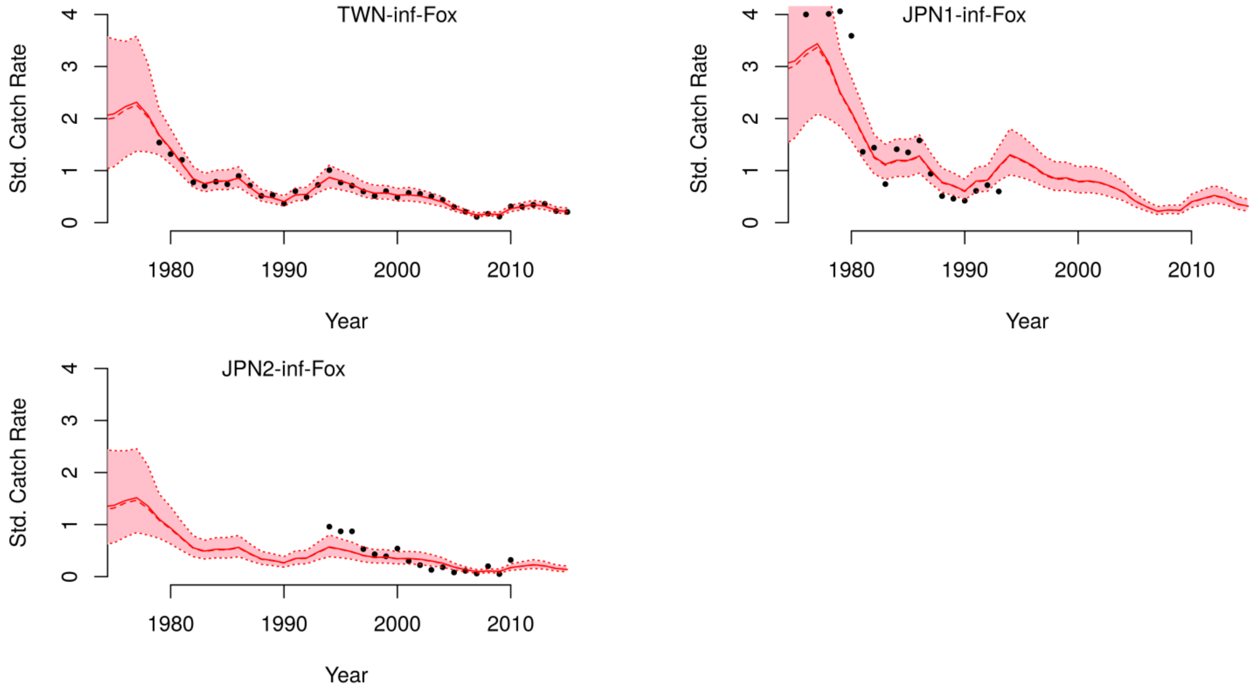

Figure 3 - Model fittings to the estimation of catch as reported in IOTC database and to the three catch time series: Taiwan (TWN), Japan – first part (JPN1), and Japan – second part (JPN2).

Residuals are shown in Figure 4. Overall there were no biases for the Taiwan (TWN) series after mid 1980's. However, the model overestimate the beginning of the time series. The fittings to the first part of the Japanese series (JPN1) were also not good for the beginning of the time series. However, the model underestimate the CPUEs, which reflect a compromise between the values of TWN and JPN1. Both CPUE series showed a decreasing trend until the beginning of 1980's, but the decrease of CPUE are stronger in JPN1 than in TWN series. The model fitting to the later Japanese series (JPN2) is not good, in the sense the model underestimate the CPUE in the mid 1990's and in the mid 2000's. However, the model fittings reflect overall time trend of the JPN2 series grossly.

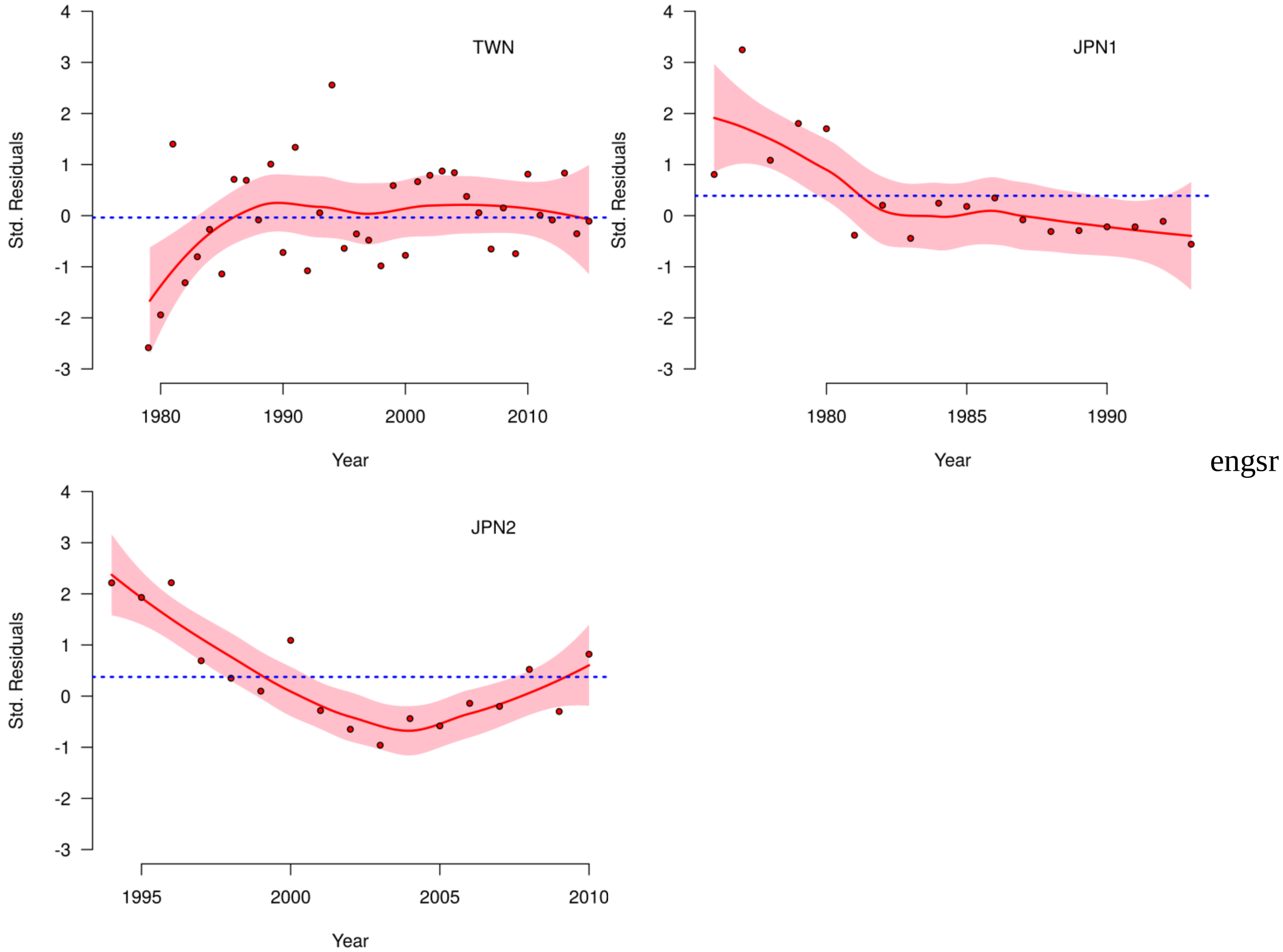

Figure 4 – Standardized residuals of the model fittings to the three catch time series: Taiwan (TWN), Japan – first part (JPN1), and Japan – second part (JPN2).

Overall residuals are shown in Figure 5. In general the model fits well the data after mid 1980's. However the fittings are biased in the beginning of the time series driven mostly by the sharp decreasing trend of the TWN and JPN1 series in a period in each the catches were not particularly very high.

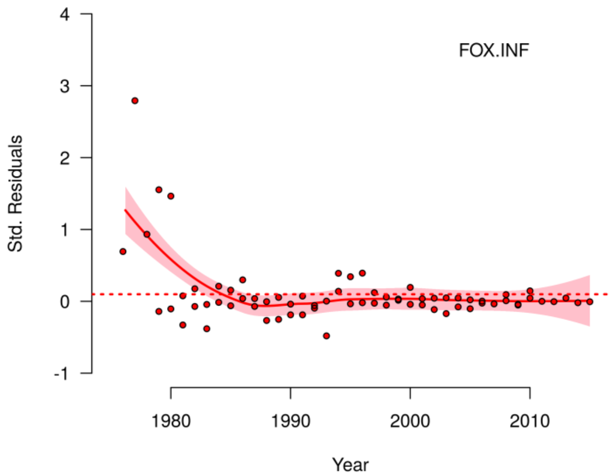

Figure 5 – Standardized residuals of the model fittings to the three catch time series: Taiwan (TWN), Japan – first part (JPN1), and Japan – second part (JPN2).

Posteriors of parameters

Priors and posteriors of r and k parameters are showed in Figure 6. The solutions of calculations conducted with the non-informative prior are showed together with those calculated with the informative prior to make easier to assess the effect of the informative prior. Notice that mod of the posterior of r calculated with the informative prior is higher than that calculated with the non-informative prior. The precision of the posterior of r with informative prior is higher than that of the non-informative prior. Data are not informative about k hence prior was flat as calculated with the non-informative prior of r. When using the informative prior of r the precision of the posterior of k increase, but the posterior is still wide. Notice also that the posteriors were bounded by the upper limit of the prior for k (20 x max(catch)). Some addition runs were conducted increasing the upper limit (e.g. 40 x max(catch)). However the right tail of the posteriors of k are heavy and were still bounded (to a less extent) by the upper limit.

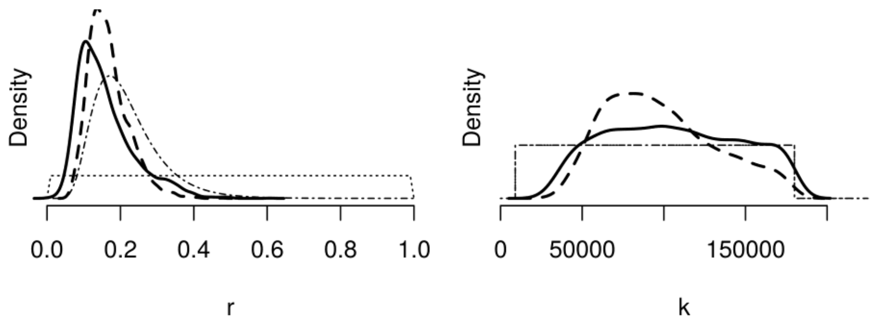

Figure 6 – Priors (thin lines) and posteriors (thick) lines of the parameters calculated with the informative and non informative priors for r. The thick solid lines stand for the posterior calculated with the non-informative prior, while the thick dashed lines stand for the posterior calculated with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

Density of benchmarks

Densities distributions of benchmarks are showed in Figure 7. Densities of Bmsy reflect the posteriors of k, in the sense they are flat because data are not informative about k. Densities distributions of Ymsy as calculated using non-informative and informative priors were similar and gave more weights to values close to 5,000 t. Posterior of the harvest ratio (Hmsy=Ymsy/Bmsy) as calculated using informative prior was shifted to the left in comparison to that calculated using non-informative prior.

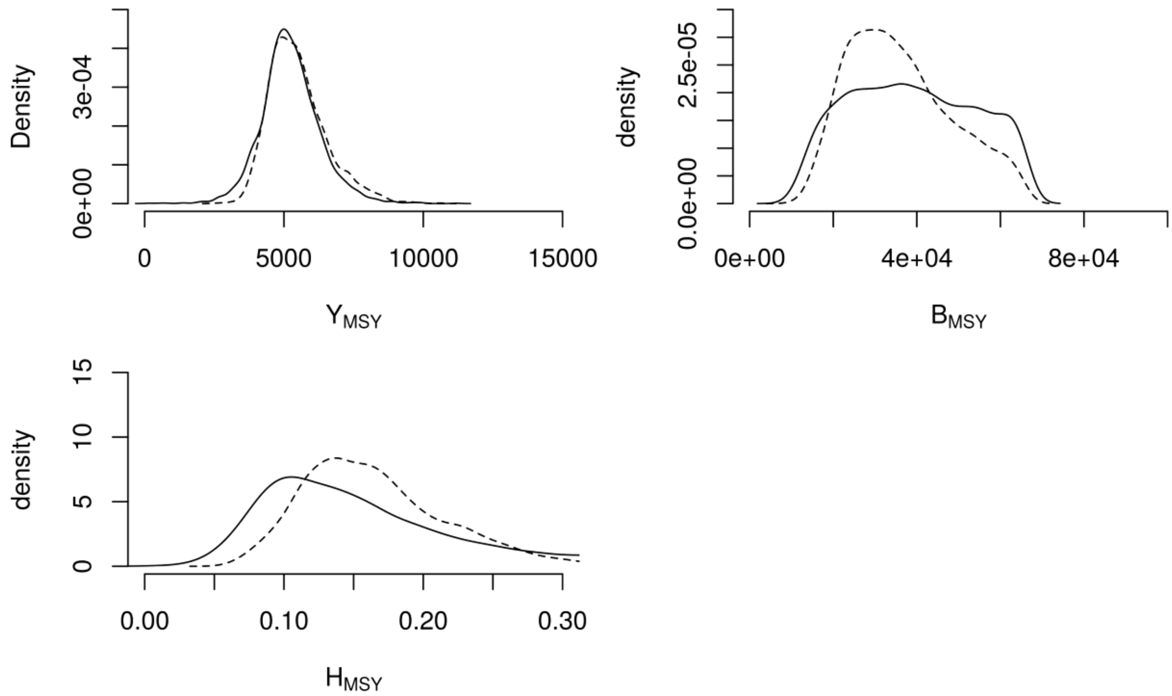

Figure 7 – Densities distributions of benchmarks related to MSY, Yield (Y), biomass (B) and harvest (Hmsy=Ymsy/Bmsy). Solid lines stand for results calculated using non-informative prior of r, while the dashed lines stand for the calculations using informative prior.

Joint posteriors and correlations

Contour plots, marginal distributions and correlations of posteriors of parameters and of Y_{MSY} as calculated are in Figure 8. Contourplot of r and k shows a "banana" shape with negative correlation which is typical when using this kind of production models. Correlations among qs were positive which was expected given because of the similar scales of the available standardized CPUE series. Overall the higher correlations were found among r, k and q, while correlations with and among τ^2 and σ^2 were low. Correlations between Y_{MSY} and the parameters were in general low.

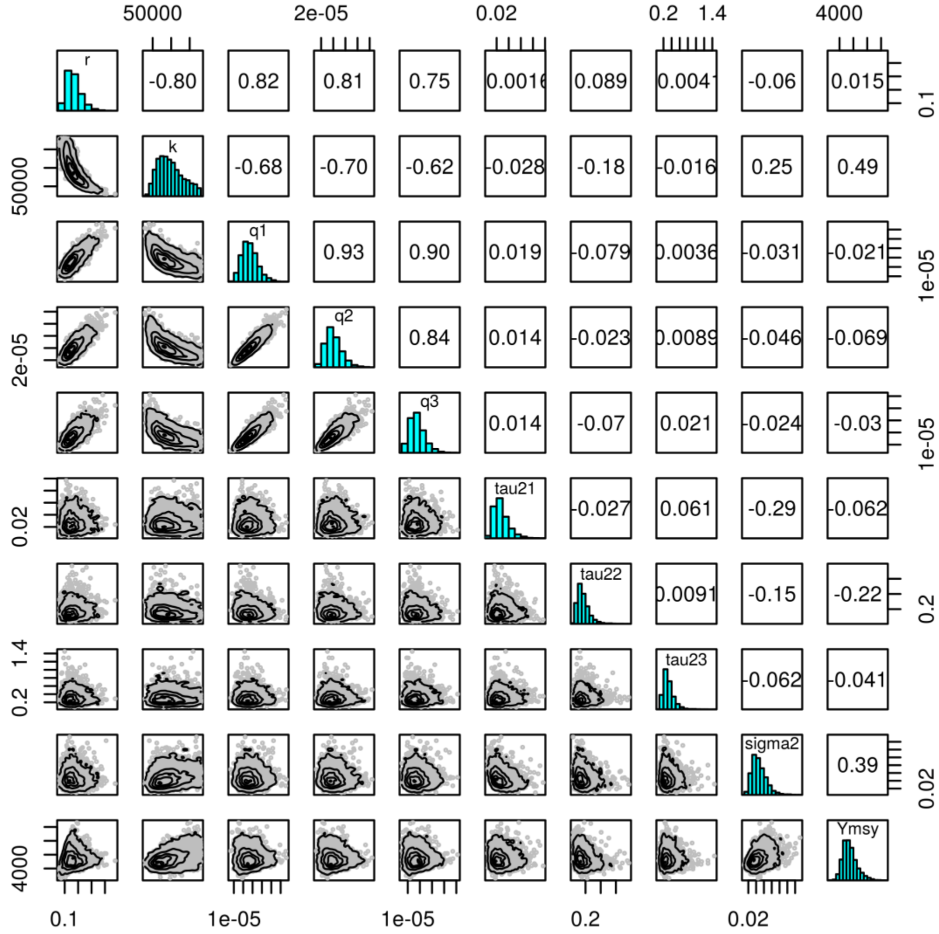

Figure 8 – Marginal and joint posterior distributions of parameters and of yield at MSY as calculated using informative prior and Fox type production model.

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 particularly wide before the end onf 1970's because there are not estimations of standardized CPUE for the beginning of the time series. Notice model fittings suggest that biomass would be very large in 1976 and then there was an sharp decrease. This pattern reflect mainly the standardized CPUE values in the beginning of the Japan time series. Median of biomass was already below 1 in the beginning of 1980's. There were oscillations since then, but overall the biomass has decreased in the last decades. The H/H_{MSY} ratio did not change much in the beginning of the time series, but it increased fast after 1976 and it surpass 1 in 1986 after a jump driven by the first peak of catch. There were fluctuations of H/H_{MSY} ratio from mid 1980's until the beginning of 2000's, followed by a peak. In general H/H_{MSY} ratio was higher than 1.5 in the last fifteen years of the time series.

The trajectory of the median of B/B_{MSY} ratio cross to values lower than 1 in 1983-1984, while the median of H/H_{MSY} ratio overpass 1 later in 1986. When the model account only for observational error this pattern will never appears, because all the decreasing trend of CPUE should be driven by catches. In the observational error only models the median of H/H_{MSY} surpass 1 before the median of B/B_{MSY} drops to values lower than 1. When the model includes observational and process errors it is assumed that changes in the trajectory of B/B_{MSY} may be driven by harvest but also but natural process which is not clearly described in simple formulation of the production model (e.g. failure of recruitment). The sharp decreasing trend of standardized CPUE of Taiwan and Japan in the end of 1970's can not be explained by harvest only because the catches in the beginning of the time series were not particularly high and were not showing an outstanding increasing trend. Hence, the causes of the outstanding decreasing trend of CPUE in the beginning of the fisheries only can be explained by process phenomena. This is why the median of B/B_{MSY} ratio crossed to values lower than 1 before the median of H/H_{MSY} ratio overpass 1.

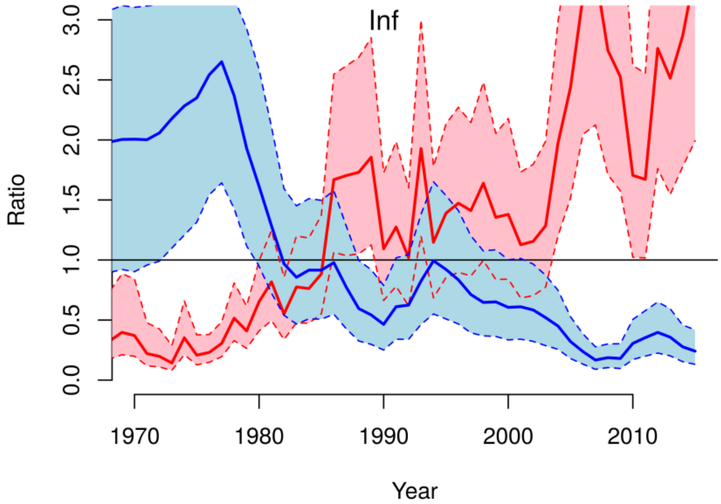

Figure 9 – Ratios between biomass in each year and harvest at MSY (B/B_{MSY}) (bluish colors) and between harvest and harvest at MSY (H/H_{MSY}) (reddish colors), as calculated using Fox type model and informative prior for r. Shaded polygons and dotted lines stand for the credibility intervals (95%),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

Kobe plot calculated using Fox model and informative prior is showed in Figure 10. Estimations of joint posterior of B/B_{MSY} and $/H_{MSY}$ were pessimistic in the sense most the posterior sample is inside the red zone which indicates that the stock was overfish ($B < B_{MSY}$) and was subject to overfishing ($H > H_{MSY}$) in 2015. Furthermore the trajectory of marginal medians of B/B_{MSY} and H/H_{MSY} indicates that the stock has been overfished during the last two decades. Notice also that the trajectory of marginal medians of B/B_{MSY} and of H/H_{MSY} cross to yellow zone and then to the red zone, which is not typical. Usually the trajectory of ratios (B/B_{MSY} and H/H_{MSY}) cross to orange zone and then to the red zone. The particular pattern found in this analyses of striped marlin was a consequence of the sharp decreasing trend of CPUEs in the end of 1970's which can not be explained by the catches (see comment above concerning Figure 8).

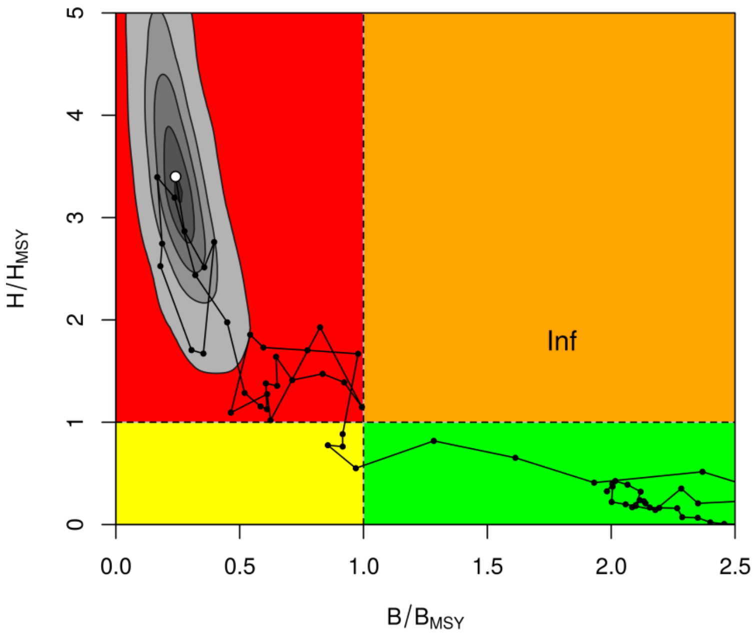

Figure 10 – Contour plotsof posteriors of H/H_{MSY} and B/B_{MSY} calculated based on the IOTC estimations of catches. Solid lines and filled circles stand for the trajectories of marginal medians. NI – non-informative prior; Inf – Informative prior.

A summary of the estimations of quantities of interest for management is in Table 1. Despite recent catches were lower than MSY, biomass in 2015 was well below the BMSY. In addition, fishing mortality was much higher than FMSY in 2015. Overall results indicate that the stock was overfished and will remain overfished unless the catches are reduced to very low values.

Table 1 – Summary of quantities of interest for management.

Management.Quantity	Aggregate.Indian.Ocean
2015 catch estimate	4368.56
Mean catch from 2011-2015	4472.02
MSY (80% CI)	5352.05(4330.28;6890.99)
Data period used in assessment	1950--2015
FMSY	0.16(0.11;0.24)
BMSY	34293.89(21441.52;54730.37)
Fcurrent/FMSY (80% CI)	3.4(2.45;4.75)
Bcurrent/BMSY (80% CI)	0.24(0.16;0.35)
Bcurrent/B0 (80% CI)	0.09(0.06;0.13)
BMSY/B0 (80% CI)	0.37(0.36;0.38)

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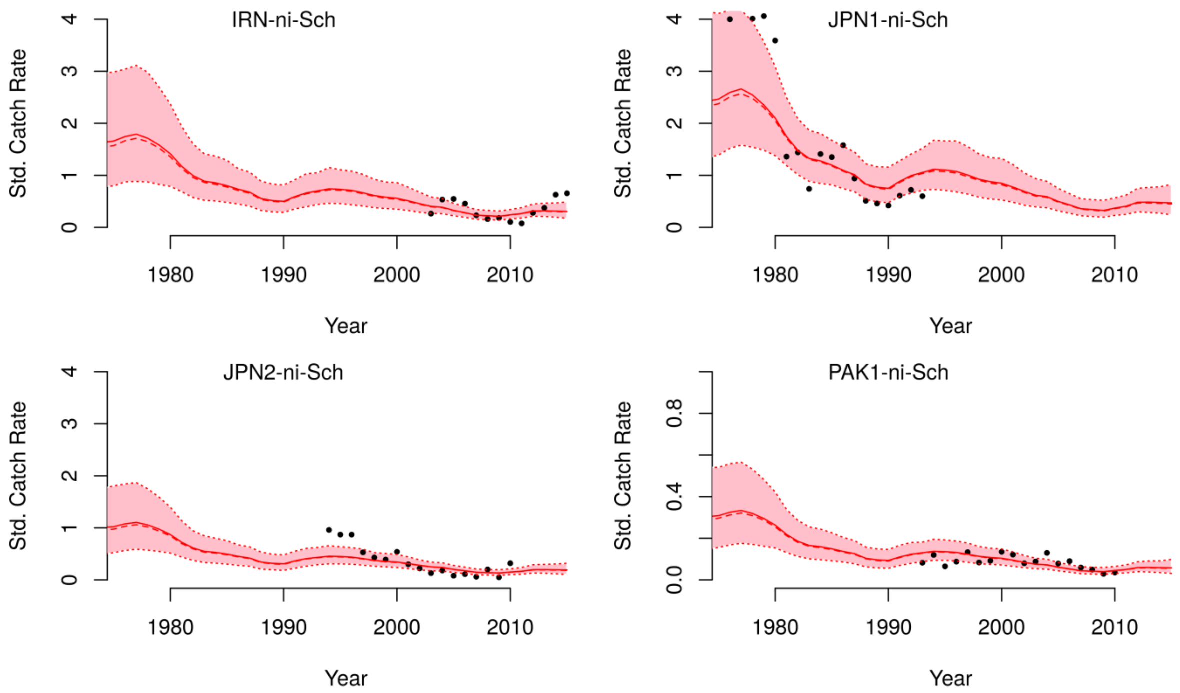
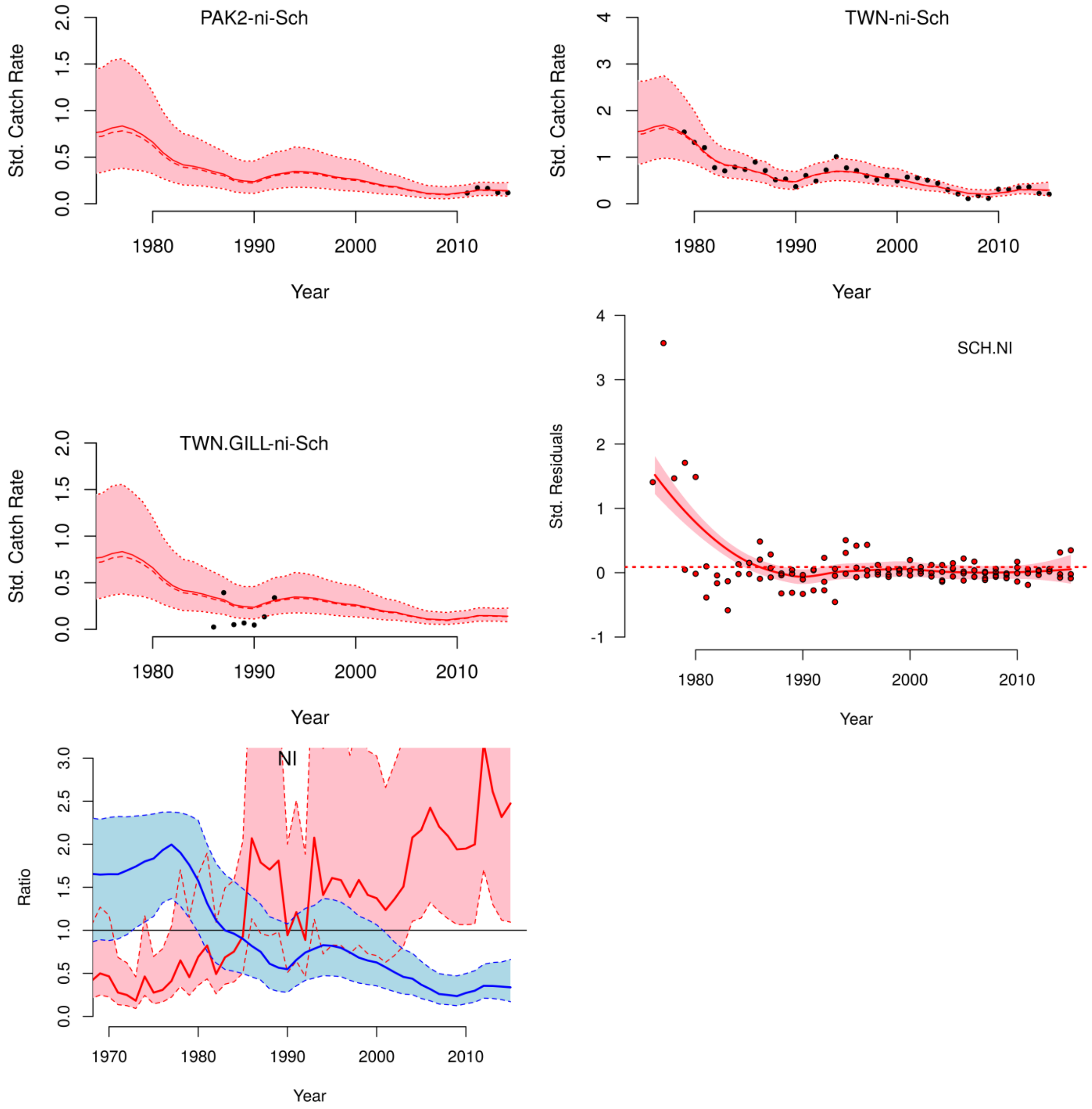
APPENDIX I

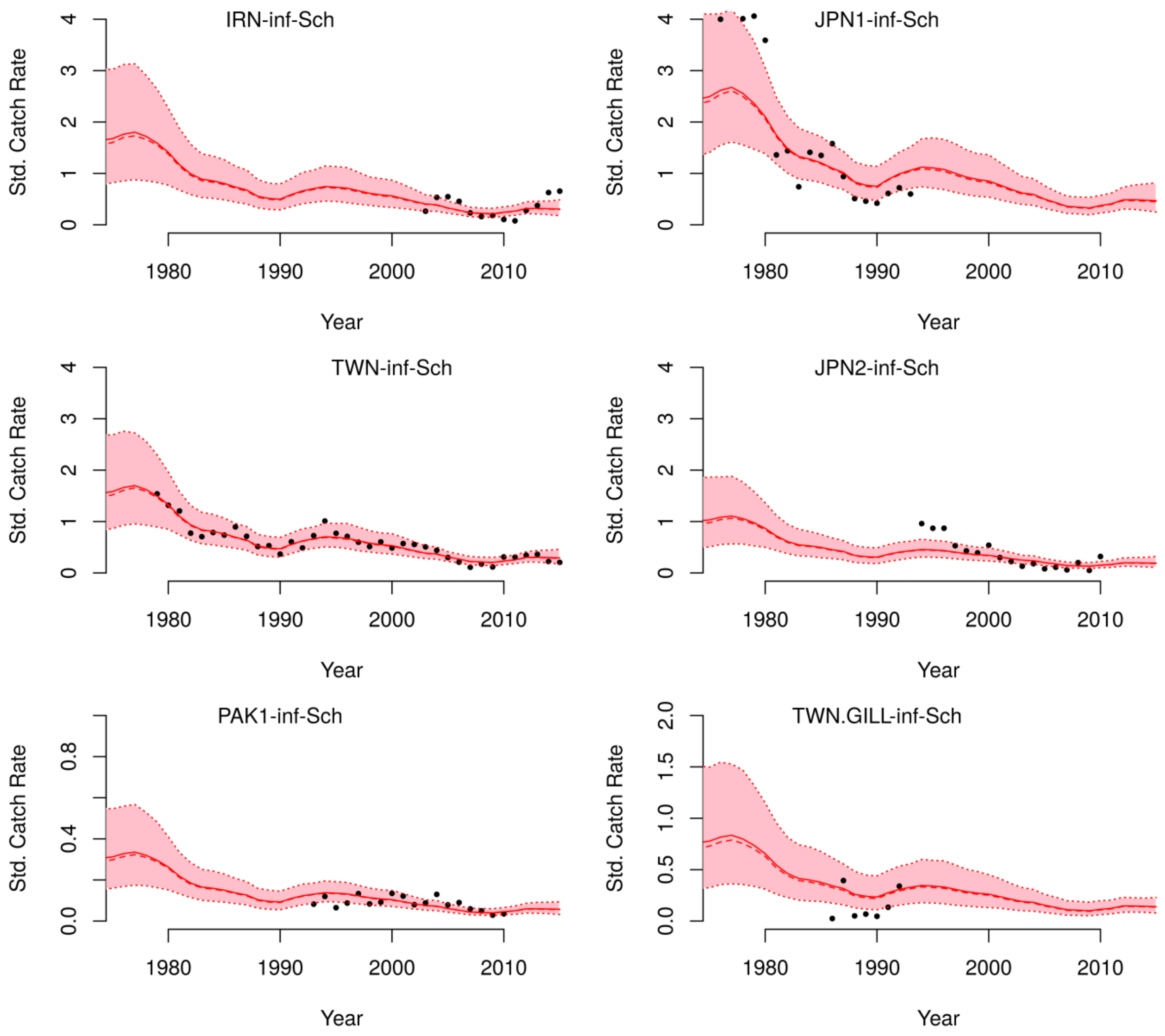
Exploratory Analysis

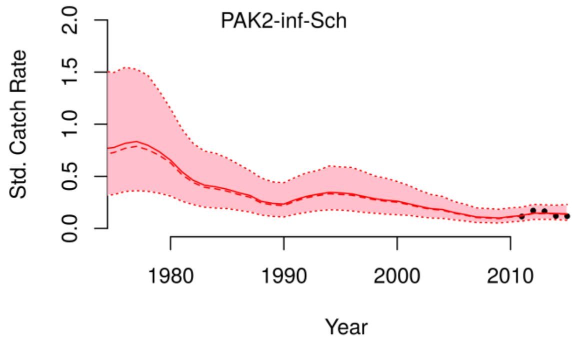
Schaefer Type – Non Informative Prior

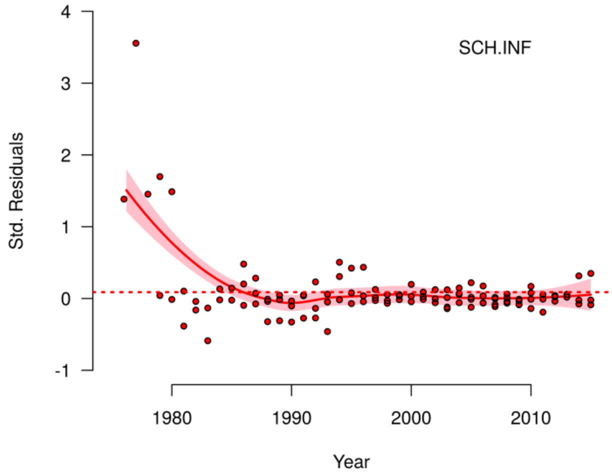


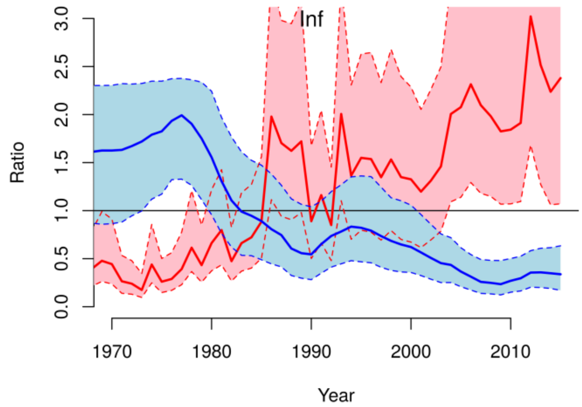


Schaefer Type – Informative Prior

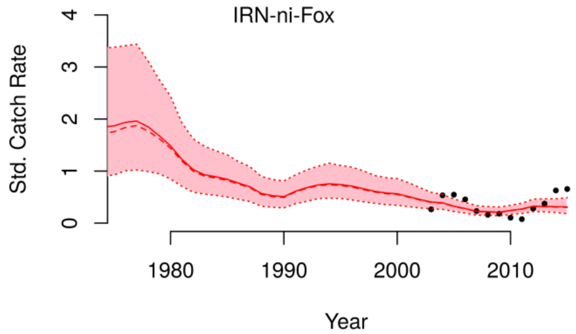

IRN-inf-Sch
JPN1-inf-Sch
TWN-inf-Sch
JPN2-inf-Sch
PAK1-inf-Sch
TWN.GILL-inf-Sch
Std. Catch Rate
Year
1980
1990
2000
2010

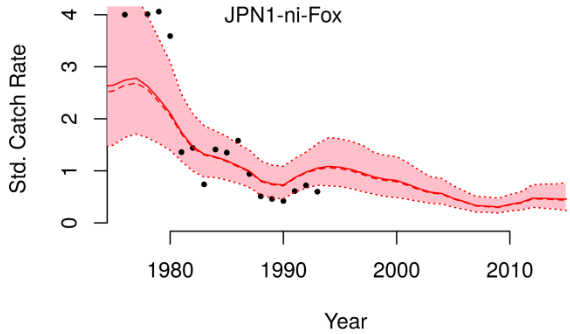


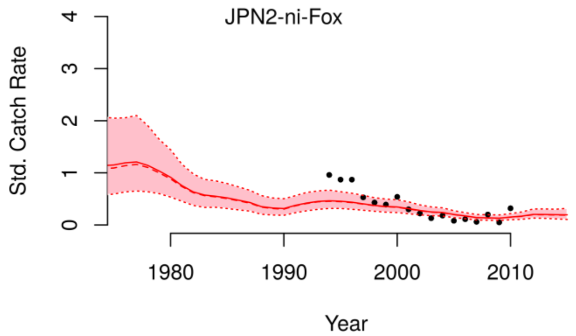


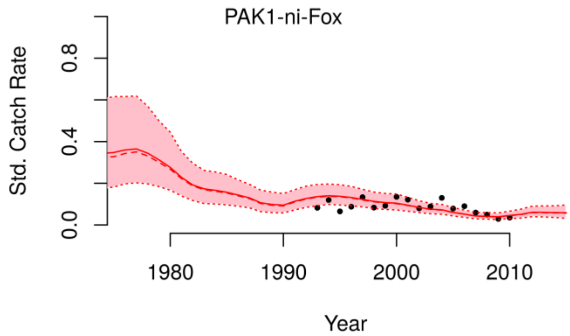


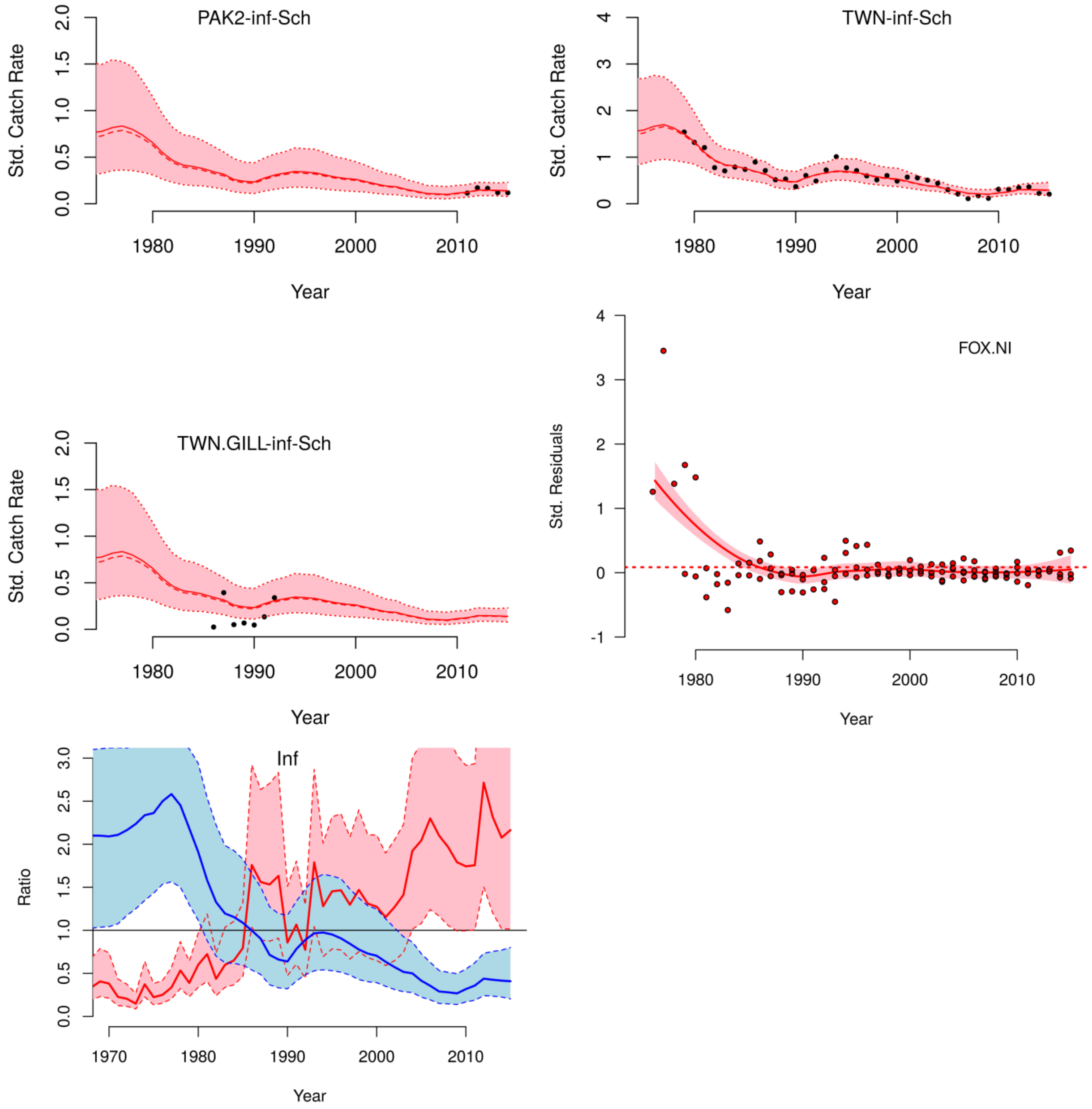
Fox Type – Non-Informative Prior



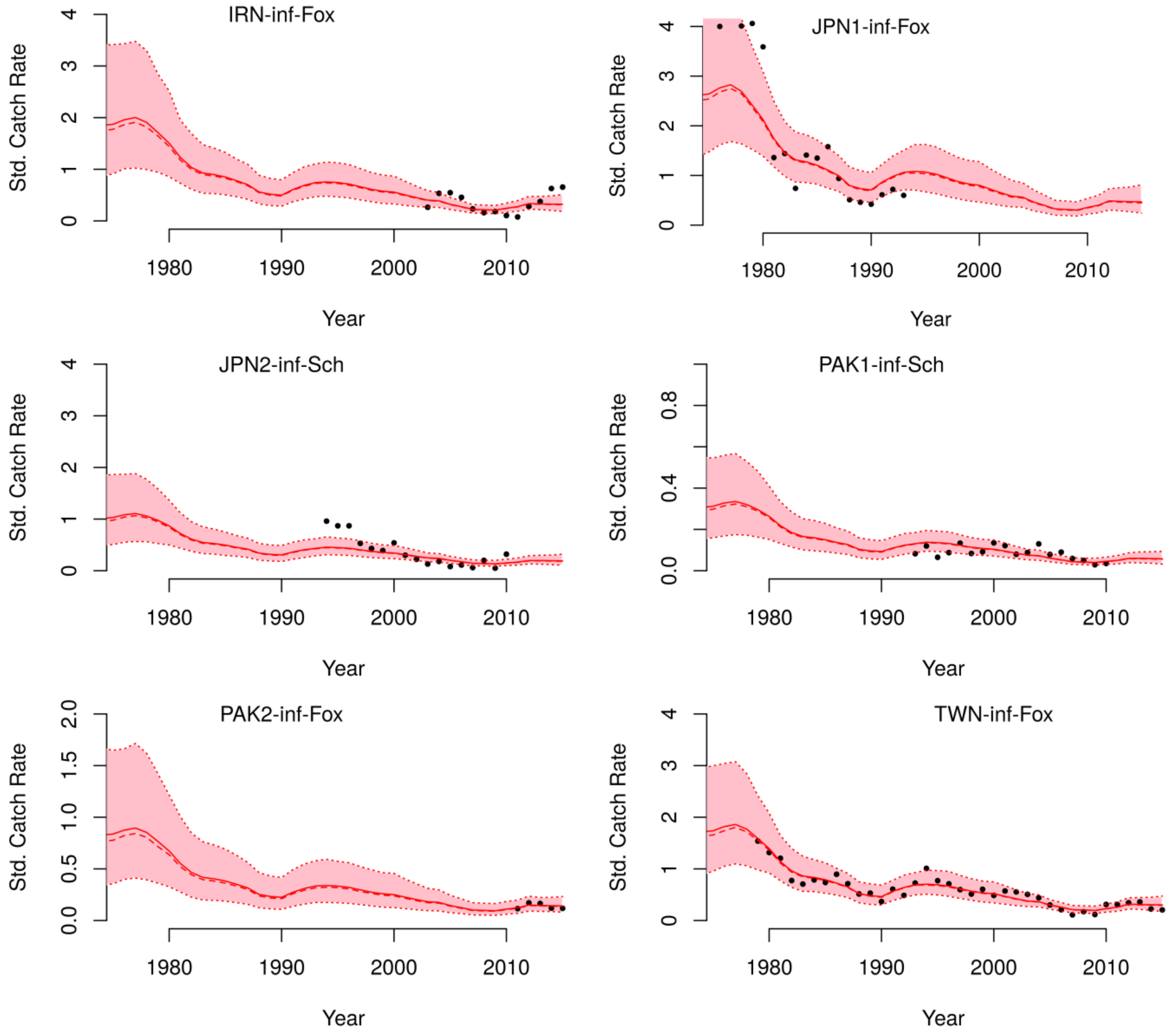


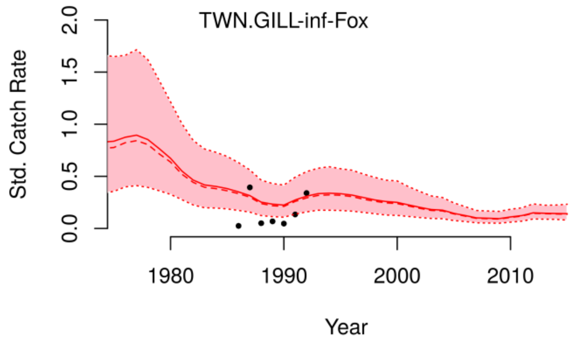


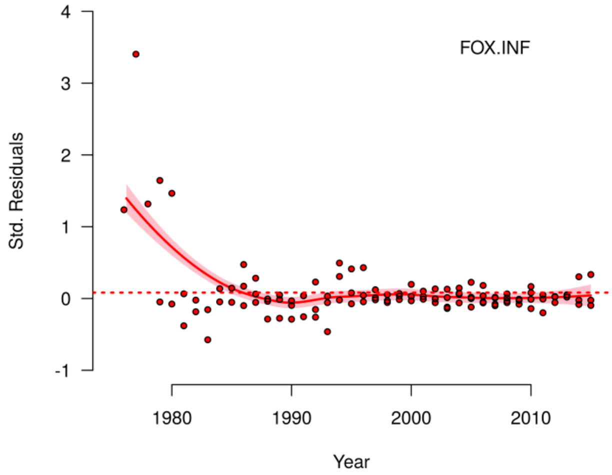


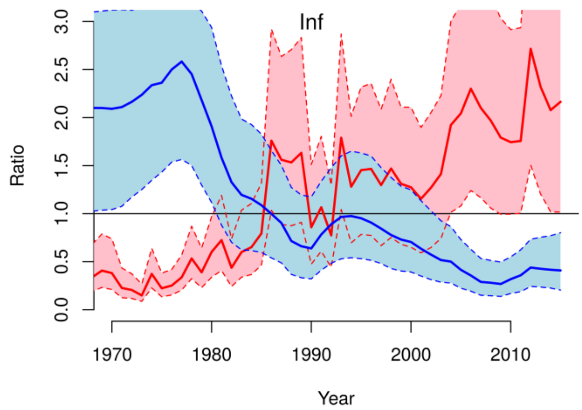


Fox Type – Informative Prior


IRN-inf-Fox
JPN1-inf-Fox
JPN2-inf-Sch
PAK1-inf-Sch
PAK2-inf-Fox
TWN-inf-Fox
Std. Catch Rate
Year
1980
1990
2000
2010

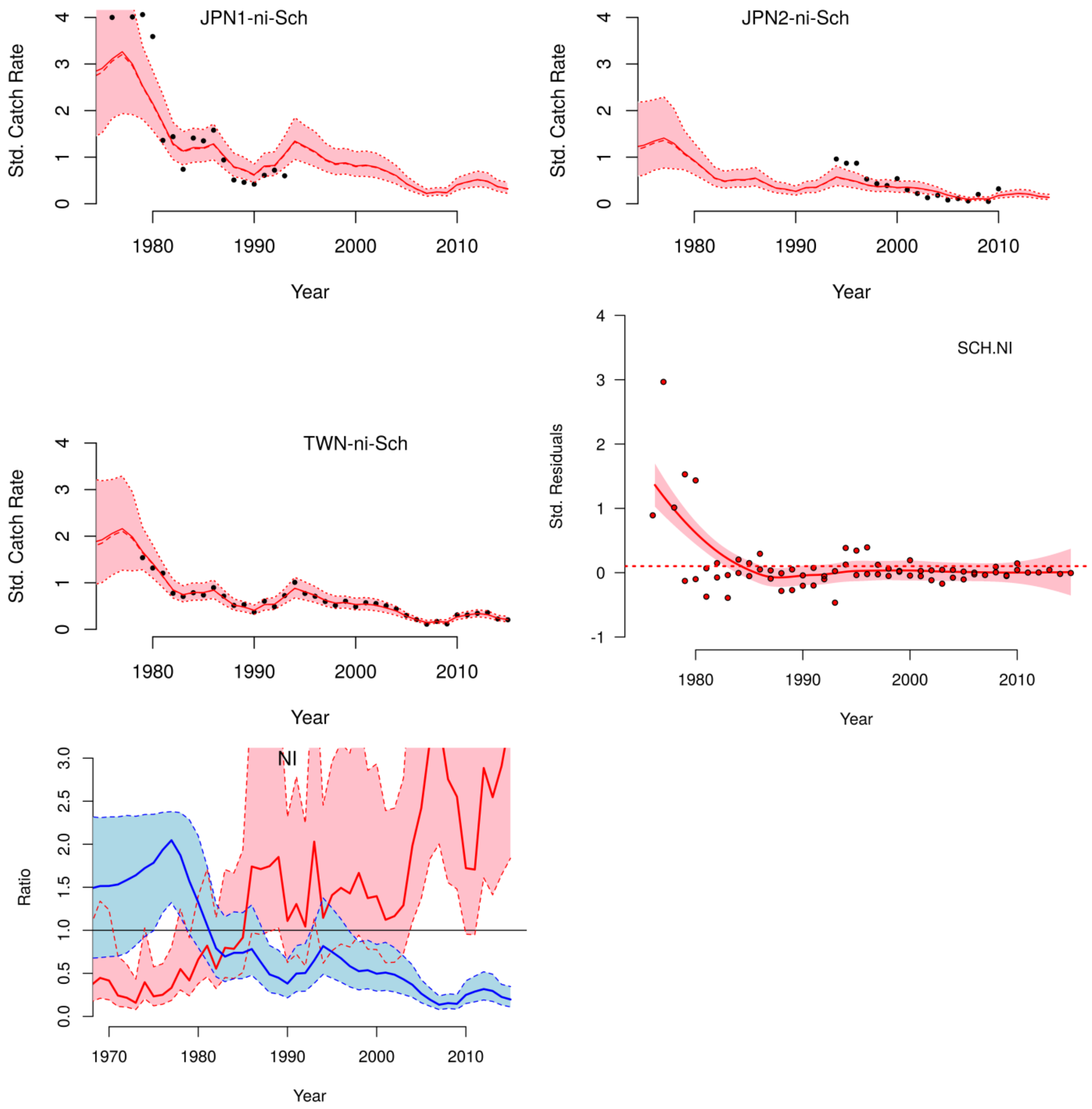




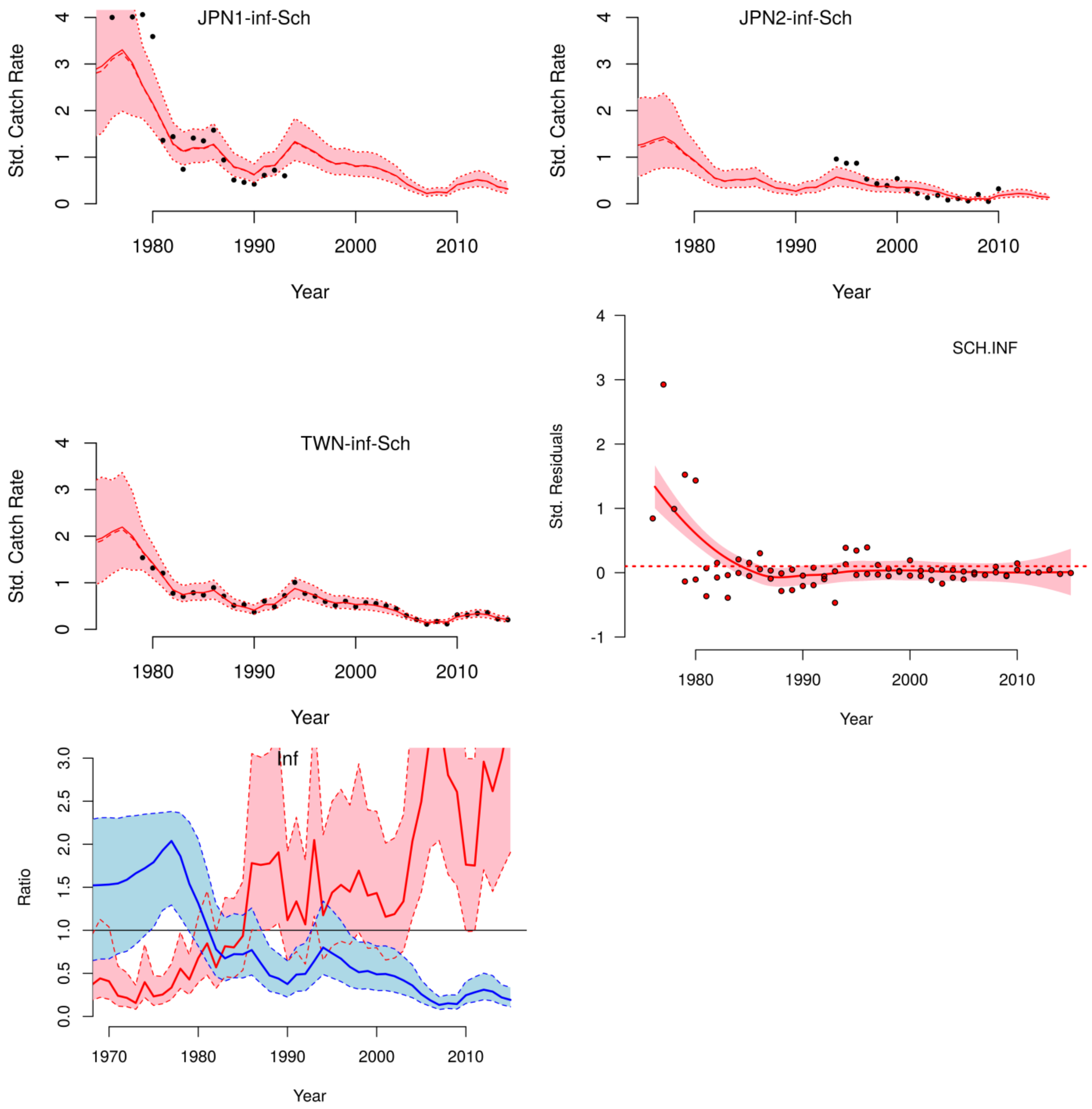


Apendix II

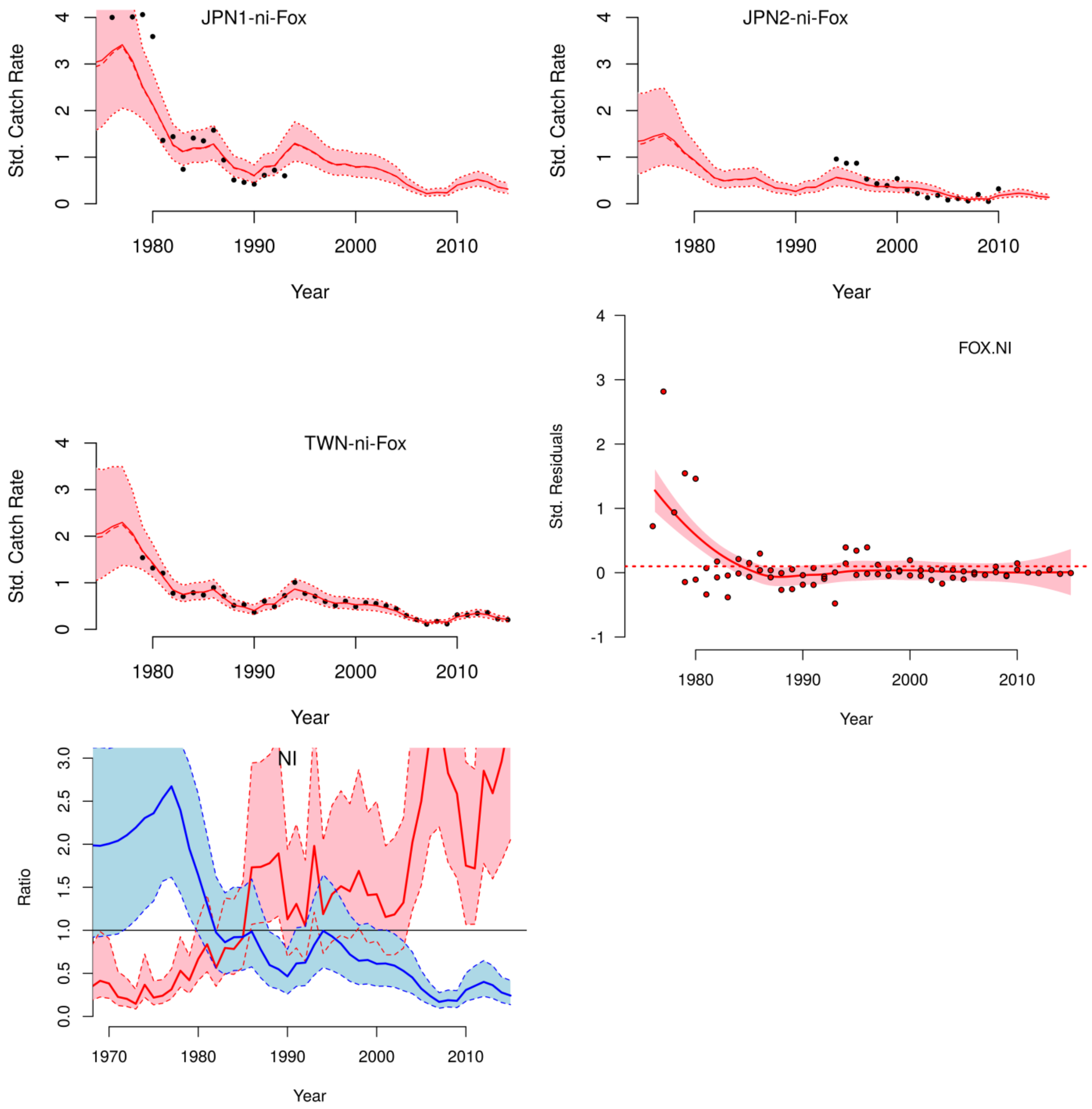
Schaefer Type – Non-Informative



Schaefer Type – Informative Prior



Fox Type – Non Informative Prior


JPN1-ni-Fox
JPN2-ni-Fox
TWN-ni-Fox
FOX.NI
NI
Std. Catch Rate
Std. Residuals
Ratio
Year