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Preliminary stock assessment of Indo Pacific sailfish (*Istiophorus platypterus*) using separated and composite estimations of relative abundance indices

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Abstract

In this paper a state-space Bayesian production model was fitted to longline and gillnet catch rate of the Indo Pacific sailfish (SFA) caught in the Indian Ocean. Most of the time series proved to be not informative about the parameters of the production models. However Sri Lanka and Iran gillnet datasets, and Japan longline dataset convey some information. Results are conflictive as estimations base on Sri Lanka database indicates the stock has been overfished, while the calculations based on the other databases indicate the stock has been fished in a moderate pace. Those results might be considered a starting point for crucial discussions about SFA, as far as the calculations were underpinned by critical assumptions concerning the reliability of the catch, and on the usefulness of the catch rate estimations as good relative abundance indices.

1. Introduction

In the Indian Ocean most of billfish is caught by longline and gillnet fleets. In general most of the longline boats of Asiatic (e.g. Japan) countries aim at tuna, while some European countries (e.g. Spanish and Portugal) targets tuna but also swordfish. The later species is an exception as all the other billfish are bycatch for the longline fleet. Hence the longline catches of several billfish species, like Indo Pacific sailfish (*Istiophorus platypterus*) (SFA) are often very low. However, gillnet and handline catches of SFA are relatively high as reported by countries which lie in the north Indian Ocean, like Iran, India, Oman, Pakistan and Sri Lanka. Standardized catch-per-unit-effort (CPUE) of SFA caught by Japanese longline dataset were provided by Okamoto and Ijima (2015), while Andrade (2015 a) has standardized the CPUE of Korean longline fleet. In addition, Andrade (2015 b) also calculated CPUE times series for Iran, Oman, Pakistan and Sri Lanka. In this paper the six CPUE time series and total catch as estimated by the Indian Ocean Tuna Commission (IOTC) were used to carried out stock assessment calculations for SFA using a state-space Bayesian production model. Separated CPUE datasets as well as composite indices were considered. It is important to highlight that the tentative calculations showed in this paper were underpinned by assumptions concerning the SFA stock structure (e.g. single stock), the approximate estimations of catches, and the reliability of the CPUEs time series as relative abundance indices. Those crucial assumptions still require further investigations. Hence the stock assessment estimations showed in this paper might be considered as starting points, instead of bases for fishery management decisions or recommendations.

2. Material and Methods

2.1 Databases

Estimations of the approximate catches of SFA were provided by the IOTC secretariat before 13th Working Party of Billfish (WPB). Explanations concerning the CPUE time series used in this paper are in Andrade (2015 a and b) and in Okamoto and Ijima (2015). However some summarizing comments are warranted. Estimations calculated by Andrade (2015 b) for gillnet fleets were based on approximate estimations of catch. Also the numbers of boats as reported in the IOTC databases were assumed to be useful proxies of the carrying capacity and effort. No standardization procedure was applied to gillnet database. In opposition, the CPUE of longline fleets were standardized. Estimations of standardized CPUEs of Japanese fleet were calculated by Okamoto and Ijima (2015) based on a detailed set by set database. However the time series of the standardized CPUE of Korea fleet was estimated based on aggregated dataset (Andrade, 2015 a). All the CPUE time series are shown in Figure 1. They were scaled by dividing them by their means to make comparisons easier.

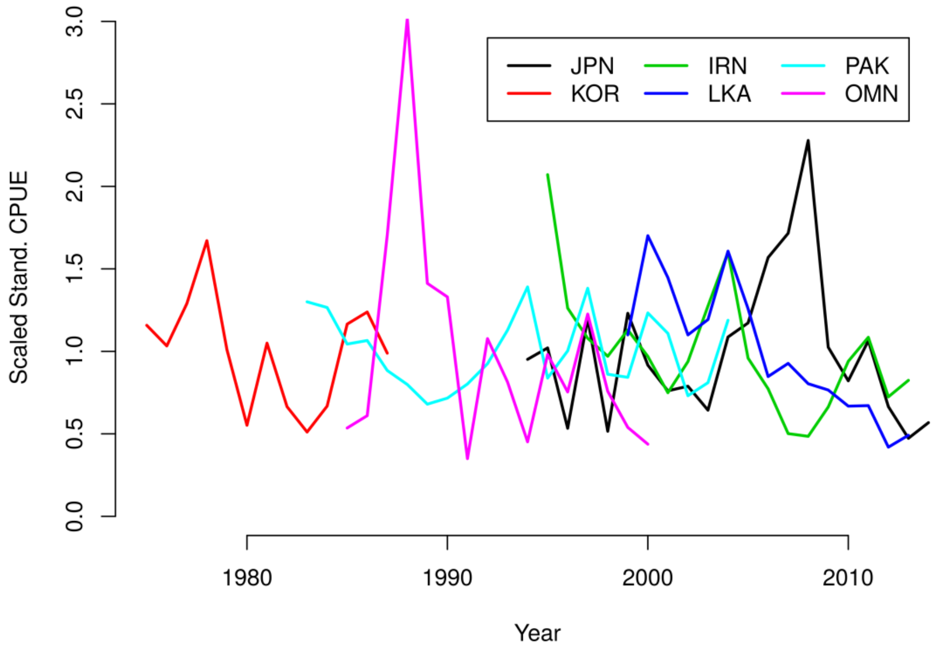


Figure 1 – Time series of standardized catch-per-unit-effort (CPUE) used in the analyses. Timi series values were scaled by dividing them by their means. Iran – IRN; Japan – JPN; Korea – KOR; Oman – OMN; Pakistan – PAK; and Sri Lanka – LKA.

2.2 Bayesian Production Model

Lognormal observational and process errors were considered when fitting the state-space production model (Schaeffer type) used here which is fully described in Meyer and Millar (1999). The parameters of the model are the carrying capacity (k), intrinsic rate of increase (r), the catchability (q), the variances of the observational and process errors (τ^2 and σ^2), and the ratios between the biomasses (B) and carrying capacity in each ith year ($P_i = B_i/k$). The code was adapted to allow calculations using separated and multiple catch rate time series (composite indices). In this paper, whenever using composite indices, equal weights were assign to each time series. However, different weights could be used as well.

Marginal “non-informative” priors were used to for key parameters. Uniform distribution was used for carrying capacity with minimum limit a bit higher than the maximum catch, and maximum limit equal to twenty times the maximum catch $k \sim U(30000{,}20 \times 30000)$. Inverse gamma distributions conveying low information $IG(1{,}0.1)$ were used for the variances of the errors. The prior for catchability was uniform on log scale $U(-45, -1)$ which is similar to Jeffrey’s non informative prior (Millar, 2002). Wide uniform distribution was used to intrinsic rate of increase $r \sim U(0{,}2)$. However, an informative prior was also considered for r. I have used lognormal distribution $r \sim lnorm(\log(0.3)\,, .6)$, which is similar to the informative prior used in the last stock assessment of Atlantic sailfish (Anon, 2010), but with higher variance. However the prior might be further discussed. Other alternatives may worth the effort. For example, Carruthers and McAllister (2011) have estimated a prior for Atlantic sailfish using demographic methods. The solution they calculated points for low productive stock (mode of r close to 0.1). The code used in this paper can be easily adapted to allow calculations with other priors.

2.3 Calculations

In this working paper Monte Carlo Markov Chains (MCMC) numerical approach was used to calculate the posterior samples of the parameters. Gibbs sampler was implemented using JAGS (Plummer, 2005) and R softwares (R Core Team 2014), and also the package *runjags* (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) of the subsequent 30000 steps of the chain, providing a set of 1000 values of the posterior distribution for each chain.

Graphs and diagnostic tests were used to assess the mixing degree of the chains and to determine whether a stationary distribution (convergence) had been reached. CODA library (Plummer et al., 2006) was used to evaluate if MCMC algorithm converged. 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 distributions.

3. Results

3.1 Relationships between catch and standardize catch rates

Marginal empiral distributions of catch and of standardized catch rates, as well as scatterplots, and linear correlations are showed in Figure 2. Notice that the correlations Japan-Pakistan, Japan-Oman, Iran-SriLanka, Iran-Oman and Sri lanka- Pakistan were positive. This indicates that those time series were not conflicting in the year timespans they overlap each other. Notice also that most of the correlations between catches and CPUE time series were negative. The exception was the correlation between total catch and Pakistan time series.

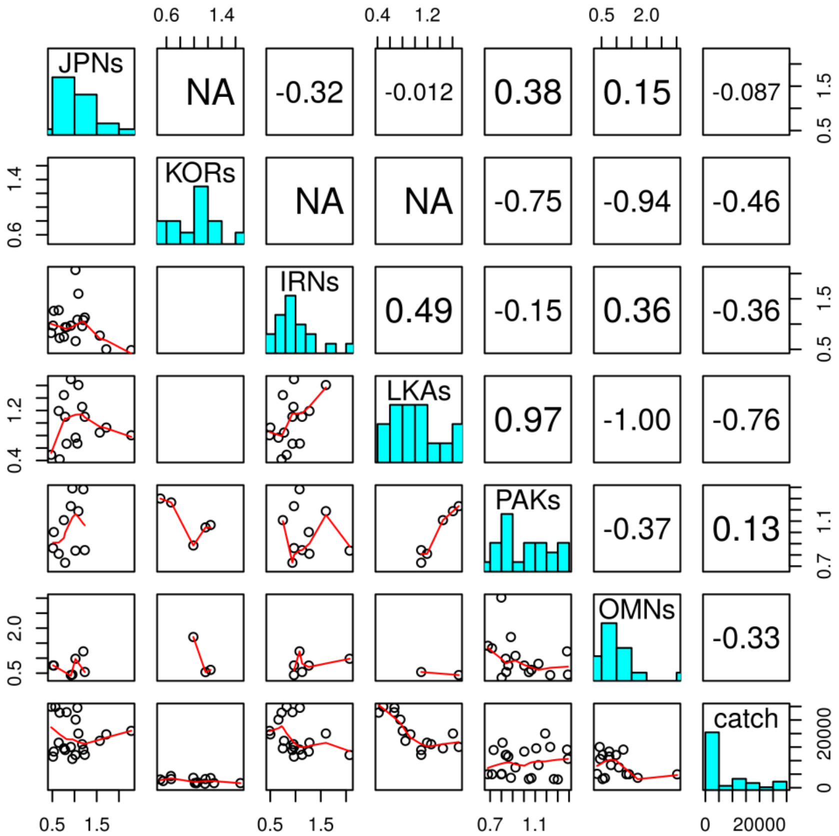


Figure 2 – Marginal distributions and scatterplots of catch and the six time series of catch rates analyzed: Japan – JPNs; Korea – KORs; Iran – IRNs; Sri Lanka – LKAs; Pakistan – PAKs; and Oman – OMNs. Number in the upper corner panels are the coefficient of correlation.

3.2 Convergence of models

Most of the models did converge, but model fitted to Oman time series using informative prior was an exception. Most of the 97.5% quantiles of Potential Scale Reduction Factor (PSRF) calculated when fitting the models were low ($\approx$ 1.01). Traceplots also indicate that models had converged, but Oman – informative prior. Overall, all the models converged satisfactorily. Autocorrelations were calculated to assess the degree of mixing of the chains. All the calculations show the correlations decrease quick with small lags, hence the results suggest good mixing of the chains.

3.3 Model fittings

Model fitted to separated logline databases are shown in Figure 3. State-space models have several parameters, including proportions in each year, hence they are very flexible and the fittings are often good. However, the models did not fit well the peak of 1978 of Korean time series, and the models also did not fit well the peaks and plunges of 1996-1999 and of 2007-2009 timespans of Japan database. Notice that the model fittings did not show clear time trend across the years as calculated based on Korea database, but a decreasing trend showed up in the end of the Japan time series.

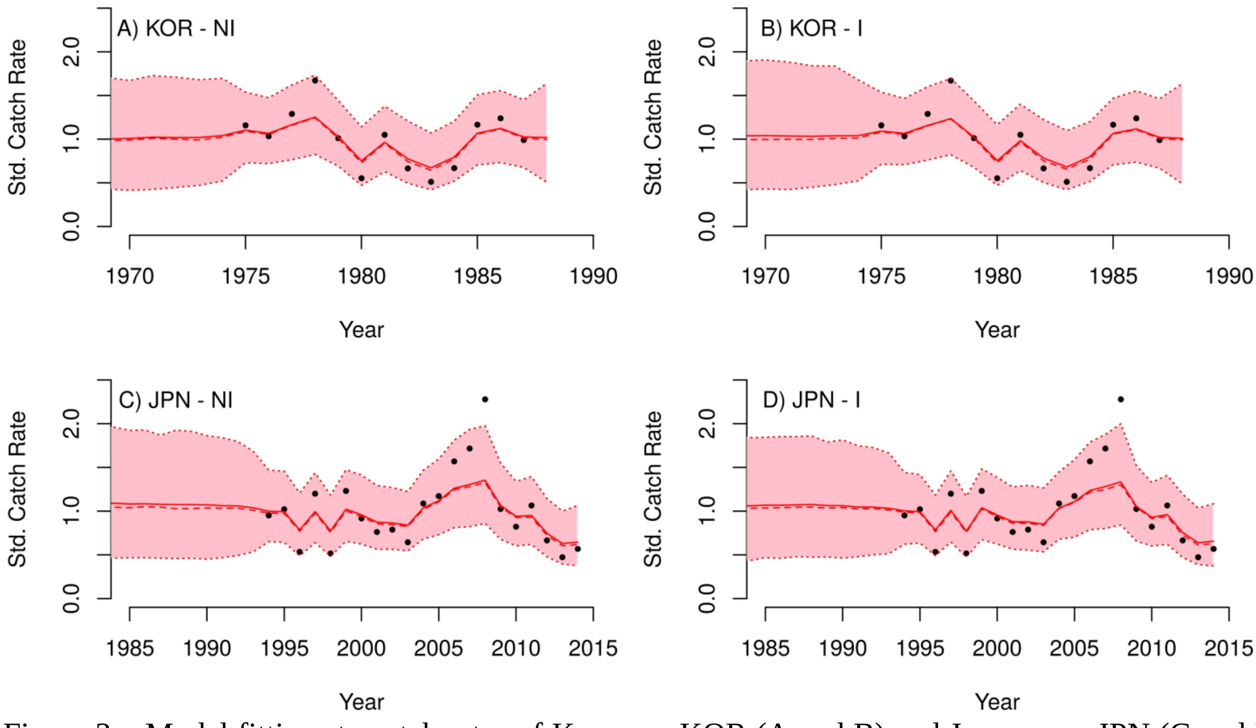


Figure 3 – Model fittings to catch rates of Korean – KOR (A and B) and Japanese – JPN (C and D) fleets. Panels at left (A and C) stand for calculations with non-informative priors, while panels at right stand for calculations with informative priors.

Most of the models fitted well to the separated gillnet time series (Figure 4), but the model fitted to Oman database using informative prior was an exception. Models fitted to Iran and Sri Lanka time series have showed decreasing time trends, while the fittings of models to data of Pakistan (informative and non-informative priors) and of Oman (informative prior) did not show any clear time trend.

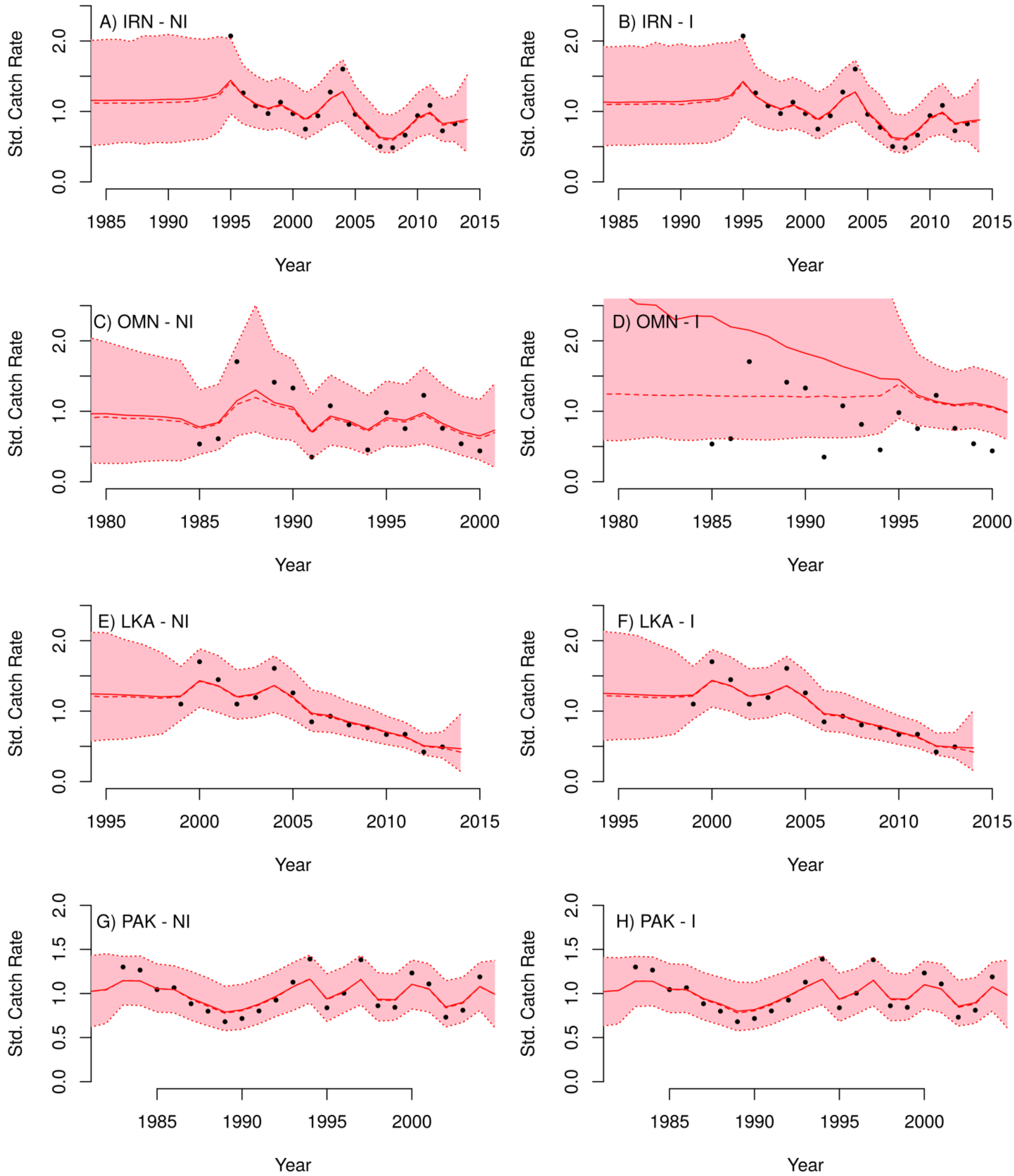


Figure 4 – Model fittings to catch rates of Iran – IRN (A and B), Oman – OMN (C and D), Sri Lanka – LKA (E and F) and Pakistan – PAK (G and H) fleets. Panels at left (A, C, E and G) stand for calculations with non-informative priors, while panels at right stand for calculations with informative priors.

Model fittings to the composite time series looks like the average of the separated model fittings. Composite model fittings were not shown.

3.4 Marginal Posterior Distributions

Marginal posteriors of key parameters r and k are shown in Figure 5. Sri Lanka database convey information about r as indicated by the high precision of the posterior (Figures 5 A and B). Iran and

Japan also convey some information about r, but the posteriors calculated based on Oman, Pakistan and Korea databases were mostly flat. Posteriors of r calculated using non-informative and informative priors were very much similar.

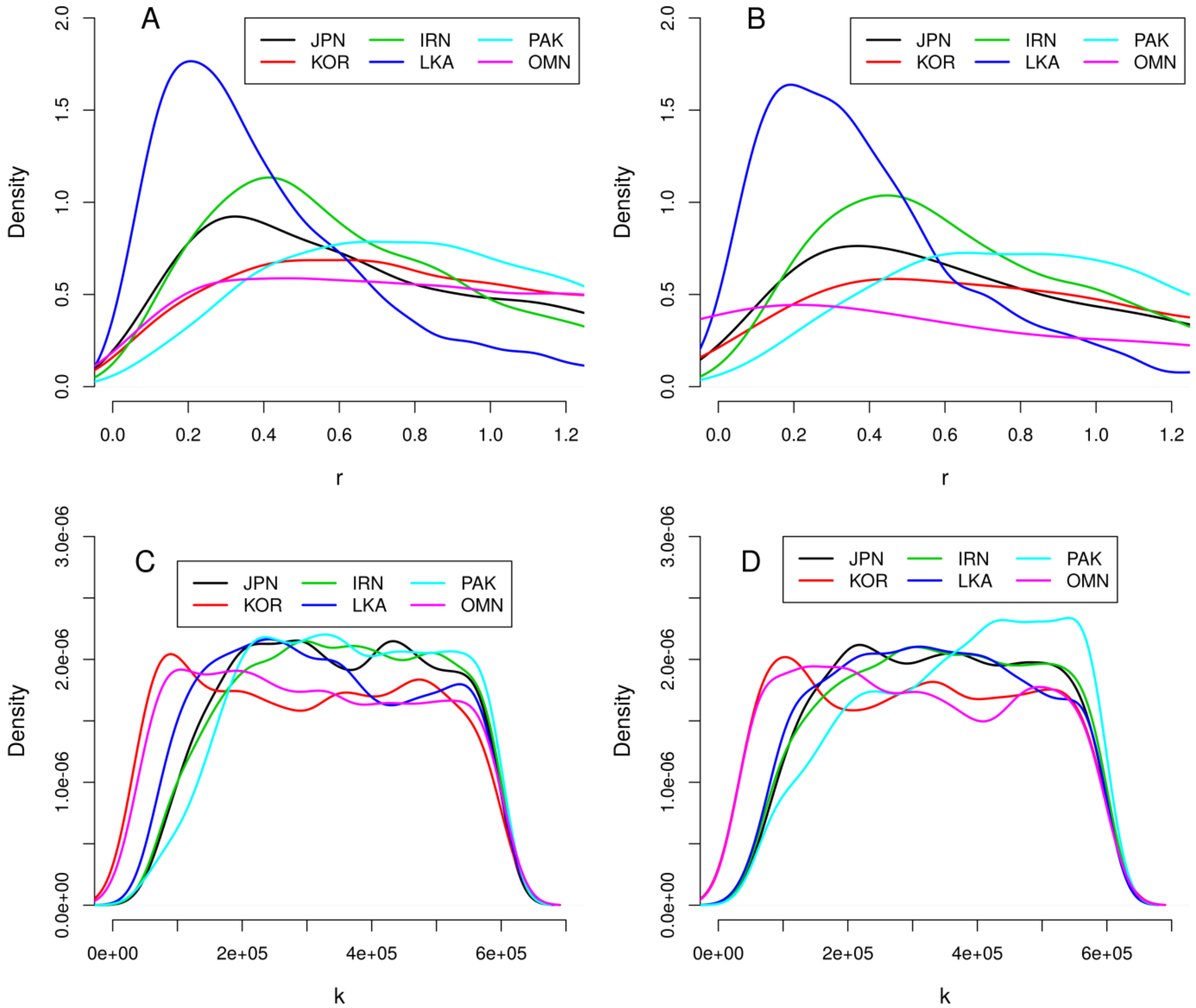


Figure 5 – Marginal posterior distributions of r (A and B) and k (C and D) parameters. Panels at left stand for calculations with non-informative prior for r, while the panels at right stand for calculations with informative priors for r.

All the datasets analyzed do not convey much information about the carrying capacity of the stock (Figure 5 C and D). Calculations with informative or non-informative priors for r did not affect much the posteriors of k.

Posteriors of yield at “Maximum Sustainable Yield” (Ymsy) are shown in Figure 6. Notice that Sri Lanka dataset conveys information about Ymsy. The precision of posteriors were high with a mode close to 22,000 t. Iran and Japan datasets also convey some information with modes close to 30,000 t. The posteriors calculated based on the other three datasets were flat.

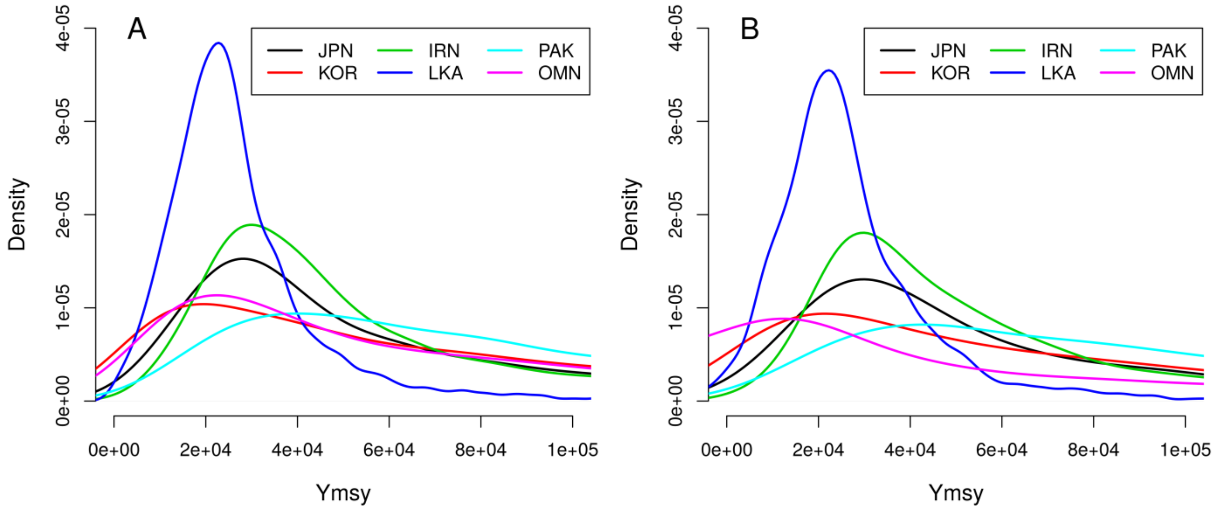
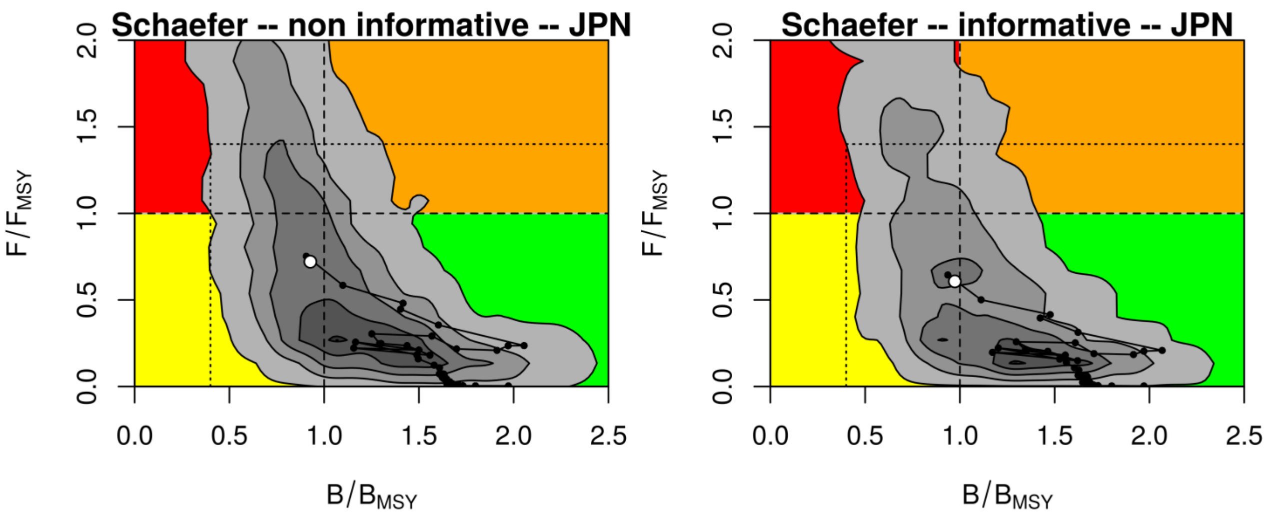
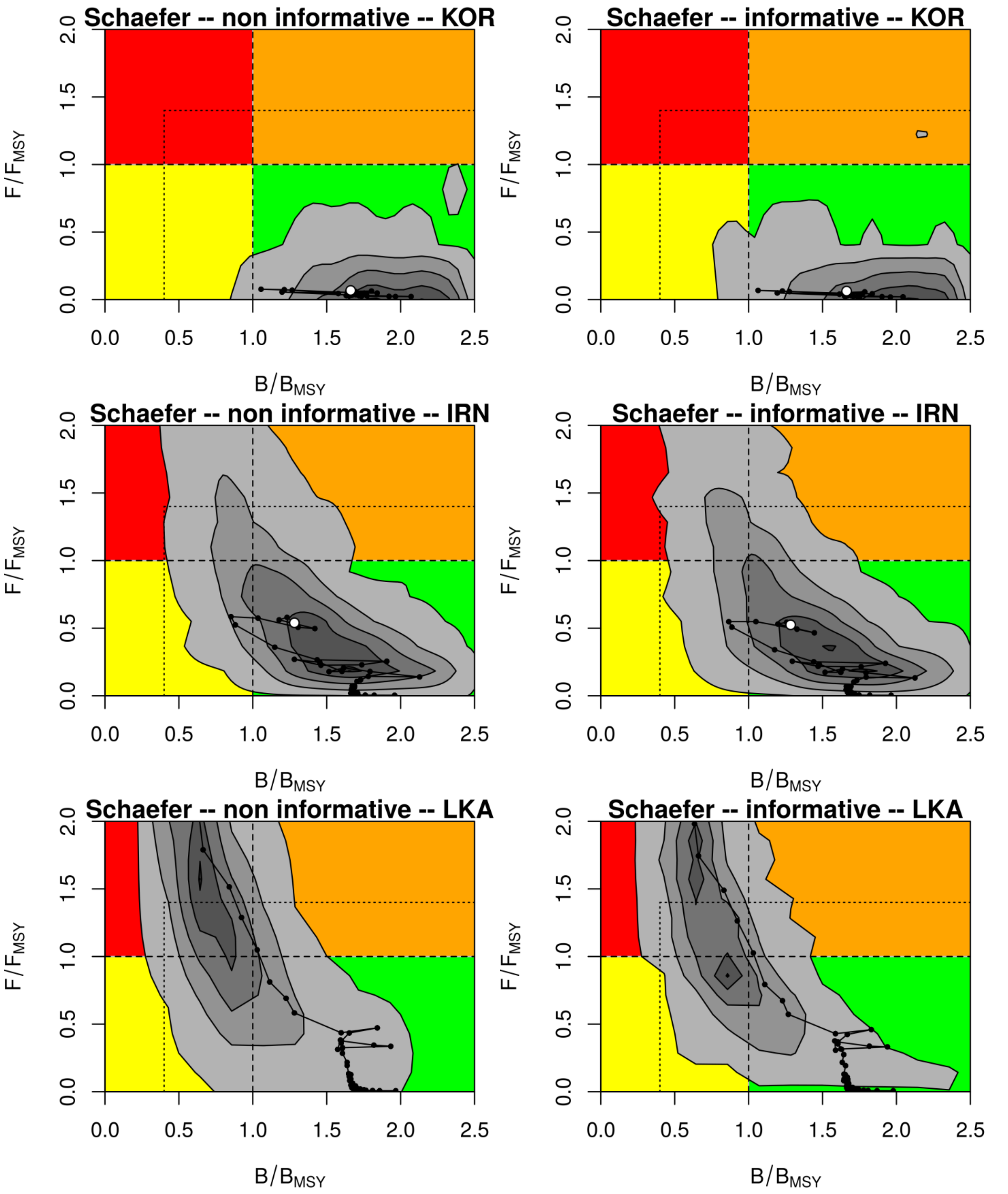


Figure 6 – Posterior distributions of yield at "maximum sustainable yield" (Ymsy). Calculations with non-informative (A) and informative (B) priors. Japan – JPN, Korea – KOR, Iran – IRN, Sri Lanka – LKA, Pakistan – PAK and Oman – OMN datasets.

3.5 Phase plots

Standard phase plots are shown in Figure 7. Notice that calculations based on Korea, Oman and Pakistan databases which do not convey much information about the parameters of the models were optimistic in the sense the kernels of the phase plots are very much in the green area (Fcurrent/Fmsy < 1 and Bcurrent/Bmsy >1). Calculations based on Iran and Japan dataset also indicate that the in the recent year the stock was not overexploited. However, they indicate that the kernel of the phase plots are have been close to (or eventually broke through) yellow or orange areas, which demands attention. Calculations based on Sri Lanka database are very much pessimistic. If we rely on Sri Lanka calculations the sailfish stock have been overfished in recent years. The calculations based of Sri Lanka are the only ones pointing for overfishing, but remind that Sri Lanka database is also the only one which conveys meaningful information about some of model parameters. All the other databases have rendered flat posteriors estimations.




Schaefer -- non informative -- KOR
Schaefer -- informative -- KOR
Schaefer -- non informative -- IRN
Schaefer -- informative -- IRN
Schaefer -- non informative -- LKA
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F/F_{MSY}
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0.0
0.5
1.0
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2.0
2.5

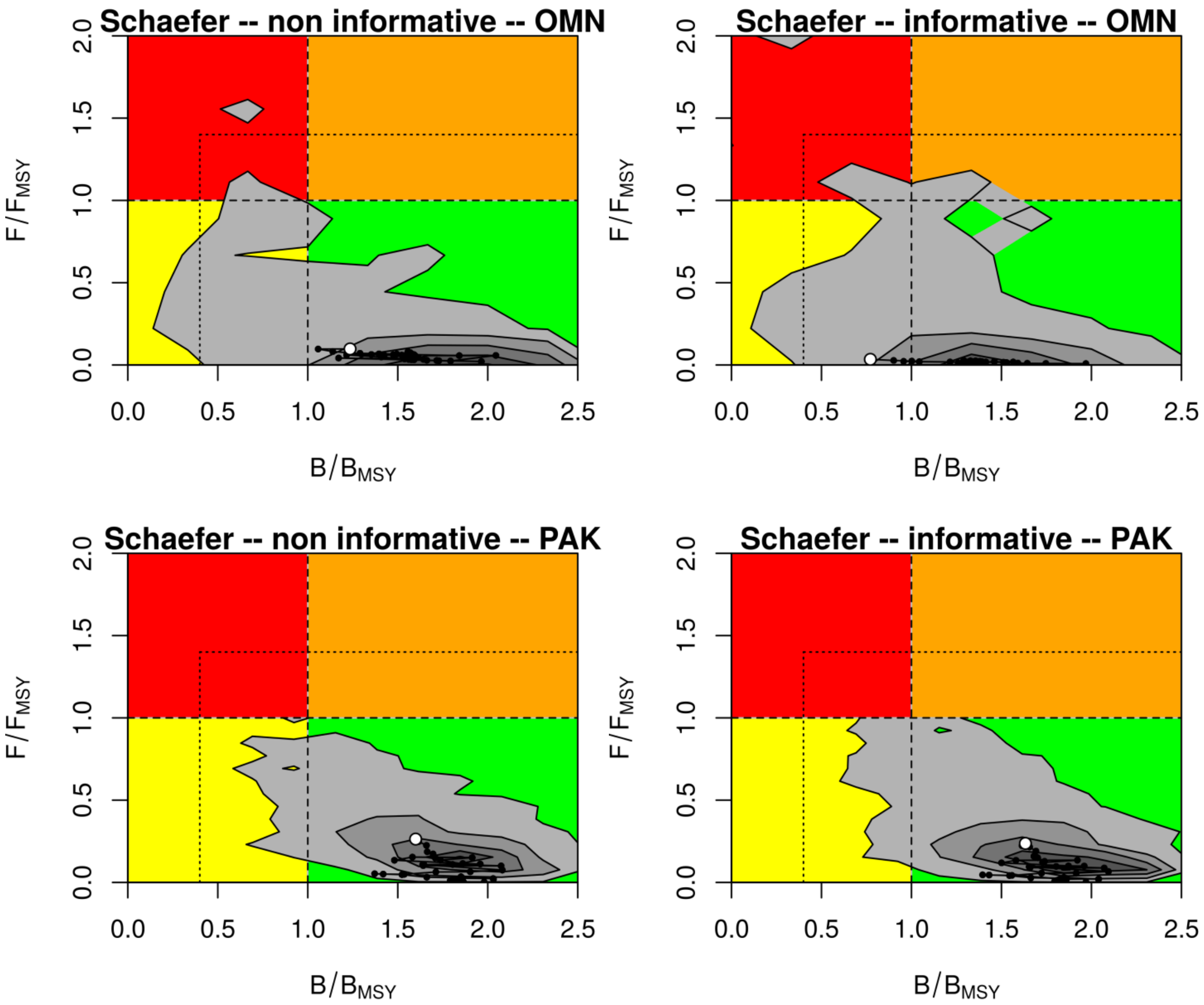

Figure 7 – Phase plots as calculated based on Japan – JPN, Korea – KOR, Iran – IRN, Sri Lanka – LKA, Oman – OMN, and Pakistan – PAK databases.

4. Remarks

Most of the analyzed databases do not convey much information about key parameters of production models, but Sri Lanka database. Calculations are conflictive, in the sense some of the estimations indicate the stock is well above the MSY, while Sri Lanka estimations indicate the stock is overfished whenever we rely on MSY as benchmark. The conflictive results stress the uncertain, but also stress that the longline and gillnet datasets analyzed convey some information. No doubt that other data sources might be pursued, but the results gathered in this very first approach indicate that the poor (or limited) longline and gillnet datasets, might be further investigated.

5. References

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