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Received: 7 October 2015

Preliminary stock assessment of yellowfin tuna (*Thunnus albacares*) in the Indian Ocean by using Bayesian biomass production model

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Abstract: A Fox-form Bayesian biomass dynamics model was developed to assess the stock status of yellowfin tuna (*Thunnus albacares*) in the Indian Ocean (1950-2014). The results showed that the median of Maximum sustainable yield (MSY) was 344,200 t, and the medians of B_{2014}/B_{MSY} and F_{2014}/F_{MSY} were 0.74 and 1.87, respectively. Thus, the stock was subject to overfishing and overfished at the end of 2014. The risk assessments suggest that the current catch level in 2014 (430, 331 t) is higher than MSY and this level can result in high risk for the stock to be overfished and subject to overfishing. Future catch should be reduced to 67% of the current level, which will lead to a 60% of probability for the biomass exceeding B_{MSY} by 2024. The results are more pessimistic than those assessed with integrated age-structured models in 2012 and this year. Because there are high uncertainties in the present assessment, we suggest that the results not be used for developing management advices, but for comparison with other model results.

1 Introduction

The Indian Ocean yellowfin tuna (*Thunnus albacares*) (YFT) was recently assessed by models in their complexity ranging from highly aggregated biomass dynamics models (e.g., ASPIC, Lee et al., 2013) to integrated age-structured models (e.g., Age structured production model, Nishida et al., 2012; Multifan-cl, Langley et al., 2012; and Stock Synthesis, Langley, 2015). However, considerable uncertainties remain in the assessment results, due to the uncertainties in catch at age/size data (IOTC, 2012), biological parameters (e.g. population spatial structure, sex ratio and growth), and the assumptions of key model parameters (e.g. steepness and natural mortality, Langley, 2015).

In this study, we chose biomass dynamics model to assess the YFT stock in order to avoid using some size data or assumptions which were considered to be uncertain. In addition, instead of using the traditional ASPIC model, we developed a continuous Fox-form Bayesian biomass dynamics model for the YFT assessment. The benefit of using Bayesian method is that prior information about model parameters from other studies or sources can be used. The results can be used to provide an opportunity to compare with other stock assessment models.

2 Data and methods

2.1 Data

Catch and standardized CPUE data were obtained from the IOTC secretariat website for the tropical tuna working party (http://www.iotc.org/meetings/17th-working-party-tropical-tunas-wptt17). Annual catch data were available from 1950 to 2014. There were two sources of standardized longline CPUE data available to be used as abundance indices, which were based on the Japanese longline fishery (Ochi, et al., 2015) and Taiwan, China longline fishery (Yeh and Chang, 2013). The Taiwan, China longline CPUE time series from 1980 to 2012 for the whole Indian Ocean was used in this assessment. The Japanese CPUE time series in region 2, 3, 4 and 5 was available from 1963 to 2014. However, following previous assessments (Langley, 2015), only the Japanese CPUE data from 1972 to 2014 were used in this assessment.

To improve computational stability, we normalized the catch and CPUE by using Eqs. (1) and (2):

$$Y_t = \frac{C_t}{C_{Max}}, \tag{1}$$

$$I_t = \frac{CPUE_t}{CPUE_{Max}}, \tag{2}$$

where C_t, Y_t, $CPUE_t$, and I_t are the catch, normalized catch, CPUE, and normalized abundance index in year t, respectively. C_{Max} and $CPUE_{Max}$ are the maximum annual catch and the maximum CPUE value in the time series, respectively.

2.2 Model

The continuous non-equilibrium Fox-form biomass dynamic model was used, in which the population dynamics can be expressed as follows (Guan et al., 2014):

$$B_{t+\Delta t} = e^{(P-e^{-r\Delta t}(P-r\ln(B_t)))/r}, \quad (3)$$

$$P = r\ln(K) - F_t, \quad (4)$$

$$F_t = \frac{\int_0^{\Delta t} B_{t+x}dx}{Y_t}, \quad (5)$$

$$\overline{B}_t = \int_0^1 B_{t+x}dx \quad (6)$$

where r is the intrinsic rate of increase, K is carrying capacity, B_t and F_t are stock biomass and fishing mortality in year t, Δt is the time interval within one year, and $\overline{B}_t$ is the average biomass in year t. If r, K, Y_t, and the biomass in the first year of the fishery are known, then F_t and B_t can be solved numerically. To estimate the parameters, the observation model for the unobserved "state" $\overline{B}_t$ is written as:

$$I_t \mid q, \overline{B}_t, \tau = q\overline{B}_t e^{\varepsilon_t} \quad (7)$$

where q is catchability, ε_t is an independent and identical normal distribution with mean 0 and precision τ (i.e., 1/variance), and $Y|X$ denotes the conditional distribution of Y given X. To improve the quality of estimation, the biomass in the first year of the fishery was reparamaterized as:

$$B_s = B_0 K, \quad (8)$$

where B_s is the biomass in the first year of the fishery (i.e. 1950), and B_0 is the ratio of B_s to K.

2.3 Priors for parameters

2.3.1 *Prior distribution of q, τ and K*

According to Eq. (2), the upper limit of q should be less than 1.0. The prior for q was assumed to be an uninformative uniform distribution from 0.0 to 1.0, denoted as U [0.0, 1.0]. The prior for the precision τ was assumed to be an uninformative gamma distribution with shape parameter and rate parameter both assigned as 0.001, denoted as G (0.001, 0.001). The prior for K was also assumed to be an uninformative uniform distribution. We assumed that the minimum and maximum values for K were those of 2 times (1.06×10^6 tonne) and 32 times (1.69×10^7 tonne) the maximum annual catch (5.29×10^5 tonne), which are wide enough to cover the reasonable range of the population's carrying capacity. The prior of K was denoted as U [2, 32].

2.3.2 *Prior for B_0*

An uninformative prior distribution was assigned to B_0. According to the assumption of the biomass dynamics model and the recent stock assessment (Lee et al., 2013; Langley, 2015), the maximum value of B_0 is less than 1.0 and the minimum value is greater than 0.1. Therefore, the prior for B_0 was denoted as U [0.1, 1]. We also considered scenarios with B_0 fixed at 0.90.

2.3.3 *Prior for r*

Three prior distributions were considered for r, i.e. one uniform distribution and two lognormal distributions with different parameter values. The lower and upper limits of the uniform distribution were assigned as 0.05 and 1.5 and the prior denoted as U [0.05, 1.5]. The median and coefficient of variance for one lognormal distribution were assigned as 0.46 and 0.22, and the prior was denoted as LM (0.46, 0.22), which was similar to Carruthers and McAllister's results (2011); the other informative prior was denoted as LM and its median and coefficient of variance were estimated as follows:

(1) Computing r by using the Euler-Lotka equation

The relationship between the intrinsic rate of increase and other life-history parameters (McAllister et al., 2001; Maravelias et al., 2010) can be described as:

$$\sum_{a=0}^{A} e^{-ra} m_a w_a S_a \gamma = 1, \tag{9}$$

where a is age, A is the maximum age, m_a is maturity at age a, w_a is weight at age a and calculated by Eqs (10), S_a is the fraction of individuals surviving from ages 0 to a and calculated by Eq. (11), and γ is the recruits-per-spawner biomass at zero spawners or maximum recruits-per-spawner and is calculated by Eqs (12) and (13).

$$w_a = cL_a^{\ b}, \tag{10}$$

$$S_a = e^{-\sum_{i=0}^{a-1} M_i}, \tag{11}$$

$$\gamma = \frac{4h}{\rho_{F=0}(1-h)}, \tag{12}$$

$$\rho_{F=0} = \sum_{a=0}^{A} w_a m_a e^{-aM_a}, \tag{13}$$

where c is a scaling constant, b is the allometric growth parameter, h is the steepness of the stock-recruit relationship, M_a is natural mortality at age a. According to Ijima et al. (2012), c and b were 1.89×10^{-5} and 3.0195, respectively. The maximum age was set at 15. The steepness was assumed to follow a beta distribution with a mean and standard deviation of 0.8 and 0.05, respectively. The other parameters were assigned as in **Table 1**. The natural mortality was drawn from uniform distribution between low and high value and fish length was drawn from normal distribution with the mean and standard deviation. If these parameters are known, the r can be solved by iteration according to Eq. (9).

Table 1. Values of parameters for Euler-Lotka equation. The data was taken from SSS3_YFT.zip and YFMFCL.zip, which were downloaded from website http://www.iotc.org/meetings/14th-session-working-party-tropical-tunas. The value of parameter at age 0 was assigned as the value at second quarter and the rest were deduced by analogy. The values of parameters for age 7 and elder were extrapolated.

Age	Maturity	Natural mortality (Low)	Natural mortality (High)	Mean Length	Standard deviation of length
0	0.0	0.7040	1.1872	35.0000	7.531
1	0.0	0.3200	0.5396	53.0000	9.32330
2	0.5	0.3200	0.5396	87.0000	10.65960
3	1.0	0.4560	0.7692	119.0000	11.59410
4	1.0	0.4444	0.7492	134.0000	12.22180
5	1.0	0.3452	0.5820	139.9762	12.63290
6	1.0	0.3216	0.5420	144.1395	12.89780
7	1.0	0.3204	0.5400	147.0689	13.09443
8	1.0	0.3204	0.5400	149.9841	13.29395
9	1.0	0.3204	0.5400	152.8993	13.49347
10	1.0	0.3204	0.5400	155.8145	13.69299
11	1.0	0.3204	0.5400	158.7297	13.89251
12	1.0	0.3204	0.5400	161.6449	14.09203
13	1.0	0.3204	0.5400	164.5601	14.29155
14	1.0	0.3204	0.5400	167.4753	14.49107
15	1.0	0.3204	0.5400	170.3905	14.69059

(2) Sampling a value for h according to its distribution.

(3) Solving Eq. (9) by iteration to get r.

(4) Repeating (2) and (3) 5000 times to get the experience distribution of *r*.
(5) Fitting the experience distribution of *r* to estimate the parameters of the lognormal distribution, i.e., the median and coefficient of variance.

2.4 Parameter estimation

According to the CPUE data and the priors of the parameters, the model was run under 15 scenarios that are denoted as S1, S2… and S15, listed in **Table 2**.

The Bayesian biomass dynamics model was coded using Blackbox Component Builder (http://www.oberon.ch/blackbox.html), WinBUGS (Lunn et al., 2000) and R (R Core Team, 2014), which can be found in Guan et al. (2014). The Brooks-Gelman-Rubin statistic (BGRs) was used to diagnose the convergence where the threshold is set at 1.1 (Kéry, 2010), i.e., the model was considered converged if BGRs is less than 1.1. We only present and analyze the results from the converged scenarios.

Table 2 Prior for each parameter

Scenario	CPUE	r	K	q	B_0	$\tau=1/\sigma^2$
S1	Jap	U(0.05,1.5)	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S2	Jap	U(0.05,1.5)	U(2.5, 32)	U(0.0, 1.0)	0.90	G(0.001,0.001)
S3	Jap	LM(0.46, 0.22)	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S4	Jap	LM(0.46, 0.22)	U(2.5, 32)	U(0.0, 1.0)	0.90	G(0.001,0.001)
S5	Jap	LM	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S6	Jap	LM	U(2.5, 32)	U(0.0, 1.0)	0.90	G(0.001,0.001)
S7	Twn	U(0.05,1.5)	U(2.5, 32)	U(0.0,1.0)	U(0.1,1.0)	G(0.001,0.001)
S8	Twn	LM(0.46, 0.22)	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S9	Twn	LM	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S10	J+T	U(0.05,1.5)	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S11	J+T	U(0.05,1.5)	U(2.5, 32)	U(0.0, 1.0)	0.90	G(0.001,0.001)
S12	J+T	LM(0.46, 0.22)	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S13	J+T	LM(0.46, 0.22)	U(2.5, 32)	U(0.0, 1.0)	0.90	G(0.001,0.001)
S14	J+T	LM	U(2.5, 32)	U(0.0, 1.0)	U(0.1,1.0)	G(0.001,0.001)
S15	J+T	LM	U(2.5, 32)	U(0.0, 1.0)	0.90	G(0.001,0.001)

Note: LM denotes the log-normal distribution; G denotes the gamma distribution. J+T indicates CPUEs from Taiwan, China and Japan longline fisheries.

3 Results

3.1 Prior distribution of intrinsic growth rate estimated by demographic methods

The **Figure 1** shows the prior distribution of intrinsic growth rate estimated by using demographic methods. A lognormal distribution was fitted to the prior distribution with the median and coefficient of variance equal to 0.75 and 0.15, respectively.

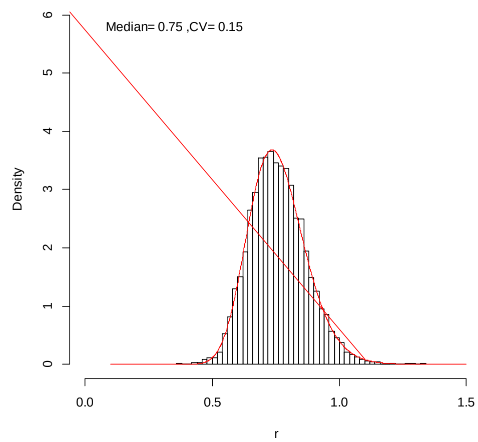

Figure 1 The prior distribution of intrinsic growth rate estimated by using demographic methods. The red line is lognormal distribution with median and coefficient of variance (CV) assumed to be 0.75 and 0.15, respectively.

3.2 The estimation of parameters

According to Gelman and Rubin's convergence diagnostic, all scenarios except for S2 were converged. The assumption of the prior distribution of *r* impacted the estimation of parameters. For example, in scenario S3 and S5 where informative prior was used, although the posterior distribution of *r* was different from its prior and its median was smaller (**Figure 2, 3**); its medians increased with the informative prior distribution in comparison with S1 (**Figure 4, Table 3**). If same CPUEs were used in the model, the median of *MSY* (Maximum sustainable yield) and B_{cur}/B_{MSY} decreased and the medians of *K* and F_{cur}/F_{MSY} increased as the median of *r* decreased (**Table 3**). Compared with the results based on the uninformative prior scenario (e.g., S1), the ranges of 80% CI (Confidence Interval) of the posterior distributions of *MSY*, *K*, *r* and F_{cur}/F_{MSY} were narrower when the informative prior was given to *r* (e.g., S3) (**Table 3**).

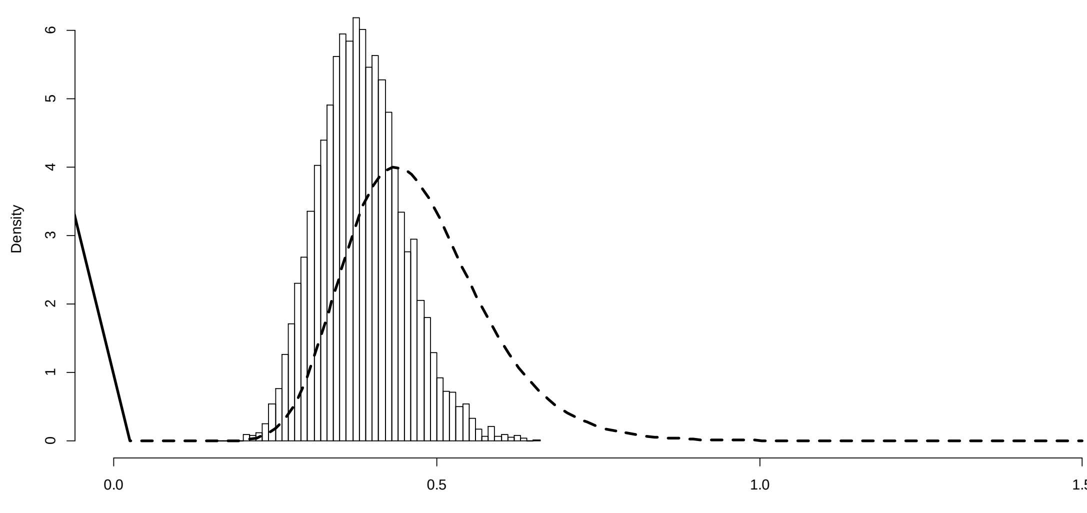

Figure 2 Posterior distributions of intrinsic growth rate for scenario S3. Dashed line is the prior distributions for the parameters.

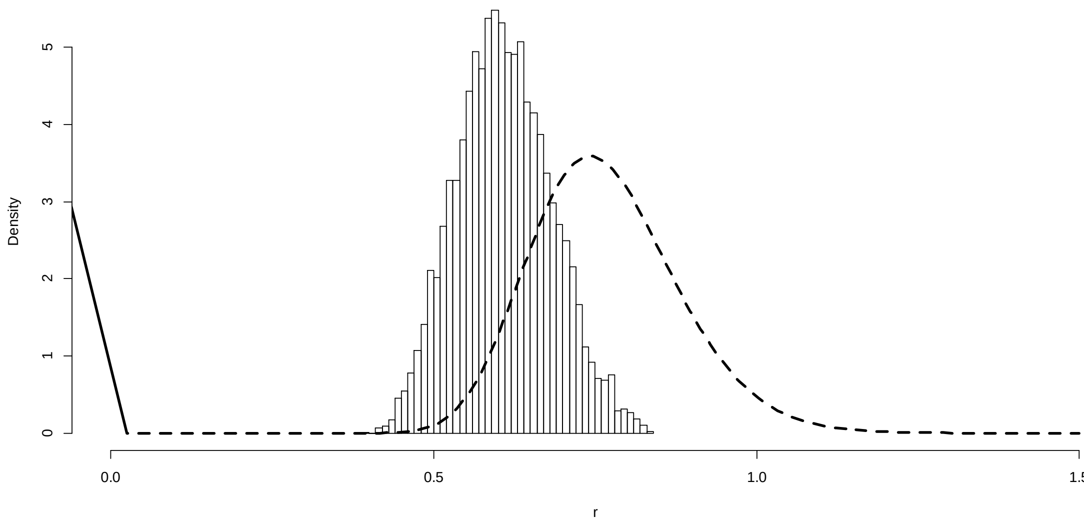

Figure 3 Posterior distributions of intrinsic growth rate for scenario S5. Dashed line is the prior distributions for the parameters.

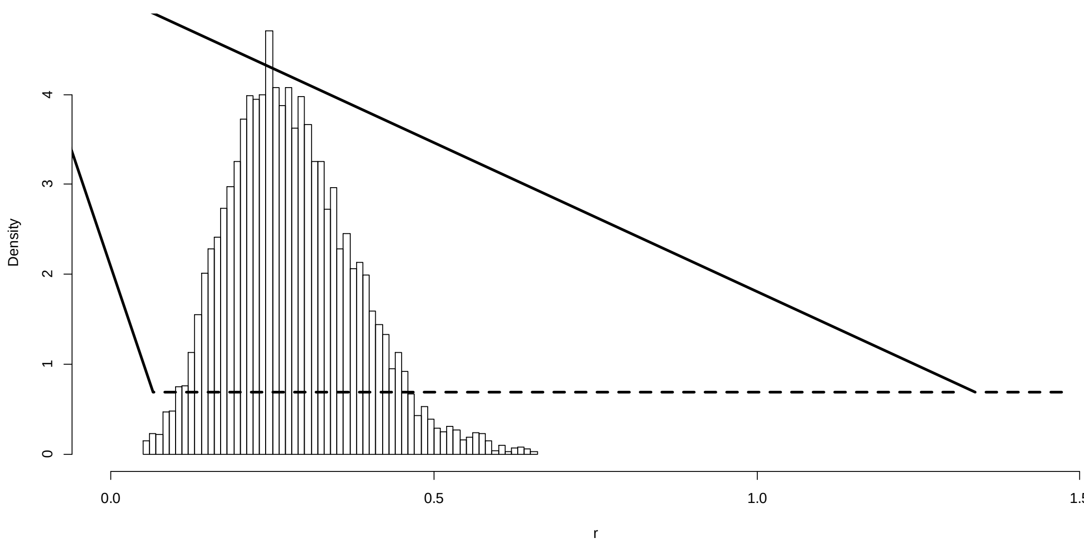

Figure 4 Posterior distributions of intrinsic growth rate for scenario S1. Dashed line is the prior distributions for the parameters.

Table 3 Results for different scenarios listed in Table 2

Scenario	MSY(10^4) (80% CI)	K(10^4) (80% CI)	r (80% CI)	R^2	MSE	F_{cur}/F_{MSY} (80% CI)	B_{cur}/B_{MSY} (80% CI)
S1	32.15 (27.94-34.72)	322.56 (229.05-473.48)	0.27 (0.16-0.41)	0.748	0.011	2.59 (2.03-3.42)	0.60 (0.50-0.70)
S2	Not convergent						
S3	34.26 (32.85-35.41)	245.22 (205.31, 297.08)	0.38 (0.30, 0.47)	0.753	0.011	2.34 (1.90, 2.94)	0.62 (0.53, 0.72)
S4	34.30 (32.84, 35.54)	243.79 (201.13, 295.50)	0.38 (0.30 , 0.48)	0.753	0.011	2.35 (1.87, 2.94)	0.62 (0.53, 0.73)
S5	36.71 (35.88 , 37.54)	164.66 (144.36, 189.40)	0.61 (0.52, 0.71)	0.751	0.011	2.06 (1.65, 2.62)	0.67 (0.58, 0.78)
S6	36.70 (35.86, 37.52)	165.24 (144.89,190.46)	0.60 (0.51, 0.70)	0.751	0.011	2.06 (1.65, 2.62)	0.67 (0.58, 0.78)
S7	46.47 (30.81,90.14)	722.61 (296.81, 1273.47)	0.20 (0.07, 0.66)	0.283	0.019	0.53 (0.21, 1.00)	1.77 (1.40, 2.26)
S8	56.22 (43.74, 104.78)	383.66 (267.73, 685.76)	0.42 (0.32, 0.55)	0.238	0.020	0.40 (0.18, 0.62)	1.94 (1.62, 2.34)
S9	73.23 (49.44, 210.32)	279.05 (184.75, 785.04)	0.73 (0.60, 0.88)	0.174	0.022	0.28 (0.08, 0.50)	2.14 (1.78, 2.53)
S10	31.86 (27.08, 34.67)	362.63 (249.45, 549.28)	0.24 (0.14, 0.38)	0.748 (0.318)	0.012 (0.045)	2.07 (1.56, 2.76)	0.72 (0.60, 0.88)
S11	31.40 (25.18, 34.47)	384.40 (257.96, 630.10)	0.22 (0.11, 0.36)	0.748 (0.318)	0.012 (0.046)	2.10 (1.59,2.89)	0.72 (0.60, 0.88)
S12	34.45 (33.04, 35.62)	255.05 (212.24, 308.19)	0.37 (0.29, 0.45)	0.755 (0.329)	0.011 (0.050)	1.86 (1.44, 2.36)	0.74 (0.62, 0.90)
S13	34.42 (33.01, 35.62)	256.11 (211.87, 312.09)	0.37 (0.29, 0.46)	0.755 (0.327)	0.011 (0.050)	1.87 (1.45, 2.37)	0.74 (0.62, 0.90)
S14	36.62 (35.85, 37.43)	173.28 (152.08, 197.76)	0.58 (0.49, 0.67)	0.752 (0.349)	0.011 (0.054)	1.68 (1.27, 2.17)	0.78 (0.65, 0.97)
S15	36.64 (35.84, 37.47)	172.49 (151.24,197.49)	0.58 (0.50, 0.67)	0.752 (0.349)	0.011 (0.054)	1.68 (1.28, 2.17)	0.78 (0.65,0.97)

Note: MSE is Mean Square Error; CI is Confidence Interval; Unit for both MSY and K is tonne.

Although there were some increasing trends in the posterior distribution of B_0 for scenarios S1 and S10 (**Figure 5**), the posterior distributions of B_0 for the other scenarios were close to uniform distributions, which means that little information in the data contributed to the estimation of B_0, implying that the values of B_0 within its interval could equally satisfy the model fitting and the influence of the prior of B_0 on the estimate of *r*, *q*, and *K* was relatively small (**Table 3**). Therefore, when the B_0 was set at 0.9 for these scenarios, the model parameter estimates except for the biomass in early years were almost similar with those when the uniform prior distribution was given to B_0 (**Table 3**).

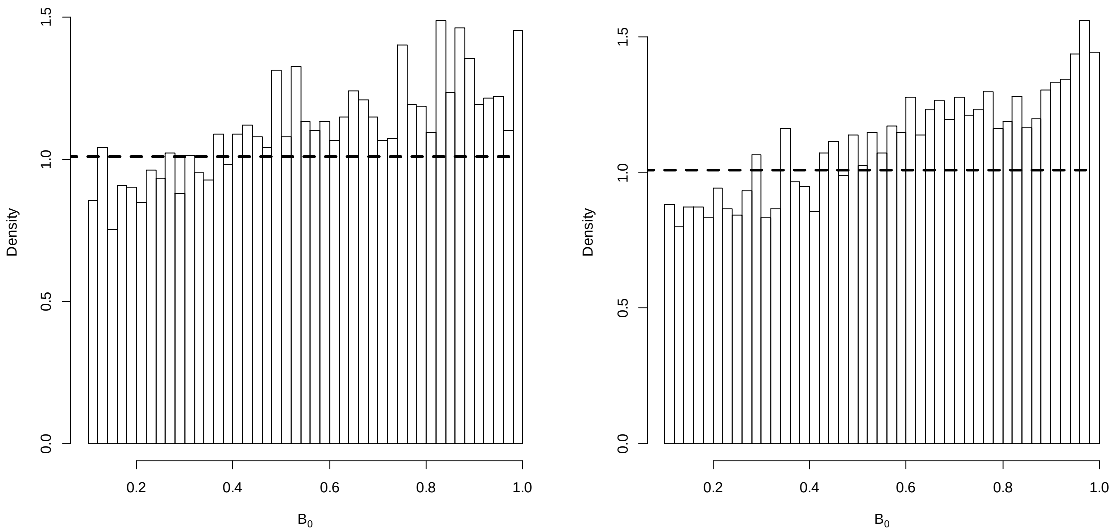

Figure 5 Posterior distributions of B0 for scenario S1 (left) and S10 (right). Dashed line is the prior distributions for the parameters.

The model fitted the standardized CPUEs from Japanese longline better than that from Taiwan, China longline (**Table 3**). When standardized CPUEs from Japan were used as abundance index in the models (S1-S6 and S10-S15), the stock was overfished and subject to overfishing. In contrast, when only standardized CPUEs from Taiwan, China were used (i.e. S7, S8 and S9), the stock was neither subject to overfishing nor overfished, and the ranges of 80% CI of the posterior distributions of *MSY*, *K*, *r* and B_{cur}/B_{MSY} were larger (**Table 3**).

Results of S7, S8 and S9 seem too optimistic to be reliable. Model fit of scenario S12 (or S13) was slightly better than that of scenarios S1, S3 (or S4), S5 (or S6), and S14 (or S15). Because there were some increasing trends in the posterior distribution of B_0 for scenario S10, it is difficult to choose a suitable value for B_0. So, we only present the results of scenario S13 to indicate the status of the stock. According to S13, the median of MSY was 344,200 t, and the medians of B_{2014}/B_{MSY} and F_{2014}/F_{MSY} were 0.74 and 1.87, respectively. Thus, the stock was considered to be overfished and subject to overfishing (**Figure 6**). The risk assessments (**Table 4, 5**) suggest that the current catch level in 2014 (430,331 t) was higher than MSY and this level can result in higher risk for the stock to be overfished and subject to overfishing. Reducing catch to 67% of the current catch level will lead to a 60% of probability that the biomass is slightly above B_{MSY} by 2024 (**Table 4**).

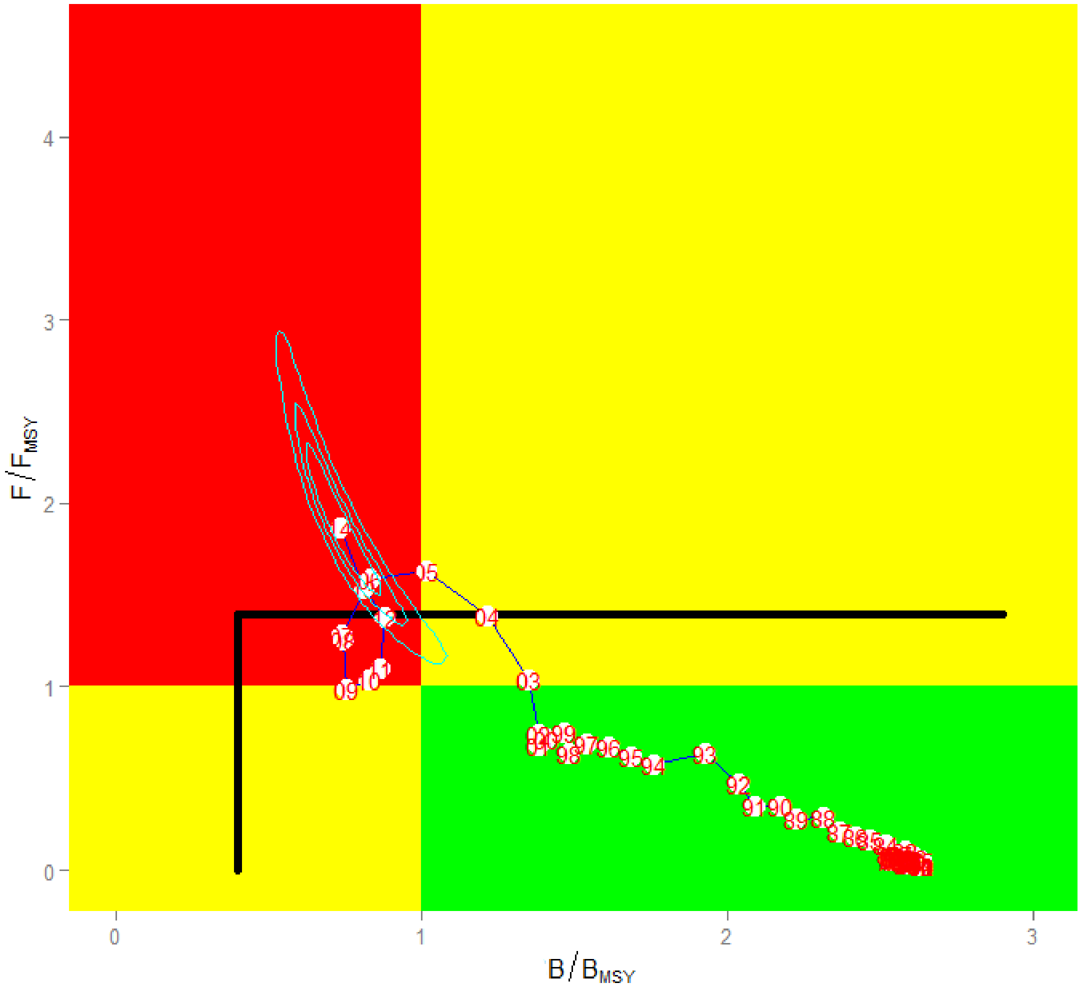

Figure 6 Kobe plot for scenario S13

Table 4 Risk matrix for B>B_{MSY} for scenario S13

Catch	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
60%	0.041	0.109	0.231	0.387	0.541	0.667	0.758	0.825	0.869	0.896	0.919
67%	0.029	0.060	0.111	0.18	0.259	0.342	0.422	0.490	0.551	0.601	0.645
70%	0.025	0.046	0.077	0.121	0.171	0.224	0.277	0.331	0.383	0.426	0.461
80%	0.014	0.017	0.021	0.024	0.028	0.032	0.036	0.039	0.043	0.046	0.05
85%	0.011	0.011	0.010	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.009
90%	0.009	0.006	0.005	0.004	0.004	0.003	0.002	0.002	0.002	0.002	0.001
100%	0.005	0.003	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
110%	0.003	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
120%	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
130%	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
140%	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 5 Risk matrix for F< F_{MSY} for scenario S13

Catch	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
60%	0.271	0.442	0.598	0.721	0.802	0.859	0.893	0.918	0.934	0.943	0.951
67%	0.120	0.192	0.275	0.362	0.444	0.515	0.573	0.622	0.66	0.693	0.718
70%	0.081	0.124	0.177	0.233	0.290	0.345	0.393	0.439	0.474	0.506	0.534
80%	0.021	0.024	0.028	0.032	0.036	0.039	0.042	0.046	0.050	0.053	0.055
85%	0.010	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
90%	0.005	0.004	0.004	0.003	0.002	0.002	0.002	0.001	0.001	0.001	0.001
100%	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
110%	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
120%	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
130%	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
140%	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

4 Discussion

There is often a strong negative correlation between *r* and *K* in biomass dynamics model due to the poor quality of the observed data and the population dynamics relationship simulated by the model. The negative correlation makes it difficult to correctly estimate *r* and *K* simultaneously, because if the estimate of *r* decreased, the *K* would compensate by increasing and vice versa, which produces multiple solutions. Under these circumstances, we need to borrow strength from the prior deduced from other information or research by using methods such as demographic analysis or meta-analysis to improve the reliability of the estimates of parameters (Babcock, 2014). In this study, we used demographic methods and meta-analysis to construct two prior distributions for intrinsic growth rate and incorporated the priors into parameter estimation. There are some improvements in goodness of fit and the CIs of the parameters get narrower for the scenarios where Japanese longline CPUE index were used. However, for scenarios S8 and S9 where the standardized CPUEs from Taiwan China longline fisheries were used, there is some deterioration in fitting (**Table 3**).

Substantial uncertainties remain in the estimation of the intrinsic growth rate, probably because there are considerable uncertainties in natural mortality and maturity at age when using a demographic method to estimate the prior. Our estimate of the prior of intrinsic growth rate is similar with Hillary's results (2008), but different from the estimate by Carruthers and McAllister (2011), where the mean and CV of intrinsic growth rate for Atlantic yellowfin tuna were 0.486 and 0.094. Because we have little information about the intrinsic growth rate of Indian Ocean yellowfin tuna and the prior have great influence on the estimate of parameters, it still needs more efforts to validate and improve the reliability of the estimate.

There are some conflicts in the standardized CPUE trends based on the longline fisheries of Taiwan, China and Japan (IOTC, 2012). The weights assigned to the two indices have great impacts on assessment of the status of the stock and currently it seems difficult to develop a reliable CPUE or assign a reliable weight to each CPUE (e.g. by using arithmetic mean or weighted mean to construct a CPUE time series).

Therefore, it is difficult to choose a scenario which mostly reflect the fishery and population dynamics and evaluate the stock status of yellowfin tuna, although scenario S13 was used as the base to draw the Kobe plot (**Figure 6**) and calculate the risk matrix (**Table 4 and 5**). Because there are high uncertainties in the present assessment, we suggest that the results not be used for developing management advices, but for comparison with other model results.

Acknowledgements

This study was financially supported by Innovation Program of Shanghai Municipal Education Commission (14ZZ147). The study was also supported by National Distant-water Fisheries

Engineering Research Center at Shanghai Ocean University (SHOU), Collaborative Innovation Center for Distant-water Fisheries based in SHOU, and International Center for Marine Studies at SHOU.

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