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Using a Bayesian biomass dynamics model to assess Indian Ocean albacore (*Thunnus alalunga*)

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Abstract: A Fox-form Bayesian biomass dynamics model was developed to assess the stock status of Indian Ocean albacore (*Thunnus alalunga*) in the Indian Ocean (1950-2014). Because the r and K tends to be negatively correlated due to the poor quality of the observed data, we used the life-history parameters to estimate the prior for r and the estimation of the median and the CV of r was 0.30 and 0.42. According to the different standardized CPUEs and the assumption of B_0, there were 12 scenarios were evaluated. Based on an uninformative uniform distribution, the estimation of B_0 seemed questionable. The value fixed for B_0 as 0.90 was not enough large, but its impacts on the estimation were small. For all the scenarios, the goodness of fit for scenario S8 is best. According to the S8, the results showed that the median of Maximum sustainable yield (MSY) was 44,000 t, and the medians of B_{2014}/B_{MSY} and F_{2014}/F_{MSY} were 1.74 and 0.53, respectively. Thus, the stock was neither subject to overfishing nor overfished at the end of 2014.

1 Introduction

Albacore tuna (*Thunnus alalunga*) is distributed throughout the Indian Ocean between 25 ºN and 45ºS and is one of the main target species of the Indian Ocean commercial tuna fishery (Chen et al., 2005). The species was initially exploited by the Japanese longline fishery in the early 1950s, followed by Korean and Taiwan China longline fisheries in the mid and late 1950s respectively (Hoyle et al., 2014). In recent years, the majority of the catches of the species have come from Taiwan China, Indonesia, Japan and Mainland China (IOTC, 2014). Longlines (including deep-freezing and fresh-tuna longliners) currently account for over 90% of the total catches of albacore, with purse seines, coastal longlines, handline, trolling and other gears accounting for the remainder (IOTC, 2014).

Substantial uncertainty exists in the fisheries data that have been available since 1950 as a result of the following issues: (1) no, or incomplete, catch data from some fleets reported to the IOTC (Indian Ocean Tuna Commission) and some reported data not classified by gear and/or species; (2) the amount of catch at size/age data being very low before 1980; (3) the size samples from the driftnet fishery of Taiwan China, over the entire fishing period from 1982 to 1992, being completely absent and the fishery accounting for over 43% of total catches during the period 1986-1990; (4) size data being highly uncertain due to the declining number of specimens and/or a change of collection protocol in recent years (IOTC, 2014). There are no fishery-independent indices of abundance for Indian Ocean albacore and the standardized CPUEs (Catch per Unit Effort) from Japanese, Korean, and Taiwan Chinese longline fisheries are used as the abundance indices. The quality of CPUE data may be questionable due to targeting shifts, changes in distribution of fishing effort and/or technological improvements in the operation of the fleet (IOTC, 2014； Hoyle et al.,2014).

To avoid using catch at size/age data and biological parameters, which were considered to be highly uncertain, Guan et al. (2014) and Matsumoto et al. (2014) chose a simple and highly aggregated model, i.e., a biomass dynamic model, as their stock assessment model. By contrast, Hoyle et al. (2014) and Zhu et al. (2014) chose an age-structured model to get a better representation of complicated population and fishery dynamics. Therefore, at present, the stock assessment models requiring data of great diversity such as ASPIC(A Stock Production Model Incorporating Covariates，Matsumoto et al., 2014)，BBDM (Bayesian biomass dynamic model, Guan et al.,2014)，ASPM (Age-Structured Production Model, Nishida et al., 2014a)，ASAP(Age Structured Assessment Program, Zhu et al., 2014) and SS3(Stock Synthesis, Hoyle et al., 2014) are all applied in the assessment of the Indian Ocean albacore stock. Although the IOTC suggested the albacore stock status should be determined by qualitatively integrating the results of the ASPIC and SS3 stock assessments (Hoyle et al., 2014; Matsumoto et al., 2014), it does not imply an endorsement of the ASPIC or SS3 over other models and there is considerable uncertainty remaining in the assessments (IOTC, 2014).

It is well recognized that assessments of the status of poor-data and data-poor fish stocks are challenging and that Bayesian analysis is one of the methods which can be used to improve the reliability of stock assessments in poor-data and data-poor situations through borrowing strength from prior information deduced from species with good-quality data or other known information (Jiao et al., 2011). In this study, we developed a continuous Fox-form biomass dynamics model using Bayesian methods based on winBUGS platform to make use of the prior information of the intrinsic rate of increase derived from life-history parameters by using demographic methods and to provide an opportunity to compare results with other stock assessment models.

2 Material and Methods

2.1 *Catch and CPUE data*

Catch and standardized CPUE data were downloaded from the IOTC secretariat website (http://www.iotc.org/meetings/6th-working-party-temperate-tunas-wptmt06). Annual catch data were available from 1950 to 2014. The IOTC website also provided different standardized CPUE time series. We only used four yearly indices derived from R1 by using regA5 model (Fig 1 and Fig 2), one yearly CPUE from Japan in Region 3 and 4 and two yearly CPUEs from Taiwan China longline on whole area or core area.

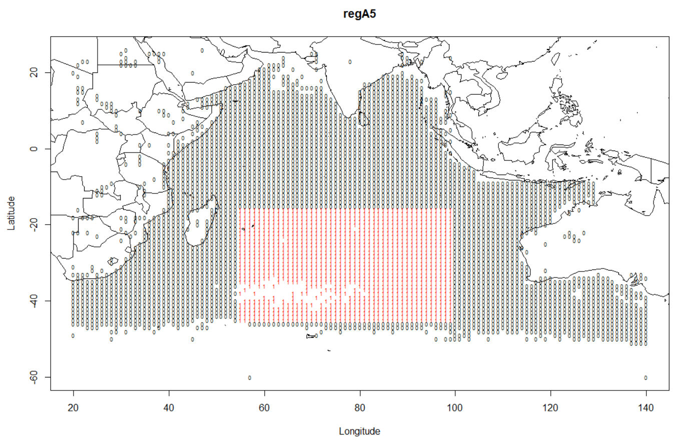

Fig 1. the area (red) used for the standardized CPUE time series (Data from IOTC)

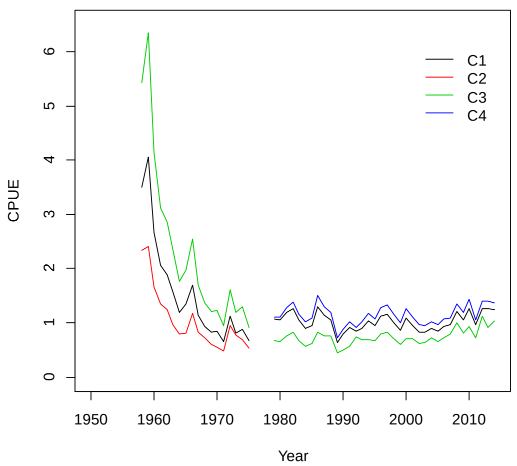

Fig 2. the standardized CPUE time series. C1, C2, C3 and C4 derived from files: Joint_regA5_R1_lognC_boat_allyrsyr.csv, Joint_regA5_R1_lognC_novess_5279yr.csv, Joint_regA5_R1_lognC_novess_allyrsyr.csv and Joint_regA5_R1_lognC_vessid_7914yr.csv respectively.

2.2 Data processing

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 catches, normalized catches, CPUE and normalized abundance index in year t, respectively. C_{Max} is the maximum annual catch and $CPUE_{Max}$ is the maximum CPUE in the time series.

2.3 ***Continuous Fox-form biomass dynamic model***

According to Guan et al. (2014), the equations for the continuous Fox-form biomass dynamics model are as follows:

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

$$P = r\ln(K) - F_t, \tag{4}$$

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

where r is intrinsic rate of increase, K is carrying capacity, B_t and F_t are stock biomass and fishing mortality in year t, respectively and Δt is the time interval that is always set as 1 year. 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, a multiplicative error structure was assumed for the normalized abundance index (i.e., I_t) and the likelihood function is Eq. (6):

$$L(data \mid B_0, r, K, q, \sigma) = \prod_t \frac{1}{I_t\sqrt{\frac{2\pi}{\tau}}} e^{-\frac{\tau(\ln(I_t) - \ln(\hat{I}_t))^2}{2}}, \tag{6}$$

$$\hat{I}_t = q\overline{B}_t, \tag{7}$$

$$\overline{B}_t = \frac{Y_t}{F_t}, \tag{8}$$

$$B_s = B_0 K, \tag{9}$$

$$\tau = \frac{1}{\sigma^2}, \tag{10}$$

where q is catchability, σ is standard deviation of I_t, B_s is the biomass in the first year of the fishery, and B_0 is the ratio of B_s to K.

2.4 ***Prior for parameters***

2.4.1 *Prior distribution of q, τ and K*

According to the catch data series and Eq. (2), the upper limit of q should be less than 1.0. Consequently, the prior given for q was an uninformative uniform distribution on the interval from 0.0 to 1.0 and denoted as U[0.0, 1.0]. The prior for the precision τ was given an uninformative gamma distribution with shape parameter and rate parameter both assigned as 0.001 and denoted as Gamma(0.001, 0.001). The prior for K was given an uninformative uniform distribution and the prior of K was denoted as U[2, 35].

2.4.2 *Prior for B_0*

The prior given for B_0 was an uninformative uniform distribution. According to an assumption of the biomass dynamics model and the recent stock assessment (Hillary, 2008; Nishida et al, 2012; Hoyle et al., 2014; Matsumoto et al., 2014), the maximum value of B_0 is less than 1.0 and the minimum value is greater than 0.25. The prior were denoted as U[0.25, 1].

2.4.3 *Prior for r*

The prior distribution for r was an informative prior, i.e. a lognormal distribution. The informative prior was denoted as LM and its mean and standard deviation on log scale 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:

$$\sum_{a=0}^{A} e^{-ra} m_a w_a S_a \gamma = 1, \tag{11}$$

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 (12) and (13)，S_a is the fraction of individuals surviving from ages 0 to a and calculated by Eq. (14), and γ is the recruits-per-spawner biomass at zero spawners or maximum recruits-per-spawner and is calculated by Eqs (15) and (16).

$$w_a = cL_a{}^b, \tag{12}$$

$$L_a = L_\infty(1 - e^{-k(a-t_0)}), \tag{13}$$

$$S_a = e^{-\sum_{i=0}^{a-1} M_i}, \tag{14}$$

$$\gamma = \frac{4h}{\rho_{F=0}(1-h)}, \tag{15}$$

$$\rho_{F=0} = \sum_{a=0}^{A} w_a m_a e^{-aM_a}, \tag{16}$$

where c is a scaling constant, b is the allometric growth parameter, h is the steepness of the stock-recruit relationship, L_∞ is the asymptotic average maximum body size, k is a growth rate coefficient, t_0 is the hypothetical age at zero length, and M_a is natural mortality at age a. The values of the parameters except h in Table 1 were assigned according to recommendation from Nishida et al.

(2014b). The steepness was assumed to obey a beta distribution with a mean and standard deviation of 0.75 and 0.15 respectively. If the parameters are known, the *r* can be solved by iteration according to Eq. (11).

Table 1. Values of parameters for Euler-Lotka equation

Parameter	Value	Parameter	Value	Parameter	Value
m_0	0.0	M_0	0.4000	A	15
m_1	0.0	M_1	0.3641	c	1.3718×10^{-5}
m_2	0.0	M_2	0.3283	b	3.0973
m_3	0.0	M_3	0.2924	L_∞	124.1
m_4	0.09	M_4	0.2566	k	0.164
m_5	0.47	M_5	0.2207	t_0	-2.2390
m_6	0.75	M_6	0.2207	h	Beta distribution
m_7	0.88	M_7	0.2207		mean：0.75
m_8	0.94	M_8	0.2207		standard deviation：0.15
m_9	0.97	M_9	0.2207		
m_{10}	0.99	M_{10}	0.2207		
m_{11}-m_{15}	1.0	M_{11}-M_{15}	0.2207		

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

(3) Solving Eq. (11) 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 mean and standard deviation on the log scale.

2.5 *Estimation of the parameters*

According to the standardized CPUE time series and the priors of the parameters, the model was run with 12 scenarios that are denoted as S1, S2… and S12 in Table 2.

Table 2. Catch data and prior assumptions of parameters used in Bayesian biomass dynamic models

Scenario	CPUE Data	*r*	*K*	*q*	B_0	τ
S1	C3	LM	U[2,35]	U[0,1]	U[0.25,1]	Gamma(0.001,0.001)
S2	C3	LM	U[2,35]	U[0,1]	0.9	Gamma(0.001,0.001)
S3	C1	LM	U[2,35]	U[0,1]	U[0.25,1]	Gamma(0.001,0.001)
S4	C1	LM	U[2,35]	U[0,1]	0.9	Gamma(0.001,0.001)
S5	C2 and C4	LM	U[2,35]	U[0,1]	U[0.25,1]	Gamma(0.001,0.001)
S6	C2 and C4	LM	U[2,35]	U[0,1]	0.9	Gamma(0.001,0.001)
S7	C3(1979-2014)	LM	U[2,35]	U[0,1]	0.9	Gamma(0.001,0.001)
S8	C1(1979-2014)	LM	U[2,35]	U[0,1]	0.9	Gamma(0.001,0.001)
S9	C4	LM	U[2,35]	U[0,1]	0.9	Gamma(0.001,0.001)
S10	TW_Whole_Area	LM	U[2,35]	U[0,1]	0.95	Gamma(0.001,0.001)
S11	TW_Core_Area	LM	U[2,35]	U[0,1]	0.95	Gamma(0.001,0.001)
S12	Jap_Area 3+4	LM	U[2,35]	U[0,1]	0.95	Gamma(0.001,0.001)

Note: U denotes uniform distribution; LM denotes lognormal distribution in which the parameters were estimated by using the demographic method; Gamma denotes gamma distribution; C1, C2, C3, C4 denote different CPUEs in Fig 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 was set as 1.1 (Kéry, 2010), which means if BGRs is less than 1.1, the model has converged. We only presented and analyzed the results of the converged scenarios.

3 Results

3.1 The estimation of *r*

The estimation of the median and the CV of *r* was 0.30 and 0.42 (Fig 3). Steepness also has a great influence on the estimation of *r* and the *r* tends to increase with steepness. According to the literature (Hillary, 2008; Hoyle et al., 2014; Zhu et al., 2014), the steepness of the Indian Ocean albacore was assumed to follow a beta distribution with a mean and CV of 0.8 and 0.05 by Hillary (2008), or set as 0.8 or 0.7 by Hoyle et al. (2014) and Zhu et al. (2014). We assumed a beta distribution with a mean and standard deviation of 0.75 and 0.15. If we chose the beta distribution assumed by Hillary (2008), the median of *r* was 0.33 but the CV decreased to 0.11. There are different estimations among authors in their estimate of the distribution of *r*, for example, the mean and CV was 0.43 and 0.14 for Indian Albacore (Hillary, 2008) or 0.285 and 0.058 for Atlantic Albacore (Carruthers and McAllister, 2011). Because the albacore stock resilience is median, which means the intrinsic rate of increase is between 0.16 and 0.50 (Musick et al., 2000), the current estimate of the intrinsic rate of increase seems reasonable.

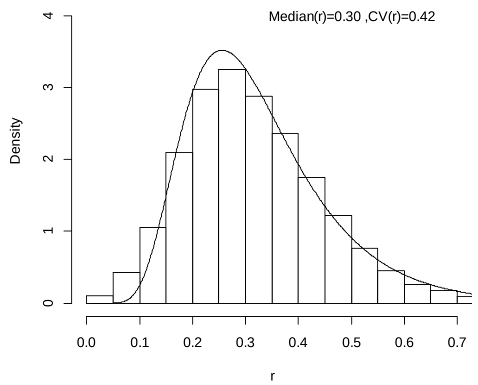

Fig 3. the distribution of r estimated by using life-history parameters

3.2 The estimation of parameters

According to Gelman and Rubin's convergence diagnostic, all scenarios were converged. The estimations of the primary parameters were shown in table 3.

Table 3. Parameter estimates of each scenario

Scenario	*r*	*K(1000t)*	B_0	*MSY(1000t)*	R^2

	2.5%	50%	97.5%	2.5%	50%	97.5%	2.5%	50%	97.5%	50%	
S1	0.14	0.33	0.68	150.8	305.7	657.3	0.30	0.76	0.99	36.1	0.07
S2	0.13	0.29	0.64	161.1	346.2	718.0	0.90	0.90	0.90	35.6	0.07
S3	0.18	0.37	0.71	182.6	381.6	1056.0	0.29	0.76	0.99	48.8	0.06
S4	0.16	0.33	0.67	196.5	426.1	1097.6	0.90	0.90	0.90	48.4	0.06
S5	0.22	0.42	0.85	264.8	683.8	1486.8	0.27	0.66	0.98	101.3	0.04
S6	0.21	0.40	0.83	276.2	741.6	1519.2	0.90	0.90	0.90	102.9	0.04
S7	0.21	0.42	0.86	442.0	1129.1	1574.5	0.90	0.90	0.90	158.1	0.02
S8	0.20	0.38	0.77	345.3	928.2	1559.0	0.90	0.90	0.90	119.7	0.03
S9	0.20	0.38	0.78	373.4	982.5	1560.8	0.90	0.90	0.90	127.9	0.03
S10	0.17	0.34	0.65	278.5	565.9	1346.6	0.95	0.95	0.95	69.0	0.21
S11	0.17	0.34	0.63	193.4	361.1	774.2	0.95	0.95	0.95	44.0	0.30
S12	0.14	0.32	0.69	193.1	523.5	1460.3	0.95	0.95	0.95	54.3	0.10

There were significant increasing trends in the posterior distribution of B_0 for scenarios S1, S3 and S5 where the prior for B_0 was assumed as a uniform distribution (e.g. for S1 and S3 in Fig 4), which made the estimation of B_0 questionable. According to the trajectory of biomass estimated by the S2, S4 and S6, The value fixed for B_0 as 0.90 was not enough large (e.g. for S2 and S4 in Fig 5 and Fig 6), but its impacts on the estimation were small (Table 3).

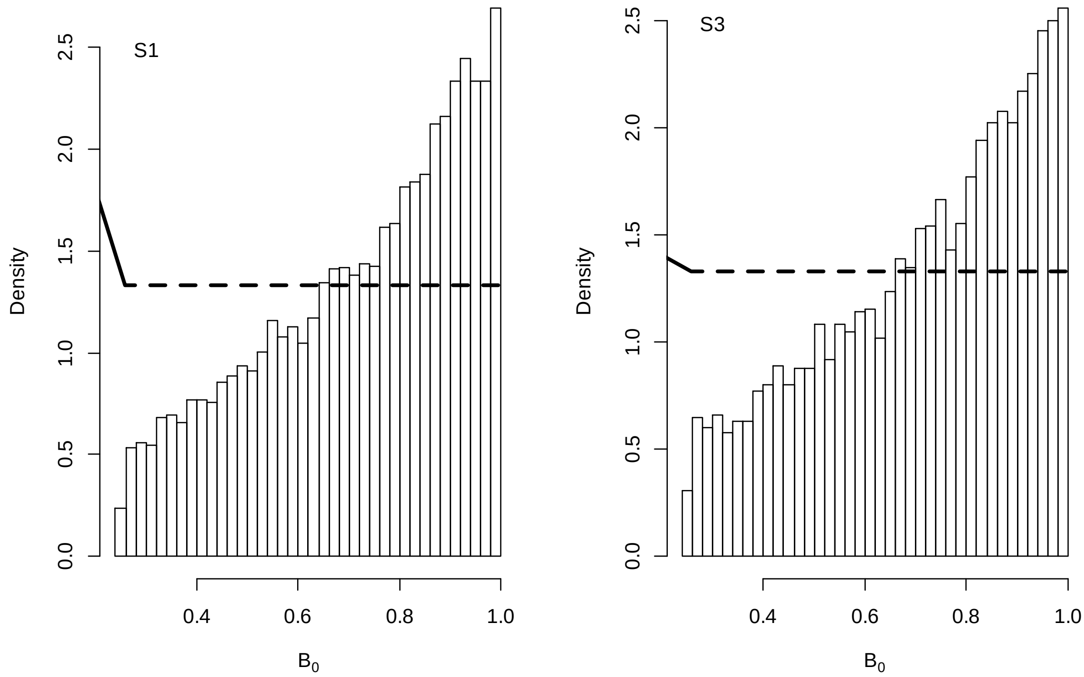

Fig 4. Posterior distributions of B_0 for scenario S1 and S3. Dashed line is the prior distributions for the parameters.

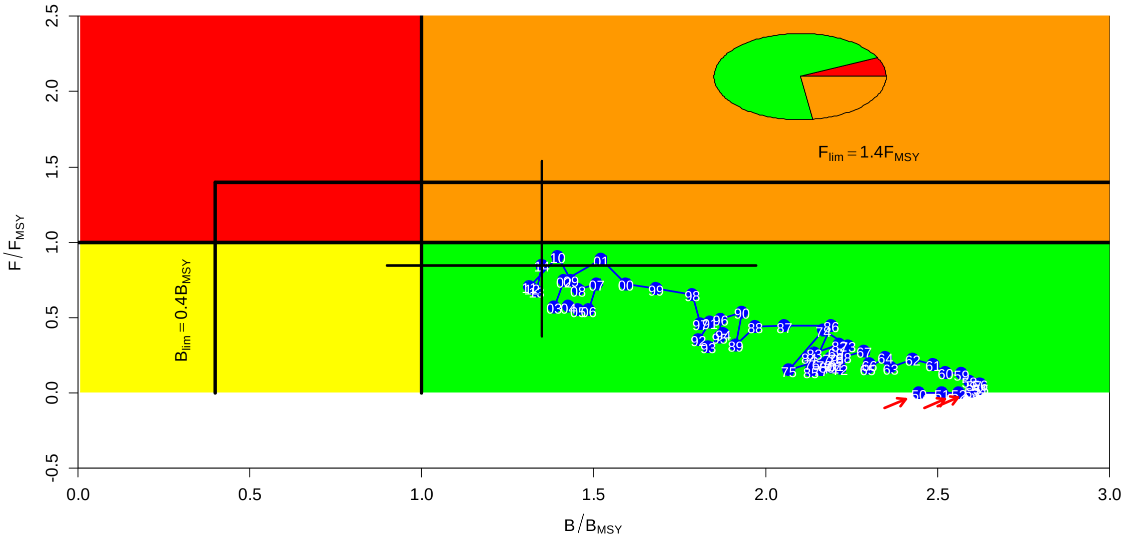

Fig 5. the trajectory of biomass estimated by the S2 where the B_0 was assumed as 0.90. The red arrows marked the unreasonable biomass estimated by model.

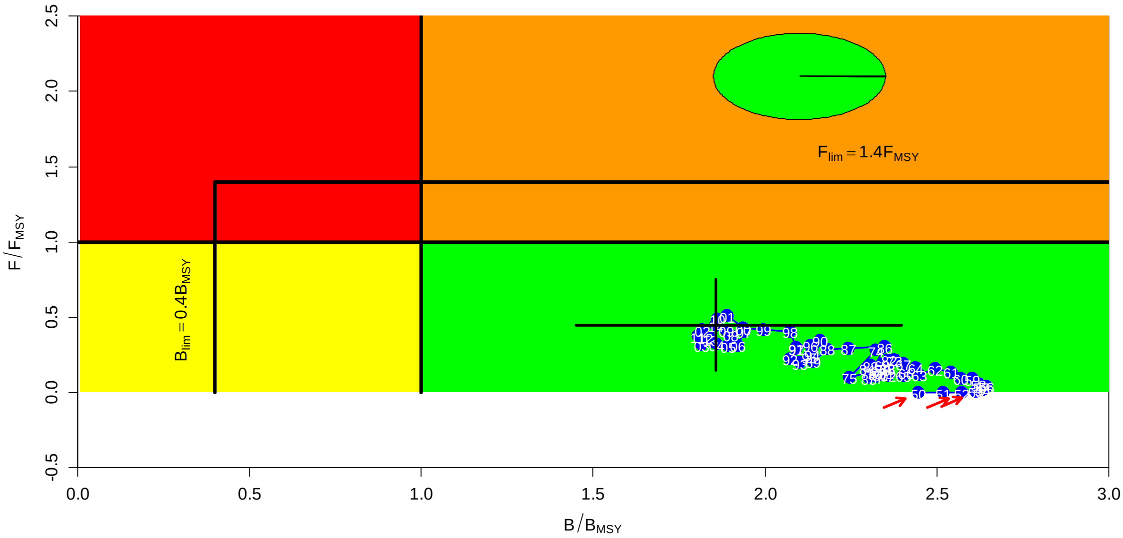

Fig 6. the trajectory of biomass estimated by the S4 where the B_0 was assumed as 0.90. The red arrows marked the unreasonable biomass estimated by model.

3.3 The goodness of fit of the scenarios

The goodness of fit for scenarios S1-S9 seems not good (Fig 7, Fig 8, and Table 3). The goodness of fit was improved when the Taiwan China longline CPUE used (Fig 8, and Table 3). The fit is also bad for Japan CPUE (Fig 8, and Table 3). For all scenarios, the S8 is fitted best (Table 3). Therefore, we chose S8 as our base case.

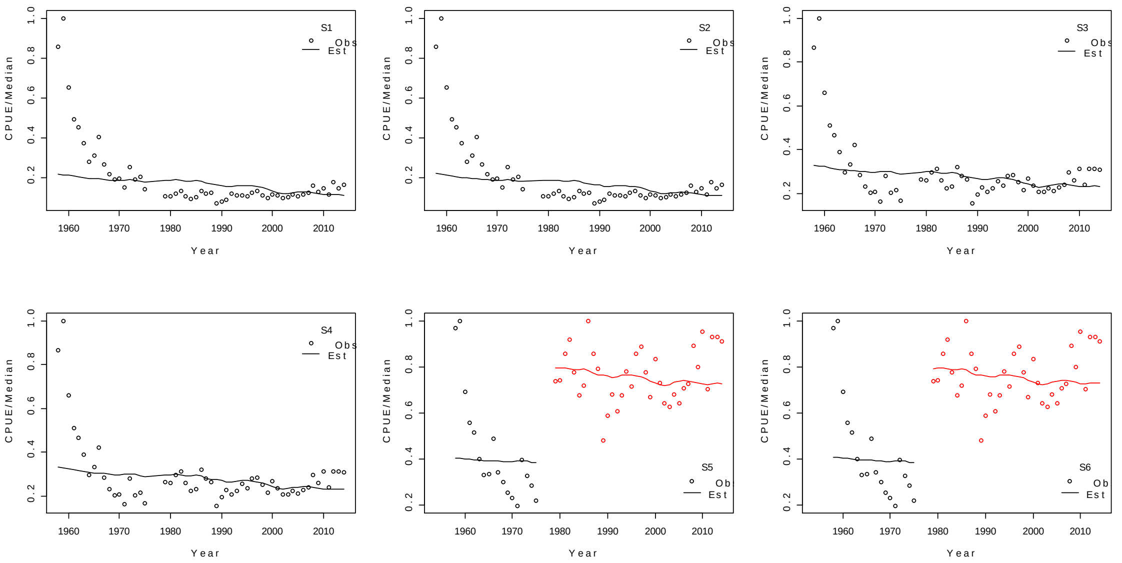

Fig 7 Observed and estimated CPUE for scenarios S1-S6

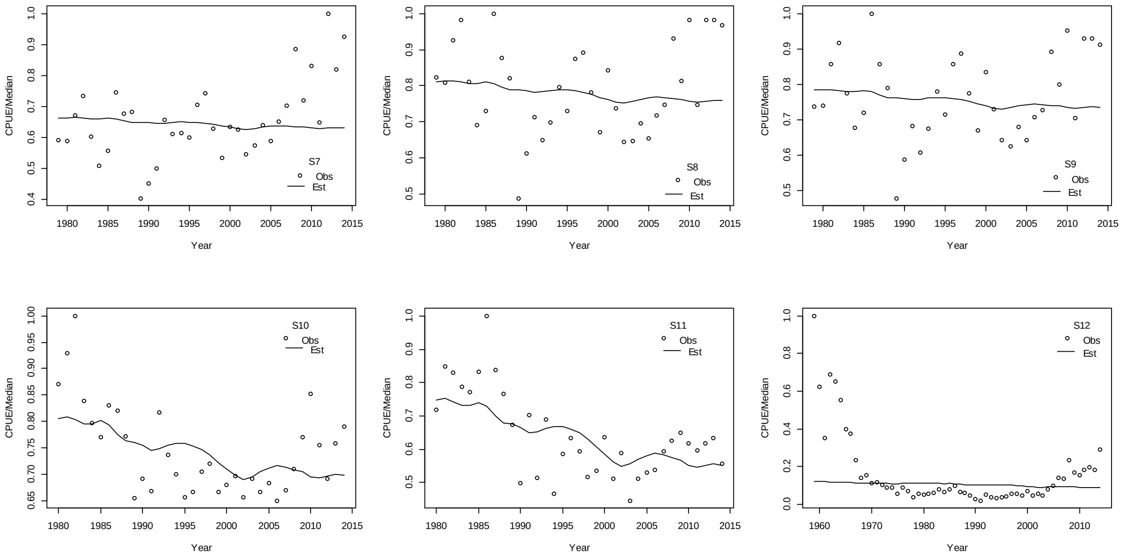

Fig **8** Observed and estimated CPUE for scenarios S7-S12

3.4 Stock status and comparison with other results

According to the S8, the median of Maximum sustainable yield (MSY) was 44,000 t, and the medians of B_{2014}/B_{MSY} and F_{2014}/F_{MSY} were 1.74 and 0.53, respectively (Table 4). The ranges of 80% CI of posterior distributions of Fcur/F_{MSY} less than 1.0 and Bcur/B_{MSY} are larger than 1.0 (Table 4). The stock is neither overfished nor subject to overfishing (Table 4, Fig.9).

Compared with the result of ASPIC run 3 (Matsumoto, 2016), which was based model, the MSY, Fcur/F_{MSY}, Bcur/B_{MSY} are similar, but the estimations of K and r were different.

Compared with the result of the stock assessment based on data in 2014, the current scenario is more optimistic (Table 5).

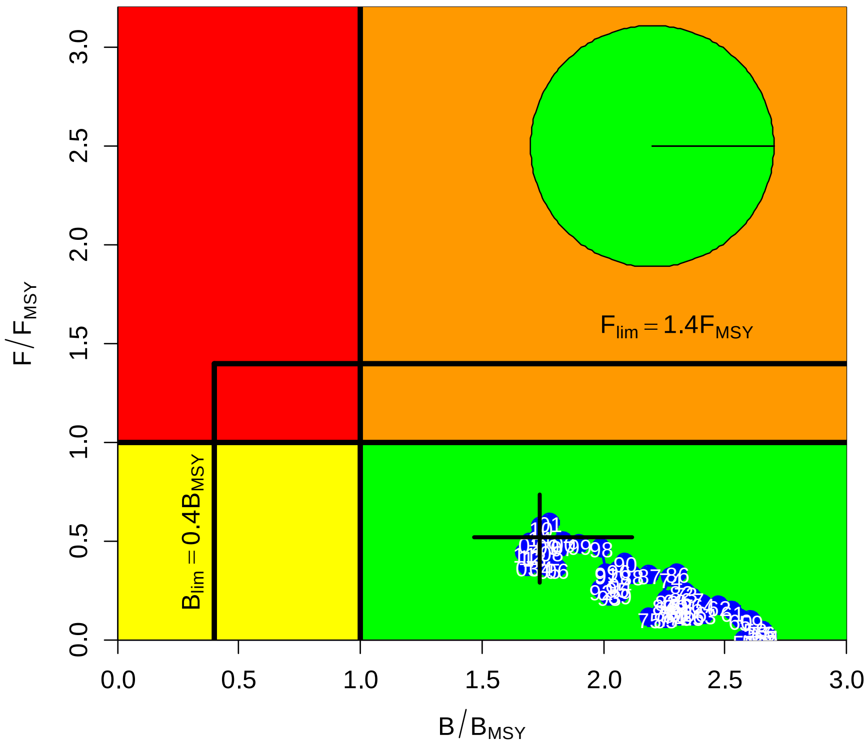

Fig 9 Kope plot for scenario S8

Table 4. Compared with ASPIC (Matsumoto, 2016)

Scenario	MSY(10^3)	*K*(10^3)	*r*	$F_{2014}F_{MSY}$	B_{2014}/B_{MSY}
	(80% CI)	(80% CI)	(80% CI)	(80% CI)	(80% CI)
S8	44.0	361.1	0.34	0.53	1.74
	(39.2-53.5)	(237.9-575.6)	(0.22-0.51)	(0.38-0.66)	(1.55-1.96)
ASPIC	43.8	287	0.42	0.55	1.65
(Run3)	(37.5-50.6)			(0.38-0.67)	(1.50-1.92)

Table 5. Compared with the stock assessment based on data in 2014

Scenario	MSY(10^3)	*K*(10^3)	*r*	F_{2012}/F_{MSY}	B_{2012}/B_{MSY}
	(80% CI)	(80% CI)	(80% CI)	(80% CI)	(80% CI)
S8	44.0	361.1	0.34	0.44	1.70
	(39.2-53.5)	(237.9-575.6)	(0.22-0.51)	(0.32-0.55)	(1.52-1.93)
2014	34.5	299.4	0.32	0.85	1.15
	(31.1-41.3)	(193.0-482.2)	(0.20-0.51)	(0.52-1.25)	(0.87-1.58)

3.5 Risk assessment

The risk assessments (Table 6, 7) suggest that the current catch level in 2014 (39707 t) was less than MSY (44000t) and this level can't result in risk for the stock to be overfished or subject to overfishing.

Table 6. Risk matrix for $B < B_{MSY}$ for scenario 8 (probability of B less than B_{MSY})

Catch	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
60%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
70%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
80%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
85%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
90%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
100%	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.4	0.5	0.7
110%	0.0	0.0	0.0	0.3	0.9	1.8	2.9	4.5	6.3	8.4	10.6
120%	0.0	0.0	0.7	2.4	5.5	10.3	15.4	20.5	25.4	30.0	34.2
130%	0.0	0.4	3.1	9.3	17.7	26.7	35.1	42.4	48.7	53.8	57.8
140%	0.0	1.5	8.8	20.8	33.7	44.8	54.0	60.8	66.2	70.8	74.2

Table 7. Risk matrix for $F > F_{MSY}$ for scenario 8 (probability of F larger than F_{MSY})

Catch	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
60%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
70%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
80%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
85%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
90%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
100%	0.0	0.0	0.1	0.1	0.2	0.3	0.4	0.7	1.0	1.2	1.5
110%	0.1	0.4	1.1	2.2	3.5	5.1	7.3	9.6	11.7	1.4	16.0
120%	0.9	3.0	6.6	11.8	17.4	22.8	27.8	32.3	36.4	40.4	43.5
130%	3.5	10.6	20.3	29.9	38.8	46.4	52.4	57.1	60.9	63.8	66.6
140%	9.8	23.9	38.5	50.4	59.1	65.1	70.1	73.7	76.6	79.1	80.9

4 Discussion

4.1 Imapcts of the standardized CPUEs

Obviously, the standardized CPUEs are the only information source for production models to estimate the parameters and different standardized CPUEs have great impacts on the results of the stock assessment (Table 3).

It seems doubtful the standardized CPUEs from A5 from 1958 to 1971 decreased by more than five times which the models fail to fit (Fig. 7), because during the early period the catch is low. This problem also exists in Japan CPUE.

It seems the standardized CPUE from Taiwan China longline in core area is more reasonable, but there is still big difference between predicted CPUE and observed CPUE.

4.2 Choice of stock assessment model

It seems reasonable to pick a model which can represent more complicated population and fishery dynamics and make use of all the information available from fisheries or biological research. However, on the other hand, a model with an increasing biological and fishery realism has a higher data quantity and quality requirement. The main advantage of age/size structure models (e.g., SS3) is that they can make full use of the age- or size-specific catch data and biological information available from fishery and biological research to increase biological and fishery realism. However, there are substantial uncertainties in the basic Indian Ocean albacore biology regarding stock recruitment relationship (e.g., assumption of steepness), sex composition, individual body growth, maturity and natural mortality (Nishida et al., 2014b; IOTC, 2014) and in the size-composition or age-composition data due to lack of size samples, unrepresentative samples, and a change of collection protocol (IOTC, 2014). As a consequence, some models (e.g., ASPM) did not converge (Zhu et al., 2014; IOTC, 2014) and the results based on the others have also been questioned (Zhu et al., 2014; Hoyle et al., 2014; IOTC, 2014).

In order to avoid using the data and making the assumptions (e.g. steepness, natural mortality, etc) with considerable uncertainty, we choose the biomass dynamics model as a stock assessment model for the Indian Ocean albacore. However the production model lack biological and fishery realism and may not correctly simulate the population dynamics with a strong age structure and impacts of changes in selectivity of fisheries, and which may be another cause for the bad goodness of fit for all scenarios. We need to do more simulations in future to assess whether the production model can be applied to this stock as done by Prager et al. (1996).

4.3 Impact of environmental factors

For all scenarios, great differences were found between the observed and the predicted normalized abundance indices (Fig 7). This may suggest that the population dynamics also relate to changes in the marine environment as well as impacts from fishing. Although introducing environmental factors into the stock assessment models is an important research topic at present, the choice of environmental variables and re-parameterization of the models to incorporate the environmental variables still needs further study.

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