

**Standardizing the tuna longline CPUE of *Thunnus obesus*: An application of “deterministic habitat based standardization” to the data in Marshall Islands Waters**

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## Abstract

To better understand the performance of "deterministic habitat based standardization ( detHBS )" and to improve the estimating accuracy of standardized CPUE, a survey on tuna longline fishery has been carried out aboard the longliner "Shenliancheng 719". Based on the survey data, and the archival tagging data, we estimated the habitat preferences of bigeye tuna (*Thunnus obesus*), respectively. The detHBS was applied to standardize the CPUE of bigeye tuna. The differences between nominal CPUE and standardized CPUEs estimated by different group data, and normalized nominal CPUE and normalized standardized CPUEs were compared by Monte Carlo permutation test, respectively. Bayesian Information Criterion (BIC) was applied to ascertain which group data is the best one for the detHBS. This study suggests that (1)the nominal CPUE was greatly different from the standardized CPUEs estimated by different group data; (2) there were no difference between normalized nominal CPUE and normalized standardized CPUEs estimated by different group data, respectively; (3) the BIC value of V group data (hook's distribution in the specific depth classes was estimated based on predicted depth; the habitat preference of depth was estimated from the CPUE based on predicted depth) was the lowest one (BIC=-2.57) and was the optimum data group to standardize the CPUEs; (4) "detHBS" improved the precision of CPUE standardization effectively .

**Keywords:** *Thunnus obesus*; CPUE standardization; deterministic habitat based standardization(detHBS); longline; Marshall Islands waters

## 1. Introduction

Many statistical models for standardizing catch per unit effort (CPUE) have been developed, including general linear models (GLM) ( Shono et al., 2000; Wang et al., 2005), general additive models (GAM) (Bigelow et al.,1999; Wise et al.,2002), deterministic habitat-based standardization (detHBS) (Hinton and Nakano,1996; Hinton and Deriso,1998; Bigelow and Labelle,1998; Bigelow et al.,1999;Bigelow et al., 2002), and statistic habitat based standardization (statHBS)( Hinton et al.,2001; Bigelow et al., 2003; Bigelow et al., 2004; Maunder et al., 2006).

GLM and GAM are the most common methods for standardizing catch and effort data with CPUE and corresponding environmental variables of a defined spatial and temporal scales being used as input data (Tian et al., 2009). GLM exhibits weakness in their limited ability to include scientific understanding about the system and an inability to include information on the scientific understanding among explanatory variables (Bigelow et al., 2004; Maunder et al., 2006). GLM and GAM do not in general use analytical reasoning to define the functional form of the relationship between the explanatory variables and CPUE (Hinton and Maunder, 2004). The variables in both models may not preferably reflect the fluctuations of the depth in which the fish inhabit. The fluctuations of the depth in which the fish inhabit might be resulted from the fluctuations of ocean thermal structure (Bigelow et al., 1999). Thus, longline CPUE standardized in GLM or GAM may not be related to the resource

abundance due to variability in fish depth distributions in which the fish inhabit (Punsly and Nakano, 1992).

A deterministic habitat-based standardization (detHBS) method was developed by Hinton and Nakano (1996) that provides an analytical framework to incorporate understanding of the distributions of the environmental, fishing gear and species habitat preference into the standardization of CPUE. However, this method is generally not used for standardization of CPUE in the other oceans of the world (Maunder et al., 2002). A statistical HBS (statHBS) was developed that allows parameter (e.g. habitat preferences, factors modifying the behavior of the gear or species) estimation based on fitting the model to observed catch and effort data (Hinton et al., 2001). But it does not mean that it will necessarily produce better estimates than other methods (Maunder et al., 2002).

Much controversy has surrounded the applications of the detHBS method (Goodyear et al., 2003; Ward and Myers, 2005; Prince and Goodyear, 2006). The poor performance of the detHBS method is probably due to problems in estimating hook depth, incomplete knowledge of habitat preferences and differences between the distribution of bigeye tuna and their vulnerability to longline gear (Ward and Myers, 2006; Bigelow and Maunder, 2007). For the tuna longline CPUE standardization, the actual depth of the hooks and the habitat preference information of each fish species are the most important parameters because the hook depths at which species are captured are fundamental to determine the species' vulnerability to longline fishing gear. Nishida et al. (2003) used the GLM and the habitat-based model/general linear

model (HBM/GLM) to standardize the Japanese tuna longline CPUE of yellowfin tuna in the Indian Ocean. As the HBM approach takes into account actual depths of habitat and gear deployed into the model, it may provide a more realistic and reliable CPUE standardization than GLM approach (Nishida et al., 2003).

However, the hook depth used in the present CPUE standardization was mostly the catenary hook depth. The habitat preference index was estimated based on the large-scale Ocean General Circulation Model (OGCM) data, or the archival tagging data. So, the accuracy of CPUE standardization should be improved and the performance of the detHBS should be ascertained.

In this study, we applied the catenary depth formula (Saito, 1992), the hook depth predicting models (Song et al., 2009), and the actual survey data to ascertain the distribution probability of hooks and habitat preferences in different depth, and temperature classes. We also applied the catenary hook depth, predicted hook depth, and the corresponding distribution probability of hook in different depth classes, temperature classes (actual survey temperature data and archival tagging data), depth habitat preference, and temperature habitat preference to standardize the CPUE of bigeye tuna by the detHBS (Hinton and Nakano, 1996; Bigelow et al., 2002). We validated the detHBS and applied the Bayesian Information Criterion (BIC) to test the standardization results in order to ascertain the optimal data for the detHBS.

## **2. Materials and methods**

## 2.1 *Materials*

Data were collected from operations on the longliner “Shenliancheng 719”. The vessel had the identical sections, with overall length of 32.28 m; registered beam of 5.70 m; registered depth of 2.60 m; gross tonnage of 97 t; net tonnage of 34 t; and main engine power of 220 KW. The vessel was equipped with super spools longlining systems.

The fishing activity was restricted principally from 3°00'N to 12°30'N and 163°00'E to 177°30'E (Fig.1). The survey sites were shown in Fig.1. The fishing operation was conducted from 27 October 2006 to 29 May 2007, with fishing for 69 days.

The longline gear consisted of 4.0 mm diameter, 90 km monofilament mainline; 360 mm diameter hard plastic floats; 4.2 mm diameter nylon float line, 26 m long; and 20 m branch lines ending in either a ring hook or a circle hook. Two configurations of fishing gear were used in the study, conventional and experimental gear. The branch line of the conventional gear consisted of three components: 3.0 mm diameter hard polypropylene line, 1.5 m long; 1.8 mm diameter hard polypropylene line, 18 m long; 1.2 mm diameter wire, 0.5 m long. The first component was attached to the second component directly; the second component was attached the third component by the barrel swivel; the third component was attached the hook directly. For the branch line of the experimental gear, the first component was attached the second component by one of three plumbic barrel swivel; one of two plumbic sinker were assembled above the hook; the fluorescent tubes were assembled on some hooks;

the other assemblage was the same as the conventional gear.

In general, the gear deployment started between 05:30 and 09:30 local time, and lasted for about 4 h. The gear retrieval generally started between 16:00 and 22:00, and lasted for 6 h. Soak-times for individual hooks ranged from 6.5 h to 16.5 h. During the gear deployment, the vessel speed was about 4.1-4.9 m·s<sup>-1</sup>, line shooter speed was 5.1-5.9 m·s<sup>-1</sup>, and the time interval between deploying the fore and after branch lines was about 8 s. The length of the mainline between two branch lines was about 44 m, and there were 25 hooks between two successive floats (HBF). The vessel used 200 circle hooks, 400 experimental hooks, 1000 ring hooks per operation. So, the total hooks per operation were about 1600 hooks.

During deploying the experimental gear, the first hook nearest the float was absent, and the second hook was instead by one of the four messenger weights (1.0 kg, 1.5 kg, 2.0 kg and 2.5 kg in the water). Each type of experimental gear was 50 branch lines and eight types were deployed with 400 branch lines.

The environmental sampling instruments included the autonomous profiling data logger (APDL) (XR-620) (RBR Co., Ottawa, Canada) and temperature depth recorder (TDR) (2050) (RBR Co., Ottawa, Canada). The measurement ranges of environmental variables and the precision of the data were shown in Song et al. (2008, 2009). Based the precision of data from the different instruments and requirements of this study, the data of depth, temperature were processed to one effective decimal place, and catch rate were processed to two effective decimal places, respectively.

Ocean Global Circulation Model (OGCM) temperature data (Behringer et al.,

1998) was downloaded from Columbia University <http://ingrid.ldeo.columbia.edu>, and the spatial resolution was  $1^{\circ} \times 1.5^{\circ}$ . Firstly, the temperature data from OGCM were pretreated. Secondly, the interpolation method was applied to calculate temperature data which was consistent with the hook depth. At last, according to the time and location of each set, the suitable temperature data were estimated.

## 2.2 Analytical methods

The data sources mainly included the catch rate of bigeye tuna per operation, the operational parameters, environment data, and the archival tagging data. In this study, the bigeye tuna catch were 318 individuals. We identified the hook codes of 304 bigeye tuna (95.60%) at which the fish were hooked. Among 318 bigeye tuna, we estimated the captured depth for 304 bigeye tuna (95.60%) and the captured temperature for 267 bigeye tuna (83.96%). We applied catenary depth formula (Saito, 1992), and the hook depth predicting models (Song et al., 2009) to calculate the hook depth and analyze the distribution probability of hook in various depth and temperature classes, and the nominal CPUE of bigeye tuna in various depth and temperature classes. Based on the nominal CPUEs of bigeye tuna, the depth-time and temperature-time of the archival tagging data, we estimated the habitat preferences and inputted it to the detHBS. Then, we standardized the CPUE of bigeye tuna in various depth and temperature classes by the detHBS. The data process procedures were shown in Fig.2.

For the conventional gear, the catenary curve equations (Saito, 1992) were used to calculate the hook depths.



$$D_j = h_a + h_b + l \left[ \sqrt{1 + \cot^2 \varphi_0} - \sqrt{\left(1 - \frac{2j}{n}\right)^2 + \cot^2 \varphi_0} \right] \quad (1)$$

$$L = V_2 \times n \times t \quad (2)$$

$$l = \frac{V_1 \times n \times t}{2} \quad (3)$$

$$k = \frac{L}{2l} = \frac{V_2}{V_1} = \cot \varphi_0 \operatorname{sh}^{-1}(\operatorname{tg} \varphi_0) \quad (4)$$

where  $D_j$  was theoretical hook depth of the conventional gear (m);  $h_a$  was the length of branch line (m);  $h_b$  was the length of float line (m);  $l$  was the half length of the main line between two floats (m);  $\varphi_0$  was the angle between the horizontal and the tangential line to the mainline, and relational with  $k$  ( $^\circ$ ). Because the angle  $\varphi_0$  was hard to be measured at sea, it was estimated by  $k$ ;  $j$  was the code of the hooks between two floats;  $n$  was the subsection numbers between two floats;  $L$  was the distance between two floats in the sea surface (m);  $V_l$  was the line shooter speed (m.  $s^{-1}$ );  $V_2$  was the vessel speed (m.  $s^{-1}$ );  $t$  was the time interval between deploying the fore and after branch lines (s).

For the experimental gear, the shape of the main line under the water was changed because of the messenger weight (Fig. 1, in Song and Zhou, 2010). In the survey, we did not measure the depths of the connecting positions where the messenger weights were connected to the main line by TDRs. We used the arithmetic mean of actual depth of corresponding weight measured in the India Ocean as the depths of the connecting positions where the messenger weights were connected to the main line. The corresponding depths of the connecting positions for the messenger weight which was 1.0, 1.5, 2.0 and 2.5 kg in the water was 54.0 m, 59.7 m, 65.0 m, and 67.7 m, respectively (Song et al., 2008).

When we calculated the hook depth of the experimental gear, we made the following assumptions in this study: (1) that the sunken depth of one type of messenger weights was the constant during the survey; (2) that the main line between position C and position D (Fig. 1, in Song and Zhou, 2010) as the catenary curve; (3) that the main line between A and C, B and D were the beeline. Based on the vertical depth of the C and D, we calculated the horizontal distance between A and C, B and D, then we calculated the horizontal distance between C and D, denoted as  $L'$ , and the equations were written as

$$D'_j = h_a + h_b + d_w + l \left[ \sqrt{1 + \cot^2 \varphi'_0} - \sqrt{\left(1 - \frac{2j}{m}\right)^2 + \cot^2 \varphi'_0} \right] \quad (5)$$

$$L' = V_2(m+4)t - 2\sqrt{(2V_1t)^2 - (d_w - h_b)^2} \quad (6)$$

$$l = \frac{V_1 \times m \times t}{2} \quad (7)$$

$$k' = \frac{L'}{2l} = \cot \varphi'_0 \operatorname{sh}^{-1}(\operatorname{tg} \varphi'_0) \quad (8)$$

where the  $D'_j$  was the hook depth of experimental gear (m);  $d_w$  was the sunken depth of the connecting position where the messenger weight was connected (m);  $\varphi'_0$  was the angle between the horizontal line and the tangent of C or D ( $^\circ$ ) (Fig. 1, in Song and Zhou, 2010);  $m$  was the HBF+1;  $k'$  was the sagging rate;  $L'$  was the horizontal distance between C and D (m); others were the same as the formula (1)-(4).

We applied the hook depth predicting models (Song et al., 2009) to predict the hook depth for the conventional gear and experimental gear. The predicted hook depth models of the conventional gear and the experimental gear were shown as follows

$$D_{f_i}' = ( V_g^{-0.218} \times j^{-0.107} \times V_w^{-0.251} \times 10^{-0.113} ) \times D_j \quad ( R=0.7158 , n=137 ) \quad ( 9 )$$

where  $D_{f_i}'$  was the predicted depth of the conventional gear,  $V_g$  was the gear drift velocity ( $\text{m} \cdot \text{s}^{-1}$ ),  $j$  was the hook code,  $V_w$  was the wind speed ( $\text{m} \cdot \text{s}^{-1}$ ).

$$D_{f_e}' = ( V_g^{-0.196} \times j^{-0.135} \times V_w^{-0.208} \times 10^{-0.110} ) \times D_j' \quad ( R=0.6356 , n=413 ) \quad ( 10 )$$

where  $D_{f_e}'$  was the predicted depth of the experimental gear.

The depth range (0 to 600 m) was group into 15 classes, (i.e., 40~80 m, 80~120 m, 120~160 m, ..., and 560~600 m); Based on the theoretical hook depth and predicted hook depth calculated by predicting models (Song et al., 2009), we estimated the theoretical hook depth and predicted hook depth for all hooks, and calculated the hook-depth distribution frequency for the theoretical hook depth and predicted hook depth by the frequency statistics method. Based on the theoretical hook depth and predicted hook depth, we calculated the corresponding temperature based on the depth-temperature profiles measured by the XR-620 and TDR 2050 for all hooks, respectively. The temperature range (7 to 30 °C) was group into 23 classes. The temperature interval was 1 °C. The numbers of hook in each temperature class were calculated based on the temperature estimated by the theoretical hook depth and predicted hook depth and the hook- temperature distribution frequency was obtained for two temperature data sets (the temperature estimated by the theoretical hook depth and predicted hook depth) by the frequency statistics method (Song et al., 2008, 2009).

Based on the theoretical hook depth and predicted hook depth, we compiled the

numbers of fish (for the fish caught by traditional gear, denoted as  $N_{ij}$ ; for the fish caught by experimental gear, denoted as  $N_{eij}$ ), and the numbers of hook (for traditional gear, denoted as  $H_{ij}$ ; for experimental gear, denoted as  $H_{eij}$ ) in various hook depth and temperature classes for the entire survey. For the experimental gear, there were four different messenger weights (denoted as  $e$ ). The catch rate ( $CPUE_{ij}$ ) of bigeye tuna in different depth and temperature classes was

$$CPUE_{ij} = \frac{(N_{ij} + \sum_{e=1}^4 N_{eij})}{(H_{ij} + \sum_{e=1}^4 H_{eij})} \quad (11)$$

where,  $j=1$  (depth);  $i=1,2,3,\dots,15$ ;  $j=2$  (temperature);  $i=1,2,3,\dots,23$ .

In this study, we used the nominal CPUE in respective depth, temperature classes and the archival tagging data (Bigelow et al., 2002; Musyl et al., 2003) to estimate the habitat preference, and the effective fishing effort (Bigelow et al., 2002) of each operation (Table 1) was calculated as

$$f_{oj} = E_o \sum_{d=1}^i h_{ojd_i} p_{jd_i} \quad (12)$$

where  $f_{oj}$  was the effective fishing effort in  $j$  environmental variables (depth,  $j=1$ ; temperature,  $j=2$ ) of  $o$  set ;  $E_o$  was the nominal fishing effort of  $o$  set ;  $h_{ojd_i}$  was the hook distribution percentage in  $d_i$  class of  $j$  variable in  $o$  set;  $p_{jd_i}$  was the habitat preference in  $d_i$  class of  $j$  variable, and was calculated as

$$P_{jd_i} = \frac{CPUE_{jd_i}}{\sum_{d=1}^r CPUE_{jd_i}} \times 100\% \quad (13)$$

where  $CPUE_{jd_i}$  was the nominal CPUE in  $d_i$  class of  $j$  variable; and  $r$  was the total classes .

By using the archival tagging data, we estimated the habitat preference by

calculating the staying time of bigeye tuna in each depth (temperature) class.

$$P_{jd_i}' = \frac{t_{jd_i}}{\sum_{d=1}^i t_{jd_i}} \times 100\% \quad (14)$$

where  $P_{jd_i}'$  was the habitat preference of bigeye tuna in  $d_i$  class of  $j$  variable;  $t_{d_i}$  was the staying time of bigeye tuna in  $d_i$  class of  $j$  variable (depth,  $j=1$ ; temperature,  $j=2$ ).

The nominal CPUE of each operation was calculated as

$$CPUE_{on} = \frac{N_o}{E_o} \times 1000 \quad (15)$$

where  $CPUE_{on}$  was the nominal CPUE in  $o$  operation;  $N_o$  was the numbers of fish caught in  $o$  operation.

The standardized CPUE of each operation was calculated as

$$CPUE_{osj} = \frac{N_o}{f_{oj}} \times 1000 \quad (16)$$

where  $CPUE_{osj}$  was the standardized CPUE in  $o$  operation of  $j$  variable.

The normalized nominal CPUE of each operation was calculated as

$$R_{on} = \frac{CPUE_{on}}{\frac{1}{u} \sum_{o=1}^u CPUE_{on}} \quad (17)$$

where  $R_{on}$  was the normalized value of nominal CPUE of  $o$  operation, and  $u$  was the numbers of operation.

The normalized the standardized CPUE of each operation was calculated as

$$R_{osj} = \frac{CPUE_{osj}}{\frac{1}{u} \sum_{o=1}^u CPUE_{osj}} \quad (18)$$

where  $R_{osj}$  was the normalized value of standardized CPUE in  $o$  operation of  $j$  variable.

The nominal CPUE and normalized nominal CPUE were compared with the

standardized CPUE and normalized standardized CPUE, respectively, using Monte Carlo permutation test (Frieze and Jerrum, 1995 ; Chen and Liu, 2007).

In this study, by the using of the Bayesian information criterion (BIC) (Maunder et al., 2002), we determined which group data was the best one for the detHBS. The value of BIC was calculated as

$$BIC = -\ln L' + \ln L - \frac{\ln(u)}{2} \quad (19)$$

where

$$L = \prod_i \frac{1}{\sqrt{2\pi\sigma}} \exp \left[ -\frac{[\ln(N_o + \delta_1) - \ln(\hat{N}_o + \delta_2)]^2}{2\sigma^2} \right] \quad (20)$$

$$\sigma = \sqrt{\frac{\sum_o [\ln(N_o + \delta_1) - \ln(\hat{N}_o + \delta_2)]^2}{n}} \quad (21)$$

$$L' = \prod_i \frac{1}{\sqrt{2\pi\sigma'}} \exp \left[ -\frac{[\ln(C'_o + \delta'_1) - \ln(\hat{C}'_o + \delta'_2)]^2}{2\sigma'^2} \right] \quad (22)$$

$$\sigma' = \sqrt{\frac{\sum_o [\ln(C'_o + \delta'_1) - \ln(\hat{C}'_o + \delta'_2)]^2}{n}} \quad (23)$$

where  $\sigma$  was the standard deviation of the difference between the observed nominal catch and the expectation of nominal catch ;  $\delta_1$  was 10 % of the mean nominal catch;  $\hat{N}_o$  was the expectation of nominal catch;  $\delta_2$  was the 10 % of the expectation of nominal catch. For the potential catch of  $o$  observation, we calculated the product  $C'_o$  between the nominal fishing effort and the standardized CPUE in  $o$  observation;  $\sigma'$  was the standard deviation of the difference between the potential catch and the expectation of the potential catch ;  $\delta'_1$  was the 10 % of the mean  $C'_o$ ;  $\hat{C}'_o$  was the expectation of the potential catch;  $\delta'_2$  was 10 % of the mean  $\hat{C}'_o$ .  $L$  was the likelihood value of the nominal catch and  $L'$  was the likelihood value of the potential catch. The

value of BIC was less, the performance of the model was better.

### **3. Results**

#### *3.1 The hook distribution in specific depth and temperature classes*

The hook distribution in specific depth and temperature classes were shown in Fig.3. For the data set calculated based on the theoretical hook depth, most hooks were distributed in 80-439.9 m ( 95.5 %); the numbers of hook distributed in the depth class of 360-399.9 m was the highest (15.43 %) (Fig.3a); for the field measured temperature data, most hooks were distributed in 8-12.99 °C (71.18 %); the numbers of hook distributed in the temperature class of 9-9.99 °C was the highest (27.83 %) (Fig.3c); for the OGCM data, most hooks were distributed in 8-11.99 °C (67.44 %); the numbers of hook distributed in the temperature class of 9-9.99 °C was the highest (27.83 %) (Fig.3e). For the data set calculated based on the predicted hook depth, most hooks were distributed in 80-279.9 m (91.39 %); the numbers of hook distributed in the depth class of 160-199.9 m was the highest (23.47 % ) (Fig.3b); for the field measured temperature data, most hooks were distributed in 10-17.99 °C (61.45 %); the numbers of hook distributed in the temperature class of 10-10.99 °C was the highest (15.53 %) (Fig.3d); for the OGCM data, most hooks were distributed in 9-14.99 °C (52.68 %); the number of hooks distributed in the temperature class of 10-10.99 °C was the highest (15.53 %) (Fig.3f).

#### *3.2 The nominal CPUE<sub>ij</sub> in specific depth and temperature classes and habitat*

*preference*

The nominal  $CPUE_{ij}$  in specific depth classes and habitat preference were shown in Fig. 4. For the theoretical hook depth, the highest nominal  $CPUE_{ij}$  was 4.86 inds per 1000 hooks (Figs.4a), and the optimal preferred depth class was 200-239.9 m (14.48 %) (Fig.4b). For the predicted hook depth, the highest nominal  $CPUE_{ij}$  was 4.43 inds per 1000 hooks (Fig. 4c), and the optimal preferred depth class was 240-279.9 m (22.84 %) (Fig. 4d).

The nominal  $CPUE_{ij}$  in different temperature classes and habitat preference were shown in Fig.5. For the theoretical hook depth, the highest nominal  $CPUE_{ij}$  was 8.15 inds per 1000 hooks (Fig. 5e), and the optimal preferred temperature class was 7-7.99 °C (13.93 %) (Fig.5f). For the predicted hook depth, the highest nominal  $CPUE_{ij}$  was 4.94 inds per 1000 hooks (Fig.5g), and the optimal temperature class was 21-21.99 °C (7.93 %) (Fig.5h) . Based on the archival tagging data, the results were shown in Fig.6. The optimal preferred depth was 400-439.9 m (16.95 %) (Fig.6a), and the optimal temperature was 8-8.99 °C (18.44 %) (Fig.6b).

### *3.3 The comparisons between nominal CPUE and standardized CPUEs*

The nominal CPUEs of all operations were shown in Fig.7 and the standardized CPUEs derived from 12 group data were shown in Fig.8. By the using of Monte Carlo permutation test we analyzed the differences between nominal CPUE and standardized CPUEs. The results showed that there were greater differences between nominal CPUE and standardized CPUEs derived from 12 group data ( $P < 0.001$ ) (Tab.2) and the standardized CPUE was higher than nominal CPUE.



### *3.4 The normalized value of nominal CPUE and standardized CPUE of each operation and the comparisons*

We compared the normalized value of nominal CPUE with the normalized value of standardized CPUE for each operation. All trends of the normalized value of nominal CPUE and standardized CPUEs were very similar (Fig.9). By the using of Monte Carlo permutation test, we analyzed the differences between normalized value of nominal CPUE and standardized CPUEs derived from 12 group data, the result showed that there were no difference (Tab. 3).

### *3.5 The value of BIC*

The value of BIC for V group data (the hook depth was the predicted depth, the habitat preference of depth was estimated from CPUE based on the predicted hook depth) was the lowest (BIC=-2.57). The value of BIC for XI group data (the hook depth was predicted hook depth, the habitat preference of temperature was estimated from CPUE based on the theoretical hook depth) was the less (BIC=-2.45) (Fig.10).

## **4 Discussions**

### *4.1 Reliability of the hooks depth distribution*

The reliability of the hooks depth distribution derived from the predicted hook depth was improved. The theoretical hook depth derived from the catenary was used in many studies (Hanamoto,1987; Suzuki et al., 1977; Gong et al., 1989; Grundinin, 1989; Ward et al., 1996; Nakano,1997). They assumed that the environmental

variables did not influence the longline shape in the water. However, in the operation, the hook depth would be shoaled (Hanamoto, 1974; Nishi, 1990; Boggs, 1992; Mizuno et al., 1995, 1998). In this study, the predicting hook depth models (Song et al., 2008) included many environmental variables, such as gear drift velocity ( $V_g$ ), wind speed ( $V_w$ ), wind direction ( $C_w$ ), angle ( $\gamma$ ) between the direction of the wind and the prevailing course in deploying the gear, angle of attack ( $Q_w$ ), and hook code ( $j$ ). The correlation coefficient between the actual hook depth measured by TDR and predicted hook depth was 0.7158, and 0.6356, for the traditional gear and experimental gear, respectively. The precision of hook depth was improved greatly.

#### *4.2 Reliability of habitat preference*

The habitat preference estimated from CPUE in each depth class based on predicted hook depth was the most available. We used different habitat preferences as the model's input, but the habitat preferences derived from various group data were different. There were great uncertainties for the depth habitat preference derived from the theoretical hook depth and its fluctuation were greatly. The reasons were the theoretical hook depth was resulted from the ideal condition. Many environmental variables influenced the actual hook depth. There were larger uncertainties for the theoretical hook depth (Song et al., 2007). The predicted hook depth was derived from the actual hook depth measured by TDR and the precision of the hook depth was improved. The depth preference and temperature preference estimated from CPUE in depth and temperature classes based on predicted hook depth were more reliable than the results based on theoretical hook depth. Depth and temperature preference derived

from archival tagging data were based on the single fish in certain time and area. That was a special case. The sampling numbers and areas should be extended. Depth and temperature preference derived from archival tagging data were much fluctuant. The reason was that bigeye tuna had particular physiological characteristics. For getting warm and breathing oxygen, it migrated between surface layer and 500 m layer once per hour during daytime (Holland et al., 1990, 1992; Brill, 1994). And for bigeye tuna, the habitat preference data from archival tags may not be appropriate (Maunder and Hinton, 2004) and the application of habitat preference data may not approximate the probability that a fish will be vulnerable to longline gear (Bigelow et al., 2003). Hence, the depth preference and temperature preference based on the predicted hook depth should be priority in applying in Habitat-based standardization.

#### *4.3 The input data of the detHBS*

The standardized CPUE based on  $v$  group data (the hook depth was predicted hook depth, the habitat preference of depth was estimated from CPUE based on the predicted hook depth) was more reliable. The value of BIC was less, the performance of the model was better. The BIC value of  $v$  group data was the less. We suggested that the environmental data whose BIC value was less should be selected as the input of the detHBS to improve the precision of CPUE standardization.

#### *4.4 The validity of the detHBS*

The detHBS was effective. In this study, we used different hook depth distribution and habitat preference and got different results of the detHBS. We also compared the results of 12 group data. For the normalized results of nominal and

standardized CPUE, the trends over time of them were very similar. The reason was that the data for analysis were the survey data of the single ship in seven months and there were smaller change in fishing gear configuration and environmental variables. Therefore, the trends between nominal CPUE and standardized CPUE based on the detHBS were very similar. For the long time series data (ie. several decades), when there were larger change in fishing gear configuration and environmental variables, the trends between nominal CPUE and standardized CPUE should be different. At that moment, the performance of the detHBS would be more obvious and reflect the trends of resource abundance index more obvious.

#### *4.5 The effect of the “detHBS”*

Habitat preference and limiting was always used to evaluate the effect that was caused by environment variables to CPUE in pelagic longline fishery. The CPUE that was not modified may be misunderstood the results from the stock assessment (Nishida et al., 2003). A reliable standardization model of CPUE will improve the accuracy for the tuna stock assessment and leading to the appropriate management measures. In this study, the “detHBS” based on v data set in standardizing CPUE could reliably describe the resource abundant of bigeye tuna. The fisheries data were usually grouped at a defined spatial and/or temporal scale, and CPUE was commonly defined by the total catch versus the corresponding fishing effort over a specific spatial scale and time (Hilborn and Walters, 1992). Different gears impacted differently on the same habitat, and different habitats had different response to the same gear (Jennings and Revill, 2007). If a hook is fished in an environment that was preferred by the

species, then it had a higher probability of capturing that species (Hinton and Maunder, 2004). The effective fishing efforts for bigeye tuna calculated by “detHBS” might reliably describe the fishing power that was fished bigeye tuna. Therefore, the different catchability among different fishing vessels and between-set could be removed by “detHBS”. The results in different annual and monthly patterns of standardized CPUEs would be different by using different models, thus affecting the interpretation of temporal variability in bigeye tuna population and greatly influencing the management measure. The reliable describe of the standardized CPUEs was the foundation of the sustainable utilization of the resources.

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## **Figure and Table Captions**

Fig. 1 Survey sites

Fig. 2 Flow chart of analysis

Fig. 3 Hook distribution in the specific depth (a: theoretical hook depth, b: predicted hook depth) , temperature(field measured data) (c: calculated based on theoretical hook depth, d: calculated based on predicted hook depth) and temperature(OGCM data) (e: calculated based on theoretical hook depth, f: calculated based on predicted hook depth) classes

Fig.4 The bigeye tuna nominal CPUE<sub>ij</sub> in specific depth (a: theoretical hook depth, c: predicted hook depth) and habitat preferences (P<sub>jdi</sub>) (b: theoretical hook depth, d: predicted hook depth)

Fig.5 The bigeye tuna nominal CPUE<sub>ij</sub> in specific temperature classes (field measured data: (a) theoretical depth, (c) predicted depth; OGCM: (e) theoretical depth, (g) predicted depth) and habitat preferences ( $p_{jd_i}$ ) (field measured data: (b) theoretical depth,(d) predicted depth; OGCM data: (f) theoretical depth, (h) predicted depth)

Fig.6 Depth habitat preference (a) and temperature habitat preferences (b) of bigeye tuna (based on the archival tagging data)

Fig. 7 Nominal CPUE for each operation

Fig. 8 Standardized CPUEs for each operation

Fig.9 The normalized nominal CPUE and normalized standardized CPUEs

Fig.10 The value of BIC for standardized CPUE derived from 16 group data

Table 1 The data used in the deterministic habitat-based model

Table 2 The results of the comparison between the nominal CPUE and the standardized CPUEs from Monte Carlo permutation test

Table 3 The results of the comparison between the normalized nominal CPUE and the normalized standardized CPUEs from Monte Carlo permutation test

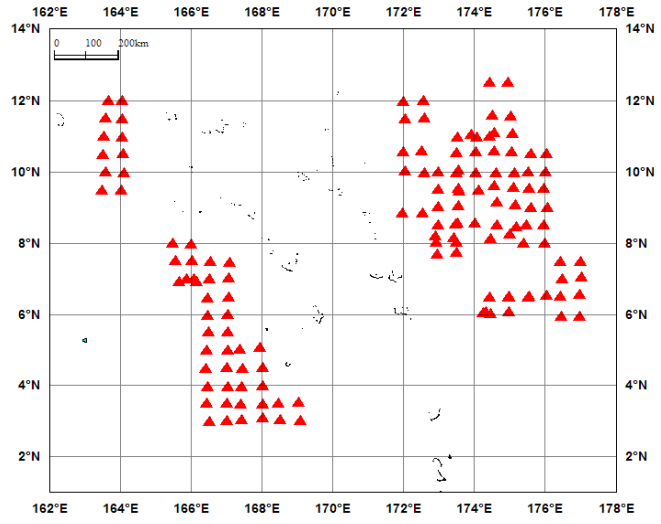


Fig. 1 Survey sites

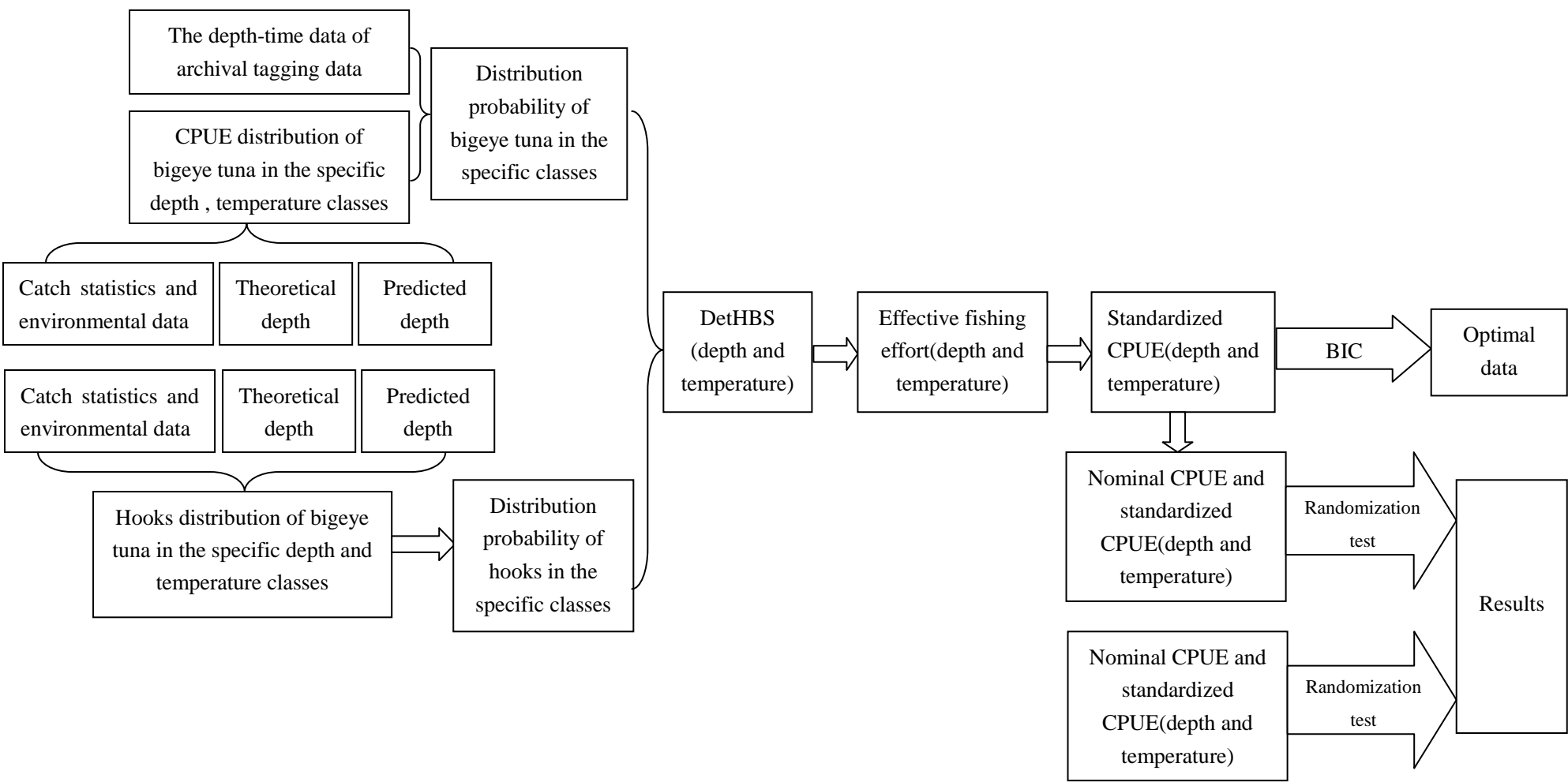


Fig. 2 Flow chart of analysis

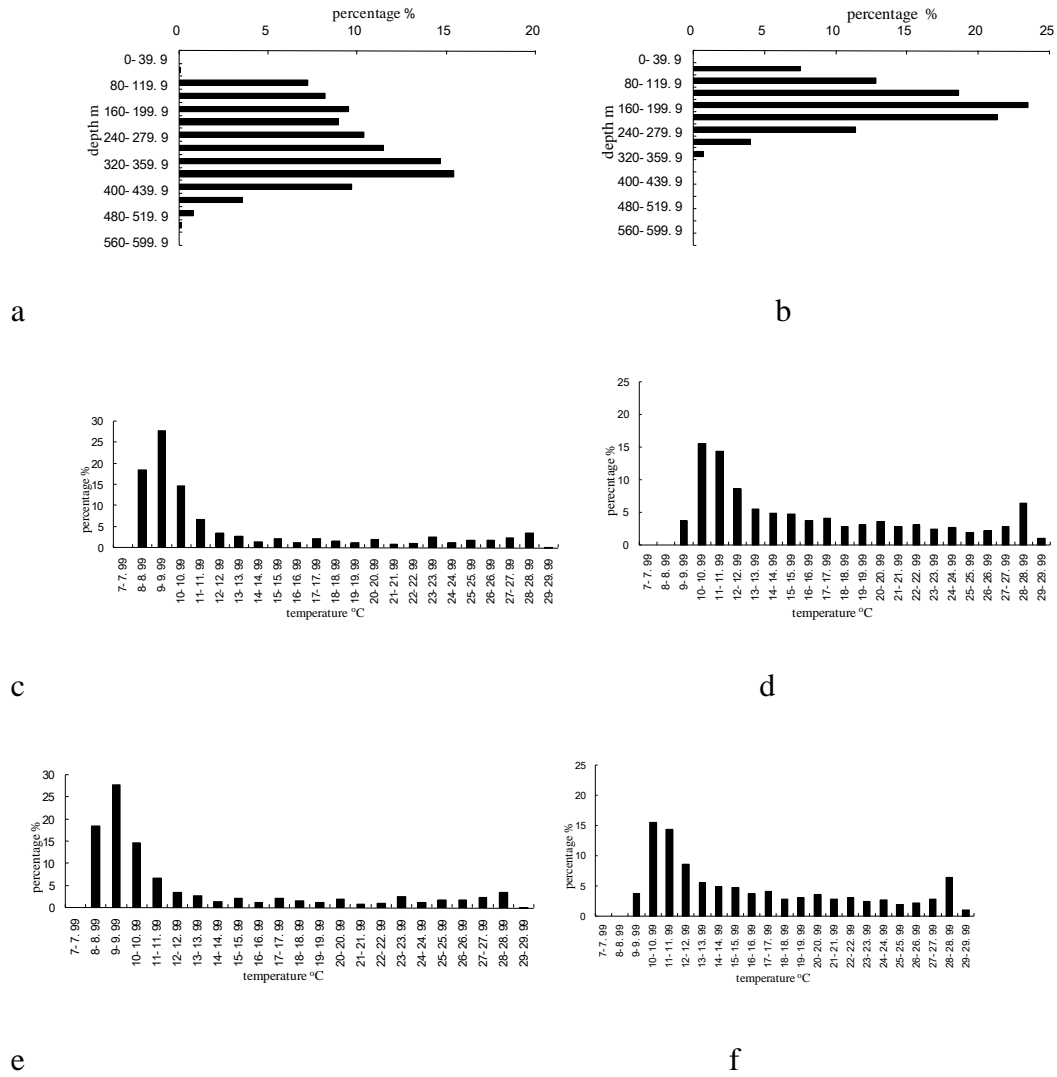
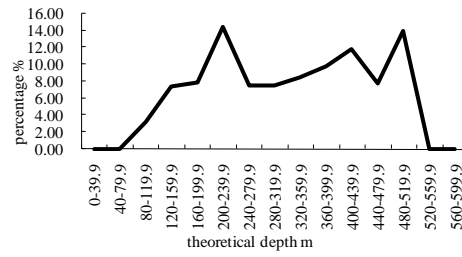
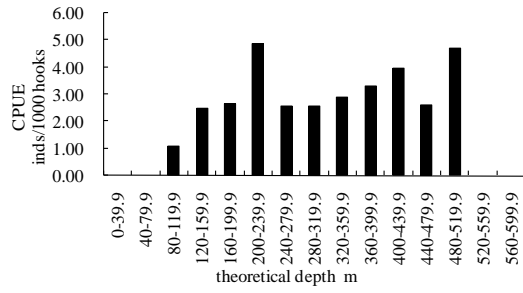


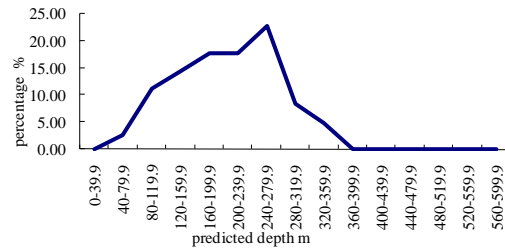
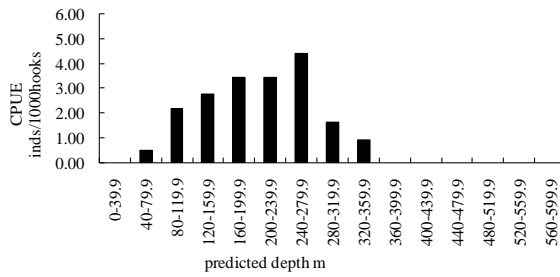
Fig. 3 Hook distribution in the specific depth (a: theoretical hook depth, b: predicted hook depth), temperature (field measured data) (c: calculated based on theoretical hook depth, d: calculated based on predicted hook depth) and temperature (OGCM data) (e: calculated based on theoretical hook depth, f: calculated based on predicted hook depth) classes





a

b



c

d

Fig.4 The bigeye tuna nominal CPUE<sub>ij</sub> in specific depth

(a: theoretical hook depth, c: predicted hook depth)

and habitat preferences ( $P_{jdi}$ ) (b: theoretical hook depth, d: predicted hook depth)

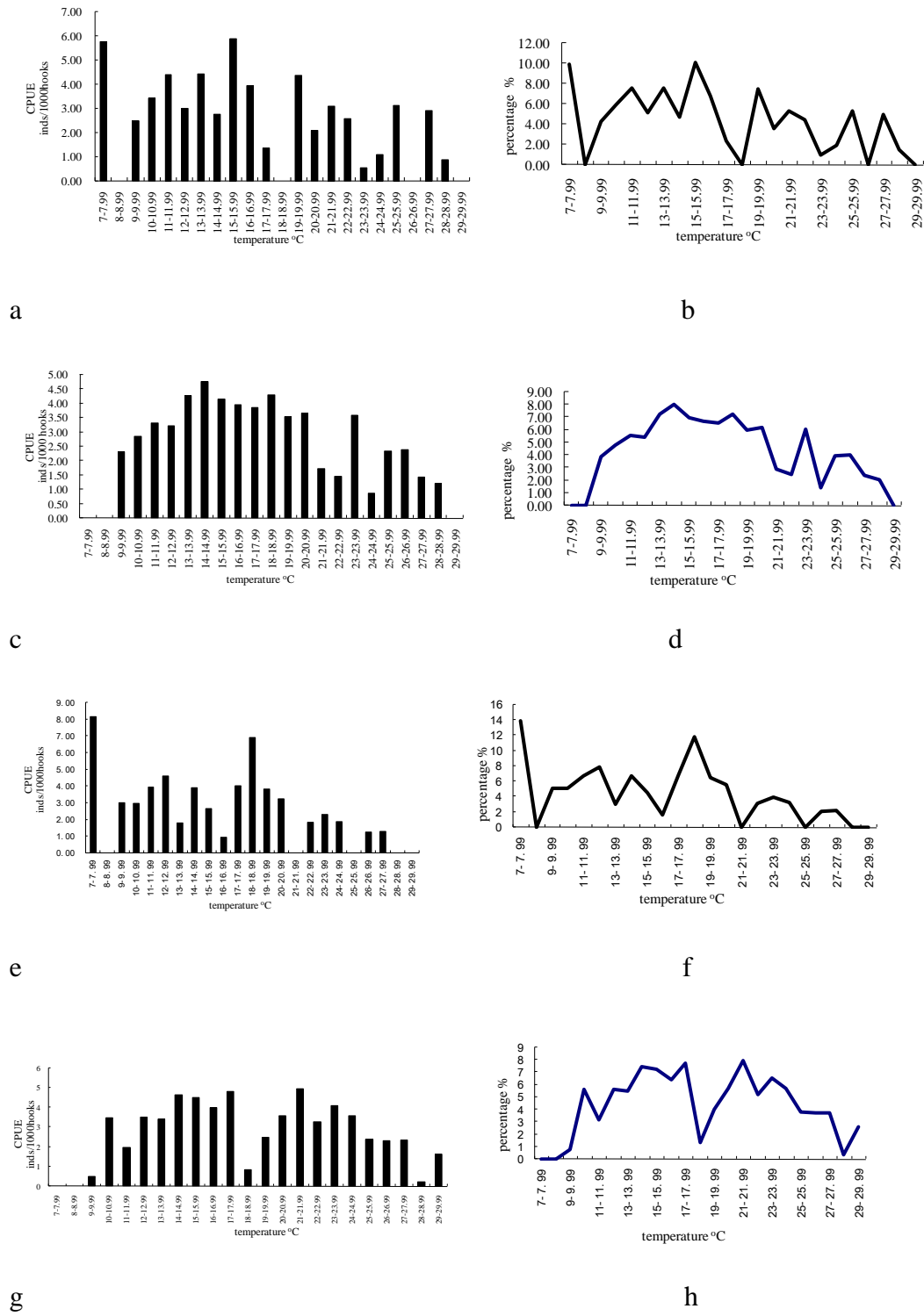
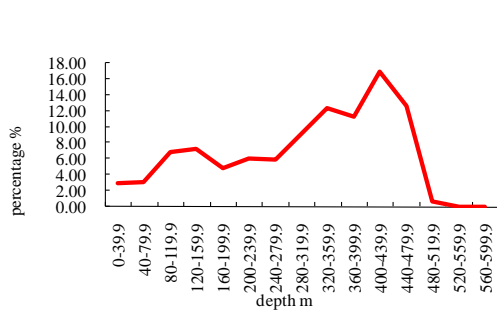
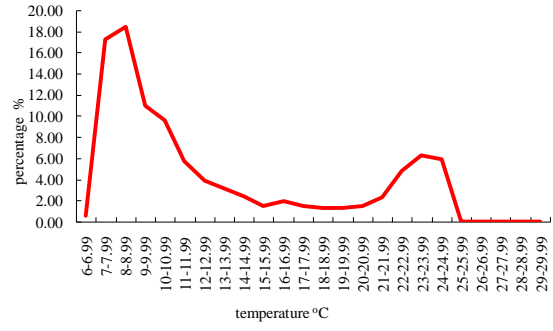


Fig.5 The bigeye tuna nominal CPUE<sub>ij</sub> in specific temperature classes (field measured data: (a) theoretical depth, (c) predicted depth; OGCM: (e) theoretical depth, (g) predicted depth) and habitat preferences ( $p_{jd_i}$ ) (field measured data: (b) theoretical depth,(d) predicted depth; OGCM data: (f) theoretical depth, (h) predicted depth)



a



b

Fig.6 Depth habitat preference (a) and temperature habitat preferences (b) of bigeye tuna (based on the archival tagging data)

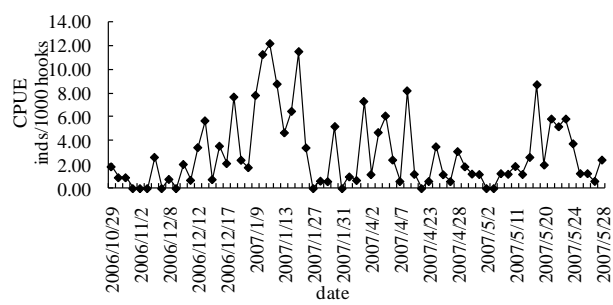


Fig. 7 Nominal CPUE for each operation

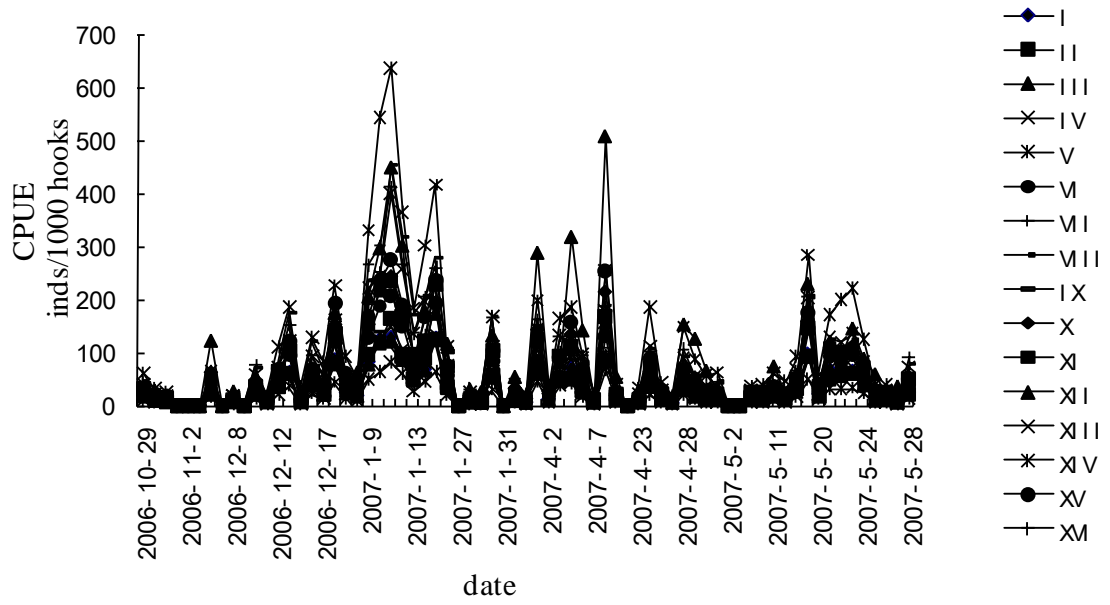


Fig 8 Standardized CPUEs for each operation

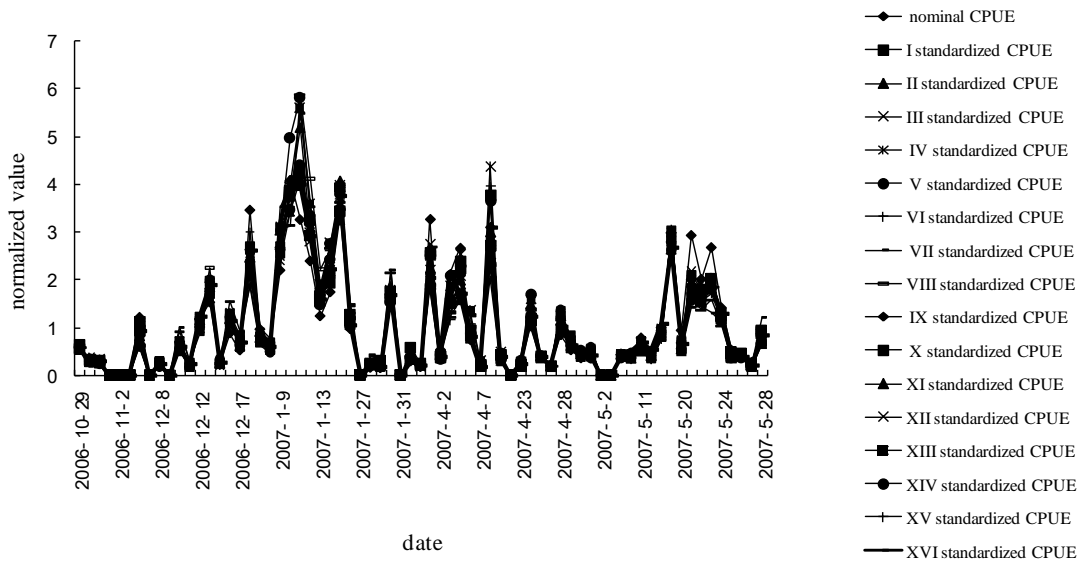


Fig.9 The normalized nominal CPUE and normalized standardized CPUEs

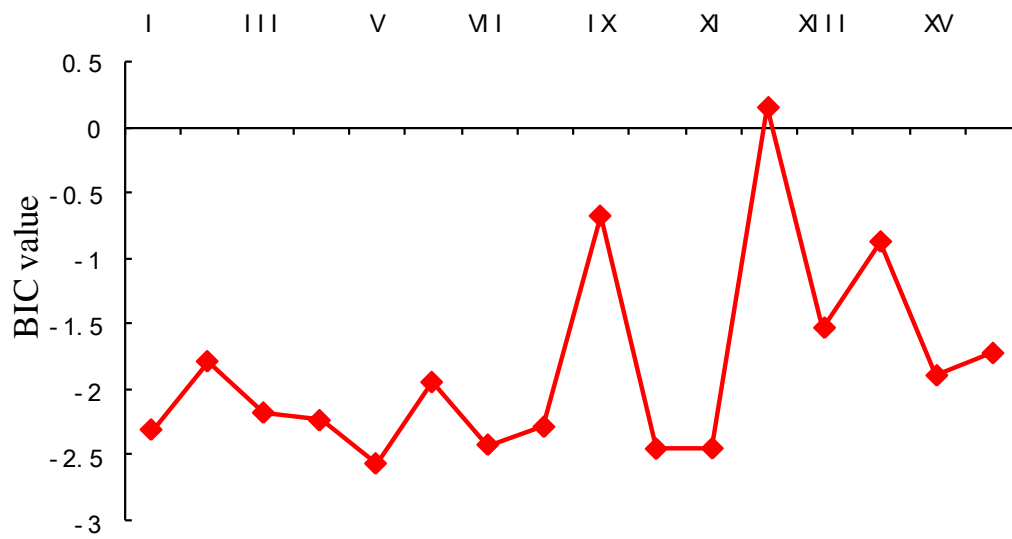


Fig.10 The value of BIC for standardized CPUE derived from 16 group data

Table 1. The data used in the deterministic habitat-based model

	Data	Hook depth	Habitat preferences
Depth habitat preferences	I		Depth habitat preferences (theoretical depth)
	II	Theoretical depth	Depth habitat preferences (predicted depth)
	III		Depth habitat preferences (archival tagging data)
	IV		Depth habitat preferences (theoretical depth)
	V	Predicted depth	Depth habitat preferences (predicted depth)
	VI		Depth habitat preferences (archival tagging data)
Temperature habitat preferences	VII		Temperature habitat preferences (theoretical depth)
	VIII	Theoretical depth	Temperature habitat preferences (predicted depth)
	IX		Temperature habitat preferences (archival tagging data)
	X	Predicted depth	Temperature habitat preferences (theoretical depth)



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	XI		Temperature habitat preferences (predicted depth)
	XII		Temperature habitat preferences (archival tagging data)
	XIII	Theoretical depth	Temperature habitat preferences (theoretical depth)
Temperature habitat preferences(OGCM)	XIV		Temperature habitat preferences (predicted depth)
	XV	Predicted depth	Temperature habitat preferences (theoretical depth)
	XVI		Temperature habitat preferences (predicted depth)

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Table 2. The results of the comparison between the nominal CPUE and the standardized CPUEs from Monte Carlo permutation test

Item	p( two-sided test)	k(simulation times)	
I	0.0000	10000	
II	0.0000	10000	
III	0.0000	10000	
IV	0.0000	10000	
V	0.0000	10000	
VI	0.0000	10000	
VII	0.0000	10000	
Nominal CPUE and standardized CPUEs	VIII	0.0000	10000
	IX	0.0000	10000
	X	0.0000	10000
	XI	0.0000	10000
	XII	0.0000	10000
	XIII	0.0000	10000
	XIV	0.0000	10000
	XV	0.0000	10000
	XVI	0.0000	10000

Table 3. The results of the comparison between the normalized nominal CPUE and the normalized standardized CPUEs from Monte Carlo permutation test

Item	p( two-sided test)	k(simulation times)
I	0.9978	10000
II	0.9983	10000
III	0.9964	10000
IV	0.9978	10000
V	0.9979	10000
VI	0.9972	10000
VII	0.9978	10000
VIII	0.9976	10000
IX	0.9372	10000
X	0.9978	10000
XI	0.9981	10000
XII	0.9844	10000
XIII	0.9980	10000
XIV	0.9987	10000
XV	0.9982	10000
XVI	0.9983	10000