# **Standardizing CPUE of yellowfin tuna** (*Thunnus albacares*)

# longline fishery using deterministic habitat based model

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**Abstract**: Data collected from a longline fishery in the Indian Ocean were used to evaluate the performance of "deterministic habitat based standardization (detHBS)" method for the *CPUE* standardization. The habitat preference indices of the yellowfin tuna (*Thunnus albacares*) were estimated for different classes of depth, temperature, chlorophyll-a, and dissolved oxygen classes. The "detHBS" was applied to standardizing the yellowfin tuna *CPUE* based on the habitat preference indices of the yellowfin tuna. The nominal *CPUE* and normalized nominal *CPUE* were compared with the standardized *CPUE* and normalized standardized *CPUE*, respectively, using the paired two-sample t-test. The results showed that (1) nominal *CPUE* was greatly different from standardized *CPUEs*; (2) there were no differences between normalized nominal *CPUE* and normalized standardized on the data of depth, temperature, and DO classes ; (3) there was difference between normalized nominal *CPUE* and normalized standardized *CPUEs* estimated based on the data. This study suggests that "detHBS" improves the precision of *CPUE* standardization effectively. The depth data were most important for "detHBS" in estimating *CPUE* of yellowfin tuna.

**Keywords:** *Thunnus albacares*; *CPUE* standardization; deterministic habitat based standardization; longline fishery; the Indian Ocean

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# 1. Introduction

Many methods have been developed and applied to standardizing catch per unit effort (*CPUE*), such as Generalized Linear Model (GLM; Okamoto and Miyabe, 2003; Okamoto *et al.*, 2004), Generalized Additive Model (GAM; Bigelow *et al.*, 1999; Wise *et al.*, 2002), and statistical habitat based standardization (statHBS; Bigelow *et al.*, 2003). The GLM and GAM are two of the most commonly used methods (Bigelow *et al.*, 1999; Punt *et al.*, 2000; Campbell, 2004) with *CPUE* and corresponding environmental variables of a defined spatial and temporal scales being used as input data (Tian *et al.*, 2009). Both models are the extensions of multiple linear regressions, but the environmental 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 result from the fluctuations of ocean thermal structure (Bigelow *et al.*, 1999). Thus, the catch rates of longline may not reflect the resource abundance which might fluctuate with the depth (Punsly and Nakano, 1992). The statHBS is more flexible, which allows for additional components on linear and nonlinear models being added to the model (Hinton *et al.*, 2001). However, this does not necessarily mean that the statHBS can produce better estimates than other methods. The quality of the estimates may be influenced by the data available to modeling (Hinton and Maunder, 2003). A deterministic habitat-based standardization (detHBS) method was initially developed by Hinton and Nakano (1996) for incorporating environmental variables, fishing gear, and species habitat preference into *CPUE* standardization. The detHBS have not frequently been applied to the *CPUE* standardization of tuna longline fishery in most oceans except for the Pacific Ocean (Bigelow *et al.*, 2003).

Much controversy surrounds the applications of the detHBS method (Ward and Myers, 2005; Prince and Goodyear, 2006). The poor performance of detHBS was attributed to the inaccuracy of hook depth estimates and differences between the distribution of pelagic species and their vulnerability to longline gear (Ward and Myers, 2006; Bigelow and Maunder, 2007). For the *CPUE* standardization of tuna longline fishery, hook depth is one of

the most influential factors in quantifying habitat preferences of fish species. Nishida *et al.* (2003) applied an approach of intergrated GLM and Habitat-based Model (HBM) to standardizing the *CPUE* of yellowfin tuna in the Indean Ocean. They included the depth distribution of longline gear and vertical distribution of yellowfin tuna into the model. The result showed that the HBM-GLM integrated approach was more effective than the GLM approach (Nishida *et al.*, 2003).

It is necessary to evaluate the effectiveness of an approach in standardizing *CPUE* using environmental variables. To evaluate the effectiveness of the detHBS method in improving the precision of *CPUE* standardization, we applied hook depth prediction model (Song, 2008) to estimate the habitat preference indices of yellowfin tuna in specific depth, temperature, chlorophyll-a, and dissolved oxygen (DO) classes based on the environmental data and catch and fishing effort data. We applied the "detHBS" (Hinton and Nakano, 1996; Bigelow *et al.*, 2003) to standardizing the CPUE of yellowfin tuna, and then compared the results by the paired two-sample t-test.

#### 2. Material and methods

#### 2.1. Materials

Details of survey fishing vessels, fishing gear and deployment methods, fishing time and area, instrumentations, and sampling methods were provided in Song *et al.* (2008, 2009) and Song and Zhou (2010).

Fisheries data, fishing operational parameters, and environmental data were collected in the survey. Of the 527 fish caught in the survey, 360 fish were caught by *Huayuanyu No.18*, and 167 fish were caught by *Huayuanyu No.19*. The hook code with which the fish was caught was recorded for 371 fish. Of the 371 fish, 314 fish were caught by *Huayuanyu No.18*, and 57 fish were caught by *Huayuanyu No.19*. Water temperature, chlorophyll-a, and DO vertical profiles were measured for 83, 28, and 28 sites, respectively. These environmental variables were measured using Submersible Data Logger (XR-620), Temperature Depth Recorder (TDR 2050) (RBR Co., Canada), and Conductivity Temperature Depth Recorder (SBE37SM, SeaBird Co., USA) after the gear was deployed.

Of the 527 fish caught in the survey, we measured depth for 293 fish (a coverage of

55.60 %), temperature for 288 fish (a coverage of 54.65 %), chlorophyll-a, and DO for 181 fish (a coverage of 34.35 %).

#### 2.2. Analytical methods

We caculated the nominal CPUE of yellowfin tuna in specific depth, temperature, chlorophyll-a, and DO classes by applying the hook depth prediction model (Song, 2008). We estimated habitat preference indices of yellowfin tuna and applyed the "detHBS" (Hinton and Nakano, 1996; Bigelow *et al.*, 2003) to standardiz the nominal CPUE of yellowfin tuna in the specific depth, temperature, chlorophyll-a, and DO classes. Because the vessel's particulars and the experience of two captains of two fishing vessels were very similar, we assumed that there were the same impacts on the *CPUE* of yellowfin tuna from the factors of the vessel's particular and the experience of captain. The impacts on the *CPUE* of yellowfin tuna from the environmental variables were different. When we standardized the *CPUE* of yellowfin tuna, the impacts on the *CPUE* of yellowfin tuna from the factors of the vessel's particular and the experience of captain tuna from the factors of the vessel's particular and the experience of yellowfin tuna from the factors of the vessel's particular and the experience of yellowfin tuna from the factors of the vessel's particular and the impacts on the *CPUE* of yellowfin tuna, the impacts on the *CPUE* of yellowfin tuna from the factors of the vessel's particular and the experience of captain. The impacts of the vessel's particular and the yellowfin tuna from the factors of the vessel's particular and the impacts on the *CPUE* of yellowfin tuna, the impacts on the *CPUE* of yellowfin tuna from the factors of the vessel's particular and the experience of captain could be ignored and the impacts of different variables on *CPUE* of yellowfin tuna is procedure was shown in Fig.1.



Fig.1 The data processing procedure

We applied the following hook depth prediction models (Song, 2008) to predict the hook depth,

$$D_{ptq} = 1.2023 V_w^{0.078} (\sin \gamma)^{0.010} q^{-0.153} D_{tq} \qquad (r = 0.8074) \tag{1}$$

$$D_{peq}' = 0.9908 (V_g')^{-0.056} q'^{-0.075} M^{-0.106} D_{eq}' \quad (r=0.7625)$$
(2)

for the traditional gear and experimental gear, respectively. In Equation (1),  $D_{ptq}$  is the predicted hook depth of traditional gear for the hook position code q;  $V_w$  is the wind speed;  $\sin \gamma$  is the sine of angle of attack  $\gamma$ ; q is the hook position code; and  $D_{tq}$  is the theoretical catenary hook depth of traditional gear for the hook position code q. In Equation (2),  $D_{peq}'$  is the predicted hook depth of experimental gear for the hook position code q';  $V_g'$  is the experimental gear drifting speed; q' is the hook position code; M is the weight of the messenger weight; and  $D_{eq}'$  is the theoretical catenary hook depth of experimental gear for the hook position code q'.

The data for the hook depth were grouped into 10 depth classes with an interval of 40 m (40-80 m, 80-120 m, ... 360-400 m). The data for the temperature were grouped into 20 classes with an interval of 1 °C (9-10 °C, 10-11 °C, ... 28-29 °C). The data for the chlorophyll-a were grouped into nine classes with an interval of 0.01  $\mu$ g L<sup>-1</sup> (0.02-0.03  $\mu$ g L<sup>-1</sup>, 0.03-0.04  $\mu$ g L<sup>-1</sup>, ... 0.09-0.10  $\mu$ g L<sup>-1</sup>) and the other classe of 0.10-1.50  $\mu$ g L<sup>-1</sup>. The data for the DO were grouped into 10 classes with an interval of 0.5 mg L<sup>-1</sup> (0.0-0.5 mg L<sup>-1</sup>, 0.5-1.0 mg L<sup>-1</sup>, ... 4.5-5.0 mg L<sup>-1</sup>). Based on the predicted hook depth, we calculated temperature, chlorophyll-a, and DO from the profiles mensured using SBE37SM, TDR2050 and XR-620, respectively, for each hook and fish. We applied frequency statistics (Tang and Feng, 2002) to calculate the numbers of hook and fish at each class of depth, temperature, chlorophyll-a, and DO, respectively.

The following equation was used to calculate the catch rates of yellowfin tuna at a specific depth, temperature, chlorophyll-a, and DO class:

$$CPUE_{ij} = \frac{(N_{iij} + \sum_{e=1}^{4} N_{eij})}{(H_{iij} + \sum_{e=1}^{4} H_{eij})}$$
(3)

where  $N_{tij}$  and  $N_{eij}$  are the numbers of fish caught by traditional gear and experimental gear in

*i* class and *j* environmental variable, respectively; and  $H_{iij}$  and  $H_{eij}$  are the numbers of hook for traditional gear and experimental gear in *i* class and *j* environmental variable, respectively. For variable depth, *j*=1 and depth class *i*=1,2,3,.....10; for variable temperature, *j*=2 and temperature class *i*=1,2,3,.....20; for variable chlorophyll-a, *j*=3 and chlorophyll-a class *i*=1,2,3,.....9; and for variable DO, *j*=4 and DO class *i*=1,2,3,.....10 (Song, 2008; 2009). The four groups of experimental gear are indexed as *e*=1, 2, 3, and 4.

We estimated habitat preference indices of yellowfin tuna based on the nominal *CPUE* data at a specific class of depth, temperature, chlorophyll-a, and DO. We calculated the effective fishing effort of each operation by applying the "detHBS" (Biglow *et al.*, 2002) using the following equation:

$$f_{rj} = E_r \sum_{i=1}^{\lambda} h_{rij} p_{ij}$$
(4)

where  $f_{rj}$  is the effective fishing effort for the *r* operation in *j* environmental variable (i.e., *j*=1 for depth, *j*=2 for temperature, *j*=3 for chlorophyll-a, and *j*=4 for DO);  $E_r$  is the nominal fishing effort for *r* operation (thousand hooks);  $\lambda$  is the numbers of class;  $h_{rij}$  is the proportion of hook number in *i* class for *r* operation in *j* environmental variable; and  $p_{ij}$  is the habitat preference index of yellowfin tuna in *i* class and *j* environmental variable calculated using the following equation:

$$P_{ij} = \frac{CPUE_{ij} \times 100\%}{\sum_{i=1}^{\lambda} CPUE_{ij}}$$
(5)

where  $CPUE_{ij}$  is the nominal *CPUE* of yellowfin tuna in *i* class and *j* environmental variable.

The equation to calculate the nominal *CPUE* of yellowfin tuna in each operation can be written as follows:

$$CPUE_m = \frac{N_r}{E_r} \times 1000 \tag{6}$$

where  $CPUE_{rn}$  is the nominal CPUE of yellowfin tuna in r operation; and  $N_r$  is the numbers of fish caught in r operation.

The equation to standardize the *CPUE* of yellowfin tuna in each operation can be written as follows:

$$CPUE_{rsj} = \frac{N_r}{f_{rj}} \times 1000 \tag{7}$$

where  $CPUE_{rsj}$  is the *CPUE* of yellowfin tuna in *r* operation standardized based on the data of *j* environmental variable.

The nominal *CPUE* of yellowfin tuna in each operation was normalized using the following equation:

$$R_{rn} = \frac{CPUE_{rn}}{CPUE_{rnm}}$$
(8)

where  $R_{rm}$  is the normalized value of nominal *CPUE* of yellowfin tuna in *r* operation.  $CPUE_{rmm}$  is the maximum value among all of  $CPUE_{rm}$ .

The standardized *CPUE* of yellowfin tuna in each operation was normalized using the following equation:

$$R_{rsj} = \frac{CPUE_{rsj}}{CPUE_{rsjm}} \tag{9}$$

where  $R_{rsj}$  is the normalized value of the standardized *CPUE* of yellowfin tuna in *r* operation *j* environmental variable. *CPUE*<sub>*rsjm*</sub> is the maximum value among all of *CPUE*<sub>*rsj*</sub>.

We compared the nominal *CPUE* with the *CPUEs* standardized using depth, temperature, chlorophyll-a, and DO classes and the normalized nominal *CPUE* with the normalized standardized *CPUEs* using the paired two-sample t-test (Tang and Feng, 2002).

#### 3. Results

#### 3.1 Hook distribution in a given class of depth, temperature, chlorophyll-a, and DO

Hook distributions in specific classes of depth, temperature, chlorophyll-a, and DO were shown in Fig.2. Most of the hooks were distributed in the depth class of 120-360 m (90.22 %), and the number of hooks distributed in the depth class of 280-320 m was the highest (19.42 %; Fig.2a). Most of the hooks were distributed in the temperature class of  $10 \sim 16 \,^{\circ}C$  (89.63 %), and the number of hooks distributed in the temperature class of  $11 \sim 12 \,^{\circ}C$  was the highest (35.15 %; Fig.2b). Most of the hooks were distributed in the chlorophyll-a class of  $0.03 \sim 0.05 \,\mu g \,^{-1}$  (88.71 %), and the number of hooks distributed in the chlorophyll-a class of

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0.04 ~ 0.05  $\mu$ g L<sup>-1</sup> was the highest (45.90 %; Fig.2c). Most of the hooks were distributed in the DO class of 1.5 ~ 3.5 mg L<sup>-1</sup> (77.84 %), and the number of hooks distributed in the DO class of 2.5 ~ 3.0 mg L<sup>-1</sup> was the highest (40.40 %; Fig.2d).

## 3.2 Nominal $CPUE_{ii}$ and preferences $(P_{ii})$ of the yellow fin tuna

Nominal  $CPUE_{ij}$  and preferences  $(P_{ij})$  of the yellowfin tuna in specific depth classes from 98 operations were shown in Fig.3a and Fig.4a, respectively. For the depth classes from 80 to 200 m, nominal  $CPUE_{ij}$  was relatively higher, which was the prefered depth of yellowfin tuna. For the depth class of 80 ~ 120 m, nominal  $CPUE_{ij}$  (8.53 fish per thousand hooks) was the highest, which was the most prefered depth of yellowfin tuna (30.19 %).



Nominal  $CPUE_{ij}$  and preferences  $(P_{ij})$  of the yellowfin tuna in specific temperature classes from 93 operations were shown in Fig.3b and Fig.4b, respectively. Fourty eight operations were from *Huayuanyu No.18*, and 45 operations were from *Huayuanyu No.19*.

Nominal  $CPUE_{ij}$  of the yellowfin tuna increased with the temperature in the range of  $12 \sim 18$  °C. Nominal  $CPUE_{ij}$  (10.01 fish per thousand hooks) and preferences ( $P_{ij}$ ) (14.49 %) of the yellowfin tuna were the highest in the temperature class of  $17 \sim 18$  °C.

Nominal  $CPUE_{ij}$  and preferences  $(P_{ij})$  of yellowfin tuna in specific chlorophyll-a classes from 28 operations were shown in Fig. 3c and Fig.4c, respectively. Nominal  $CPUE_{ij}$  (17.63 fish per thousand hooks) and preferences  $(P_{ij})$  (29.20 %) were relatively higher in the chlorophyll-a class of 0.09 ~ 0.10 µg L<sup>-1</sup>.









Fig.4 The yellowfin tuna preferences  $(P_{ij})$  in specific depth, temperature, chlorophyll-a, and dissolved oxygen classes

Nominal  $CPUE_{ij}$  and preferences  $(P_{ij})$  of the yellowfin tuna in different classes of DO from 28 operations were shown in Fig.3d and Fig.4d, respectively. Nominal  $CPUE_{ij}$  (average 4.14 fish per thousand hooks) and preferences  $(P_{ij})$  (average 30.19 %) were steadier in the DO class of  $1.5 \sim 3.5$  mg L<sup>-1</sup>. Nominal  $CPUE_{ij}$  (14.38 fish per thousand hooks) and preference  $(P_{ij})$  (44.53 %) were the highest in the DO class of  $1.0 \sim 1.5$  mg L<sup>-1</sup>.

## 3.3. The nominal and standardized CPUE for each operation

For different *CPUE* values derived from the data of *Huayuanyu No.18* nominal *CPUE* had the lowest value. The standardized *CPUE* estimated based on temperature data (10.90  $\sim$  1261.04 fish per thousand hooks) was the highest, but lower based on chlorophyll-a data (10.58  $\sim$  502.43 fish per thousand hooks) and depth data (4.82  $\sim$  467.50 fish per thousand hooks). The standardized *CPUE* estimated using the DO data (4.28  $\sim$  251.82 fish per thousand hooks) was the lowest (Fig.5a).





Fig.5 The nominal CPUE and standardized CPUE of yellowfin tuna (a: Huayuanyu No. 18; c: Huayuanyu No. 19) and the normalized nominal CPUE and normalized standardized CPUE of yellowfin tuna (b: Huayuanyu No. 18; d: Huayuanyu No. 19) in the operations

For different *CPUE* data of *Huayuanyu No.19*, nominal *CPUE* was the lowest. The standardized *CPUE* estimated using temperature data ( $10.19 \sim 257.79$  fish per thousand hooks) was relatively high; but lower based on depth data ( $4.02 \sim 95.57$  fish per thousand hooks; Fig.5c).

Based on the results of paired two-sample t-test, the nominal *CPUE* were significantly different from the standardized *CPUEs* estimated based on the data of depth, temperature, chlorophyll-a and DO classes (p < 0.05).

#### 3.4 Normalized nominal and standardized CPUEs for each operation

The normalized nominal *CPUE* and normalized standardized *CPUE* of yellowfin tuna for *Huayuanyu No. 18 and 19* were shown in Fig.5b and Fig.5d, respectively. For *Huayuanyu No. 18*, the normalized nominal *CPUE* relatively consistented with the normalized standardized *CPUE* which were estimated based on depth, temperature, chlorophyll-a, and DO data (Fig.5b). For *Huayuanyu No. 19*, the normalized nominal CPUE was consistent with the standardized *CPUE* which were estimated based on depth, temperature, chlorophyll-a , and DO data (Fig. 5d).

Based on the results of paired two-sample t-test, there were no significant differences between normalized nominal *CPUE* and normalized standardized *CPUEs* estimated based on the data of depth, temperature, and DO classes ( $p \ge 0.05$ ). There was difference between normalized nominal *CPUE* and normalized standardized *CPUE* estimated based on the data of chlorophyll-a data ( $0.001 \le p = 0.002 \le 0.05$ ).

# 4. Discussion

#### 4.1 Reliability of the hook distribution in specific depth classes

In this study, the reliability of hook distribution in specific depth, temperature, chlorophyll-a, and DO classes and nominal CPUE were improved (Song and Gao, 2006). Many studies applied catenary curve equation (Nishida *et al.*, 2003) to calculate the hook depth. These studies assumed that the longline gear was not affected by environmental factors (Hanamoto, 1987, 1974; Suzuki *et al.*, 1977; Gong *et al.*, 1989; Grundinin, 1989; Ward *et al.*, 1996 and Nakano, 1997). In fact, fishing depth of hooks would be shoaled because of the influence of oceanic environmental factors. The fishing depth of hooks tended to be shallower than the catenary hook depth (Saito, 1973; Hanamoto, 1974; Nishida, 1990; Boggs, 1992; Mizuno *et al.*, 1998, 1999; Bigelow *et al.*, 2006). The drifting speed ( $V_g$ ), wind speed ( $V_w$ ), wind direction ( $C_w$ ), angle of attack ( $\gamma$ ), wind angle ( $Q_w$ ), and hook position code (q) of the fishing gear were included in the development of the predicted hook depth model, leading to improving the estimation precision of hook depth. The correlation coefficients between the predicted hook depth and the TDR-mensured hook depth for traditional and experimental fishing gears were 0.8074 and 0.7625, respectively.

#### 4.2 The reliability of habitat preference indices

The reliability of habitat indices estimated for the yellowfin tuna in specific depth, temperature, chlorophyll-a, and DO classes was improved. The relationship between the distribution of yellowfin tuna and the environmental variables (habitat selection) was mainly studied by analyzing the data of archival tag (Biglow *et al.*, 2002), acoustic telemetry (Cayre, 1991; Cayre and Marsac, 1993; Marsac, 1998), and the mesoscale World Ocean Database (Cayre and Marsac, 1993). The number of fish which were analyzed in those studies was limited in both archival tag and acoustic telemetry. That might not express the habitat preference of yellowfin tuna in general. For the studies using mesoscale oceanographic or (and) long term average data, the temporal and spatial resolutions also need to be improved (Song *et al.*, 2008).

The habitat preference indices of this study were estimated based on the nominal *CPUE* for each class of depth, temperature, chlorophyll-a, and DO. Bach *et al.* (2003) suggested that

instrumented longlines could be used to study the vertical behavior of pelagic species. Longlines monitored by TDRs were superior in some ways to acoustic telemetry or archival tagging because longline monitoring can sample a large number of individuals of different sizes and species in different environmental conditions. They also suggested that the vertical distributions of the catches were a good indicator of natural depth distributions of fish if the entire depth ranges of various species were within the range of depths fished by longline hooks. In this study, the fishing depth of hook was from 40 to 400 m, which basically covered the whole vertical distribution range of yellowfin tuna (Song, *et al.*, 2008).

# 4.3 Effectiveness of "detHBS"

The "detHBS" was found to be effective in this study. There was large difference between the nominal CPUE and the standardized CPUEs which were estimated based on the data of depth, temperature, chlorophyll-a, and DO classes. The normalized standardized CPUEs have almost similarly trend, it indicated that one of the data set of depth, temperature, chlorophyll-a, and DO can be used to standardize CPUE. There were differences between the distribution of pelagic species and their vulnerability to longline gear (Ward and Myers, 2006; Bigelow and Maunder, 2007). In this study, the targeting species was bigeve tuna (Thunnus obesus) while the yellowfin tuna was the bycatch species. Since the mid-1970s, the longline fishing methods were changed from mainly 'regular' sets (5–6 hooks between floats) to 'deep' sets (> 10 hooks between floats) (Suzuki et al., 1977; Hanamoto, 1987). The effectiveness of longline gear in catching yellowfin tuna was decreased by this innovation because the inhabiting depth of yellowfin tuna was shallower than that of the bigeye tuna (Song et al., 2008; 2009). The effective fishing efforts for the yellowfin tuna were less than those of bigeye tuna or the nominal efforts. The standardized CPUE of yellowfin tuna should be higher than that of the nominal CPUE (Figs. 5a, 5c). The reliability of hook distribution, and the reliability of habitat indices estimated for the yellowfin tuna were improved. The "detHBS" interpreted the effect of physiological, behavioural, and environmental data to longline fishery catch and effort (Bigelow et al., 2002). Thus the "detHBS" was effective. The precision of standardized CPUE of yellowfin tuna could be improved if the inputs of "detHBS" were estimated based on the depth, temperature, chlorophyll-a, and DO classes

data. There was no significant deference between normalized nominal *CPUE* and normalized standardized *CPUEs* which were estimated based on the data of depth, temperature, and DO classes. This might result from only usage of two vessels' data; short time duration (four months); small variability of the environmental variables; and fixed gear configuration in this study. There was diference between normalized nominal *CPUE* and normalized standardized *CPUE* estimated based on the data of chlorophyll-a data. This might result from the sampling stations about the chlorophyll-a data were relatively less and the prefered chlorophyll-a classes were relatively narrower (0.07 ~ 0.08  $\mu$ g L<sup>-1</sup>, and 0.09 ~ 0.10  $\mu$ g L<sup>-1</sup>). There was relatively higher bias for the chlorophyll-a data.

#### 4.4 The optimum data set in standardizing CPUE

This study suggests that the depth data set was the optimum data set in standardizing *CPUE*. The depth distribution of longline gear was considered as the combined effects of set configuration, between-set variability in hook distribution and shoaling due to ocean currents (Bigelow *et al.*, 2002). The variation in fishing depths of longlines and the depth of the preferred habitat of yellowfin tuna can be used to standardize longline *CPUE* in order to provide an unbiased estimator of yellowfin tuna relative abundance. We suggest to using the depth data set to standardize *CPUE* if the "detHBS" was used.

## 4.5 The effect of the "detHBS"

Habitat preference and limitation were often used to evaluate the effects of environmental variables on *CPUE* in pelagic longline fisheries. The *CPUE* that was not standardized may lead to misunderstanding of subsequent stock assessment (Nishida *et al.*, 2003). A reliable standardization model for *CPUE* can improve the accuracy for the tuna stock assessment and management. In this study, the "detHBS" based on depth data set in standardizing *CPUE* can reliably describe the resource abundance of yellowfin tuna. The fisheries data are usually grouped at a defined spatial and/or temporal scale, and *CPUE* is commonly defined by the total catch versus the corresponding fishing effort over a specific spatial scale and time (Hilborn and Walters, 1992). Different gears tend to have different

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impacts on the same habitat, and different habitats have different response to the same gear (Jennings and Revill, 2007). If a hook is fished in an environment that is preferred by the species, then it has a higher probability of capturing that species (Hinton and Maunder, 2003). The effective fishing efforts for the yellowfin tuna calculated by "detHBS" might reliably describe the fishing power that is fishing for yellowfin tuna. Therefore, the different catchability among different fishing vessel, and between-set can be removed by "detHBS". The results in different annual and monthly patterns of standardized *CPUEs* will be different by using different models in standardizing *CPUEs*, thus affecting the interpretation of temporal variability in the yellowfin tuna population and greatly influencing the management measure. The reliable describe of the standardized *CPUEs* is the foundation of the sustainable utilization of the resources.

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