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Integrated habitat index of bigeye tuna (*Thunnus obesus*) in the Indian Ocean based on longlining data

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ABSTRACT

Two surveys of bigeye tuna, *Thunnus obesus*, fishing ground were carried out on board of the Chinese longliners in 2005 and 2006 at the high seas of the Indian Ocean for a better understanding of variables influencing the spatial distributions of bigeye tuna. Models were developed to estimate integrated habitat indices (*IHI*) of bigeye tuna in the respective depth class and the water column of the survey sites to predict the spatial distribution of the bigeye tuna in the Indian Ocean. These models were developed based on the bigeye tuna catch rate in the respective depth class, and the synchronal environmental variables (water temperature, salinity, chlorophyll-a, and dissolved oxygen) obtained in the survey by the using of quantile regression. The results suggest: (1) in general, the predict power of *IHI* models developed in this study were relative higher; (2) in 2005, in the survey area, the optimal inhabiting depth class of bigeye tuna was 160-240 m, the *IHI* within the area defined by 1ºN-6ºN, 62ºE-68ºE were higher; (3) the *IHI* models developed for 2005 were applied to specific area, period, and *La Nina* year; The area where the *IHI* models to be developed should be limited in the same ocean environmetal system; (4) the method to predict the spatial distribution of bigeye tuna suggested by this study could be used to the other pelagic fish species caught by longline.

Key words: integrated habitat index, longline, the Indian Ocean, and *Thunnus obesus*

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INTRODUCTION

Bigeye tuna (*Thunnus obesus*) is the most valuable of the tropical tunas targeted by the pelagic longline fisheries, which has resulted in extensive studies of this species in all oceans. Recent studies in the Indian Ocean have focused on biological characteristics (Chantawong, 1999; Nootmorn, 2004); resource assessment (Nishida et al. 2001; Ricard and Basson 2002; Fonteneau et al. 2004); and the distribution of bigeye tuna in relationship to oceanographic and habitat parameters (Somvanshi and Bhargava, 1999). Various investigators have attempted to learn more about the bigeye tuna's habitat selection by analyzing catch statistics and oceanographic variables averaged over time and space (Mohri and Nishida, 1999a 1999b; Feng and Xu, 2004).

There are a great of the models to study the habitat (environment) of organisms, *e.g.* general linear regression model (Clark et al.,1991;Labonne et al., 2003), general linear additive models (Swartzman et al.,1992; Maravelias, 1999), multiple linear regression models (Beamish and Lowartz, 1996), regression tree models (Norcross, 1997; Turgeon and Rodríguez, 2005), Logistic regression models (Guay, 2000; Turgeon and Rodríguez, 2005), habitat suitability index (HSI) models (Tamis et al., 1998; Benjamin, 1999; Bigelow et al., 2002; Nishida et al., 2003; Valavanis et al., 2004; Vinag et al., 2006; Wang , 2006; Kroll et al., 2006; Gillenwatera et al., 2006; Vincenzi et al.,2007), and quantile regression models (Terrell et al., 1996; Dunham et al., 2002; Eastwood et al., 2003; Wang, 2006; Feng et al., 2007; Song et al., 2007). Some of studies combined these models and geographic information system to build the fish habitat maps (Riou et al., 2001; Stoner et al., 2001). Although many studies have succeeded at the ecological studies by the using of these models, the respective defects were still existed in them. The common defects are (1) that these models were used to study the relationship between the dependent variable and the independent variables based on the least square regression, and (2) that some environment variables were not included in these models. There are two assumptions in these models: (1) the data were fit for the normal distribution, and (2) the deviations of the data were a constant to all observations. These assumptions fail to be conformed to in the ecological studies because some external impact variables that influence the activity of organism can't be measured, and the data of the measured variables were the integrated results from a lot of variables, including some of the missing variables. These missing variables may covary with the measured variables, and influences the responses of the organism to the measured variables. The great data from survey were variation points. The result based on estimation of mean or median (central tendency) species responses to environmental variables couldn’t accurately reflect the relationship between measured variables and organism reaction (Stoner et al., 2001). Thus, it is difficult to explain a fundamental principle of the biology study——the law of limiting factors on species’ responses, also called Liebig’s law of the minimum by these models. Conventional correlation and regression methods are not applicable to the study of the correlation in ecology (Thomson et al., 1996). Terrell et al. (1996) studied 35 datasets and found that the data from the 13 out of 35 datasets did not agree with the assumptions of the least square regression.

Although *HSI* models have a number of advantages in the study of ecology, and have been extensively used by the ecologist, the models also have some of assumptions that in most cases can not be substantiated. Specifically, these models assume that: (1) all variables included in the model have equal influence in defining habitat quality; (2) all variables included in model are independently and have no interaction among them; (3) the integrate influence of the variables to the organism can be combined in a simple mathematical relationship; (4) all significant variables influencing the distribution of the species have been included in the model (Eastwood and Meaden, 2004). Brown et al. (2000) solved the first defect of the *HSI* model by changing the weighing coefficients of variables in the model based on the significance of variables’ influence to the organism. But, it was primarily relied on expert’s experience and decision to define variable’s weighing coefficient. Most biologist calculated *HSI* generally by geometric mean. William and Maughan (2004) pointed out that the geometric mean could not simulate the integrate relationship well between organism and each variable.

Wang (2006) and Feng et al. (2007) combined quantile regression models with *HSI* models to study the relationship between the horizontal distribution of bigeye tuna and the environmentsal variables. In their studies, they used the mesoscale fishery average data and the average data of the environmental variables. These mesoscale data have lost the internal meaningful information. Some of the irrationalities were also existed in their studies because they used the geometric mean to calculate the integrate suitability index. The catch rate data were the average nominal catch rate for 22 years (1975-1997) in the square grid of 1°×1°, and the environmental data were obtained from World Ocean Atlas 98 (WOA98, interpolated data by kriging using the World Ocean Database 98 that were collected in field by many research vessels during about 100 years). For these mesoscale oceanographic or (and) long term average data, the temporal and spatial resolution also need to be improved. These data could not reflect the fluctuation of environmental variables accurately where the bigeye tuna inhabited, and the influences of great scopes events (e.g. *El Nino*, Rossby wave, ocean current, and monsoon) to the habitat of bigeye tuna. The catch rates were not standardized in their studies. All these factors affected the accuracy of the results. Moreover, they did not analyze the habitat variables of bigeye tuna in different depth classes.

Bigelow et al. (2002) did not include potential differences in impacts of different environmental variables on the distribution of bigeye tuna. They did not include interactions among the different environmental variables when they analyzed the influances of the environmental variables to the distribution of bigeye tuna either. The analysis of the integrate influence of the environmental variables to the distribution of bigeye tuna, including interaction, were need to be improved.

From a purely statistical viewpoint, quantile regression is a robust technique for parameter estimation that has all the advantages of ordinary least-squares regression but with the additional advantage of being distribution-free. It can be used to estimate the effects of limiting factors and thus provide the best estimate of how a species might be responding to changes in its environment variables (Eastwood and Meaden, 2004). When the errors were not normal distribution and a part of the limiting factors that limited the species was mensurated, it could provide many estimating results in different quantile. Therefore, it could reflect the responses of the species to the habitat variables represented in the model more accurately, especially the regression models of the upperbound quantile. The relationships between the dependent and independent variables could be better understood. Both homoscedastic and heteroscedastic error distributions are accommodated by this techniques (Cade and Noon, 2003; Wu and Ma, 2006).

In this study, the Integrated Habitat Indices (*IHI*) models of the bigeye tuna in the Indian Ocean were developed based on the fine-scale field mensurated data in the Indian Ocean in 2005. The field mensurated data included the vertical profiles of temperature, salinity, Chlorophyll-a concentration, dissolved oxygen concentration, three dimensions (3D) current velocity, and the catch rate data of bigeye tuna. *IHI* models were built by the using of quantile regression, and introducing the interactions among the environmental variables. *IHI* models could be used to provide reliable and precautionary estimates of bigeye tuna' responses to the environmental variables and predicte the spatial distribution of bigeye tuna. These models were validated by the independent field measured environment variables, and fishery data measured in the survey and the log book data of three Chinese large scale longliners. The aim of this study was to select an upper quantile model able to best define limiting factors and delineate potential habitat given the environmental data available for model construction and provides reference to the study of fishing condition forecasting.

MATERIAL AND METHOD

Data collection

Data were collected from operations on two longliners Huayuanyu No.18 and, Huayuanyu No.19 in 2005. The vessels had the identical specifications, e.g. overall length, 26.12 m; registered beam, 6.05 m; registered depth, 2.70 m; gross tonnage, 150 t; net tonnage, 45 t; main engine power, 407 kW. Data were also collected from operation on the longliner Yueyuanyu No.168 in 2006. The vessel had the identical specifications, e.g. overall length, 25.68 m; registered beam, 6.00 m; registered depth, 2.98 m; gross tonnage, 125 t; net tonnage, 44 t; main engine power, 318.88 kW. Three longliners were equipped with the same fishing equipments included super spool (type:

III - 48" x 80") and super spool line shooter (type: LS-4).

The configuration of gears used in the study in 2005 and 2006 were shown in Table 1. There were two kinds of branch lines, the overall length was 15 m (18 m in 2006) and the maximum diameter was 5 mm. One kind of the branch lines was the conventional fishing gear which was originally used on the vessel (Table 2). The figuration of the conventional fishing gear under the water was indicated in Fig.1 a. Another kind branch line was the experimental branch line. According to the different messenger weights and rigs used to construct the branch line, the experimental branch line was assembled as 16 types of branch line (Table 2). The figuration of the experimental fishing gear under the water in 2005 and 2006 were indicated in Fig. 1 b, and Fig. 1 c, respectively.

Fishing methods: in general, the gear deployment started between 00:00 and 06:00 local time, and it lasted for about 5 hours. Gear retrieval generally started between 12:00 and 15:00. Soak-times for individual hooks ranged from about 8 to 12 hours. During gear deployment in 2005 (2006), the vessel speed was about 4.3 m s^{-1} (3.855 m s^{-1}), line shooter speed was 5.58 m s^{-1} (5.147 m s^{-1}), and time interval between deploying fore and after branch lines was about 7.8 s (8.0 s). The length of main line between two branch lines was 43.5 m (41.2 m) and there were 23-25 (21-23) hooks between successive floats (HBF). The length of the main line was about 1090 m (906 m), and the sea surface horizontal distance was about 870 m (678 m) between successive floats. Each vessel used 368 experimental branch lines per set in 2005 (Longliner Huayuanyu No.18 used the types of 9-16, and Longliners Huayuanyu No.19 used the types of 1-8). Yueyuanyu No.168 used 272 experimental branch lines per set in 2006 (1-8 and 9-16 types were used alternately). The total hooks per set ranged from 400 to 2400. The bait was the blue markerel scad (*Decapterus macrosoma*, about 150 g) and the squids (*Loligo SPP.*, about 150 g). For the experimental gear, the branch line was not deployed at the first two deploying signals or at the last two deploying signals between two successive floats. A messenger weight was deployed at the second signal before or after deploying the float, respectively. The main line length from the connecting site of float line to the messenger weight was about 87 m (83 m) in 2005 (2006) , and two branch lines were absent. The HBF was reduced to 19-21 (17-19) in 2005 (2006), and the other parameters of deploying were not changed.

The sampling sites were selected based on the traditional bigeye tuna fishing grounds of the Indian Ocean, but the actual sampling sites were slightly different from the planned one due to logistical problems. The fishing activity was restricted principally to 0º47´N - 10º16´N and 61º40´E - 70º40´E in 2005 (Fig. 2). The sampling sites in 2005 were shown in Fig. 2. The vessel operations were conducted from September 15 to December 12 in 2005, with the boat fishing for 54 days. The sampling activity was mainly limited within the area defined by 03º07´S-04º07´N, 62º12´E-71º15´E from October 1 to November 30 in 2006 (Fig. 2). There were 36 sampling sites in 2006 (Fig. 2).

The environmental sampling instruments included Submersible Data Logger (SDL), XR-620 (RBR Ltd., Ottawa, Canada) and Temperature Depth Recorders (TDR), TDR-2050 (RBR Ltd., Ottawa, Canada) (14 in total), Conductivity Temperature Depth Recorder (CTD), SBE37SM (SeaBird Co., Bellevue, USA) and 3D Aquadopp Current Meter (ACM), Aquadopp-2000 (the sampling sites were same as that of the XR-620) (NORTECK Co., Vangkroken, Norway). The measurement range of temperature, conductivity, dissolved oxygen, and chlorophyll-a of XR-620 are 5 to 35 °C, 0 to 2 mS cm^{-1}, 0 to 150 %, 0.02 to 150 μg L^{-1}, respectively. The precision of the data is 0.002 °C, 0.0003 mS cm^{-1}, 1 % of dissolved oxygen measurement range, and less than 2 % of chlorophyll-a measurement range, respectively. Depth measurement error of the TDR-2050 was within ±0.05 % in depths of 10 to 740 m, and temperature was measured to ±0.002 °C. The conductivity was measured to 0.0003 s m^{-1} with the SBE37SM, and the temperature was measured to ±0.002 °C. The Aquadopp-2000 measured the 3D current (East/North/Up) in different depths, and the measurement error was within ±0.005 m s^{-1}. All of these measurement errors were cited from the manufacturer's manual. Considering the accuracies of data from varied instruments and requirements of the study, the data of depth, and temperature were processed to one effective decimal place, salinity, dissolved oxygen, and catch rate to two decimal places, and chlorophyll-a and 3D current to three decimal places, respectively.

The measurement methods of the instruments were as follows: while deploying the longline, TDRs were attached to the connecting sites of main line to the messenger weight, and the connecting sites of the main line to the branch line for various branch lines in the conventional or experimental gear. Finally, the hook depth of every hook position code was measured by TDRs. The length of the ropes which were used to link the TDRs were same as that of the branch lines. The total length of the steel wire for deploying the Aquadopp-2000 and XR-620 was about 600 m, but its actual depth reached was from 150 m to 580 m because of the impacts of wind and current. The total length of the steel wire for deploying the SBE37SM was about 400 m. The Aquadopp-2000, XR-620, and SBE37SM was deployed at the start or end position of deploying the longline.

The following data were also collected: deployment position and time, course and speed, line shooter speed, number of HBF, time interval between deploying fore and after branch lines, number of hooks, time of retrieving lines, hook position code at which fish was caught, number of hooked tuna per fishing operation, and hooked positions of tuna.

During the two surveys, the fishing boats were targeting bigeye tuna, and the bycatch included yellowfin tuna (*Thunnus albacares*), swordfish (*Xiphias gladius*), albacore (*Thunnus alalunga*) and billfish (Istiophoridae).

Data preparing

The hooked bigeye tuna were grouped into water depth classes as follows. For the survey in 2005, the related data from two longliners were used. Observations obtained at depths ranging from 40 to 400 m, divided into nine depth classes of 40 m each, were used in the analyses of 2005. Because no bigeye tuna was caught in the depth class of 40 - 80 m, no further anylysis was conducted to bigeye tuna in this depth class.

For the survey in 2006, observations obtained at depths ranging from 40 to 480 m, divided into 11 depth classes of 40 m each, were used in the analyses of 2006. Because few bigeye tuna was caught in the depth classes of 320 - 480 m, and there were larger sampling bias, no further anylysis was conducted to bigeye tuna in those depth classes.

The catch rate of bigeye tuna for depth class $j, CPUE_j$, was defined as

$$CPUE_j = \frac{U_j}{f_j} \times 1000 \qquad (1)$$

where j denotes depth class j, U_j is the number of bigeye tuna hooked at depth class j, f_j is the number of hooks deployed at depth class j, and j = 1, 2, 3, ······,8 (in 2005) or j =1,2,3,……,7 (in 2006).

The cacth rate, $CPUE_{ij}$, of depth classe j at sampling station i, was defined as:

$$CPUE_{ij} = \frac{N_{ij}}{H_{ij}} \times 1000 \qquad (2)$$

where H_{ij} is the number of hooks deployed in station i at depth class j, and N_{ij} is the number of bigeye tuna caught in station i at depth class j. N_{ij} was calculated as

$$N_{ij} = \frac{N_j}{N} \times N_i \qquad (3)$$

where N_j is the number of bigeye tuna caught at depth class j during the survey, N is the number of bigeye tuna caught during the survey, N_i is the number of bigeye tuna caught at sampling station i, and $i=1,2,3……54$ (in 2005); $i=1,2,3……31$ (in 2006). In 2005, the data on depth of capture were collected for 244 of the 624 bigeye tuna caught (39.1%). In 2006, the data on depth of capture were collected for 189 of the 223 bigeye tuna caught (84.8%).

The following procedures were used to analyze the catch rate data at the specific depth classe and in each sampling station: (1) to calculate the theoretical depth of each hook, using the catenary curve equation (Saito, 1992); (2) to calculate the hook depth rate (denoted as P) , using the arithmetic average hook depth recorded by TDR versus the theoretical depth of respective hook; (3) to calculate the logarithm of P , N_h (hook position code), V_w (wind velocity), sinQ_w (Q_w is the angle between the direction of the wind and the prevailing course in deploying the gear), $\sin\gamma$ (γ is the angle of attack between the prevailing course in deploying the gear and direction that the fishing gear was drifting), and V_g (gear drift velocity, for the survey of 2005; or $\tilde{K}_c$, the parameter of current shear, for the survey of 2006); (4) to analyze the correlation between the logarithm of P and the other variables; (5) for the survey of 2005, to use a stepwise regression method (Tang and Feng, 2002) to select a model for predicting the logarithm of P from the logarithm of N_h, V_w, sinQ_w,

$\sin\gamma$, and V_g; for the survey of 2006, to quantify the relationship model between the logarithm of P and the logarithm of N_h, V_w, $\sin Q_w$, and $\sin\gamma$, K℅, and the grouping mode for conventional gear (137 hooks) and experimental gear (138 hooks) with an analysis of covariance by a completely randomized design in GLM (SPSS version 13.0); (6) to estimate the average depth at which each hook operated, based on the above procedures; and (7) to calculate the overall catch per unit of effort (CPUE_j) for each depth class based on the catches of bigeye tuna during the experimental period and the catch rate of bigeye tuna at depth class j in sampling station i, CPUE_{ij} (Song et al., 2006;Song et al., 2007;Song et al., 2008). The overall CPUE_j for 2005 were shown in Fig. 3.

Calculation method of the weighted average environmental variable was based on the catch rate of each depth classe. Because the XR-620 was only used on “Huayuan No.18” to measure the data in 2005, the data measured by XR-620 and the fisheries data from “Huayuan No.18” were analyzed for the survey of 2005. Bigeye tuna were caught at different depths. The environmental variables were different, and the abundances of fish were also different at different depths. The CPUEs of bigeye tuna at various depth reflected the time that fish were at those depths, and the probability that a fish encountered the fishing gear. Weights were assigned to the environmental variables at different depths to calculate the average value of each environmental variable in each sampling station. The weighted average values of environmental variables response the surrounding environmental variables which the bigeye tuna were preferable. The weighted average value of an environmental variable, ENV_i was calculated, following Wang (2006) as

$$ENV_i = \sum CPUE_j ENV_{ij} / \sum CPUE_j \qquad (4)$$

where the environmental variables included temperature (T_i) , salinity (S_i), chlorophyll-a concentration (Ch_i), dissolved oxygen concentration (DO_i), horizontal current (HC_i), and vertical current (WC_i) in sampling station i, and ENV_{ij} was the value of environmental variables (*i.e.*, T_{ij} , S_{ij} , Ch_{ij}, DO_{ij}, HC_{ij}, and WC_{ij}) in sampling station i at depth j (*i.e.*, 40-80 m, 80-120 m, 120-160 m,……, 440-480 m). T_{ij} , S_{ij}, Ch_{ij}, and DO_{ij} were the arithmetic means measured by XR-620 and in sampling station i at depth j. HC_{ij} and WC_{ij} were the arithmetic means measured by

Aquadopp-2000 in sampling station *i* at depth *j*.

The vertical shear of the horizontal current component (denoted as $\tilde{K}$,) was estimated by integrating the original data measured with Aquadopp-2000 from the near-surface to the predicted deepest hook depth (*z*) (Bigelow et al., 2006) for each sampling station *i*. The coefficient $\tilde{K}$ was used to caculated the hook depth in the survey of 2006, and the potential CPUE of the water column (from the near-surface to the deepest hook depth) in the sampling station *i* in the survey of 2005. The equation was written as

$$K = \log\left(\frac{\int_0^z \left\| \frac{\partial \vec{u}}{\partial z} \right\| dz}{Z} \right) \tag{5}$$

The above expression can be approximated as

$$\tilde{K} = \log\left\{ \frac{\sum_{n=1}^{N} \left[\left(\frac{u_{n+1} - u_n}{z_{n+1} - z_n} \right)^2 + \left(\frac{v_{n+1} - v_n}{z_{n+1} - z_n} \right)^2 \right] (z_{n+1} - z_n)}{\sum_{n=1}^{N} (z_{n+1} - z_n)} \right\} \tag{6}$$

where $\tilde{K}$ is the log-transformed vertical shear, u_n the zonal velocity component of layer *n*, v_n the meridional velocity component of layer *n*, and z_n the depth of layer *n*.

Developping $CPUE_{ij}$ and $CPUE_i$ models by quantile regression

Quantile regression was initially developed by econometricians, *e.g.* Koenker and Bassett (1978) during the 1970's. The least-squares regression is designed to estimate models through the mean (or centre) of data distributions by minimizing the sum of squared deviations. The quantile regression is eatimated by minimizing the sum of absolute deviations. Quantile regression model could be written as

$$\hat{Y} = \beta X \tag{7}$$

the objective function of the quantile method could be written as

$$\min\left[\sum_{(y_i \geq x'_i \beta)} \theta \left| y_i - x'_i \beta \right| + \sum_{y_i \leq x'_i \beta} (1-\theta) \left| y_i - x'_i \beta \right| \right] \tag{8}$$

or as

$$\min_{\beta \in Rk} \sum_i \rho\theta(y_i - x'_i \beta) \tag{9}$$

where $\rho\theta(\varepsilon)$ was the "test function", defined as:

$$\rho\theta(\varepsilon) = \begin{cases} \theta\varepsilon & \varepsilon \geq 0 \\ (\theta - 1)\varepsilon & \varepsilon \leq 0 \end{cases} \tag{10}$$

For the model, it might be defined the conditional quantile function of x at θ as

$$Qy(\theta / x) = x'\beta, \quad \theta \in (0,1) \tag{11}$$

Quantile regression varies with the θ value, which ranges from 0 to 1. It can be used to get the corresponding predictor of y at the distribution of x with the different θ value. The algorithm developed by Cade and Richards (2001) was used for the quantile regression analysis.

In this study, quantile regression parameters were estimated using the BLOSSOM statistics software which developed by Midcontinent Ecological Science Center, U.S.Geological Survey (Cade and Richards, 2001).

In this study, the independent variables in the quantile regression model included six single variables: temperature (T_{ij}), salinity (S_{ij}), chlorophyll-a concentration (Ch_i), dissolved oxygen concentration (DO_{ij}), horizontal current (HC_i), and vertical current (WC_i), and 15 interaction terms resulting from six single variables.

The regression model for describing the relationship between the expected catch rate at depth class j in sampling station i, $\hat{CPUE}_{ij}$ versus T_{ij}, S_{ij}, Ch_{ij}, DO_{ij}, HC_{ij}, WC_{ij}, and the interaction terms was

$$\begin{aligned} \hat{CPUE}_{ij} = {} & C_j + a_j T_{ij} + b_j S_{ij} + c_j Ch_{ij} + d_j DO_{ij} + e_j HC_{ij} + f_j WC_{ij} + g_j TS_{ij} + h_j TCh_{ij} + i_j TDO_{ij} + j_j THC_{ij} + k_j TWC_{ij} \\ & + l_j SCh_{ij} + m_j SDO_{ij} + n_j SHC_{ij} + o_j SWC_{ij} + p_j ChDO_{ij} + q_j ChH \\ & + s_j DOHC_{ij} + t_j DOWC_{ij} + u_j HCWC_{ij} + \varepsilon_{ij} \end{aligned} \tag{12}$$

where C_i was the constant, TS_{ij} was the interaction of temperature and salinity, TCh_{ij} was the interaction of temperature and chlorophyll-a concentration, …… , $HCWC_{ij}$ was the interaction of horizontal current and vertical current, and ε_{ij} was the error term in sampling station i at depth j. The a_j, b_j, c_j, d_j, e_j, f_j,……, u_j were their respective parameters.

The regression model for describing the relationship between the expected catch rate in sampling station i, $\hat{CPUE}_i$ versus T_i, S_i, Ch_i, DO_i, $\tilde{K}_i$, WC_i and the interaction terms was:

$$\hat{CPUE}_i = C' + a'T_i + b'S_i + c'Ch_i + d'DO_i + e'\tilde{K}_i + f'WC_i + g'TS_i + h'TCh_i + i'TDO_i + j'T\tilde{K}_i + k'TWC_i + l'SCh_i + m'SDO_i$$
$$+ n'S\tilde{K}_i + o'SWC_i + p'ChDO_i + q'Ch\tilde{K}_i + r'ChWC_i + s'DO\tilde{K}_i + t'DOWC_i + \varepsilon_i' \qquad (13)$$

where C' was the constant, TS_i was the interaction of temperature and salinity, TCh_i was the interaction of temperature and chlorophyll-a concentration, …… , $\tilde{K}WC_i$ was the interaction of vertical shear and vertical current, ……. , and ε_i' was the error term of expected catch rate in sampling station i. The a', b', c', d', e', f', ……, u' were their respective parameters.

Nineteen quantiles for $\theta = 0.05, 0.10, 0.15, \ldots\ldots, 0.95$ were chosen to build the model. When θ is close to 0 or 1, the parameters of quantile regression model are influenced by extremity values significantly, and more instability. It is better to select $\theta = 0.5$-0.95 to build the upper quantile model (Feng et al., 2007). For the quantile regression, all variables were initially included in the model. Then the statistical significance of each variable in the model was evaluated by the rank-score test. If the significance value, P, was greater than 0.05, the variable was excluded from the model. The P values for all variables and their interaction terms included in the model were re-evaluated whenever a variable was excluded. This process was repeated until the P values of all the independent variables and their interaction terms in the model were less than or equal to 0.05. If the interaction term was included in the model, two single variables of this interaction term were also included in the model. In this procedure, the optimal model was developed.

Developing IHI_{ij} models

Based on the regression (Eq. 12), $\hat{CPUE}_{ij}$ was estimated in sampling station i at depth j. IHI_{ij} was derived from $\hat{CPUE}_{ij}$ and $\hat{CPUE}_i$. The equation was written as

$$IHI_{ij} = \frac{\hat{CPUE}_{ij}}{\hat{CPUE}_{\max}} \tag{14}$$

where $\hat{CPUE}_{\max}$ was the maximum value of all $\hat{CPUE}_{ij}$ in sampling station i at depth j and $\hat{CPUE}_i$ in sampling station i.

Developing $\overline{IHI_i}$ *models*

Based on the optimal model equation (Eq.13), $\hat{CPUE}_i$ was estimated in sampling station i. $\overline{IHI_i}$ was derived from $\hat{CPUE}_{ij}$ and $\hat{CPUE}_i$. The equation was written as

$$\overline{IHI_i} = \frac{\hat{CPUE}_i}{\hat{CPUE}_{\max}} \tag{15}$$

The expression of IHI isolines

Based on the estimates derived above, the IHI isoline distribution maps were developed using the software Marine Explore 4.0 (Environment Simulation Laboratory Co. Ltd., Shimizu, Japan).

The prediction power of IHI *model*

The paired two samples t-test (Tang and Feng, 2002) was used to calculate the Poisson correlation coefficients between prediction IHI_{ij} and the respective observed indices in sampling station i at depth j and the Poisson correlation coefficients between $\overline{IHI_i}$ and the respective observed indices in sampling station i. The observed index was the ratio of the observed $CPUE_{ij}$ (or $CPUE_i$) versus the maximum among the observed $CPUE_{ij}$ in sampling station i at depth j and $CPUE_i$ in sampling station i. The correrations between IHI_{ij} and the respective observed index in sampling station i at depth j , and the correration between $\overline{IHI_i}$ and the respective observed index in sampling station i were analyzed. The arithmetic mean of IHI_{ij} was calculated, and its tendency line was compared to the tendency line of bigeye tuna's catch rate in the specific depth class.

The validation of IHI_{ij} *model*

In this study, because of the data limitation, the data mensurated by CTD from "Huayuanyu No.19" in 2005 was used to validate the catch rate ($\hat{CPUE}_{ij}$) prediction model about the depth class of 240 - 280 m. The catch rate of the bigeye tuna in each sampling station at the depth class of 240 m- 280 m were caculated. A comparision between the prediction catch rate and the observed catch rate at the depth class of 240 - 280 m was conducted by the paired two samples t-test (Tang and Feng, 2002). The observed catch rate, predicted catch rate by the model, and the *IHI* isoline at the depth class of 240 - 280 m were mapped by the using of the Marine Explore 4.0 software.

Within the area in the vicinity of 1ºN and between 62ºE and 69ºE, the environmental data of each relevant station were measured in 2005 and 2006 (Table 3). The environmental data measured in 2006 in the relevant station at depth *j* were input into the respective catch rate prediction models developed in 2005 to predicte the catch rate in the relevant station at depth *j*. A comparision between the predicted catch rate and the observed catch rate in the relevant station at depth *j* measured on board of Yueyuanyu 168 in 2006 was conducted by the paired two samples t-test (Tang and Feng, 2002).

The validation of $\overline{IHI_i}$ *model*

(1) Validation by the using of the observed bigeye tuna catch rate data of "Huayuanyu No.19" collected in 2005

The observed norminal bigeye tuna catch rate data of "Huayuanyu No.19" collected in 2005 and the $\overline{IHI_i}$ isolines estimated for 2005 were mapped by the using of the Marine Explore 4.0 software and analyzed qualitatively. The $\overline{IHI_i}$ model developed for the survey in 2005 was validated.

(2) Validation by the using of the logbook data of three Chinese large scale longliners

The nominal CPUE from three Chinese large scale longliners' logbook (operating time and areas were Apr. to Aug. 2006, 10ºS-8ºN, 41ºE-61ºE; Apr. 2006 to

Feb. 2007, 9ºS-10ºN, 40ºE-66ºE; and Jan. 2007 to Feb. 2008, 12ºS-10ºN, 52ºE-92ºE, respectively) were standardized by the using of GLM model (Okamoto et al., 2001; Nishida et al., 2003; Campbell, 2004; Okamoto et al., 2004; Shono et al., 2005). The model was written as

$$LN(CPUE+CONSTANT)=INTERCEPT+YE_{\delta}+MO_{\varepsilon}+LON_{\tau}+LAT_{\psi}+(YE\times MO)_{\delta\varepsilon}+(YE\times LON)_{\delta\tau}+(YE\times LAT)_{\delta\psi}+(MO\times LON)_{\varepsilon\tau}+(MO\times LAT)_{\varepsilon\psi}+(LON\times LAT)_{\tau\psi}+(ERROR)_{\delta\varepsilon\tau\psi} \quad (16)$$

where, *LN*: natural logarithm; *CONSTANT*: constant, 10% of the overall average nominal CPUE (0.9 in this case); *INTERCEPT*: intercept (the overall average nominal CPUE); YE_{δ}: the effect of δ year, from 2006 to 2008; MO_{ε}: the effect of ε month, from Jan. to Dec.; LON_{τ}: the effect of longitude, from 40 ºE to 92 ºE; LAT_{ψ}: the effect of latitude, from 12ºS to 10ºN; $(YE\times MO)_{\delta\varepsilon}$: the effect of interaction between year and month; $(YE\times LON)_{\delta\tau}$: the effect of interaction between year and longitude; $(MO\times LON)_{\varepsilon\tau}$: the effect of interaction between month and lonitude; $(MO\times LAT)_{\varepsilon\psi}$: the effect of interaction between month and latitude; $(LON\times LAT)_{\tau\psi}$: the effect of interaction between longitude and latitude; $(ERROR)_{\delta\varepsilon\tau\psi}$: Error.

The standardized catch rates in the grid of 1º×1º derived from the data collected on three Chinese large scale longliners were calculated and mapped with the $\overline{IHI_i}$ isolines by the using of the Marine Explore 4.0 software within the areas defined by 0º-11ºN, 60ºE-72ºE. The relationship between the standardized catch rates and the $\overline{IHI_i}$ isolines was analyzed qualitatively. The $\overline{IHI_i}$ models developed for the survey in 2005 were validated.

RESULTS

The catch rate $\hat{CPUE}_{ij}$ *in the sampling station i at depth classes j*

The parameters of the prediction models of the catch rate $\hat{CPUE}_{ij}$ in the sampling station *i* at depth classes *j* in 2005 were obtained by the using of quantile regression (Table 4).

Catch rate $\hat{CPUE}_i$ *in station i*

The optimal model of the catch rate $\hat{CPUE}_i$ in 2005 at the sampling station *i* was developed by the using of quantile regression. For Eq. 13, the optimal models were shown as

$$\hat{CPUE}_i = 42.56 - 3.35T_i + 114.47Ch_i \qquad (\theta = 0.70\text{, for 2005}) \qquad (17)$$

For Eq.17, the catch rate was positively correlated with the weighted average of chorophyll-a concentration and negatively with the weighted average of temperature. When θ was 0.70, the optimal model was derived.

The prediction power of IHI_{ij} *model*

The Poisson correlation coefficients between the predicted IHI_{ij} and the observed indices at the depth class *j* in 2005 were shown in Table 5. The Poisson correlation coefficients were assumed to indicate the prediction power of the IHI_{ij} model. When the Poisson correlation coefficient was less than 0.400, 0.400-0.499, 0.500-0.699, and greater than 0.700, the prediction power of the IHI_{ij} model were defined as inferior, medium, good, and excellent, respectively.

The tendency line of the arithmetic average of IHI_{ij} was compared to the tendency line of the catch rate in the specific depth class. The tendency line of the arithmetic average of IHI_{ij} *at* each depth class was similar to the tendency line of the catch rate in relevant depth class in 2005 at some depth classes (except the classes of 80-120 m or 360-400 m, Fig. 3).

The distributions of IHI_{ij} *at different depth classes and* $\overline{IHI_i}$

Based on the data collected in 2005, the distributions of IHI_{ij} at different depth classes were shown in Fig. 4, and the distributions of $\overline{IHI_i}$ were shown in Figs. 6 or 7. Based on the survey in 2005 (Fig.4), for the depth class of 80-120 m, the IHI was relatively higher (0.26-0.32) in the areas defined by 4ºN-6ºN, 64ºE-65º30´E; 1ºN-2ºN, 65ºE-67ºE; and 2ºN-6ºN, 67ºE-68º30´E. The IHI was relatively lower in most of the other areas. For the depth class of 120-160 m, the IHI was relatively higher (0.26-0.34) in the area defined by 1ºN-2ºN, 66ºE-67ºE. The IHI was relatively lower in most of the other areas. For the depth class of 160-200 m, the IHI was the highest one of the all depth classes. The IHI was relatively higher (0.60-0.90) in the area defined by 1ºN-2ºN, 66ºE-68ºE. The IHI was relatively lower in most of the other areas. For the depth class of 200-240 m, the IHI was relatively higher (0.32-0.40) in the area defined by 1ºN-6ºN, 62ºE-70ºE. The IHI was relatively lower in most of the other areas. For the depth class of 240-280 m, the IHI was relatively higher (0.15-0.27) in the area defined by 1ºN-3ºN, 63ºE-68ºE. The IHI was relatively lower in most of the other areas. For the depth class of 280-320 m, the IHI was relatively higher (0.09-0.16) in the area defined by 3ºN-6ºN, 62ºE-69ºE. The IHI was relatively lower in most of the other areas. For the depth class of 320-360 m, the IHI was relatively higher (0.27-0.48) in the areas defined by 1ºN-1º30´N , 63ºE-64º 30´E, and 4ºN-6ºN, 63ºE-64º30´E. The IHI was relatively lower in most of the other areas. For the depth class of 360-400 m, the IHI was the lowest one of all depth classes. The IHI was relatively higher (0.06-0.10) in the area defined by 1ºN-6ºN, 62ºE-68º30´E. The IHI was relatively lower in most of the other areas.

Based on the distribution of the $\overline{IHI_i}$ in 2005 (Figs.6 or 7), the $\overline{IHI_i}$ was relatively higher (0.17-0.39) in the area defined by 1ºN-6ºN, 62ºE-69ºE. The $\overline{IHI_i}$ was relatively lower in most of the other areas.

The validation of IHI_{ij} *models*

The data mensurated by CTD from “Huayuanyu No.19” in 2005 were used to validate the catch rate ($\hat{CPUE}_{ij}$) prediction model about the depth class of 240 - 280 m. A comparision between the prediction catch rate and the observed catch rate at the depth class of 240 - 280 m was conducted by the paired two samples t-test (Tang and Feng, 2002). It was suggested that there was no significant difference between them (Table.6).

Based on the CPUEs observed on “Huayuanyu No.19”, and predicted by the models, and the IHI isolines at depth class of 240 -280 m in 2005, the distribution trend of the observed CPUEs and model predicted CPUEs were similar to the distribution trend of IHI isolines at that depth class. While the CPUEs were higher, the IHI were higher too, especially in the area defined by 5ºN-8ºN, 61ºE-71ºE (Fig.5).

Within the area in the vicinity of 1ºN and between 62ºE and 69ºE, a comparision between the predicted catch rate and the observed catch rate in the relevant station measured on board of Yueyuanyu 168 in 2006 was conducted by the paired two samples t-test (Tang and Feng, 2002). It was suggested that there were no significant differences between the predicted CPUEs of the models and the observed CPUEs in 2006 at the depth classes except for the depth classes of 80-120m, or 240-280m (Table.7).

The validation of $\overline{IHI_i}$ *model*

(1) Validation by the using of the observed bigeye tuna catch rate data of "Huayuanyu No.19" collected in 2005

The observed norminal bigeye tuna catch rate data of "Huayuanyu No.19" collected in 2005 was consistent with the $\overline{IHI_i}$ isolines distribution in the area defined by 5ºN-8ºN, 61ºE-71ºE in 2005. There were a little different tendency between the observed norminal catch rate and the $\overline{IHI_i}$ isolines distribution in the area defined by south of 4ºN (Fig.6).

(2) Validation by the using of the logbook data of three Chinese large scale longliners

The standardized catch rates in the grid of 1º×1º derived from the data collected on board of three Chinese large scale longliners were calculated and mapped with the $\overline{IHI_i}$ isolines by the using of the Marine Explore 4.0 software within the areas defined by 0º-11ºN, 60ºE-72ºE (Fig. 7).

In the south of 7ºN, the $\overline{IHI_i}$ isolines distribution in 2005 were similar to the standardized catch rates distribution of the 1º×1º grid which derived from the data collected from three Chinese large scale longliners in the area defined by 0º-11ºN, 60ºE-72ºE. $\overline{IHI_i}$ and catch rates were higher in the area defined by 2ºN-4ºN, 60ºE-69ºE, but in the area defined by 2ºN-4ºN, 60ºE-69ºE, most of the $\overline{IHI_i}$ and catch rates were lower. However, in the area defined by 7ºN-11ºN, 60ºE-72ºE, there was difference between $\overline{IHI_i}$ and catch rates because three Chinese large scale longliners did not fish in the area defined by 7ºN-11ºN, 64ºE-72ºE. The predicted result of the model in this area could not be validated (Fig.7).

DISCUSSION

The prediction power of some models was lower, why?

In this study, habitat models of the upper bounds of bigeye tuna-habitat relationships were developed from the quantile regression method. These models were developed for the depth classes of 80-120 m, 120-160 m, 160-200 m, 200-240 m, 240-280 m, 280-320 m, 320-360 m, and 360-400 m, and the $\overline{IHI_i}$ in 2005. In table 5, the prediction power of the model in the depth class of 280-320 m was lower compared to the prediction power of the models in the depth classes of 80-120 m, 120-160 m, 240-280 m, and 360-400 m in 2005. It was due to that: (1) the more important habitat factors limiting the organism were not included in the model; (2) there were large sampling errors, including small sample size, the bias of the hook depth calculation, and the sampling bias of the ocean environmental data, especially in the depth classes of 80-120 m, 120-160 m, and 360-400 m in 2005. Therefore, caution is required in applying the models that the prediction power was lower because there are some uncertainties in these models.

The prediction power of the IHI model was good in general

The prediction power of the IHI model was good in general. The trend of the arithmetic average value of IHI at each depth class was similar to the trend of the catch rate at the respective depth class in 2005 except for the depth classes of 80-120 m, or 360-400 m. The trends of IHI at the depth classes of 80-120 m, and 360-400 m were not consistent with the trends of the catch rate (Fig.3). It might be resulted from that the catch rate of bigeye tuna had large samplying bias at this two depth classes. Because the IHI were relatively higher at the depth class of 160-240 m, it was suggested that the optimal inhabiting water depth of bigeye tuna was 160 - 240 m. This is consistent with the conclusion (160-220 m) of Song et al. (2006) who studied the bigeye tuna's optimal inhabiting water depth class in the Indian Ocean.

The reasons for the prediction power of the IHI_{ij} models were good in general and there was the bias in a portion of results after validation

The IHI_{ij} prediction models at each depth class (except for the depth class of 360-400 m) in 2005 could be used to predicte the catch rate of bigeye tuna in the respective depth class. The reasons were that (1) the prediction power of the prediction model at the depth class of 240-280 m was inferior, and this prediction model could be used to predict the catch rate of bigeye tuna at this depth class based on the result of the paired two samples t-test (Table 6); and (2) the prediction power of the other prediction models at the other depth classes were greater than that of the depth class of 240-280 m except for the depth class of 360-400 m (Table 5) .

The distribution trend of the observed and model predited catch rate of bigeye tuna for the depth class of 240-280 m in the area defined by south of 4ºN were different from the *IHI* distribution trend in 2005 (Fig.5). There was strong southwest monsoon current in this area. The southwest monsoon current made the hook depth shoaling. The hooks could not be deployed in the bigeye tuna's preference inhabiting depth. There was large uncertainty or variation as a result of small sample size. All of these reasons resulted in the lower observed catch rate (even equal to 0). For the area defined by south of 4ºN, the relevant ocean environmental data were not measured by "Huayuanyu No.19". Therefore, the catch rate of bigeye tuna in that area could not be predited.

Within the area in the vicinity of 1ºN and between 62ºE and 69ºE, based on the paired two samples t-test (Tang and Feng, 2002), there were no significant difference between the predicted CPUEs of the models in 2005 and the observed CPUEs in 2006 at the depth classes except for the depth classes of 80-120 m, or 240-280 m (Table.7). It might be resulted from the lower prediction power of the models at the depth classes of 80-120 m, and 240-280 m (Table 5).

The reasons for the prediction power of the $\overline{IHI_i}$ *models were good in general and there was the bias in a portion of results after validation*

The $\overline{IHI_i}$ model had good prediction power. The results predicted from the $\overline{IHI_i}$ models reflected the distribution and the habitat environment selection of the bigeye tuna in the survey areas, generally. In the area defined by 6ºN-8ºN, 61ºE-71ºE, the distribution trend of the observed CPUEs of bigeye tuna from "Huayuanyu No.19" in 2005 was similar to the distribution trend of $\overline{IHI_i}$ isolines in 2005. But, the distribution trend between them was different in the area defined by south of 6ºN (Fig.6), which was due to that: there was strong southwest monsoon current in the area defined by south of 6ºN; the southwest monsoon current made the hook depth shoaling; the hooks could not be deployed in the bigeye tuna's preference inhabiting depth; and the observed CPUEs of bigeye tuna were very lower (even equal to 0) in the area defined by south of 6ºN.

Both similar and different distribution areas were exist for the $\overline{IHI_i}$ distribution of the predicted result in 2005 and the distribution of the standardized catch rates in the grid of 1º×1º derived from three Chinese large scale longliners. In the area defined by 1ºN～2ºN, 65ºE～68ºE, the *IHIs* were higher, but the standardized catch rates were lower (Fig.7), which was due to that: there was equator undercurrent in this area; the equator undercurrent made the hook depth shoaling; the hooks could not be deployed in the bigeye tuna's preference inhabiting depth; and the observed CPUEs of bigeye tuna were very lower. Actually, there were bigeye tuna in this area, namely, the model predicted result was bilievable. During the survey, in the relevant locations, the catch rates of the experimental gear using the messenger weight of "Huanyuanyu No.18" were higher than that of the traditional gear. The model predicted results were validated.

The distribution trends of the $\overline{IHI_i}$ isolines in 2005 were not consistent with the distribution trend of the standardized catch rates in the grid of 1º×1º derived from three Chinese large scale longliners in the survey areas absolutely because the gears used by three Chinese large scale longliners were different from that of the survey longliners, and the fishing area of three Chinese large scale longliners and the sampling sites in the survey were limited. The operation time of three Chinese large scale longliners was from Apr. 2006 to Feb. 2008. The survey time was from Sep. to Dec. in 2005. It was the *La Nina* year in 2005, the *El Nino* year in 2006, and the normal year in 2007. The environmental data of three years were different. The area where to develop the *IHI* model should be limited in the same ocean environmetal system. *IHI* prediction models which developed by the data collected in 2005 could be used in the *La Nina* year.

Outlook

In this study, the prediction models were the preliminary models. The models in 2005 were developed by the using of the data collected in 30 operations. The synchronization needs to be improved. Six environmental variables (*e.g.* temperature, salinity, chlorophyll-a concentration, dissolve oxygen concentration, horizontal current, and vertical current), and their interaction terms were considered in developing the *IHI* models, whereas other variables, such as depth of the thermocline, abundance of zooplankton, and trophic interactions may be important in influencing the distribution of bigeye tuna. Failure to include such variables, if they are important, would reduce the reliability of the results, of course. These effects should be incorporated into future studies. The ecological significance needs farther study and discussion.

In addition, there are limitations in predicting the spatial distribution of the fish from fisheries data alone. The fisheries data may cover only limited habitats because of the limitations on the depths to which the hooks can be deployed, temporal scales, and areas covered by the fishery. Thus future surveys should include data covering wide ranges of depth, time, and area to better quantify the spatial distribution of bigeye tuna.

CONCLUSION

The quantile regression models could be used to reflect the habitat selection of bigeye tuna more accurately than the ordinary least-squares regression models. The prediction power of *IHI* models which were developed in this study was relative higher, generally. In 2005, in the survey area, the optimal inhabiting depth class of bigeye tuna was 160-240 m, the *IHI* within the area defined by 1ºN-6ºN, 62ºE-68ºE were higher, and the *IHI* within the other areas were lower. The area where the *IHI* models to be developed should be limited in the same ocean environmetal system. The *IHI* models developed for 2005 were applied to the specific areas defined by 1ºN-10ºN, 61ºE-71ºE, in the period from Sep. to Dec. of the *La Nina* year. Caution is required in applying the models that the prediction power is lower because there are some uncertainties in these models. The method to predict the spatial distribution of bigeye tuna suggested by this study could be used to the other pelagic fish species caught by longline.

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Table 1. The configuration of gears in the survey of 2005 and 2006 .

Year	Main line			Float		Float line			Branch line
	Diameter (mm)	Material	Length (km)	Diameter (mm)	Material	Diameter (mm)	Material	Length (m)	Length (m)
2005	3.6	Nylon monofilament	110	360	Plastics	6	Nylon	22	15
2006	3.6	Nylon monofilament	110	360	Plastics	6	Nylon	30	18

Table 2. The configuration of conventional and 16 experimental branch lines.

Gear	Type[1)]	Messenger weight (kg) [2)]	Weight (g) of barrel swivel[3)]	Weight (g) of sinker[4)]	Is there luminous sleeve ?
Conventional	1	/	10	/	/
Experimental	1	0.5	75	18.75	yes
	2	0.5	60	18.75	yes
	3	0.5	45	11.25	no
	4	0.5	10	11.25	no
	5	1.0	75	18.75	no
	6	1.0	60	18.75	no
	7	1.0	45	11.25	yes
	8	1.0	10	11.25	yes
	9	1.5	75	11.25	yes
	10	1.5	60	11.25	yes
	11	1.5	45	18.75	no
	12	1.5	10	18.75	no
	13	2.5	75	11.25	no
	14	2.5	60	11.25	no
	15	2.5	45	18.75	yes
	16	2.5	10	18.75	yes

1) For the experimental gear, types 1- 8 were used by Hua Yuan yu No. 19, types 9 - 16 were used by Hua Yuan yu No. 18.

2) The messenger weight was made of cement and sand. The messenger weight used in the experimental gear changed from 0.5 kg (2005) to 2 kg (2006).

3) The barrel swivel connected the first segment and the secondsegment of the branch line. This is a swivel made of the lead and shaped like a barrel to prevent entanglement with the branch lines.

4) The lead sinker was moored in the wire and above the hook to weight the hook.

Table 3. Parallelism survey stations in 2005 and 2006.

Date	2005		Date	2006	
	Longitude (E)	Latitude (N)		longitude(E)	latitude(N)
17 Sep.	63°16´	1°21´	10 Oct.	63°25´	1°10´
18 Sep.	63°56´	0°47´	14 Oct.	64°21´	0°55´
19 Sep.	65°15´	1°21´	14 Oct.	64°21´	0°55´
20 Sep.	66°18´	1°18´	20 Oct.	66°01´	0°44´

Table 4. The parameters of the optimal prediction models for the survey in 2005.

Depth classes (m)	80-120	120-160	160-200	200-240	240-280	280-320	320-360	360-400
quantile θ	0.70	0.55	0.95	0.55	0.50	0.85	0.75	0.70
C_j (Constant)	32.58	20.16	152509.50	-0.74	734.88	708.03	19075.20	401.94
$a_j(T_{ij})$	0	-1.32	-8993.37	0	0	0	0	0
$b_j(S_{ii})$	0	0	-4334.80	0	-20.71	-20.32	-541.16	-11.52
$c_j(Ch_{ii})$	12.84	54.48	-482056.00	0	0	279.89	-433001.00	143.62
$d_j(DO_{ij})$	-1.39	0	-2900.04	2.40	0	0	5.92	0
$e_j(HC_{ij})$	0	0	7.52	0	0	0	34.65	0
$f_j(WC_{ij})$	0	8.69	0	0	0	0	0	0
$g_j(TS_{ij})$	0	0	255.94	0	0	0	0	0
$h_j(TCh_{ij})$	0	0	-2018.72	0	0	0	0	0
$i_j(TDO_{ij})$	0	0	8.00	0	0	0	0	0
$j_j(THC_{ij})$	0	0	0	0	0	0	0	0
$k_j(TWC_{ij})$	0	0	0	0	0	0	0	0
$l_j(SCh_{ij})$	0	0	14423.00	0	0	0	12275.71	0
$m_j(SDO_{ij})$	0	0	78.78	0	0	0	0	0
$n_j(SHC_{ij})$	0	0	0	0	0	0	0	0
$o_j(SWC_{ij})$	0	0	0	0	0	0	0	0
$p_j(ChDO_{ij})$	0	0	0	0	0	0	0	0
$q_j(ChHC_{ij})$	0	0	0	0	0	0	0	0
$r_j(ChWC_{ii})$	0	0	0	0	0	0	0	0
$s_j(DOHC_{ij})$	0	0	-3.78	0	0	0	-12.16	0
$t_j(DOWC_{ij})$	0	0	0	0	0	0	0	0
$u_j(HCWC_{ij})$	0	0	0	0	0	0	0	0

Table 5. The Poisson correlation coefficients between predicted *IHI* and the observed *IHI* and the prediction power for 2005.

Depth class (m)	Poisson correlation coefficient	Prediction power
40 - 80	/	/
80-120	0.389	inferior
120-160	0.360	inferior
160-200	0.770	excellent
200-240	0.478	medium
240-280	0.334	inferior
280-320	0.582	good
320 - 360	0.591	good
360 - 400	0.271	inferior
Total average	0.621	good

Table 6. The result of paired two samples t-test for CPUE of bigeye tuna between the model prediction and the observation at the depth class of 240-280 m.

	Predicted CPUE	Observed CPUE
Average	4.24	4.25
Variance	4.24	229.67
Observations	39	39
Poisson corelation coefficient	0.111469614	
df	38	
t Stat	-0.005999999	
P(T<=t) two-way	0.995244111	

Table 7. The *P*-value of paired two samples t-test for CPUEs of bigeye tuna between the model prediction in 2005and observation in 2006 in respective depth class on parallelism stations.

Depth class (m)	*P*
80 ~ 120	0.000991909
120 ~ 160	0.229859088
160 ~ 200	0.28072543
200 ~ 240	0.051356006
240 ~ 280	0.004108947
280 ~ 320	0.220199562

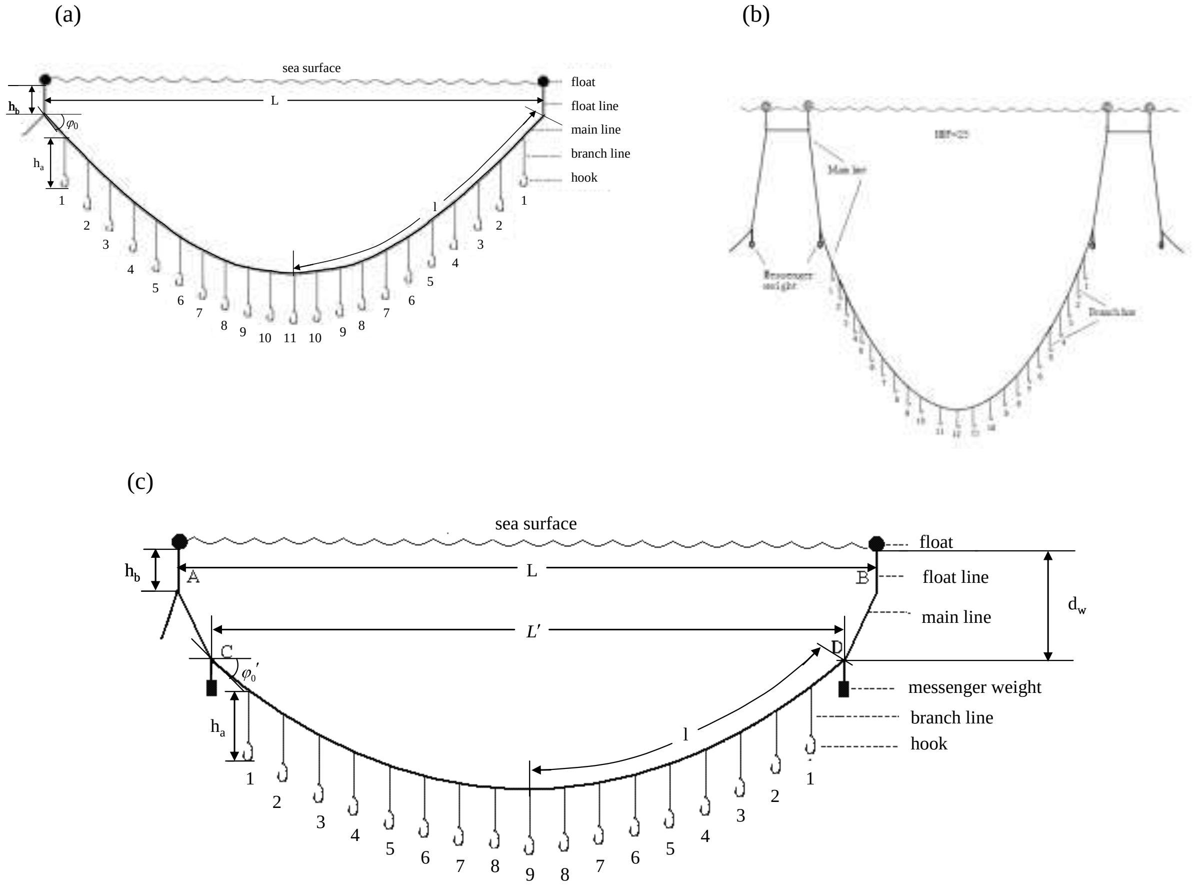


Figure 1. The figuration of fishing gear under the water

(a: conventional fishing gear, HBF=25; b:experimental fishing gear in 2005, HBF= 23;

c:experimental fishing gear in 2006, HBF= 17)

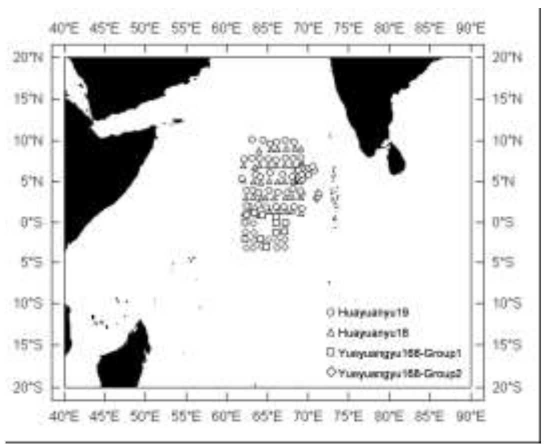


Figure 2. Huayuanyu 18, and 19 measured positions in 2005 andYueyuanyu 168 measured positions in 2006

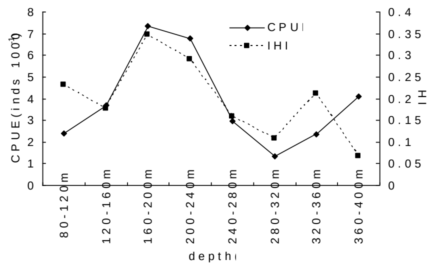
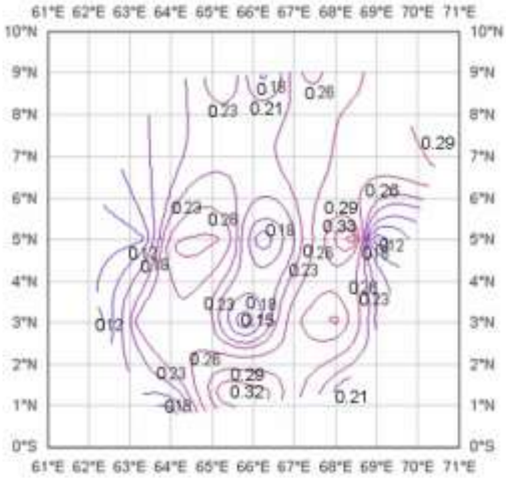
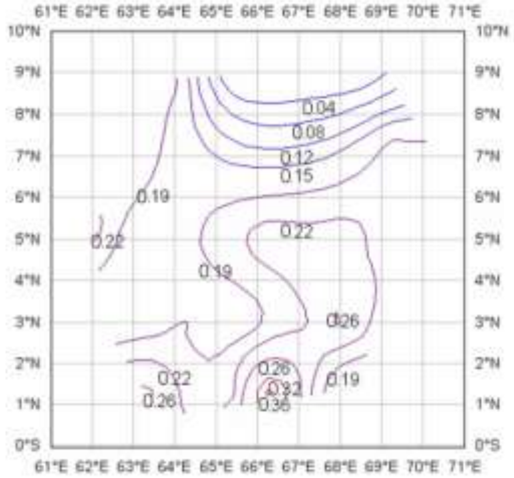


Figure 3. The arithmetic average IHI_{ij} and the catch rates of bigeye tuna in the specific depth class in 2005

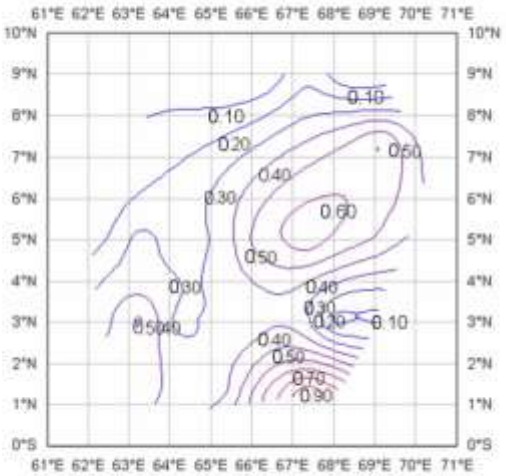
(a) 80-120 m



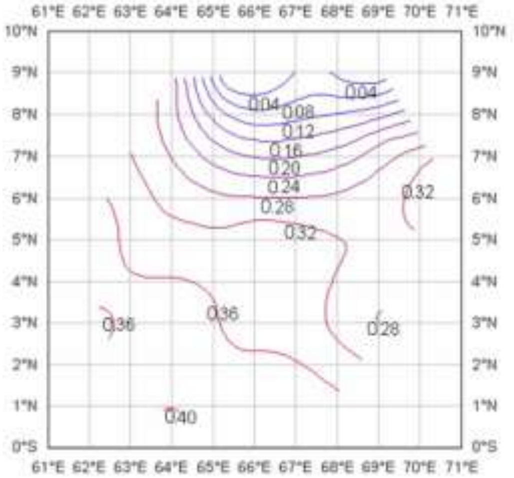
(b) 120-160 m



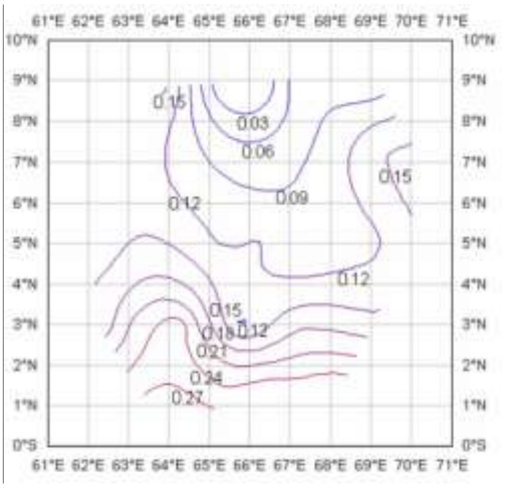
(c) 160-200 m



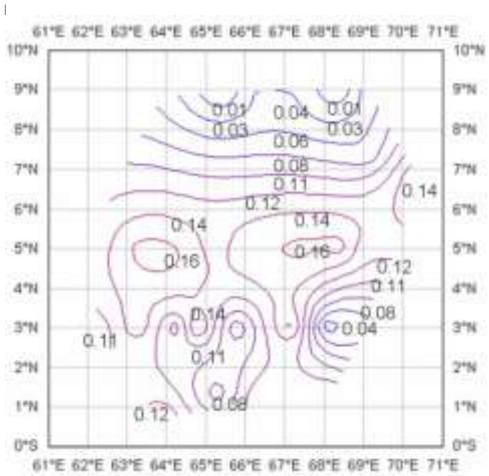
(d) 200-240 m



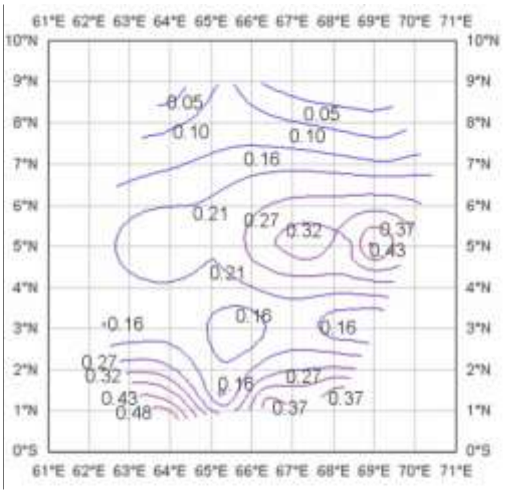
(e) 240-280 m



(f) 280-320 m



(g) 320-360 m



(h) 360-400 m

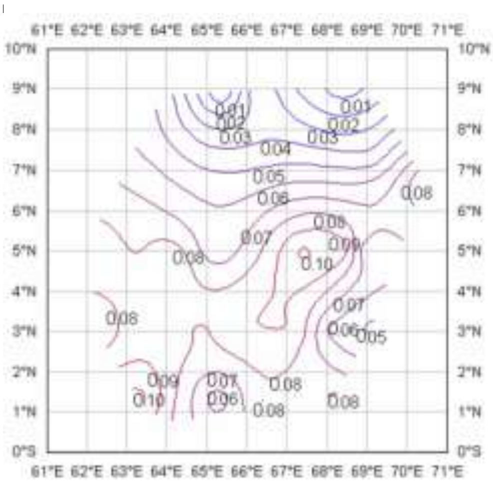


Figure 4. The IHI_{ij} distributions at different depth classes in 2005 (a: 80-120 m; b: 120-160 m; c:160-200 m; d: 200-240 m; e: 240-280 m; f: 280-320 m; g: 320-360 m; h: 360-400 m).

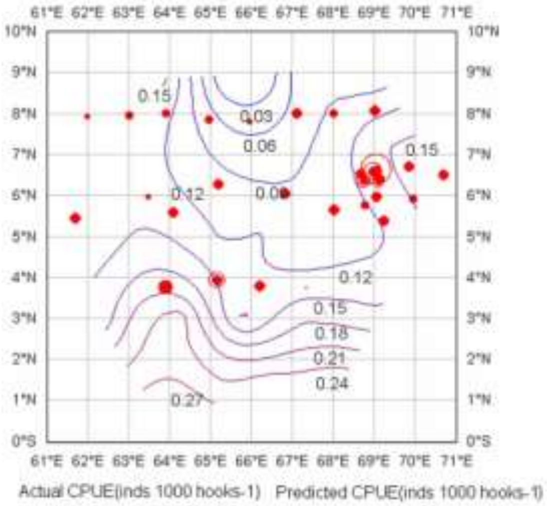


Figure 5. The model predicted and observed bigeye tuna CPUEs by the using of the data from Huayuanyu 19 and the *IHI* isolines distribution at the depth class of 240-280 m in 2005.

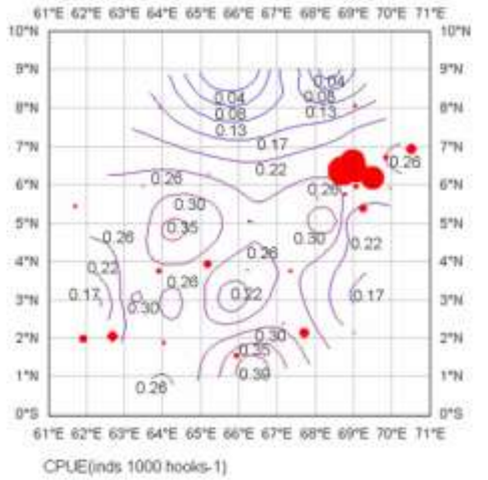


Figure 6. The observed bigeye tuna CPUEs of Huayuanyu 19 and the $\overline{IHI_i}$ isolines distribution in 2005

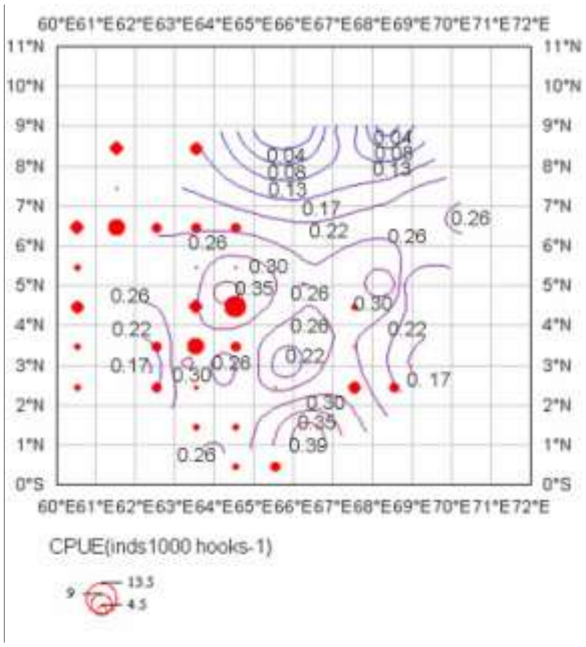


Figure 7. The standardized CPUEs of bigeye tuna from three Chinese large scale longliners and the $\overline{IHI}$ isolines of the bigeye tuna in the survey area of 2005.