Developing an integrated habitat index for yellowfin tuna *(Thunnus albacares)* in the Indian Ocean based on longline fisheries data

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Abstract: Study on spatial distribution of tunas and tuna-like species will be benefit to the conservation and management of fishery resources, and the promotion of fishing condition forecasting technology. A survey on tuna fishery has been carried out aboard of the longliners *Huayuanyu No. 18* and *Huayuanyu No. 19* in the Indian Ocean in 2005. Based on the survey data collected by *Huayuanyu 18*, the vertical profile data of temperature, salinity, chlorophyll-a concentration, dissolved oxygen concentration and the catch rate data of yellowfin tuna (*Thunnus albacares*) were applied to develop the "Integrated Habitat Index (*IHI*)" models by the quantile regression method. The data collected by *Huayuanyu No.19* were also applied to validate these models. The results showed that the optimal inhabitting depth of yellowfin tuna was from 80 to 160 m in the survey area; the *IHI* in the area of 3°30′N～8°30′N, 62°E ～64°E was the highest; the *IHI* in the area of 3°N～6°N, 64°E～70°E area was realative higher; the main environmental variables which affected the distribution of yellowfin tuna in specific depth stratum were different; the weighted average of temperature and dissolved oxygen concentration effected to the spatial distribution of yellowfin tuna significantly. The quantile regression method could be used to study the pelagic species spatial distribution.

Key words: *Thunnus albacares*; integrated habitat index; quantile regression; Indian Ocean

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1. Introduction

There are many methods to study organisms' habitats (environment), *e.g.*, general linear regression models (Clark *et al.*, 1999; 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 *et al.*, 1997; Turgeon and Rodriguez, 2005), logistic regression models (Norcross *et al.*, 1999; Guay *et al.*, 2000;Turgeon and Rodríguez, 2005), habitat suitability index (HSI) models (Brown *et al.*,2000;Cade and Noon,2003; William and Maughan,2004), 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; Song and Zhou, 2010). Some of the studies include combinations of these models and geographic information systems (GIS) to construct fish habitat maps (Riou *et al.*, 2001; Stoner *et al.*, 2001).

Although general linear regression models, general linear additive models, multiple linear regression models, regression tree models and logistic regression models have their advantages, they also have some disadvantages (Song and Zhou, 2010). These models include some assumptions that, in most cases, are not satisfied in a study. Specifically, these models include the assumptions that: (1) all variables included in the model have equal influence in defining habitat quality; (2) all variables included in the model are independent, i.e., there are no interactions among them; (3) the integrated influence of the variables to the organism can be combined in a simple mathematical relationship; and (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 problem with the HSI model by changing the weighted coefficients of the variables in the model in accordance with the importance of their influence to the organism. However, decisions as to what weighted coefficients should be used are made by individual scientists, and are based primarily on their judgments. Most biologists (e.g., Feng *et al.*, 2007) employed geometric means in their calculations of HSI. William and Maughan (1985) suggested that the geometric mean might not simulate the integrated relationship well between an organism and each environmental variable. Quantile regression has all the advantages of ordinary least-squares regression, and an additional advantage of being distribution-free. It can be used to estimate the effects of limiting factors, and thus provide a good means to evaluate how a species may respond to changes in its environmental variables (Eastwood and Meaden, 2004). When the errors are not normally distributed and only part of the limiting factors is measured, it can yield several estimation results in different quantiles, and may more accurately reflect the responses of a species to habitat variables, particularly for the regression models of the upper quantile (Cade and Noon, 2003; Wu and Ma, 2006).

In this study, an Integrated Habitat Indices (*IHI*) model was developed for yellowfin tuna (*Thunnus albacares*) in the Indian Ocean based on the data collected by *Huayuanyu No. 18*

(HYY18) in a survey conducted in 2005. The *IHI* models were constructed using the quantile regression method with the consideration of interactions among environmental variables. The *IHI* models were then used to evaluate responses of yellowfin tuna to environmental variability and to predict their spatial distributions. The models were validated with the environment variables and fishery data collected by *Huayuanyu No. 19 (HYY19)*. The objectives of this study are to (1) select an upper-quantile model identifying key environmental variables with respect to tuna distribution; (2) define key habitat variables, given the environmental data available for this study; and (3) develop forcasting capacity for yellowfin tuna spatial distribution based on the key habitat variables.

2. Materials and methods

2.1 Materials

2.1.1 Survey vessels

Data were collected from operations on two longliners, *HYY18* and *HYY19*, in 2005. Two vessels' specifications are same. They were equipped with super spool and chill sea water equipment. Two vessels' length over all, mould breadth, mould depth, gross tonnage, net tonnage and main engine power is 26.12 m, 6.05 m, 2.70 m, 150.00 t, 45.00 t and 407.00 kW, respectively.

2.1.2 Survey duration and area

The vessels fished for 54 days between September 15 and December 12 in 2005. Fishing took place mainly between about 1°N and 10°N and between about 62°E and 70°E (Fig. 1). The data collected locations were shown in Fig.1. During the two surveys, the fishing vessels targeted bigeye tuna (*Thunnus obesus*), and the bycatch included yellowfin tuna, swordfish (*Xiphias gladius*), albacore (*Thunnus alalunga*) and billfishes (Istiophoridae).

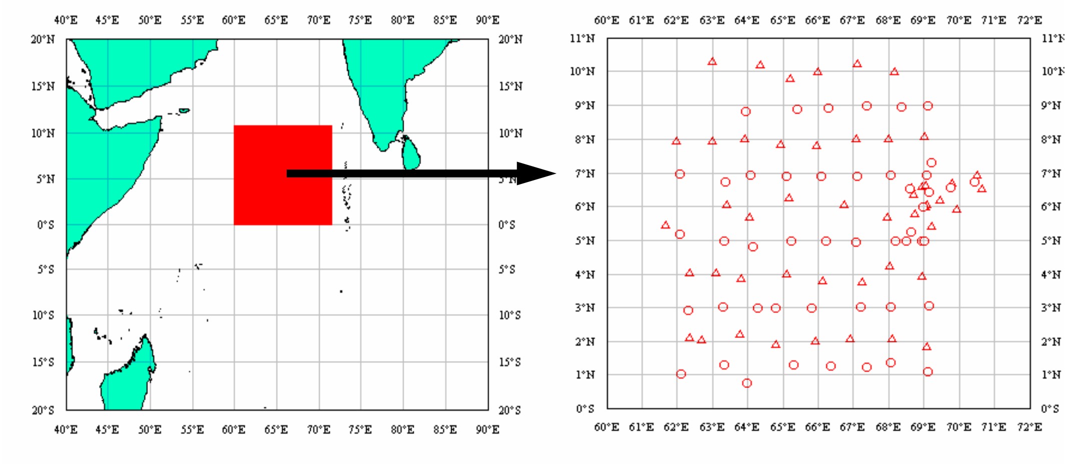


Fig. 1 *Huayuanyu 18* and *Huayuanyu 19* measured positions in 2005

(○*Huayuanyu 18*；△ *Huayuanyu 19*)

2.2 Data processing

The catch rate of yellowfin tuna for station *i*, $CPUE_i$, was clculated as follows:

$$CPUE_i = \frac{U_i}{f_i} \times 1000 \quad (1)$$

where *i* denotes station, U_i is the number of yellowfin tuna hooked at station *i*, f_i is the number of hooks deployed at station *i*, and *i*=1,2,3, ..., 48.

The data for the yellowfin tuna caught were grouped into depth strata. For the survey of 2005, the data were assigned to seven depth strata of 40 m each (80-120 m, 80-120 m, … 320-360 m).

The catch rate, $CPUE_{ij}$, of *HYY18* at sampling station *i* in depth stratum *j* was calculated by:

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

where H_{ij} is the number of hooks deployed by *HYY18* at station *i* in depth stratum *j*, and N_{ij} is the number of yellowfin tuna caught by *HYY18* at station *i* in depth stratum *j*. N_{ij} was calculated as:

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

where N_j is the number of yellowfin tuna caught by *HYY18 and HYY19* in depth stratum *j* during the survey, following Song *et al.* (2008; 2009), *N* is the number of yellowfin tuna caught by *HYY18 and HYY19* during the survey. In 2005, the data on depth of capture were collected for 299 of the 516 yellowfin tuna (56.8%). N_i is the number of yellowfin tuna caught by *HYY18* at sampling station *i*, and *i* = 1, 2, 3, . . ., 48.

The catch rate of yellowfin tuna in depth stratum *j*, $CPUE_j$, was clculated as follows:

$$CPUE_j = \frac{N_j}{f_j} \times 1000 \quad (4)$$

where *j* denotes stratum, f_j is the number of hooks deployed at stratum *j*, and *j*=1,2,3, ..., 7.

The weighted average value of environment variables based on the catch rate of different depth stratum at sampling station *i* was calculated, following Song *et al.* (2007) ,and Song and Zhou (2010), as:

$$ENV_i = \sum CPUE_j ENV_{ij} / \sum CPUE_j \quad (5)$$

where ENV_i was the weighted average environmental variable of whole water bin, the environmental variable includes 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) at sampling station *i* from *HYY 18*, and ENV_{ij} was the value of the above environmental variables at sampling station i in depth stratum j (*i.e.*, 80～120 m, 120～160 m, . . ., 320～360 m). T_{ij}, S_{ij}, Ch_{ij}, and DO_{ij} were the arithmetic means measured with the XR- 620 at sampling station i in depth stratum j. HC_{ij} and WC_{ij} were the arithmetic means measured with the Aquadopp-2000 at sampling station i in depth stratum j.

The shear of horizontal current component (denoted as ξ) was estimated by integrating the original data measured with the Aquadopp-2000 from the near-surface to the largest predicted hook depth (z) at each sampling station i (Bigelow *et al.*, 2006). The coefficient ξ was used to study the potential *CPUE* of sampling station i.

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

where ξ was the shear of horizontal current component, v_n was the Nouth-South component of current in the n depth stratum, u_n was the East-Weat component of current in the n depth stratum, z_n was the depth of n depth stratum.

Thermocline intensity (TI_i) (°C m^{-1}) was calculated by temperature profile measured by XR-620 at station i as:

$$TI_i = \frac{T_u - T_b}{D_b - D_u} \quad (7)$$

where T_u , T_b , D_u , and D_b was thermocline's upper temperature (°C), bottom temperature (°C), upper depth (m) and bottom depth (m).

2.3 Developing quantile regression models

In this study, the prediction model was developed based on the data measured by *HYY 18* at the 30 sampling stations. The following six variables were considered as the independent variables in the quantile regression models: temperature (T_{ij}), salinity (S_{ij}), chlorophyll-a concentration (Ch_{ij}), dissolved oxygen concentration (DO_{ij}), horizontal current (HC_{ij}), and vertical current (WC_{ij}). Fifteen interaction terms of these six variables were also considered.

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

$$\hat{CPUE}_{ij} = C_j + a_jT_{ij} + b_jS_{ij} + c_jCh_{ij} + d_jDO_{ij} + e_jHC_{ij} + f_jWC_{ij} + g_jTS_{ij} + h_jTCh_{ij} + i_jTDO_{ij} + j_jTHC_{ij} + k_jTWC_{ij}$$

$$+l_j SCh_{ij} + m_j SDO_{ij} + n_j SHC_{ij} + o_j SWC_{ij} + p_j ChDO_{ij} + q_j ChHC_{ij} + r_j ChWC_{ij}$$
$$+s_j DOHC_{ij} + t_j DOWC_{ij} + u_j HCWC_{ij} + \varepsilon_{ij} \qquad (8)$$

where C_j is the constant, TS_{ij} is the interaction of temperature and salinity, TCh_{ij} is the interaction of temperature and chlorophyll-a concentration, . . ., $HCWC_{ij}$ is the interaction of horizontal current and vertical current, and ε_{ij} is the error term at sampling station i in depth stratum j. The values of a_j, b_j, c_j, d_j, e_j, f_j . . . *and* u_j are their corresponding parameters.

The full regression model for describing the relationship between the expected catch rate at sampling station i, $\hat{CPUE}_i$ versus weighted average T_i , S_i , Ch_i , DO_i , ξ_i , WC_i, TI_i and the interaction terms can be written as:

$$C\hat{P}UE_i = C'_j + a'_j T_i + b'_j S_i + c'_j Ch_i + d'_j DO_i + e'_j \xi_i + f'_j WC_i + g'_j TI_i + h'_j TS_i + i'_j TCh_i + j'_j TDO_i + k'_j T\xi_i$$
$$+l'_j TWC_i + m'_j TTI_i + n'_j SCh_i + o'_j SDO_i + p'_j S\xi_i + q'_j SWC_i + r'_j STI_i + s'_j ChDO_i + t'_j Ch\xi_i + u'_j ChWC_i +$$
$$v'_j ChTI_i + \mathrm{w}'_j DO\xi_i + x'_j DOWC_i + \mathrm{y}'_j DOTI_i + \mathrm{z}'_j \xi WC_i + xx'_j \xi TI_i + x\mathrm{y}'_j WCTI_i + \varepsilon'_i \qquad (9)$$

where C_j' is the constant, TS_i is the interaction of temperature and salinity, , . . . $WCTI_i$ is the interaction of vertical current and thermocline intensity; ε_i' is the error term of expected catch rate at sampling station i. The a_j', b_j', c_j', d_j', e_j', f_j' … … $x\mathrm{y}'_j$ are their corresponding parameters.

It is more appropriate to select θ values between 0.50 and 0.95 to build the upper-quantile model (Feng *et al.*, 2007). For the quantile regression, all variables were initially included in the model. The statistical significance of each variable in the model was then evaluated by the rank-score test (Cade and Richards, 2001). 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, then obtained the optimal model. In this study, we used the statistical software Blossom to process the data, which was developed by Midcontinent Ecological Science Center (U.S.Geological Survey).

2.4 Developing IHI_{ij} models in specific stratum

Based on the regression (Eq. 8), $\hat{CPUE}_{ij}$ was estimated at sampling station i in depth stratum j . IHI_{ij} was calculated by the following equation:

$$IHI_{ij} = \frac{\hat{CPUE}_{ij}}{\hat{CPUE}_{\max}} \qquad (10)$$

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

2.5 Developing $\overline{IHI}$ model

Based on the estimated model (Eq. 9), $\hat{CPUE}_i$ at sampling station *i* was estimated. $\overline{IHI}$ was derived from $\hat{CPUE}_{ij}$ and $\hat{CPUE}_i$ using the following equation:

$$\overline{IHI} = \frac{\hat{CPUE}_i}{\hat{CPUE}_{\max}} \tag{11}$$

2.6 Developing IHI_j model

Based on the $\hat{CPUE}_{ij}$ at sampling station *i* in depth stratum *j* , IHI_j was derived from $\hat{CPUE}_{ij}$ using the following equation:

$$IHI_j = \frac{1}{48}\sum_{i=1}^{48}\hat{CPUE}_{ij} \tag{12}$$

2.7 The expression of *IHI* isolines

Based on the estimates derived above, the *IHI* isoline distributions were developed using the software Sufer 6.0 (Golden Software, 1996).

2.8 The predictive power of the *IHI* model

The paired two-sample t-test (Tang and Feng, 2002) was used to calculate the Poisson correlation coefficients between predicted IHI_{ij} and observed $CPUE_{ij}$ and between predicted IHI_j and observed $CPUE_j$. The Poisson correlation coefficients were assumed to indicate the predictive power of the *IHI* models. The predictive power of the *IHI* models were qualitatively analyzed by plotting the map of predicted IHI_j and observed $CPUE_j$. Because *HYY 19* just mesured the temperature and salinity data in the survey, and the predictive model about 80-120 m depth stratum included the variables of temperature and salinity, the measured environmental data from *HYY 19* could be applied to predicte *IHI* in the depth stratum of 80-120 m. The predictive power of the model was qualitatively analyzed by mapping the distribution of predicted *IHI* isoline and the nominal *CPUE* of yellowfin tuna in the depth stratum of 80-120 m.

2.9 Validation of the $\overline{IHI}$ model

The $\overline{IHI}$ model was validated by applying to the survey data from *HYY 19* (operation duration and area were Sep.～Dec. 2005 and 0ºN～8ºN, 61ºE～71ºE, respectively). The nominal *CPUE* from *HYY 19* and the $\overline{IHI}$ isoline from *HYY 18* at all stations were mapped and qualitatively analysed the accuracy of the $\overline{IHI}$ model.

3. Results

3.1 Catch rate, $\hat{CPUE}_{ij}$

The estimated parameters of the predictive models of the catch rate, $\hat{CPUE}_{ij}$, at sampling station i, depth stratum j were summarized in Table 1. The predictive models of the catch rate, $\hat{CPUE}_{ij}$, were developed with a different value of quantile (θ). The value of quantile (θ) was from 0.75 to 0.90 for various depth strata. The key environmental parameters to construct the $\hat{CPUE}_{ij}$ models for various depth strata were different from depth strata (Table 1).

3.2 The catch rate, $\hat{CPUE}_i$

The optimal model of the catch rate, $\hat{CPUE}_i$ at sampling station i was developed. When θ was 0.95, the optimal model was derived as:

$$C\hat{P}UE_i = -220.81 + 13.56T_i + 219.98DO_i - 13.25TDO_i \qquad (\theta = 0.95) \qquad (10)$$

The Poisson correlation coefficients between predicted and observed value was 0.67 (Table 2). Weighted average T_i, DO_i, and the interaction term TDO_i were identified as key variables (Eq. 10).

3.3 The predictive power of the IHI_{ij} model

The Poisson correlation coefficients and predictive power between the predicted IHI_{ij} and observed $CPUE_{ij}$ are shown in Table 2. When the Poisson correlation coefficient was <0.400, 0.400–0.499, 0.500–0.699, and $\geq$ 0.700, the predictive powers of the IHI_{ij} model were defined as inferior, medium, good, and excellent, respectively (Song and Zhou, 2010). The trend lines of IHI_j was calculated and compared with those of the catch rates $CPUE_j$ in the specific depth stratum (Fig.2). The *IHI* isolines distribution was shown in Fig.3.

In Fig.2, the IHI_j and $CPUE_j$ in the corresponding depth stratum had almost similar trend, but there were a little differences for the depth strata of 160～200 m and 240～280 m. The *IHI* isoline distributions in specific depth strata at different stations were shown in Fig.3. The highest and relative higher *IHI* area were shown in Table 3. The area of higher *IHI* in depth stratum 80～120 m (Fig.3a) were more similar to that of 120～160 m depth stratum (Fig.3b). For the depth stratum 160～200 m (Fig.3c), the *IHI* was much less than that of the previous two depth strata, and the

Table 1 Estimation parameters of optimal predicting equation

Depth stratum(m)	80-120	120-160	160-200	200-240	240-280	280-320	320-360
Quantile θ	0.90	0.85	0.75	0.85	0.90	0.80	0.85
C_j （constant）	256.73	-4226.95	-8333.64	-52.03	-491.38	5.02	139.22
$a_j(T_{ij})$	-10.19	-27.20	-12.92	0	36.60	0	-11.61
$b_j\ (S_{ij})$	0	132.89	240.67	0	0	0	0
$c_j\ (Ch_{ij})$	0	0	0	1549.15	14501.80	0	0
$d_j\ (DO_{ij})$	0	0	8.80	0	0	0	0
$e_j(HC_{ij})$	0	0	0	0	0	-5.20	-214.08
$f_j\ (WC_{ij})$	0	5646.19	0	0	0	206.03	0
$g_j\ (TS_{ij})$	0	0	0	0	0	0	0
$h_j\ (TCh_{ij})$	0	0	0	0	-1082.29	0	0
$i_j\ (TDO_{ij})$	0	0	0	0	0	0	0
$j_j\ (THC_{ij})$	0	0	0	0	0	0	17.76
$k_j\ (TWC_{ij})$	0	-319.79	0	0	0	0	0
$l_j\ (SCh_{ij})$	0	0	0	0	0	0	0
$m_j\ (SDO_{ij})$	0	0	0	0	0	0	0
$n_j\ (SHC_{ij})$	0	0	0	0	0	0	0
$o_j\ (SWC_{ij})$	0	0	0	0	0	0	0
$p_j(ChDO_{ij})$	0	0	0	0	0	0	0
$q_j\ (ChHC_{ij})$	0	0	0	0	0	0	0
$r_j\ (ChWC_{ij})$	0	0	0	0	0	0	0
$s_j\ (DOHC_{ij})$	0	0	0	0	0	0	0
$t_j\ (DOWC_{ij})$	0	0	0	0	0	0	0
$u_j\ (HCWC_{ij})$	0	0	0	0	0	-434.82	0

highest *IHI* was only 0.31. For the depth stratum 200～240 m (Fig.3d), the *IHI* was less than that of the depth stratum 160～200 m, and the highest *IHI* was only 0.13. For the depth stratum 240～280 m (Fig.3e), the *IHI* was less too, the highest *IHI* was only 0.13. For the depth stratum 280～320 m (Fig.3f), the highest *IHI* was only 0.07. For the depth stratum 320～360 m (Fig.3g), the highest *IHI* was only 0.09. For the whole water bin at all stations (Fig.4), the distribution was almost similar to that of the depth strata 80～120 m and 120～160 m. From the above analysis, the *IHI* distribution in depth stratum 80～120 m was more similar to that of 120～160 m depth stratum. Their *IHI* distributions represented the *IHI* distribution of whole water bin. The *IHI* from 160 to 360 m depth strata were all less, and became much less with the depth deepening. The validation result of the predicted model of the depth stratum 80-120 m was shown in Fig.4. In Fig.4, the high catch rate distributed in the area of the high *IHI*. The distribution of *IHI* which was predicted by using the measured environmental data was similar to the oberserved catch rate distribution.

Table 2 The Poisson correlation coefficients between predicting *IHI* and the observed *CPUE* and the predictive power.

Depth stratum(m)	Poisson correlation coefficients	Predictive power
80-120	0.52	good
120-160	0.68	good
160-200	0.70	excellent
200-240	0.43	medium
240-280	0.72	excellent
280-320	0.53	good
320 - 360	0.59	good
Arithmetic average of all depth strata	0.60	good
The whole water bin	0.67	good

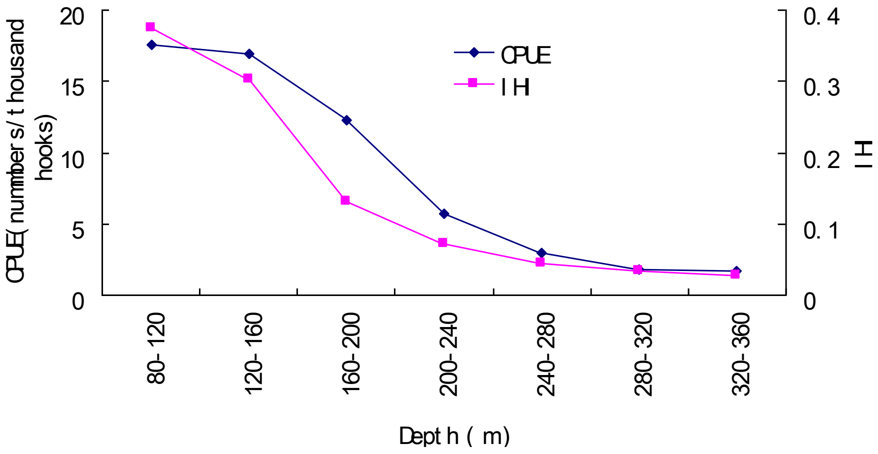
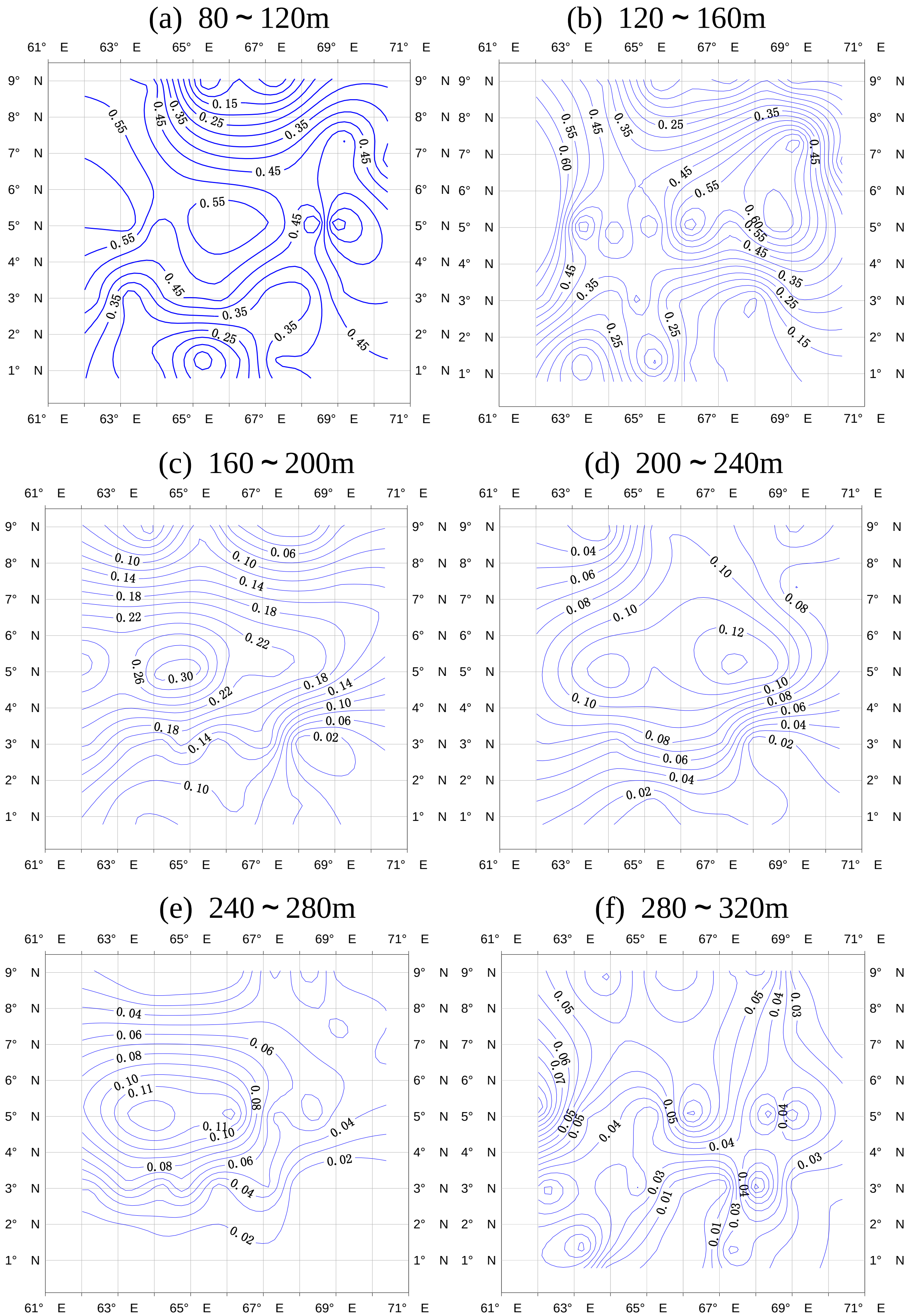


Fig. 2 The IHI_j and the $CPUE_j$ of yellowfin tuna in respective depth stratum

3.4 Validation of the $\overline{IHI}$ model

Applying the longline fishery data from *HYY 19* in 2005 to validate the $\overline{IHI}$ model, in the area of 1ºN～9ºN,61ºE～71ºE, the validation result of the $\overline{IHI}$ model for the water bin was shown in Fig.5. The higher catch rate was mainly in the area of 4°N～9°N, 62°E～63°30′E, 2°30′N～6°N, 64°30′E～67°30′E, and which distributed in the higher *IHI* area. There was no significant difference between the distribution of catch rate and *IHI* in the other areas.


(a) 80～120m
(b) 120～160m
(c) 160～200m
(d) 200～240m
(e) 240～280m
(f) 280～320m
61° E 63° E 65° E 67° E 69° E 71° E
1° N 2° N 3° N 4° N 5° N 6° N 7° N 8° N 9° N

(g) 320～360m

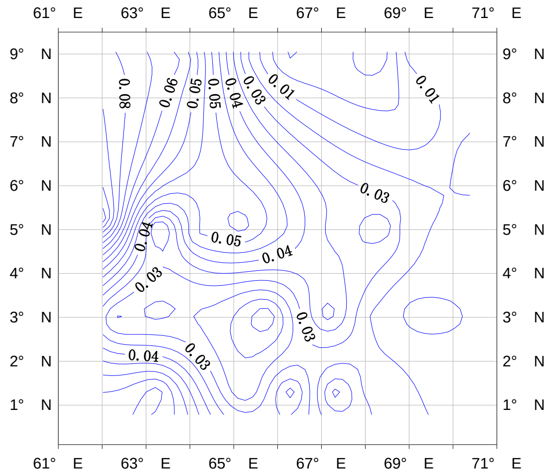


Fig. 3 The IHI_{ij} distribution in respective depth strata (a：80～120m；b：120～160m；c：160～200m；d：200～240m；e：240～280m；f：280～320m；g：320～360m

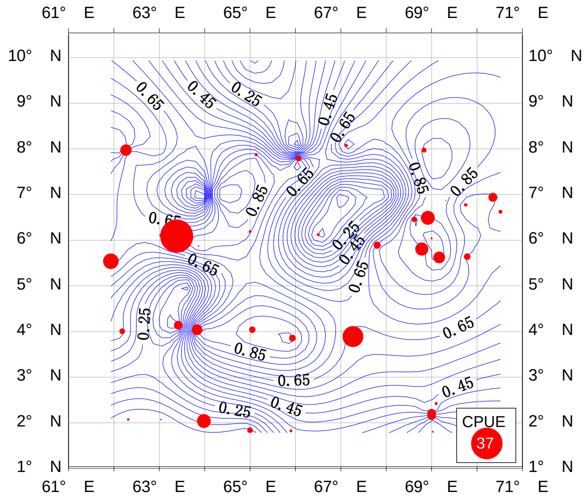


Fig. 4 The catch rates of yellowfin tuna in depth stratum 80-120m from *Huayuanyu 19* and theisolines of yellowfin tuna's IHI_i predicted using the field measured environmental data of *Huayuanyu 19.*

Table 3 The area boundary with the relatively greater *IHI* and the value of *IHI*

Depth stratum (m)	Area	Relative higher value
80-120	4°N～9°N, 62°E～64°E; 3°30′N～6°N, 64°E～70°30′E	0.50-0.69
120-160	3°N～9°N, 62°E～63°30′E; 4°30′N～7°30′N, 66°E～69°30′E	0.50-0.70
160-200	4°N～6°N, 63°30′E～66°E	0.20-0.31

200-240	4°N～8°N, 63°E～69°E	0.10-0.13
240-280	4°N～6°N, 63°E～67°E	0.10-0.13
280-320	4°N～9°N, 61°E～68°30′E	0.05-0.10
320 - 360	4°N～9°N, 62°E～66°30′E	0.03-0.09
The whole water bin	4°N～9°N, 62°E～63°30′E; 2°30′N～6°N, 64°30′E～67°30′E	0.35-0.72

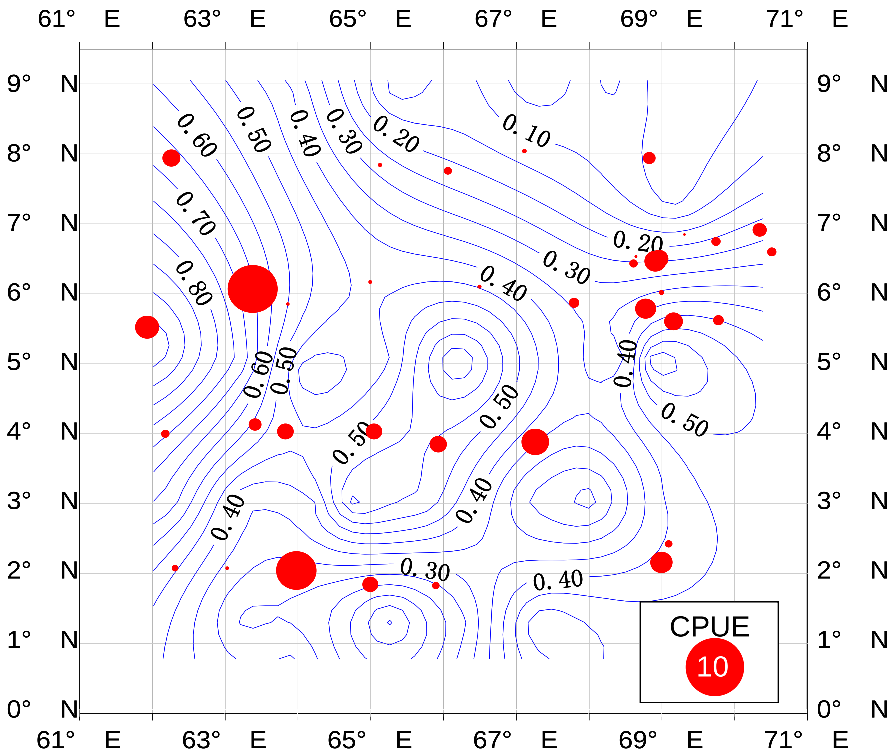


Fig.5 The catch rates of yellowfin tuna from *Huayuanyu 19* and the isolines of the yellowfin tuna's $\overline{IHI}$ predicted by using the field measured environmental data of *Huayuanyu 18*

4. Discussion

4.1 Why were the predictive powers of some models less than those of others?

The predicted power at the depth stratum of 200～240 m was medium and the Poisson correlation coefficient was the least at this depth stratum (0.43) (Table 2). The reasons why the predicted power at this depth stratum was medium may result from the great sampling bias (samall sample) at the depth stratum of 200～240 m, lack of considering some important habitat variables limiting the distribution of yellowfin tuna. Consequently, it should enlarge the sampling and measure more environmental data to improve the predicting power of the model.

4.2 The predictive power of the *IHI* model

In general, the predictive power of the *IHI* model was good. The trends of the IHI_j were similar to those of the $CPUE_j$ of yellowfin tuna at the respective depth strata (Fig.2). The *IHI* and catch rate was relatively high at the depth strata of 80～120 and 120～160 m, which indicated that the optimal inhabiting depth of yellowfin tuna was from 80 to 160 m. Mohri and Nishida (2000) suggested that the optimal depth range of yellowfin tuna was from 80 to 120 m. Song *et al.* (2008) suggested that the depth stratum of 100.0～179.9 m was the frequently swimming depth range for yellowfin tuna and the optimal swimming depth stratum was 120.0～139.9 m. The results of Mohri and Nishida (2000) and Song *et al.* (2008) were almost consistent with the result of this study.

4.3 The effectiveness of IHI_{ij} predictive models

In general, the IHI_{ij} predictive models were effective, which showed the spatial distribution of yellowfin tuna. The *IHI* value of yellowfin tuna was higher in depth strata of 80～120 m and 120～160 m, and the distribution area of high value was consistent with each other (Fig.3). In the other five depth strata, the *IHI* value was lower, and there were some differences among the distribution of *IHI*. The reasons were as follows. The distributions of yellowfin tuna at different depth strata were different. The factors to effect the distribution of yellowfin tuna at different depth strata were also different (Table 1). The yellowfin tuna have obvious habitat selection, and were easyly affected by the environmental variables, such as temperature, salinity and so on (Block *et al*., 2007). The yellowfin tuna has the apparent seasonal south-northward migration characteristic, and its migration path was relevant to the route of current moving (Antonio *et al*., 2004). The distribution of yellowfin tuna have greatly influenced by the water temperature, salinity, and dissolved oxygen (Korsmeyer *et al*., 1997). In the different depth strata, the environment variables were different. Owing to the limt of *HYY 19* samplying data, we could only apply the model of the depth stratum 80～120 m to validate the effectiveness of the IHI_{ij} predictive model. The high catch rate area of the depth stratum 80～120 m from *HYY 19* was almost consistent with the high IHI_j area (Fig.4). The predictive models in the depth strata were effective.

4.4 The effectiveness of $\overline{IHI}$ predictive model

In general, the predictive power of the $\overline{IHI}$ model was good. In the areas of 4°N～9°N, 62°E～63°30′E, and 2°30′N～6°N, 64°30′E～67°30′E, the distribution area of higher catch rate from *HYY 19* was almost consistent with the distribution area of higher *IHI* (Fig.5). So, the model was effective. Moreover, the distribution of $\overline{IHI}$ was also consistent with the distribution of *IHI* at the depth stratum of 80～160 m. Therefore, the distribution of IHI_j at the depth stratum of 80～120 m or 120～160 m could be applied to roughly estimate the horizontal distribution of yellowfin tuna in the whole water mass.

4.5 Key environmental parameters to influence the spatial distribution of yellowfin tuna

The temperature and dissolved oxygen were the crucial variables to the spatial distribution of yellowfin tuna. For the $\overline{IHI}$ predictive model, there was the close relationship between the predicted *CPUE* and the weighted average temperature and dissolved oxygen. Temperature was the main limiting factor to effct the migration of yellowfin tuna, which limited the heart's capacity to export dissolved oxygen, then influenced the swimming speed of yellowfin tuna (Maury *et al*., 2001). Nishida *et al*. (2001) found that the distribution of adult yellowfin tuna was influenced by the spatial and seasonal change of water temperature. Brill *et al.* (1999) found that the temperature, dissolved oxygen and thermocline depth influenced the spatial distribution of yellowfin tuna, and the temperature and dissolved oxygen also influenced the spawning behavior of yellowfin tuna in the Hawaii islands waters. Schaefer (1996) oberserved the moving path of yellowfin tuna was influenced by the seasonal change of 18℃ sea surface temperature isoline. Block *et al*. (1997) suggested a large number of yellowfin tuna gathered into the dissolved oxygen concentration 6.8～8.6 mg L^{-1} area by the acoustic elemetry study. We suggest that the temperature and dissolved oxygen data should be input into the model to standardize the yellowfin tuna *CPUE*.

4.6 Outlook

We only used the temperature, salinity, chlorophyll-a, dissolved oxygen concentration, horizontal current, vertical current, and the interaction terms of these six variables to develop the "integrated habitat index" models. These environmental variables were measured at 30 sampling stations. We didn't consider the depth of thermocline, abundance of plankton, and the trophic level which might influence the distribution of yellowfin tuna. We suggest that all or some of these environmental variables should be considered in the future study.

5. Conclusion

The *IHI* models developed in this study could reflect the habitat selection of the yellowfin tuna more accurately, in gernral. The predictive power of *IHI* models developed in this study was good. We suggest this method could be used to study the spatial distribution of pelagic fishe caught by longline fishery. The optimal inhabiting depth stratum of yellowfin tuna was 80～160 m in the survey area. The *IHI* within the area defined by 4°N～9°N, 62°E～63°30′E had the largest values, and the *IHI* in 2°30′N～6°N, 64°30′E～67°30′E had larger values, the *IHI* in the other areas had smaller values. We suggest that the temperature and dissolved oxygen data should be included in the CPUE standardization to estimate the relative aboundance of yellowfin tuna.

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