COMPARATIVE STUDY ON JAPANESE TUNA LONGLINE CPUE STANDARDIZATION OF YELLOWFIN TUNA (*THUNNUS ALBACARES*) IN THE INDIAN OCEAN BASED ON TWO METHODS: - *GENERAL LINEAR MODEL (GLM) AND HABITAT-BASED MODEL (HBM)/GLM COMBINED* - *(1958-2001)*

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ABSTRACT

We attempted to compare results of two methods to standardize yellowfin tuna CPUE of Japanese tuna longline fisheries, i.e., General Linear Model (GL M) and Habitat-based Model (HBM)/GLM combined approach. In the CPUE standardization for the Indian Ocean tropical tuna (yellowfin and bigeye) in the past, the GLM has been primarily used. Although the HBM approach has been developed and applied mainly for billfishes, in recent years the HBM has also been applied for the tropical tuna in the Pacific Ocean. As the HBM approach takes into account actual depths of habitat and gear deployed into the model, it may provide a more realistic and reliable CPUE standardization. Thus, as a first attempt using the HBM/GLM for the Indian Ocean tropical tuna, we shall evaluate results produced by the two approaches, then we shall discuss the feasibility whether the HBM/GLM approach can be recommended for future CPUE standardizations. As a first step, we use minimum information (depth distribution of longline gear and vertical distribution of yellowfin tuna) to carry out a fundamental HBM/GLM without considering specific oceanographic data such as shear current, depth specific temperature and oxygen. As the HBM/GLM combined approach was resulted to be more effective than the GLM approach, we further discussed the research needs to conduct more practical and accurate HBS/GLM analyses in the future.

Contents

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1. INTRODUCTION

In this paper, we attempt to compare results of two methods to standardize yellowfin tuna (*Thunnus albacares*) (YFT) Catch-Per-Unit-Effort (CPUE) of Japanese tuna longline fisheries, i.e., *General Linear Model (GLM) and Habitat-based Model (HBM)/GLM combined approach.* In the CPUE standardization for the Indian Ocean tropical tuna (YFT and bigeye tuna: BET, *Thunnus obesus*) in the past, the GLM has been primarily used (Shono *et al*, 2002 and Nishida, 2000 for YFT, Okamoto *et al*, 2001 for BET and many others). Although the HBM approach has been developed and applied mainly for billfishes (Hinton and Nakano, 1996, Yokawa and Takeuchi, 2002 and many others), in recent years the HBM has also been applied for the tropical tuna in the Pacific Ocean (Bigelow *et al*., 2002 for BET and Bigelow *et al*., 2003 for YFT). As the HBM approach takes into account actual depths of habitat and gear deployed into the model, it may provide a more realistic and reliable CPUE standardization. Thus, as a first attempt using the HBM/GLM for the Indian Ocean tropical tuna, we shall evaluate results produced by the two approaches, then we shall discuss the feasibility whether the HBM/GLM approach can be recommended for future CPUE standardizations. As a first step, we use minimum information (depth distribution of longline gear and vertical distribution of yellowfin tuna) to carry out a fundamental HBM/GLM without considering specific oceanographic data such as shear current, depth specific temperature and oxygen that were used by Yokawa and Takeuchi (2002), Bigelow *et al* (2002 and 2003) and others in their papers. If the HBM/GLM combined approach is recognized to be more effective than the GLM approach, we shall further discuss the research needs to conduct more practical and accurate HBS/GLM analyses in the future.

2. DATA

Table 1 summarizes the data used in this paper and the sources of the data.

Table 1 List of the data used in this paper

Type	Parameters and resolutions	Source	Objectives
Japanese tuna longline commercial fisheries data (1958-2001)	Catch, effort and number of hooks between floats (HBF) by month and 5°x5° area	National Research Institute of Far Seas Fisheries (NRIFSF), Japan	To conduct GLM & HBM
Marine environmental data	Surface Sea Temperature (SST) by month and 2°x2° area (1958-2001)	Sub-arctic Gyre Experiment (SAGE) complied by Japan Meteorological Agency, Japan	
	Southern Osculation Index (SOI) by month (1958-2001)	National Oceanic and Atmospheric Administration (NOAA), USA	
	Thermocline depth (at 20°C) (*) by month and 5°x5° area (1958-2001)	JEDAC data set (Scripps Institution of Oceanography) and GAO data set (Gestionnaire d'Applications Océanographiques) compiled by Institut de Recherche pour le Développement (IRD), France	
Experimental tuna longline fishing data in the Indian Ocean (1982-86)	Species of catch by each hook and hook depth (m)	Japan Marine Resources and Research center (JAMARC), Japan	To compute effective effort in the HBM

(*) See Appendix A for estimation procedures.

3. METHODS AND RESULTS

3.1 GLM ANALYSES

(1) Model

A method similar to that used by Shono *et al* (2002) is applied for the GLM based CPUE standardization. The sampling unit for this case is 'month and 5x5 areas'. For the GLM procedure, the SAS/STAT package (Version 8.2) was utilized. Initially, the full model including two-way interactions, as shown in equation (1), was applied for the whole Indian Ocean (Fig. 1). However other interaction terms were not included because of missing data which created non-convergent problems in the parameters estimation of the GLM process.

$$Log_e(N\_CPUE_{ijkl}+constant) = INTERCEPT + Y_i + M_j + A_k + G_l + SST + SOI + TD$$
$$+ (Y*M)_{ij} + (Y*A)_{ik} + (M*A)_{jk} + (M*G)_{jl} + (A*G)_{kl} + (SST*M)_j + (SST*A)_k + (SOI*M)_j + (SOI*A)_k$$
$$+ (TD*Q)_j + (TD*A)_k + (ERROR)_{ijkl},$$
$$\text{with } (ERROR)_{ijkl} \sim N(0, \sigma^2) \qquad (1)$$

, where

constant	*:10% of the overall average nominal CPUE(see Campbell et al, 1996) (0.87193 for this case)*
log	*: national logarithm,*
N_CPUE	*: nominal CPUE (number of yellowfin catch per 1000 hooks),*
INTERCEPT	*: intercept (mean N_CPUE),*
Y_i	*: effect of year (1958-2001),*
M_j	*: effect of month (Jan., Feb., - Dec.),*
A_k	*: effect of sub-area (A1-A5) adopted by the WPTT in 2002 (see Fig. 1),*
G_l	*: effect of gear: HBF (6 classes corresponding to those used in the HBM) (class 1: 5- 6, class 2: 7-9, class 3: 10-11, class 4: 12-15, class 5: 16-20, class 6:21-25) Note: Data with NHB: 3-4 were not included as such LL was for catching swordfish at night.*
SST	*: effect of sea surface temperature (continuous variable by month & 5x5 area),*
SOI	*: effect of southern oscillation index (continuous variable by month),*
INTERACTIONS	*: two-way interactions.*

Although the Japanese longline data are available for 1952-2001, only the period 1958-2001 is considered because:

no solutions were obtained in the initial GLM attempt for 1952-57 for the equation (1): as the Japanese tuna longline fisheries in the earlier years were not fully developed (covered) in the Indian Ocean, we face problems dealing with an un-balanced (missing) data structure of the GLM analyses and unstable (unexpected large) CPUE values;
we need to keep catchability homogenous for reliable and consistent quality analyses by excluding the data in the earlier years.

$$Log_e(N\_CPUE_{ijkl} + constant) = INTERCEPT + Y_i + M_j + A_k + G_l + SST + TD + (Y*M)_{ij} + (Y*A)_{ik} + (M*A)_{jk}$$
$$+ (M*G)_{jl} + (A*G)_{kl} + (SST*M)_j + (SST*A)_k + (TD*M)_j + (TD*A)_k + (ERROR)_{ijkl},$$
$$\text{with } (ERROR)_{ijkl} \sim N(0, \sigma^2) \qquad (2)$$

In order to address the problem of zero catch, 10% of the overall average nominal CPUE (see Campbell *et al*, 1996 for details), is added to each nominal CPUE value. The area stratification is shown in Fig. 1, which was agreed upon by the 2001 IOTC/WPTT meeting. The number of hooks between two floats (HBF) is divided into 6 classes corresponding to Bigelow *et al* (2002).The HBF information are available for 1966 and 1975-2001, but those for 1958-65 and 1967-74 are missing. The HBF for the period 1958-65 is estimated using the spatial pattern of HBF of 1966, and the HBF for the period 1967-74 from the average pattern of 1966 and 1975. We also add the effect of surface sea temperature (SST), southern oscillation index (SOI) and thermocline depth (TD) to the model as environmental factors that may have also affected yellowfin abundance. In the GLM analyses, Y, Q, A, G, SST, SOI and TD are treated as the main effect. The estimation procedure for TD is described in Appendix A.

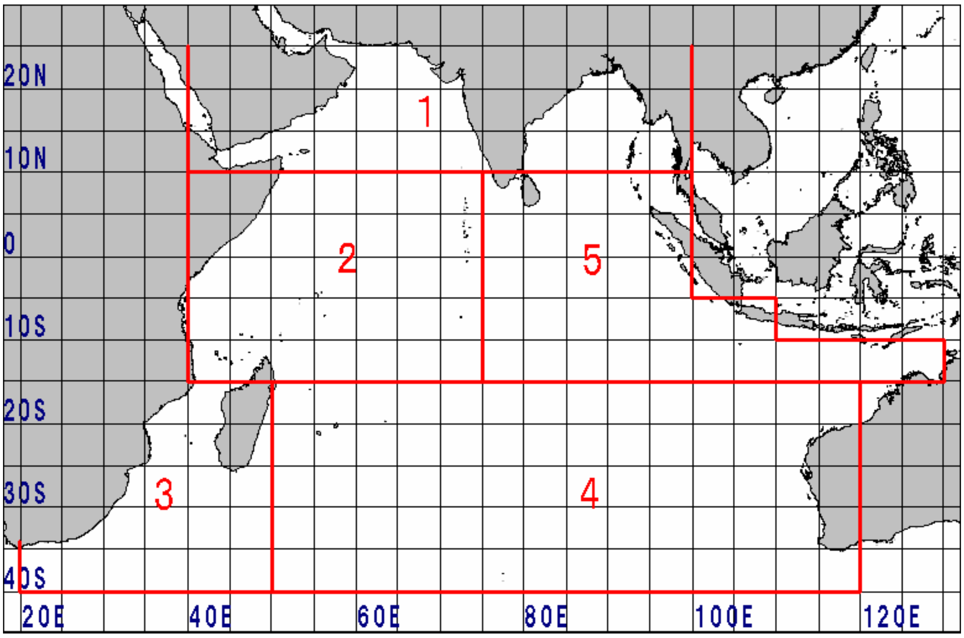


Fig. 1 Five sub-areas for yellowfin tuna LL CPUE standardization adopted by the 2002 WPTT.

We ran the full model (1) for the whole area, but, GLM runs were not converging. After investigation, we found that the full model could converge if SOI-related terms are excluded. Thus we modified the GLM as in equation (2) below:

Then, the GLM were re-ran and finally converged. Results of the SAS outputs are listed in Appendix B.

(2) Abundance Index

The Abundance index in year i is estimated by *exp {Least Squared Means of YEAR effect in SAS-GLM procedure} - constant.* Shono *et al* (2002) described details on the computation procedures for the abundance index.

$$f_{at} = E_{at} \sum_{d} h_{atd} \, p_{atd} \qquad (3)$$

, where

f : *effective fishing effort,*

a : *a particular area stratum,*

t : *a particular month stratum,*

E : *number of hooks,*

d : *a particular depth zones of the longline hooks deployed,*

h_{atd} : *proportion of hooks fishing in depth zone d in area a during time period t,*

p_{atd} : *proportion of yellowfin tuna in area a d uring time period t occurring in depth zone d.*

3.2 HABITAT-BASED MODEL (HBM) ANALYSES

In the HBM approach, we need to estimate the effective fishing effort reflecting the actual swimming depth of fish and the actual depth of the longline gear deployed. Hence, in order to carry out a reliable HBM, we need to incorporate two fundamental elements i.e., 'longline gear configuration' and 'depth specific distribution of yellowfin tuna'. Then, to evaluate accurate effective fishing effort, we need to use relevant oceanographic and ecological information affecting these two elements, for example, depth specific ocean temperature and oxygen at given depth levels, that influence yellowfin tuna vertical distribution, and shear current that affects gear configuration, etc. These information can be obtained, for example, from the oceanographic observation, archival and pop-up tagging experiments. However, in the Indian Ocean, information based on tagging is extremely limited unlike in other two Oceans. Hence, we carry out our analyses using the substituted information from the Pacific Ocean and some available (but limited) information in the Indian Ocean, which will be explained in the this section.

(1) Effective fishing effort

We define effective fishing effort (f) in a particular area (indexed by *a*) and quarter (indexed by *t*) stratum as the weighted sum of longline hooks (*E*) fishing in different depth zones (indexed by *d*) throughout the vertical habitat:

The key elements in the estimation of effective longline effort are the specification of the depth distribution of the gear (h_{atd}) and the depth distribution of yellowfin tuna (p_{atd}). These aspects of the analysis are discussed in the following two sections.

(2) Depth distribution of longline gear

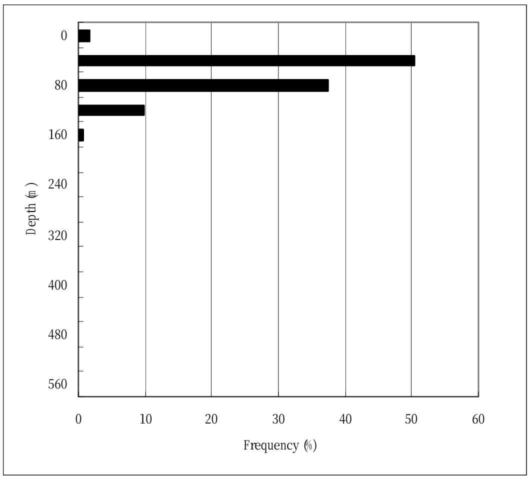
For h_{atd}, we apply the distribution proposed by Bigelow *et al* (2002) in the Pacific (refer to Appendix C for details). For the purpose of determining approximate hook depth distributions, these authors aggregated the HBF information into six categories used by Japanese longliners: 5-6 HBF (regular LL gear), 7-9 HBF (intermediate LL gear), 10-11 & l2-15 HBF (deep LL gear) and l6-20 & 2l-22 HBF (ultra deep LL gear). Yellowfin or bigeye tuna longline sets were usually conducted by day fishing at moderate (100-250 m) to deep depths (100-400m) with gear of five HBF or greater. There were the data corresponding to 3-4 HBF, however, they were deleted prior to analysis because these shallow gear types were used mainly to target swordfish at night. Then, by randomly generating between- and within-set variability into the theoretical gear configuration (defined by catenary geometry), they estimated the hook depth distributions for 15 depth bins of 40 m (range, 0-600 m) through 50,000 trials for six gear categories. In our analyses, we used the percent frequency distribution of these estimated hook depth distributions (Fig. 2).

(3) Yellowfin habitat preferences as determinants of depth distribution

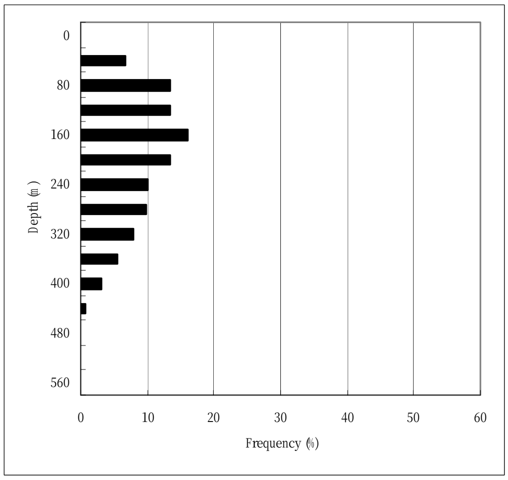
Vertical distribution within habitat-based approaches is typically defined by acoustic tracking, archival tags and physiological information (Bigelow *et al*, 2002). In the Indian Ocean, there has been ultrasonic tagging experiments (Cayré, 1991; Cayré and Marsac, 1993; Marsac et al, 1998), but they have been conducted in restricted areas of the western basin (Seychelles, La Réunion, Comoros) and concerned mainly FAD-associated fish (which exhibit a particular swimming behaviour compared to that observed away from aggregating devices).

The available information which is relevant on a large scale for the Indian Ocean comes from experimental tuna longline fishing conducted by the Japan Marine Resources and Research Center (JAMARC) in 1982-86. The surveyed areas in each year are shown in Fig. 3. The surveys were conducted during the entire year in these five years. In the experiments from 1982-83, depth recorders were attached above the hooks, while those for 1984-86, depth recorders were not used but hook specific catch by species were recorded. Therefore, the depth of fish caught in 1984-86 was estimated by Mohri *et al* (1997) with the same equation, C1 (page 24). In this paper, depth specific yellowfin catch and effort for five years were processed by quarter and sub-area. Average frequency distribution of YFT CPUE by 40m intervals corresponding to Fig. 2 were computed by quarter and sub-area by assigning the highest frequency scaled to be 1 (Fig. 4). Missing frequency in a particular quarter and sub-area were substituted by neighboring time and sub-area strata.

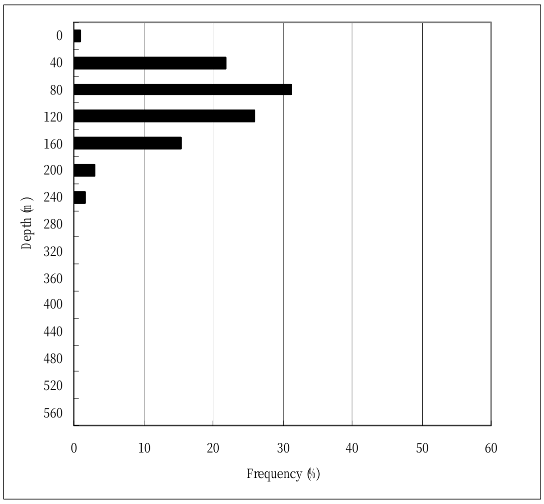
(g1) 5-6 HBF



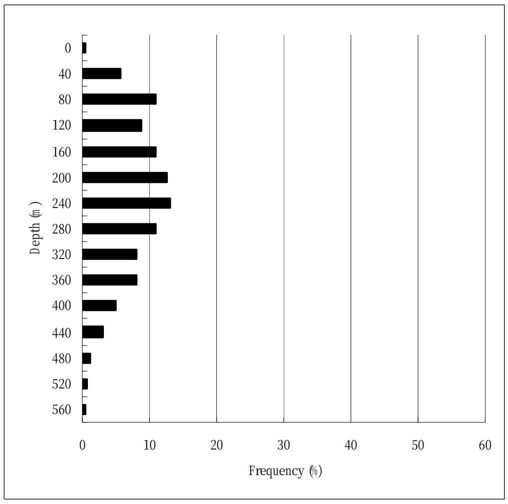
(g4) 12-15 HBF



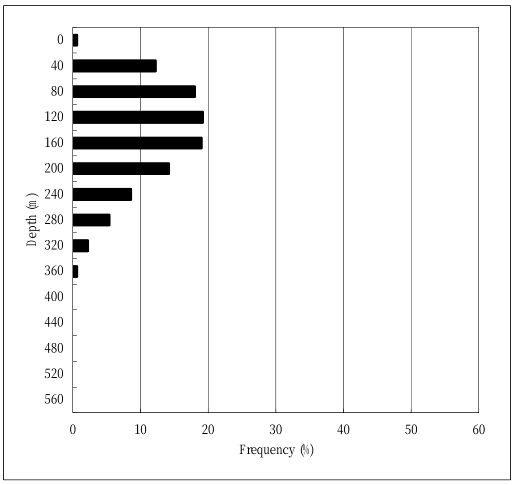
(g2) 7-9 HBF



(g5) 16-20 HBF



(g3) 10-11 HBF



(g6) 21-22 HBF

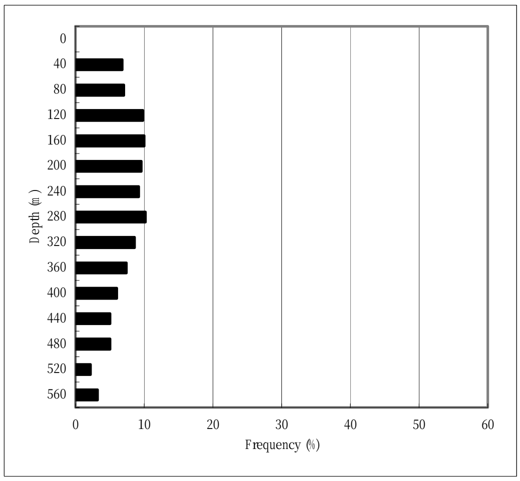
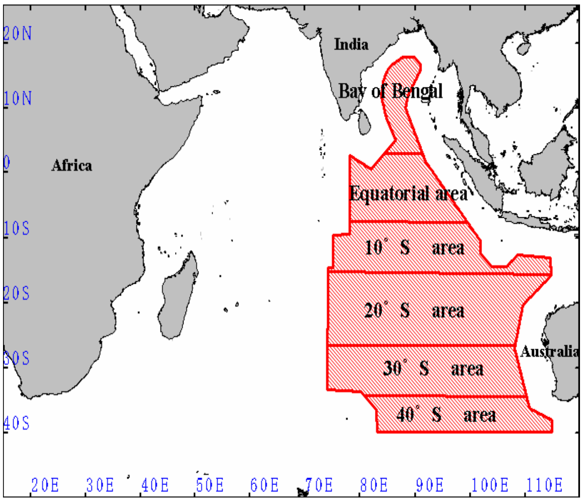
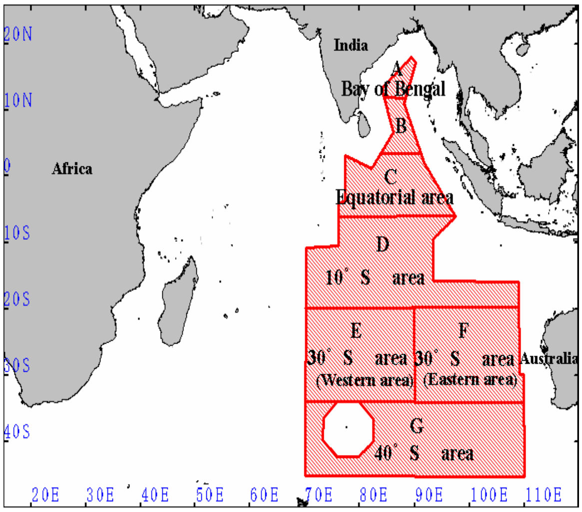


Fig. 2 Percent frequency distribution of hook depth in six gear configurations within the Japanese tuna longline fishery (after Bigelow et al, 2003). HBF: hooks between floats.

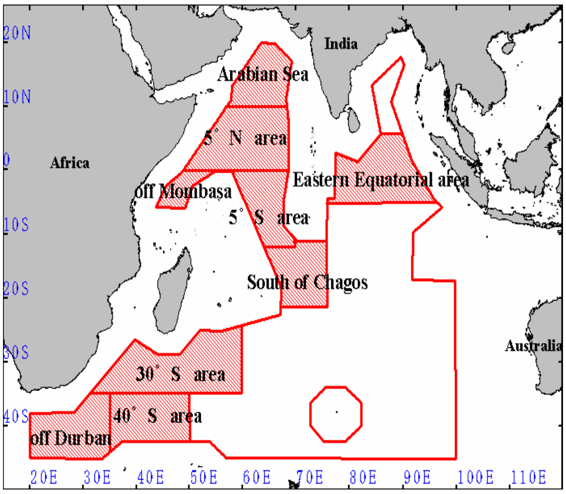
1982



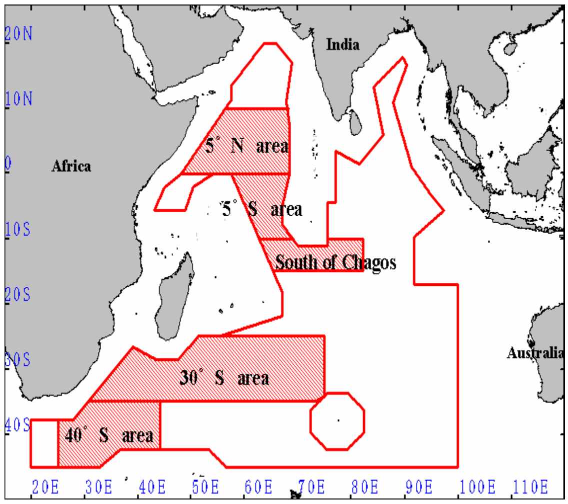
1983



1984



1985



1986

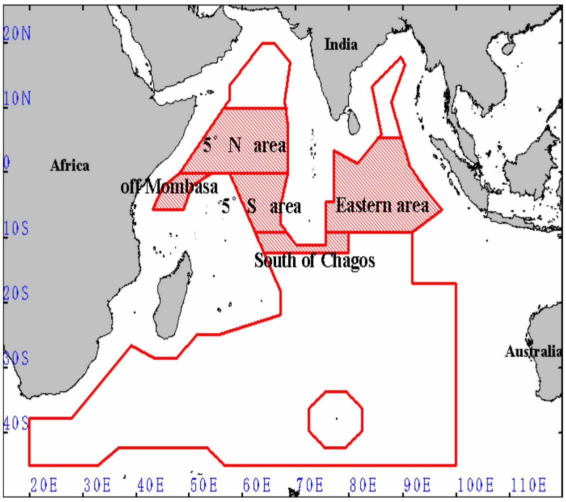
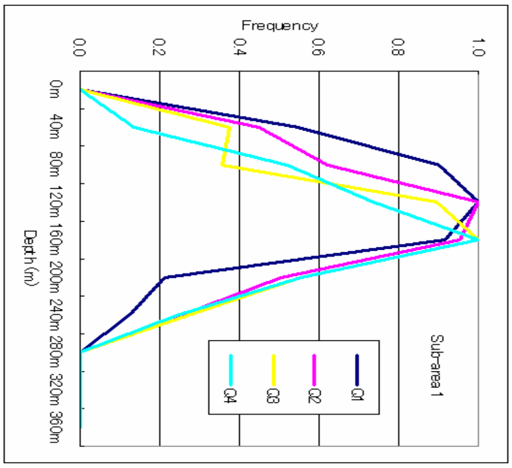
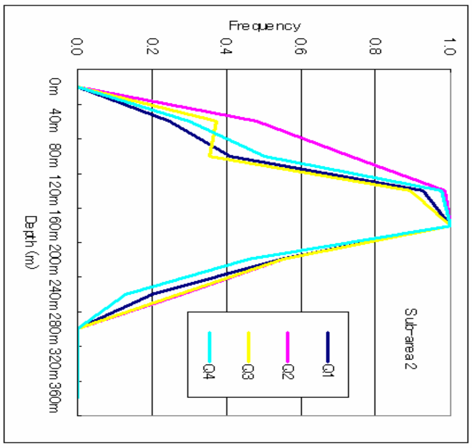


Fig. 3 Survey areas (shaded areas) of the JAMARC's experimental tuna longline fishing in the Indian Ocean (1982-86).

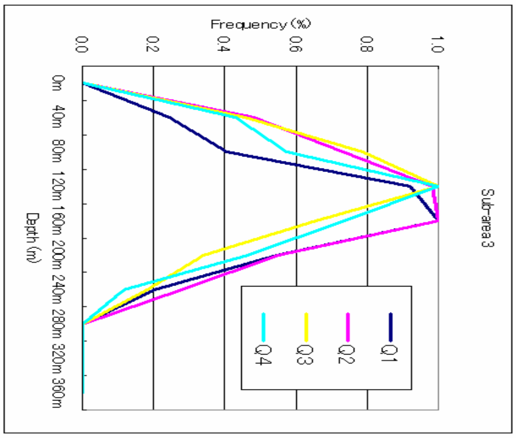
Sub-area 1



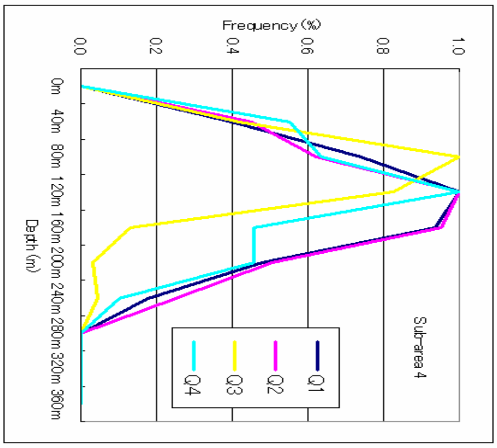
Sub-area 2



Sub-area 3



Sub-area 4



Sub-area 5

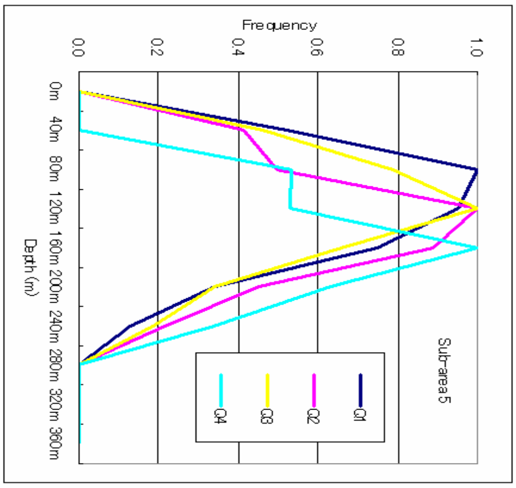


Fig. 4 Depth specific frequency distribution of yellowfin tuna habitat by quarter and sub-area based on the information from the JAMARC's experimental tuna longline fishing in 1983-86. Highest frequency is scaled to 1.

(4) Effective-fishing effort (HBM) based CPUE

By applying equation (3), we estimated effective fishing effort by incorporating information on hook depth (Fig. 2) and yellowfin vertical distribution (Fig. 4) for each year, month and 5°x5° area. Then, effective fishing effort (HBM) based CPUE was computed by (number of yellowfin tuna x 1000)/ (effective effort) by year, month and 5°x5° area and month. Then, annual effective fishing effort (HBM-based) CPUE are computed by averaging those by month and 5x5 area.

3.3 HBM/GLM COMBINED ANALYSES

In the same way as the GLM analyses except excluding G (gear) effects related terms, we conducted the HBM/GLM combined analyses using the effective fishing effort or the HBM based CPUE for the whole area by the equation (4) below and Appendix D shows the results of the SAS GLM outputs. The reason to exclude G (gear) effects related terms is to avoid representing a double standardization of the gear effect (ICCAT, 2003).

$$Log_e(E\_CPUE_{ijkl}+constant\ ) = INTERCEPT + Y_i + M_j + A_k + SST + TD + (Y^*M)_{ij} + (Y^*A)_{ik} + (M^*A)_{jk} + (SST^*M)_j + (SST^*A)_k + (TD^*Q)_j + (TD^*A)_k + (ERROR)_{ijkl},$$

$$\text{with } (ERROR)_{ijkl}, \sim N(0, \sigma^2) \qquad (4)$$

, where E_CPUE : the effective effort based CPUE (number of yellowfin catch per 1000 effective hooks)

constant : 1.78559 for the whole area.

3.4 COMPARISONS

(1) Nominal effort vs. effective (HBM) effort

The HBM procedure reduces the magnitude of changes of the effective effort compared to the nominal effort (Fig. 5).

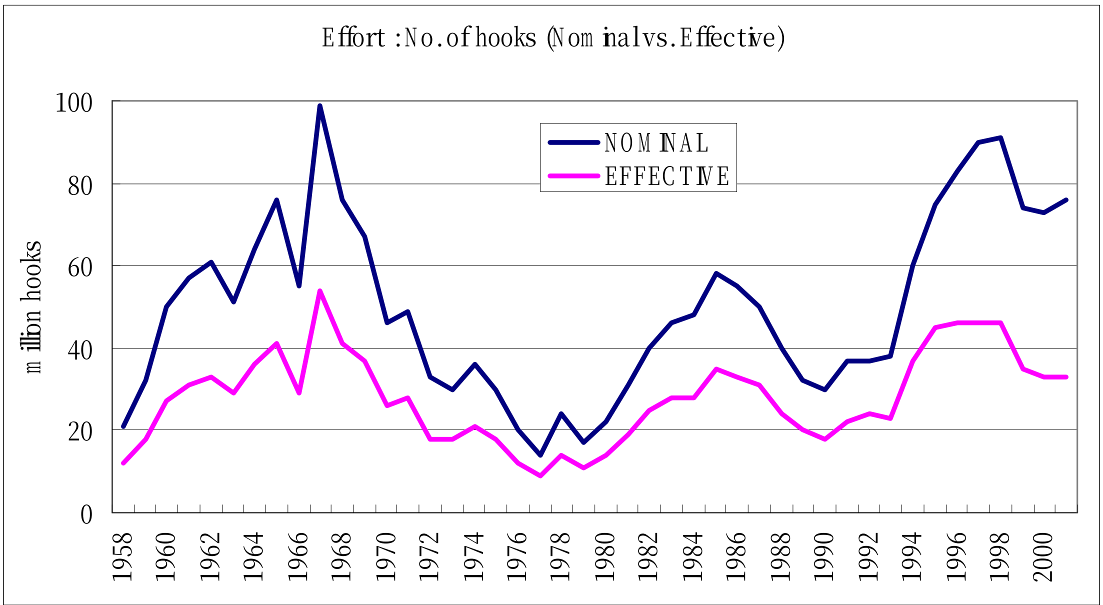


Fig. 5 Annual trend of nominal fishing effort and the effective fishing effort by the HBM.

(2) Four types of CPUE (NOMINAL vs HBM vs GLM vs HBM/GLM)

Fig. 6 shows the annual trends of four types of CPUE (NOMINAL vs HBM vs GLM vs HBM/GLM)

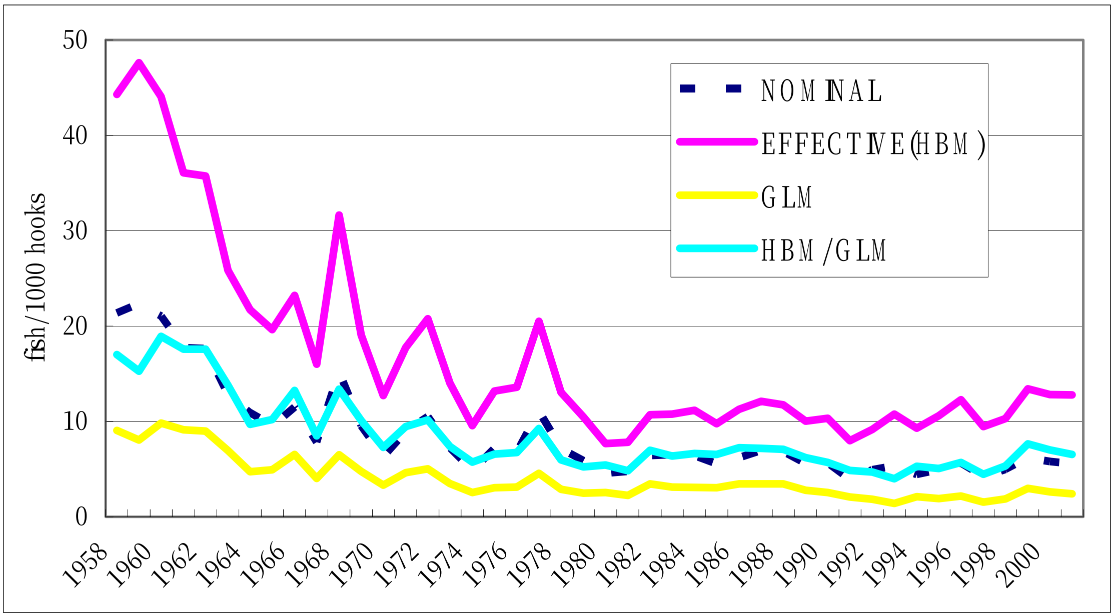


Fig. 6 comparison of annual trends of four types of CPUE (NOMINAL vs. HBM vs. GLM vs. HBM/GLM)

(3) Four types of scaled CPUE (NOMINAL vs. HBM vs. GLM vs. HBM/GLM)

Fig. 7 shows the comparison of annual trends of four types of scaled CPUE (NOMINAL vs. HBM vs. GLM vs. HBM/GLM). Actual average values of four indices are set to 1 for objective comparisons.

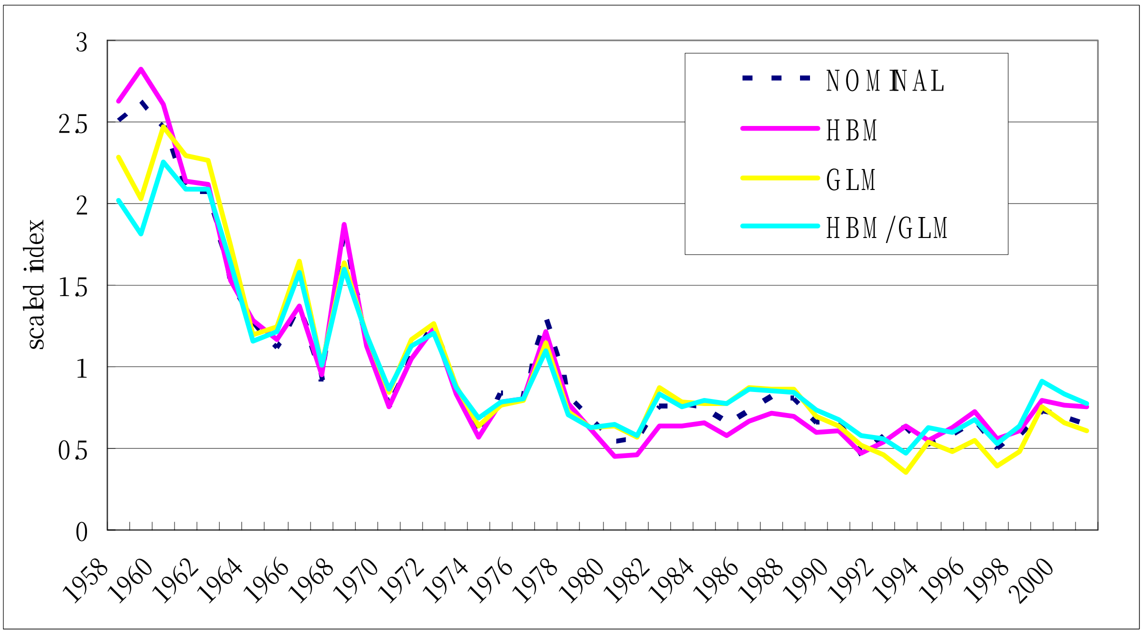
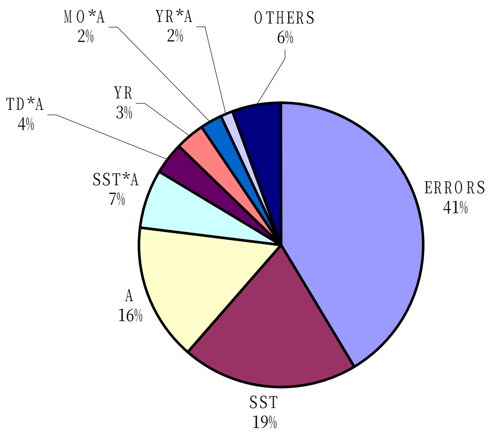
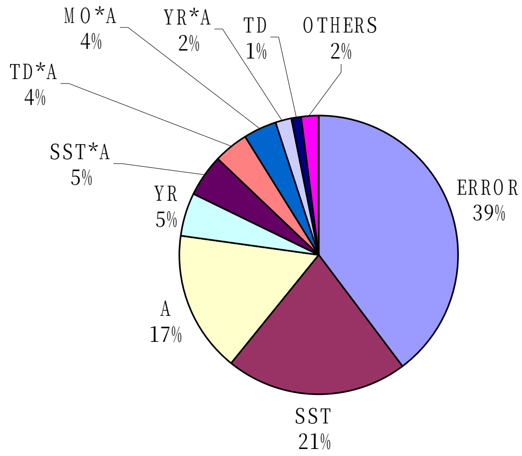


Fig. 7 Comparison of annual trends of four types of scaled CPUE (NOMINAL vs. HBM vs. GLM vs. HBM/GLM).

Table 2 shows comparisons of the fitness and variances between GLM and HBM/GLM and also factors affecting the CPUE standardization.

Table 2 comparisons of fitness and variances between GLM and GLM/HBM and factors affecting the CPUE standardization.

	GLM analyses	GLM/HBM combined analyses
R^2	58.5%	60.2%
CV	43.9 %	30.9%
F values (ANOVA)	53.2	63.1
AIC	75,999	75,152
Factors affecting CPUE Standard-ization		

(Note) AIC: Akaike's Information Criteria
A: sub-area (see Fig. 3), SST: Surface Sea Temperature (^oC) , TD: Thermocline Depth (m) at 20^oC

4. DISCUSSIONS

(1) Why do the standardized CPUE between GLM and GLM/HBM appear very similar ?

Standardized annual CPUE trends between GLM & GLM/HBM are unexpectedly quite similar (Fig. 7) unlike those for YFT in the Pacific analyzed by Bigelow *et al* (2003), which showed large discrepancies between the two series.

Possible two reasons of the similar trends in the Indian Ocean are as follows:

(a) Constant vertical distribution of yellowfin tuna

We used a constant vertical distribution of yellowfin tuna in our analysis based on the JAMARC's experimental tuna longline fishing data (Fig. 4), which indicates the catch rates are relatively low in the upper layers of the water column (0-80 m) possibly due to a lack of sampling in these shallow strata. Furthermore, as this factor is largely influenced by oceanographic conditions seasonally and annually, we need to incorporate additional information such as depth specific temperature, dissolved oxygen, thermocline depth, etc. as Bigelow *et al* (2002 and 2003) and others did using the acoustic and pop-up satellite tagging data. If vertical distribution of YFT based on the acoustic data were used, then a larger difference between the GLM and HBM/GLM were expected, i.e., effective effort would be much less, typically 10-20% of total effort in the Pacific. For this initial application, we used a rather static approach that doesn't consider oceanographic information, thus we may be able to expect potential improvements in the HBM/GLM approach if we incorporate more oceanographic information as discussed.

(b) Constant gear efficiency to catch YFT

According to Fig. 8 showing the annual trends of six gear compositions, three stages can be considered over time in the gear configuration : 1958-1975 when (g1) regular LL was the sole gear used, 1976-1993 when (g2)-(g4) deep LL became dominant and 1994-2001 when the occurrence of the (g5)-(g6) ultra deep LL configurations increased sharply. Based on Figs. 2 and 4, gear type (g1) cover about 70% of YFT swimming depth (2nd best efficient gear for YFT), (g2)-(g4) for 70-90% (the most efficient gear configuration for YFT), while (g5)-(g6) covers about 50% (the least efficient configuration). Hence, effective efforts do reflect the efficiencies in each of the three stages as shown in Fig. 9. Indeed, the ratio of effective effort over the nominal effort exhibit stable levels during the stages 1 and 2, with a slightly higher level during the second stage where the configuration considered as the most efficient for YFT was deployed. During stage 3, the higher proportion of deep and ultra deep LL led to a concomitant decrease of the effective effort on YFT.

We can notice a slight positive trend of the HBM-based CPUE starting in 1993, that could be explained by a lesser number of hooks set in the YFT habitat range (Fig. 10). For the two first stages, the levels of effective effort are very similar and cannot affect significantly the GLM analyses. A very different situation occurred in the Pacific where the effective effort exhibited large fluctuations and was likely to produce effects on the GLMs, as shown by Bigelow *et al*. (2003).

<===1st stage ======><====2nd stage =======><==3rd =>

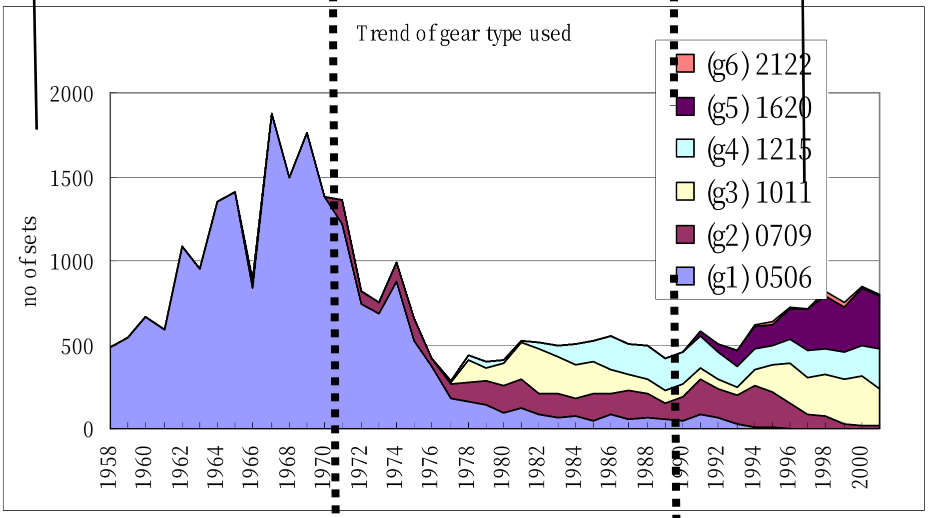


Fig. 8 Annual trends of compositions of six gear types.

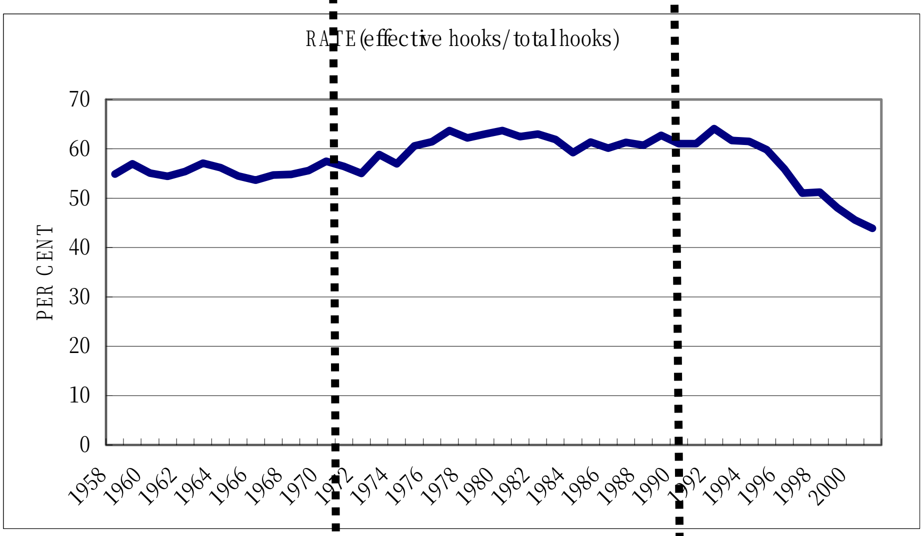


Fig. 9 Annual trend of the rates of effective effort (HMB based hooks) over the nominal fishing efforts (hooks)

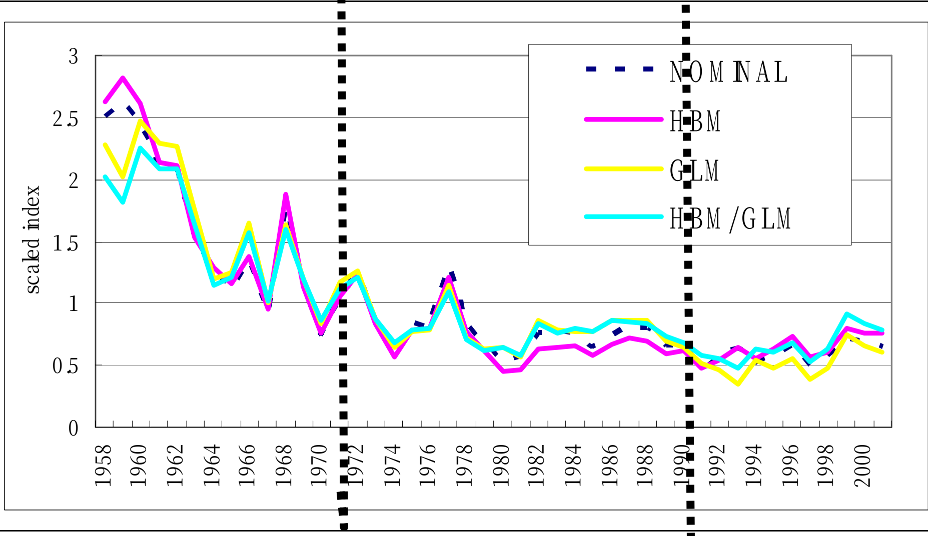


Fig. 10 Scaled annual trends of four indices (Fig. 7 is re-drawn)

(2) Should we use the GLM/HBM standardization?

Based on the results in our study, there are likely no significant different on the CPUE standardization between GLM and HBM/GLM. However, according to Table 2, it is understood that the GLM/HBM is slightly superior to the GLM in terms of correlation coefficients, CV, F values in the ANOVA tables and AIC. This implies that CPUE standardization by GLM/HBM have slightly better fitness and less variability to the model than in the GLM. In addition, we expect better fitness of HBM/GLM if we shall include more oceanographic-related information as discussed previously. Thus, as a conclusion at this stage, it is suggested to use the GLM/HBM for the longline tropical tuna CPUE standardization in the Indian Ocean if necessary information were available for the GLM/HBM.

(3) Trends of the YFT abundance

Based on Fig. 6 and 7, standardized YFT CPUE by both GLM and HBM/GLM show the continuous decreasing trend from 1958 to 2001 in general, although there are some extended fluctuations along the decreasing trends. The level of CPUE in the recent years is roughly 1/3 of the levels in the beginning period (late 1950's). Standardized CPUEs in 2000-2001 were slightly higher than those in the previous decade (1990's).

(4) Factors affecting the CPUE standardization

Based in Table 2, it was resulted that primary factors affecting CPUE standardization were SST, A (sub-area), SST*A (sub-area) and thermocline depth (TD)*sub-area (A) which account more than 75% besides errors between data and the models. This implies that SST and A (sub-area) are important elements in the standardization.

(5) Research needs to conduct the GLM/HBM

Several recommendations can be made to improve the number of relevant information and data to incorporate in future studies on habitat based models in the Indian Ocean. They are summarized thereafter:

- to conduct archival & pop-up tagging experiments that provide direct and simultaneous information of the location and depth of the fish along with their ambient environment;
- to update oceanographic information and compute factors such as shear currents in depth and dissolved oxygen concentration. As the dissolved-oxygen observation are still sparse, further statistical analysis is required to use the temperature to infer the oxygen concentration in a given range of depth (see Marsac 2002, for some results in this respect);
- to emphasize the need of ocean circulation models in the Indian Ocean : such operational models are already available in the Pacific and Atlantic Oceans, but we are now verging on getting similar models in the Indian Ocean, notably through the Mercator program. These models provide information on temperature, salinity and currents at different depths. We can notice that the depths where the longline is operating is very precisely described by the models.
- To develop a method to incorporate the thermocline depth that we applied (Appendix A) and also available ultrasonic tagging data to the HBM/GLM.
- In addition to the data component itself, we should acknowledge that a 5° x 5° block size is not a satisfactory scaling as long as we want to introduce environmental factors that can vary greatly in space and time in the GLMs. This is particularly the case for thermocline depth (TD) at the edge of currents with opposite directions, like between the latitudes 5°S to 10°S, in the subtropical convergence and along major upwelling that occur seasonally in the west and northwest of the Indian Ocean. In order to match with the resolution of the fishery data, the TD values are strongly smoothed and do not reflect accurately the gradients in time and space. We should recommend that the longline catch and effort database be redistributed by 5° longitude x 2° longitude blocks for a reanalysis of the different types of GLMs, and the HBM/GLM in particular.

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REFERENCES:

BIGELOW, K.A., HAMPTON, J. AND MIYABE, N. (2002): Application of a habitat-based model to estimate effective longline fishing effort and relative abundance of Pacific bigeye tuna (*Thunnus obesus*). *Fish. Oceanogr.* **11**:3: 143-155.

BIGELOW, K.A., HAMPTON, J. AND MIYABE, N. (2003): Sensitivity of temperature determinants in a habitat-based model for yellowfin in the western and central Pacific. ICCAT/SCRS/03/ 038:1-16.

BOGGS, C.H. (1992): Depth, capture time, and hooked longevity of longline-caught pelagic fish: timing bites of fish with chips. *Fish. Bull. U.S.* **90**:642-658.

CAMPBELL, R.A., G. TUCK. ,S. TSUJI AND T. NISHIDA (1996): Indices of abundance for southern bluefin tuna from analysis of fine-scale catch and effort data (SBFWS/96/16): 34pp.

CAYRÉ, P. (1991): Behaviour of yellowfin tuna (*Thunnus albacares*) and skipjack tuna (*Katsuwonus pelamis*) around Fish Aggregating Devices (FADs) in the Comoros Islands as determined by ultrasonic tagging. *Aquat. Living Resour*., **4**, 1-12.

CAYRÉ, P. AND MARSAC, F. (1993): Modelling the yellowfin tuna (*Thunnus albacares*) vertical distribution using sonic tagging results and local environmental parameters. *Aquat. Living Resour*., **6**, 1-14.

HINTON, M.G. AND NAKANO, H. (1996): Standardizing catch and effort statistics using physiological, ecological, or behavioral constraints and environmental data, with an application to blue marlin (*Makaira nigricans*) catch and effort data from Japanese longline fisheries in the Pacific. *Inter-Am. Trop. Tuna Comm. Bull.* **21**:171-200

ICCAT (2003): Report of the ICCAT working group on assessment methods (ICCAT/2003/ 013):13pp.

JAMARC (1985): Report of the experimental tuna longline fishing in the Indian Ocean in 1982: 105pp.

JAMARC (1985): Report of the experimental tuna longline fishing in the Indian Ocean in 1983: 103pp.

JAMARC (1986): Report of the experimental tuna longline fishing in the Indian Ocean in 1984: 113pp.

JAMARC (1986): Report of the experimental tuna longline fishing in the Indian Ocean in 1985: 101pp.

JAMARC (1988): Report of the experimental tuna longline fishing in the Indian Ocean in 1986: 120pp.

MARSAC, F. (1998): GAO : an oceanographic applications manager for fisheries biologists. In Ardill (Ed) Proceedings of the Expert Consultation on Indian Ocean Tunas, 7th session, IOTC, Victoria, Seychelles, 9-14/11/98. *IOTC Proceedings **1*** : 257-264.

MARSAC, F. (2002): Changes in depth of yellowfin tuna habitat in the Indian Ocean: an historical perspective 1955-2001. 4th session of the IOTC working party on tropical tunas, Shangaï, Chine, 3-1/06/2001. WPTT/02/33. *IOTC Proceedings* **5** : 450-458

MARSAC, F., AND CAYRÉ, P. (1998): Telemetry applied to behaviour analysis of yellowfin tuna (*Thunnus albacares*, Bonnaterre, 1788) movements in a network of fish aggregating devices. *Hydrobiologia*, 371/372: 155-171.

MOHRI, M., HANAMOTO, E., NEMOTO M AND TAKEUCHI, S. (1997): Vertical Distribution of Bigeye Tuna in the Indian Ocean as Seen from Deep Tuna Longline Catches. *Bull. Japan. Soc. Fish. Oceanogr*.,**61**: 10-17.

MIZUNO, K., OKAZAKI, M. AND MIYABE, N. (1998): Fluctuation of longline shortening rate and its effect on the underwater longline shape. *Bull. Far Seas Fish. Res. Lab.* **35**:155-164.

MIZUNO, K., OKAZAKI, M., NAKANO, H. AND OKAMURA, H. (1999): Estimating the underwater shape of tuna longlines with micro-bathythermographs. *Inter-Am. Trop. Tuna Comm., Special Report* **10**, pp.35.

NISHIDA, T. (2000): Standardization of the Japanese longline catch rates of adult yellowfin tuna (*thunnus albacares*) in the western Indian Ocean by General Linear Model (1975-98). IOTC/ WRTT/00/10: 7pp.

OKAMOTO, H., MIYABE, N. AND MATSUMOTO, T. (2001): GLM analyses for standardization of Japanese longline CPUE for bigeye tuna in the Indian Ocean applying environmental factors. WRTT/01/21:37pp.

SHONO, H., OKAMOTO, H. AND NISHIDA, T. (2002): Standardized CPUE for yellowfin tuna (*Thunnus albacares*) of the Japanese longline fishery in the Indian Ocean by Generalized Linear Models (GLM) (1960-2000).IOTC/WRTT/02/12: 10pp.

SUZUKI, Z., WARASHINA, Y. AND KISHIDA, M. (1977): The comparison of catches by regular and deep tuna longline gears in the western and central equatorial Pacific. *Bull. Far Seas Fish. Res. Lab.* **15**:51-89.

UOZUMI, Y. AND OKAMOTO, H. (1997): Research on the hook depth of longline gear in the 1995 research cruise of the R/V Shoyo Maru. *Working Paper 3, 7th Meeting of the Western Pacific Yellowfin Research Group,* 18-20 June, Nadi, Fiji, pp. 20.

WHITE, W. B. (1995): Design of a global observing system for gyre-scale upper ocean temperature variability. *Prog. Oceanogr.*, **36**, 169-217.

YANO, K. AND ABE. O. (1998): Depth measurements of tuna longline by using time-depth recorder. *Nippon Suisan Gakkaishi* (in Japanese, with English abstract) **64**:178-188.

YOKAWA, K AND TAKEUCHI, Y. (2002): Estimation of abundance index of white marlin caught by Japanese longliners in the Atlantic Ocean. ICCAT/SCRS/02/060:21pp.

Appendix A Procedure to estimate thermocline depth

The current data set used in this paper merges two data sets. The first one is the 2° latitude-by-5° longitude reanalysis computed from all quality-controlled vertical profiles in the existing archive (White, 1995) and updated to 2001 at the Environmental Data Analysis Center (JEDAC) located at the Scripps Institution of Oceanography. This data set comprises temperature at depth, and we interpolated between levels to obtain TD, the depth of the 20°C which is commonly used to depict the core of the thermocline. TD observations are then obtained by month and 2°x5° area. However, the data coverage showed important spatial gaps, notably in the southern Indian ocean (south of 30°S), in the Mozambique Channel and in the Bay of Bengal. Therefore, we used the GAO (Gestionnaire d'Applications Océanographiques) database (Marsac, 1998) that covers the whole Indian Ocean north of 60°S, to fill the spatial gaps within the range of the YFT distribution. Individual quality-controlled temperature profiles were averaged in 2°x5° areas and month, where data from the JEDAC were lacking.The final data coverage is shown in the following figure (Fig. A1).

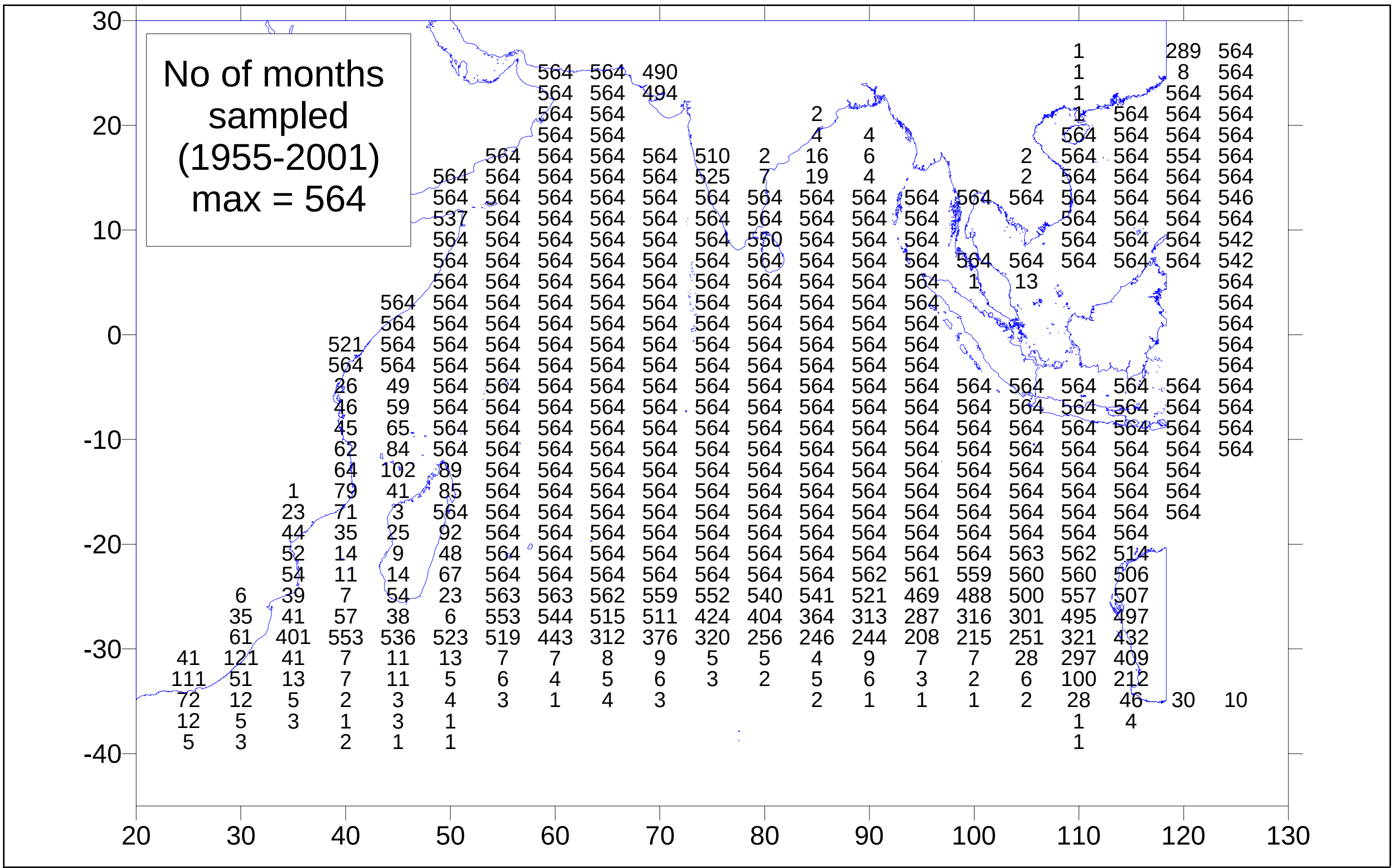

Fig. A1 Coverage in time and space of the merged TD data used in the present analysis

Following the first step of compiling information, we needed to fill the temporal gaps. As shown on the figure, the areas that were filled using GAO are not continuous time series. We used the available information at each time step and an interpolating method (inverse squared distance) to estimate TD values at the grid nodes of the non-sampled areas, according to the equation:

$$\hat{Z}_j = \frac{\sum_{i=1}^{n} \frac{Z_i}{h_{ij}^{\beta}}}{\sum_{i=1}^{n} \frac{1}{h_{ij}^{\beta}}} \qquad \text{with} \qquad h_{ij} = \sqrt{d_{ij}^2 + \delta^2}$$

where :

h_{ij}	is the effective separation distance between grid node 'j' and the neighboring point 'i'
$\hat{Z}_j$	is the interpolated value for grid node 'j'
Z_i	are the neighboring points
d_{ij}	is the distance between grid node 'j' and the neighboring point 'i'
β	is the weighting power (set at 2 in the present study)
δ	is the smoothing parameter (set at 0 in the present study)

The inverse squared distance is known to be an exact interpolator when we do not specify any smoothing factor, which was the case in the present analysis. It was calculated using a specific script written in the Surfer 7.05 environment. Actually, we also had to reshape the initial grid of 2°x5° to a 5°x5° grid to match with the LL data set. This procedure gave continuous TD fields in space and time over the whole period at each 5° x 5° node.

Finally, in order to have a TD value corresponding to the whole 5° x 5° area where fishing is carried out, we estimated average values at each time step in the middle of each 5° x 5° block, using the 4 surrounding grid nodes. The result is a slightly smoothed TD field compared to that of the preceding step.

Appendix B SAS outputs of the GLM runs for the nominal CPUE standardization.

General Linear Models Procedure
Class Level Information

Class	Levels	Values
YR	44	1958 1959 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001
MO	12	1 2 3 4 5 6 7 8 9 10 11 12
A	5	1 2 3 4 5
G	6	1 2 3 4 5 6

Number of observations in data set = 33457

NOTE: Due to missing values, only 33330 observations can be used in this analysis.

General Linear Models Procedure

Dependent Variable: N_HR

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	859	24637.69085947	28.68182871	53.24	0.0001
Error	32470	17492.86711801	0.53873936		
Corrected Total	33329	42130.55797747			

R-Square	C.V.	Root MSE	N_HR Mean
0.584794	43.88138	0.73398867	1.67266550

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YR	43	822.36034338	19.12465915	35.50	0.0001
MO	11	58.93970639	5.35815513	9.95	0.0001
A	4	358.24160989	89.56040247	166.24	0.0001
G	5	30.73329414	6.14665883	11.41	0.0001
SST	1	114.84803675	114.84803675	213.18	0.0001
TD	1	4.40659096	4.40659096	8.18	0.0042
YR*MO	473	857.67182577	1.81325967	3.37	0.0001
YR*A	172	1489.24559353	8.65840461	16.07	0.0001
MO*A	44	598.98948371	13.61339736	25.27	0.0001
MO*G	55	74.48404171	1.35425530	2.51	0.0001
A*G	20	121.51844566	6.07592228	11.28	0.0001
SST*MO	11	52.57161060	4.77923733	8.87	0.0001
SST*A	4	154.48039618	38.62009905	71.69	0.0001
TD*MO	11	22.15261794	2.01387436	3.74	0.0001
TD*A	4	81.80372174	20.45093043	37.96	0.0001

Appendix C Procedure to estimate depth distribution of longline gear (Bigelow *et al*, 2002)

(1) Predicting hook depth distribution from gear configuration

The actual depth at which longline gear fishes is known to be influenced by the set configuration, such as the number of hooks between floats, floatline and branchline lengths, distance between branchlines, sagging rate of the mainline (Fig. C1) and a variety of environmental factors, particularly wind and currents (Suzuki *et al*., 1977; Boggs, 1992; Mizuno *et al*., 1998, 1999). The depth of the longline is typically altered by varying the length of mainline between floats and the sagging rate of the mainline [ratio of horizontal distance between two floats and the stretched length of mainline between two floats (Suzuki *et al*., 1977)]. While actual fishing depth has been measured in several studies with time-depth-recorders (TDRs) (Boggs, 1992; Uozumi and Okamoto, 1997; Mizuno *et al*., 1998, 1999), fishing depth measurements are rarely available from commercial longline sets. However, the number of hooks between adjacent mainline floats (HBF), which is routinely recorded on Japanese longline logbooks, can be used along with other information on set configuration to estimate the approximate depth distribution of longline hooks using catenary geometry (Suzuki e*t al.,* l977):

$$D_j = h_a + h_b + L\left\{(1+\cot^2\phi)^{1/2} - \left[(1-2\frac{j}{N})^2 + \cot^2\phi\right]^{1/2}\right\} \qquad \text{(C1)}$$

,where D_j is the depth of the *j*-th hook, h_a is the length of the branch line, h_b is the length of the float line, *L* is half of the length of the mainline between two floats, *N* is HBF + l, *j* is the *j*-th branch line from the float line, and ϕ is the angle between the horizontal and tangential line of the mainline. The parameter is solved by iteration of the sagging rate (*HL*/2 *L*, Fig. C1).

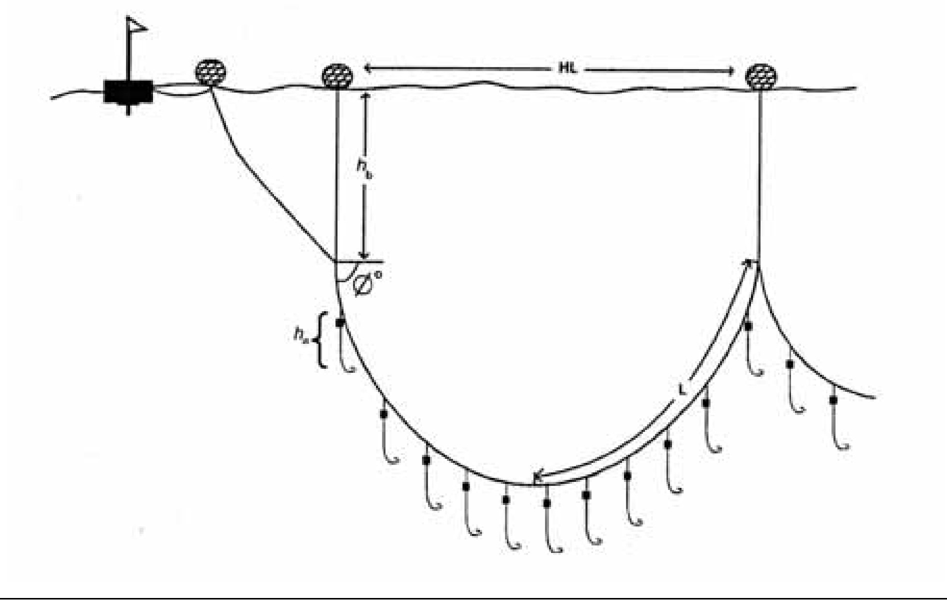

Fig. C1 *Configuration of a pelagic longline. h_a is length of branch line, h_b is length of float line, HL is the horizontal length between two floats, L is half of the length of the mainline between two floats and ϕ the angle between the horizontal and tangential line of the mainline.*

The catenary parameters {h_a = 26.3 m, h_b = 19.4 m, *L* = [(50m)*(HBF + l)/2], $\phi = 60^\circ$, sagging rate = 0.72} were estimated from data collected by at-sea observers deployed on Japanese vessels (212 longline sets) in the l990s (unpublished observer data, SPC, BPD5 98848, Noumea Cedex, New Caledonia). Thus, using equation 1 it is possible to estimate the depth of longline hooks for various HBF categories.

From l966 to l996, gear configuration in the Japanese longline fishery ranged from 3 to 22 HBF. Yellowfin or bigeye tuna longline sets were usually conducted by day fishing at moderate (100-250 m) to deep depths (100-400 m) with gear of five HBF or greater. Data corresponding to 3-4 HBF were deleted prior to analysis because these shallow gear types were used mainly to target swordfish at night. For the purpose of determining approximate hook depth distributions, the remaining HBF information were aggregated into six categories: 5-6 HBF (regular gear), 7-9 HBF (intermediate gear), and 10-11, 12-15, 16-20 and 21-22

HBF (deep gear).

(1) Between-set and within-set variability

The catenary estimation results in a single depth estimate for each longline hook; however, actual hook depths vary both between and within longline sets. We characterized between-set hook-depth variability for each HBF value by randomly generating l000 values of φ from a normal distribution ($\mu = 60^o$, $\sigma = 11.3^o$ unpublished data, SPC) and computing D_j for each. Within-set variability in longline fishing depth has been estimated using TDR data (Boggs, l992; Yano and Abe, l998). Boggs (l992) observed that the deepest hook on a longline set has the greatest movement and calculated a 30% variation (- l00 m) in settled depth of the deepest hook on a set deployed to > 300 m. Similarly, Yano and Abe (l998) found a linear increase in depth fluctuation as hooks were deployed deeper. Based on data from Yano and Abe (l998), the relationship between the standard deviation of hook depth D_j and hook number *j* (the hooks closest to the floats are numbered 1) was:

$$\sigma(D_j) = 8.73 + 4.4j \quad (r^2 = 0.64) \qquad \text{(C2)}$$

Within-set variability in D_j was characterized by generating 500 random samples of hook depths from normal distributions of mean D_j and standard deviation $\sigma(D_j)$ for each of the l000 estimates of D_j obtained previously; thereby producing 500 000 estimates of D_j for each HBF value of five through 22. Aggregate hook-depth distributions (40-m depth bins) corresponding to the six HBF categories were produced by aggregating the individual hook distributions within those categories (See Fig. 2 in the text).

Appendix D: SAS outputs of the GLM/HBM combined runs for the effective fishing effort based CPUE standardization

General Linear Models Procedure
Class Level Information

Class	Levels	Values
YR	44	1958 1959 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001
MO	12	1 2 3 4 5 6 7 8 9 10 11 12
A	5	1 2 3 4 5

Number of observations in data set = 33457

NOTE: Due to missing values, only 33330 observations can be used in this analysis.

General Linear Models Procedure

Dependent Variable: E_HR

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	779	25997.55096024	33.37297941	63.13	0.0001
Error	32550	17207.40341087	0.52864527		
Corrected Total	33329	43204.95437111			

R-Square	C.V.	Root MSE	E_HR Mean
0.601726	30.89175	0.72707996	2.35363820

Source	DF	Type III SS	Mean Square	F Value	Pr > F
YR	43	1203.85075068	27.99652909	52.96	0.0001
MO	11	45.70881886	4.15534717	7.86	0.0001
A	4	374.00667654	93.50166914	176.87	0.0001
SST	1	118.86279661	118.86279661	224.84	0.0001
TD	1	5.80873181	5.80873181	10.99	0.0009
YR*MO	473	879.68860271	1.85980677	3.52	0.0001
YR*A	172	1924.87187482	11.19111555	21.17	0.0001
MO*A	44	930.57305409	21.14938759	40.01	0.0001
SST*MO	11	45.41701475	4.12881952	7.81	0.0001
SST*A	4	111.60338827	27.90084707	52.78	0.0001
TD*MO	11	15.68748580	1.42613507	2.70	0.0018
TD*A	4	89.56608871	22.39152218	42.36	0.0001