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Title: Separation of the Taiwanese regular and deep tuna longliners in the Indian Ocean using bigeye tuna catch ratios

Running title: Separating Taiwanese regular and deep tuna longliners

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ABSTRACT

Taiwanese longline fisheries (LL) in the Indian Ocean usually catch albacore tuna (ALB), swordfish (SWO) and yellowfin tuna (YFT) by the regular LL, on the contrary, bigeye tuna (BET) by deep LL. Thus these two types of LL are considered to be different gears as they catch different tuna species. Regular or deep type LL is defined by number hooks per basket (NHB), i.e., regular LL if $6 \leq$ NHB ≤ 10 and deep LL if $11 \leq$ NHB ≤ 20. However, the NHB information was available only in some of the recent LL data (1995-99). This situation has been causing problems of biased results in the stock analyses in the past. Under such backgrounds, the objective of our study is to explore an effective method to separate two types of LL considering species compositions. After various attempts, we found that some intervals of BET catch ratios were resulted to be most effective in separating regular and deep type LL, i.e., $0.8 \leq$ BET/(BET+ALB) ≤ 1 and $0 \leq$ BET/(BET+ALB+SWO) ≤ 0.40 respectively. Using these two separators, we classified the LL type known data set (1995-99) (learning data set). Then we found that 67.7% data were correctly classified, while 23.1% were un-classified (11.9 % for zero catches and 11.2% classified into both LL types) and 9.2% for mis-classification. Then, using the developed methods, we classified the unknown LL type in the historical data (1979-99) and computed nominal CPUE of four species. As a result, their CPUE trends are reasonably depicted.

KEY WORDS: *bigeye tuna catch ratios, classification error, Indian Ocean, regular and deep tuna longline, learning data set, separators.*

INTRODUCTION

The industrial tuna longline fisheries (LL) in the Indian Ocean started in 1952 (Japan), 1954 (Taiwan), 1966 (Korea), and 1980's (Indonesia, Sri Lanka and other developing countries).[1] The total catches of all LL fisheries gradually increased from 20,000 t in 1952 to 170,000 t in 1967, then decreased and stabilized at the 100,000 t - 150,000 t level in 1968-1991. After 1992, the total catches suddenly shifted to the higher level and stabilized at the 200,000 t - 300,000 t level in 2000 (IOTC database) (Fig. 1).

The LL is composed of a mainline and many branch lines with hooks at the terminal end. The fishing depth of LL depends on the number of branch lines between two floating balls and the length of the branch lines (Fig. 2). The fishers call the number of branch lines between two floating balls as ‘basket’. If LL formed the theoretical catenary curve, location of hooks can represent the depth of the hooks deployed, which implies the depth of fish caught or the swimming depth of fish. There are two types of LL, i.e., regular LL and deep LL, which is defined by number of hooks between two floats (NHB). The regular LL has less number of NHB, while the deep LL has more number of NHB. The boundary number of NHB between regular LL and deep LL is slightly different by country.

Since around 1986, the Taiwanese longliners in the Indian Ocean equipping the super-cold storage, started to catch bigeye tuna (*Thunnus obesus*) (BET) by the deep LL. Their target species is different from the Taiwanese traditional longliners (regular LL or shallow LL), which primarily catches albacore (*Thunnus alalunga*) (ALB), swordfish (*Xiphias gladius*) (SWO) and yellowfin tuna (*Thunnus albacares*) (YFT) in the Indian Ocean.

There were no NHB information in the past, which have been caused biases on standardizing the nominal catch-per-unit-effort (CPUE) and CPUE based stock assessments for tuna and billfish resources because all catch and effort data from both regular LL and deep LL had been pooled when analyzed.[2] In order to conduct more realistic or unbiased tuna fisheries resources analyses, it is necessary to separate these two types of LL, i.e., regular LL and deep LL, because they target different species, hence they need to be treated as different gears.

Under such circumstances, Taiwanese government decided to collect the NHB information through the logbook of fishing vessels since 1995 in all three Oceans. Then, Taiwanese fishery biologists had started to put efforts to develop the methods to separate the regular LL and deep LL in the Indian Ocean.[3-5] They used the NHB information and species compositions of the LL data to separate regular LL and deep LL, and then to estimate ALB CPUE. The results showed the robust and smooth trends in both LL, although the trends without separation showed the sharp decrease in the combined LL, which were unlikely realistic and accurate.[3, 4] In those studies, catch ratios of BET over ALB was used to separate regular LL and deep LL.

However, we need to put focus on BET, YFT, ALB and SWO when we consider the method for separation as they are the primary catch species of Taiwanese LL in the Indian Ocean. Therefore, the objective of this paper is to develop more general and accurate separators considering these four species. As an initial trail, we used the exploratory data analyses to separate these two types LL data.

MATERIALS AND METHODS

Two data sets were used in this study, i.e., (1) regular and deep known LL data set (learning data set) and (2) regular and deep type unknown LL data set. The source of these data is from the Overseas Fisheries Development Council of the Republic of China (Taiwan). Table 1 shows the types of the LL data. About 40% of the Taiwanese LL set-by-set data in 1995-1999 have the NHB information in the Indian Ocean, which were treated as the regular and deep type known LL data set (learning data set) (Table 2). The regular and deep unknown data set (all data in 1979-1994 and also 60% of the data in 1995-1999) didn't contain the NHB information. Using these regular and deep known LL data sets, we will develop the most effective separators to classify into two groups. As explained previously, we attempt to use BET, YFT, ALB and SWO by looking at the unique species compositions in regular and deep LL. Then, we attempt to separate the LL type unknown data to regular or deep LL and evaluate classification powers of these separators.

RESULTS

Using the learning data set, we initially investigated the definition of regular LL and deep LL by analyzing the NHB information. As a result, it was found that the range of NHB in this data set was 6 – 20, which had two clear modes (Fig. 3). The lower number of NHB implied the regular or shallow LL, while the higher for the deep LL. Based on the patterns of Fig. 3 and also the fishing custom of Taiwanese LL fishers, this study defines the regular LL with $6 \leq$ NHB ≤ 10, while the deep LL with $11 \leq$ NHB ≤ 20.

In order to investigate the most effective separators, we further investigated the species compositions by regular and deep LL using the learning data set (Fig. 4). In the regular LL, ALB is the major species (61.8%), while those for BET, YFT, and SWO are 8.8%, 11.6% and 7.3% respectively. On the contrary, in the deep LL, the major species is BET (46.8%), while species compositions of ALB, YFT, and SWO are 13.9%, 22.1% and 8.5% respectively. Therefore, we can understand that ALB might be the most effective indicator to separate regular and deep LL as its compositions between these two gears are largely fluctuated (13.9% vs. 61.8%). However, ALB is exploited only southern part of the Indian Ocean[6], hence ALB is not considered to be the useful indicator. Although BET compositions are less fluctuated (46.8% vs. 8.8%), BET is exploited in much wider areas in the Indian Ocean. In addition, BET distributes in deeper waters (150-400m) and it is the target species of the Taiwanese deep LL in the Indian Ocean. Hence, BET catch ratios are considered to be the most effective in separating regular and deep LL. Therefore, this study adopted the BET catch ratios as the effective separators by combining catches of other three species. Then, we attempt following four BET ratios defined as follows:

$$BET\ ratio(1) = \frac{BET}{BET + YFT} \tag{1}$$

$$BET\ ratio(2) = \frac{BET}{BET + YFT + SWO} \tag{2}$$

$$BET\ ratio(3) = \frac{BET}{BET + ALB} \tag{3}$$

$$BET\ ratio(4) = \frac{BET}{BET + ALB + SWO} \tag{4}$$

From these four ratios, the best separator will be selected if the BET ratio has the highest value in the deep LL data, while the BET ratio has the lowest value in the regular LL data set.

In evaluating these four BET ratios, we need to exclude zero catches because we can not compute values of BET ratios, i.e., BET=YFT=0 for BET ratio(1), BET=YFT=SWO=0 for BET ratio(2), BET=ALB=0 for BET ratio(3) and BET=ALB=SWO=0 for BET ratio(4). Hence, these zero data were excluded when we evaluated four BET ratios.

Table 3 shows the results of the evaluation of four BET ratios. According four BET ratios, it was resulted that the annual average BET ratio(3) = 0.922 was the highest and its SE = 0.235 was the lowest in the deep LL data set, while the average BET ratio(4) = 0.225 was lowest and its SE = 0.311 was lowest in the regular LL data set. Therefore, BET ratio(3) was adopted as the best separator for the deep LL and BET ratio(4) as the best separator for the regular LL.

Then, using the learning data set, we further investigated these separators by breaking into class interval by 0.1 to learn which intervals produce the highest classification powers. Table 4 shows the results, which show correct and incorrect classification of deep and regular LL separated by BET ratio(3) and (4). Table 4 also shows the differences between correct and incorrect sets, which suggests that $0.8 \leq BET\ ratio(3) \leq 1$ and $0 \leq BET\ ratio(4) \leq 0.40$ are the most effective range intervals to separate deep and regular LL separation respectively as these intervals produce positive correct classifications.

Using these interval ranges of two separators, we further investigated which combinations of these intervals produce the highest correct classification. Table 5 shows the results, i.e., the best range was resulted to be $0.8 \leq BET\ ratio(3) \leq 1$ and $0 \leq BET\ ratio(4) \leq 0.40$. Fig. 5 summarizes the results, which suggested that 67.7% data were correctly classified, while 23.1% were un-classification (including 11.9 % for zero catches and 11.2% classified into both LL types) and 9.2% for errors misclassification. This implies that we can expect that 67.7% of the unknown data can be correctly classified into regular or deep LL if the unknown data patterns were similar to those of the learning data set. For the unclassified data, it is possible to substitute the stably classified (regular or deep) LL data neighboring to unclassified data. This is because the LL operation patters are almost homogenous within the small time-area scale unit.

Using the BET ratio(3) and BET ratio(4) separators, we classified the unknown LL type data sets (the whole 1979-94 data and 60% of the 1995-99 data). Then, we computed the nominal CPUE of ALB, BET, YFT, and SWO from 1979-99 by regular and deep LL and depicted their trends (Fig. 6). According to Fig. 6 nominal CPUE of ALB by the deep LL was very low because ALB was not the target species for the deep LL. The nominal CPUE of YFT by the deep LL showed the stable trend, but that of BET showed the decreasing trend. The values of ALB by the regular LL are high and it showed the robust but fluctuated trend. BET and YFT were not the target species for regular, but still some catches. In addition, the regular to target SWO began in 1992. The Taiwanese LL usually catches YFT using the regular or shallow lines. However, the values of nominal YFT CPUE of deep LL were higher than those of regular LL in Fig. 6. This is because the deep LL usually operates in the equatorial area, while the regular LL in high Latitude area in the Indian Ocean. The former area has higher YFT density than that of the latter area.[1]

DISCUSSION

The CPUE trend of Indian BET shows the decreasing trend in 1979-99, which result is similar to that of Japanese LL in the Indian Ocean.[7] That is both country's LL exploited the same stock shows the same trend. On the other hand, the whole catches of Indian ALB were stable between 8,300 t and 38,500 t as well as the average catch was about 19,200 t in 1979-99. Among the whole ALB catches, the Taiwanese catches were between 5,800 t and 22,500 t as well as the average catch was about 13,600 t in the same time (IOTC database). That is half Indian ALB catch at least came from the Taiwanese LL during the period. The assessment of the stock status was robust and the estimated maximum sustainable yield (MSY) was about 25,000t by many studies formerly.[3-6] That is the stock status of Indian ALB should be robust but fluctuated although there had sharply decreasing trend in the late 1990s owing to the high catch caught by the Taiwanese gill net fishery.[8] In other word, the applied method can separate the Taiwanese LL data into the deep and regular LL data effectively in this study.

It is expected that the developed criteria of $BET\ ratio(3)$ and $BET\ ratio(4)$ can classify unknown LL type in 67.7% of accuracy if the LL data patterns were similar to those of the learning data sets, while the rest of the data (23.3%) will be un- or mis- classified.

Three reasons why there are 23.3% of incorrect classification are that (a) 10-20% of BET is also caught by the regular LL which weaken the separation power, (b) the LL shape is assumed to be the theoretical cartenary curve in this paper, hence if this assumption were violated, the separation ability especially for BET ratio(3) will be weaken (means more misclassification errors) as deep LL catch less BET and (c) there are considerable amount of zero catch situations which make the separation impossible.

There is a possible solution to find mis- or un- classified LL data. After we separate daily base LL data into either regular or deep type, we map resultant distributions of two LL types. Then, if we find isolated heterogeneous LL types among the homogenous LL type, they are considered to be the misclassified data. However, this approach will take a huge workload and time to check all the historical data. But by conducting this error check, we can minimize the mis- and un- classified data. This checking works need to be conducted by wide range of professionals including tuna scientists, tuna fishers, industry and managers to get common understandings and agreements.

From Table 3, it was clearly resulted that BET ratios including YFT were not effective i.e., BET ratio (1) and BET ratio(2). This is probably because YFT occasionally moved to the deeper waters (deeper than 150m) although it usually distributed in the depth range of the regular LL (from 50-150m) [9-10], which probably weaken the separation ability.

For the 5^0x5^0 area and monthly LL type unknown data in 1967-78, we will extend the same criteria by the same way considering that 5^0x5^0 area and month is one sampling unit in the future.

In this paper, we did not consider BET ratios by season and area. In the future, the seasonal and regional variations need to be incorporated into the criteria in order to establish more practical separators. In addition, the exploratory data analyses were used in this paper, as the first step, to search the effective separators. However, in the future, the statistical method such as the logistic generalized linear model (GLM) or the neural network analysis is planned to apply as the next step.[11]

In applying the developed methods to other LL data in different Oceans and countries, we need to search best effective separators by examining species compositions and target species carefully, instead of just simply applying the developed BET separators in this paper.

Finally, if we could separate regular and deep LL accurately, it is expected that results of the tuna LL CPUE standardization and CPUE based stock assessments using VPA, ASPM, and ASPIC models etc. will become more reliable and robust.[11]

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Table 1 Type of the Taiwanese LL data in the Indian Ocean (1967-99).

Year	Area unit	Time unit	NHB* Information
1967-1978	$5^0 \times 5^0$	Monthly	Not available
1979-1994	$5^0 \times 5^0$	Daily	Not available
1995-1999	$5^0 \times 5^0$	Daily	available in the 40% of the data

*Number of Hooks per Basket.

Data source: Overseas Fisheries Development Council of the Republic of China

Table 2 Number of operations of Taiwanese tuna longline fisheries in the Indian Ocean by regular LL, deep LL and other type LL (1955-99). [(A) and (B) are used as the learning data sets in this paper.]

Year	Data type*				Available data
	Regular LL	Deep LL		Others	(%)
	(A)	(B)	(A)+(B)	(C)	[(A)+(B)]/[(A)+(B)+(C)]
1995	4330	2786	7116	12238	36.77
1996	5929	4955	10884	13608	44.44
1997	3948	5547	9495	16008	37.23
1998	4977	5007	9984	14057	41.53
1999	2955	6156	9111	12278	42.60
Total	22139	24451	46590	68189	40.59

* The regular LL is defined as 6 ≤NHB ≤ 10 and deep LL as 11 ≤ NHB ≤20, while others include the data with NHB≤5, 21≤NHB or without NHB information.

Table 3 Results of four BET ratios in the learning data sets.

BET * *ratio*	Year	Number of regular LL data sets	Average value	SE	Number of deep LL data sets	Average value	SE
(1)	1995-99	18908	0.594	0.399	24065	0.712	0.280
(2)	1995-99	19682	0.427	0.371	24357	0.620	0.286
(3)	1995-99	18322	0.357	0.400	23183	$\boxed{0.922}$	$\boxed{0.235}$
(4)	1995-99	19916	$\boxed{0.225}$	$\boxed{0.311}$	23637	0.772	0.293

Note (1)

$$* \quad BET\ ratio(1) = \frac{BET}{BET+YFT}; \quad BET\ ratio(2) = \frac{BET}{BET+YFT+SWO};$$

$$BET\ ratio(3) = \frac{BET}{BET+ALB}; \quad BET\ ratio(4) = \frac{BET}{BET+ALB+SWO}$$

Note (2): Following 0(zero) catch cases are excluded in the computations, i.e., data with BET=YFT=0 for BET (1), BET=YFT=SWO=0 for BET (2), BET=ALB=0 for BET (3) and BET=ALB=SWO=0 for BET (4).

Table 4 Results of classification by $BET\ ratio(3)$ (deep LL separator) and $BET\ ratio(4)$ (regular LL separator) by class interval.

Note: Two separators were applied to the regular & deep LL type known learning data set (1995-99) to classify into two group excluding 0 catch data BET=ALB=0 for BET (3) and BET=ALB=SWO=0 for BET (4).

Interval	$BET\ ratio(3)$ (deep LL separator)			$BET\ ratio(4)$ (regular LL separator)		
	(A) No. of mis-classification	(B) No. of correct classification	(B)-(A) Difference	(C) No. of correct classification	(D) No. of mis-classification	(C)-(D) Difference
0.0 ≤ ratio ≤ 0.1	8605	1080	-7525	$\boxed{11043(**)}$	1704	$\boxed{9339}$
0.1 < ratio ≤ 0.2	1552	187	-1365	$\boxed{2449(**)}$	532	$\boxed{1917}$
0.2 < ratio ≤ 0.3	868	135	-733	$\boxed{1387(**)}$	451	$\boxed{936}$
0.3 < ratio ≤ 0.4	738	147	-591	$\boxed{1032(**)}$	534	$\boxed{498}$
0.4 < ratio ≤ 0.5	707	145	-562	755	829	-74
0.5 < ratio ≤ 0.6	503	133	-370	367	789	-422
0.6 < ratio ≤ 0.7	514	195	-319	350	1379	-1029
0.7 < ratio ≤ 0.8	455	322	-133	354	2559	-2205
0.8 < ratio ≤ 0.9	306	$\boxed{625(*)}$	$\boxed{319}$	470	3793	-3323
0.9 < ratio ≤ 1.0	4074	$\boxed{20214(*)}$	$\boxed{16140}$	1709	11067	-9358
Total	18322	23183		19916	23637	

(*) total correct n=20,839 and (**) total correct n=15,911

Table 5 Result of the classification by different ranges of BET (3) and BET (4) producing positive correct classification (refer to Table 4).

Range of BET(3)➔		0.8≤BET(3)≤1.0				0.9≤BET(3)≤1.0			
Range of BET(4)➔		0≤BET(4)≤0.1	0≤BET(4)≤0.2	0≤BET(4)≤0.3	0≤BET(4)≤0.4	0≤BET(4)≤0.1	0≤BET(4)≤0.2	0≤BET(4)≤0.3	0≤BET(4)≤0.4
Resultant Classification	type	Number (%)	Number (%)	Number (%)	Number (%)	Number (%)	Number (%)	Number (%)	Number (%)
Un-classified	Number of 0 catch: BET=ALB=0 (inc. BET=ALB=SWO=0)	5,529 (11.9%)							
	Number of the data classified into both LL types by BET(3) & BET (4)	3,263 (7.0)	3,890 (8.4)	4,518 (9.7)	5,225 (11.2)	3,256 (7.0)	3,868 (8.3)	4,456 (9.6)	5,105 (10.9)
Correct classification	(A) Number of correctly classified data into REGULAR LL by BET ratio (4) excluding those classified into both type	8,477 (18.2)	10,543 (22.6)	11,569 (24.8)	12,283 (26.4)	8,482 (18.2)	10,557 (22.7)	11,619 (24.9)	12,385 (26.6)
	(B) Number of correctly classified data into DEEP LL by BET ratio (4) excluding those classified into both type	20,142 (43.2)	19,898 (42.7)	19,631 (42.1)	19,242 (41.3)	19,519 (41.9)	19,281 (41.4)	19,018 (40.8)	18,635 (40.0)
Mis-Classification	Number of misclassified data	9,179 (19.7)	6,730 (14.4)	5,343 (11.5)	4,311 (9.2)	9,804 (21.0)	7,355 (15.8)	5,968 (12.8)	4,936 (10.6)
Total	Number of the learning data set (1995-99)	46,590 (100%)							
Expected prob. of correct classification	(A)+(B)	28,619 (61.4)	30,441 (65.3)	31,200 (66.9)	31,525 $\boxed{(67.7)}$ ***highest***	28,001 (60.1)	29,838 (64.0)	30,637 (65.7)	31,020 (66.6)

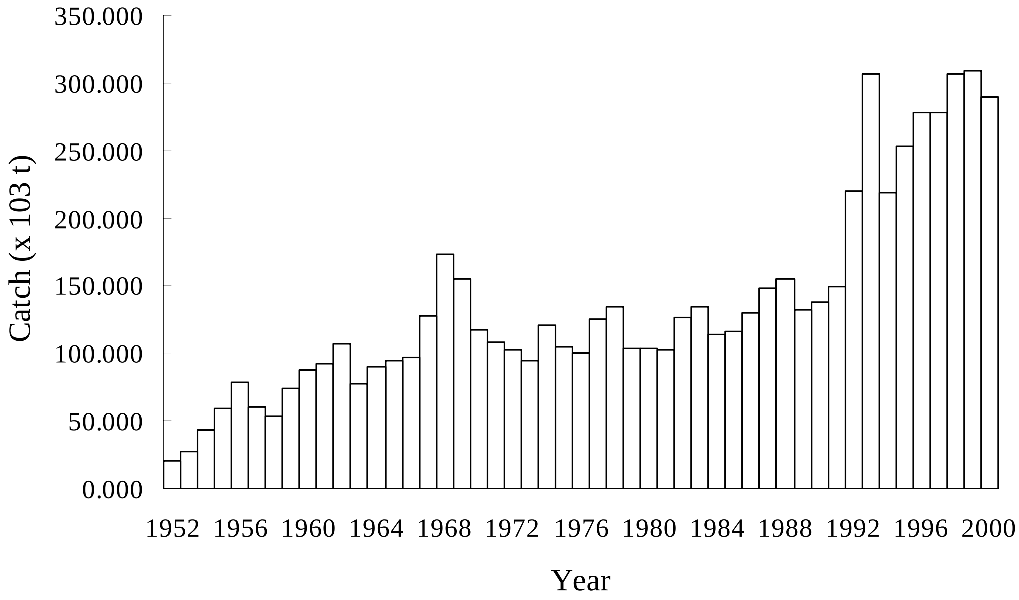


Fig. 1 Trend of tuna production by the longline fisheries in the Indian Ocean (1952-2000)

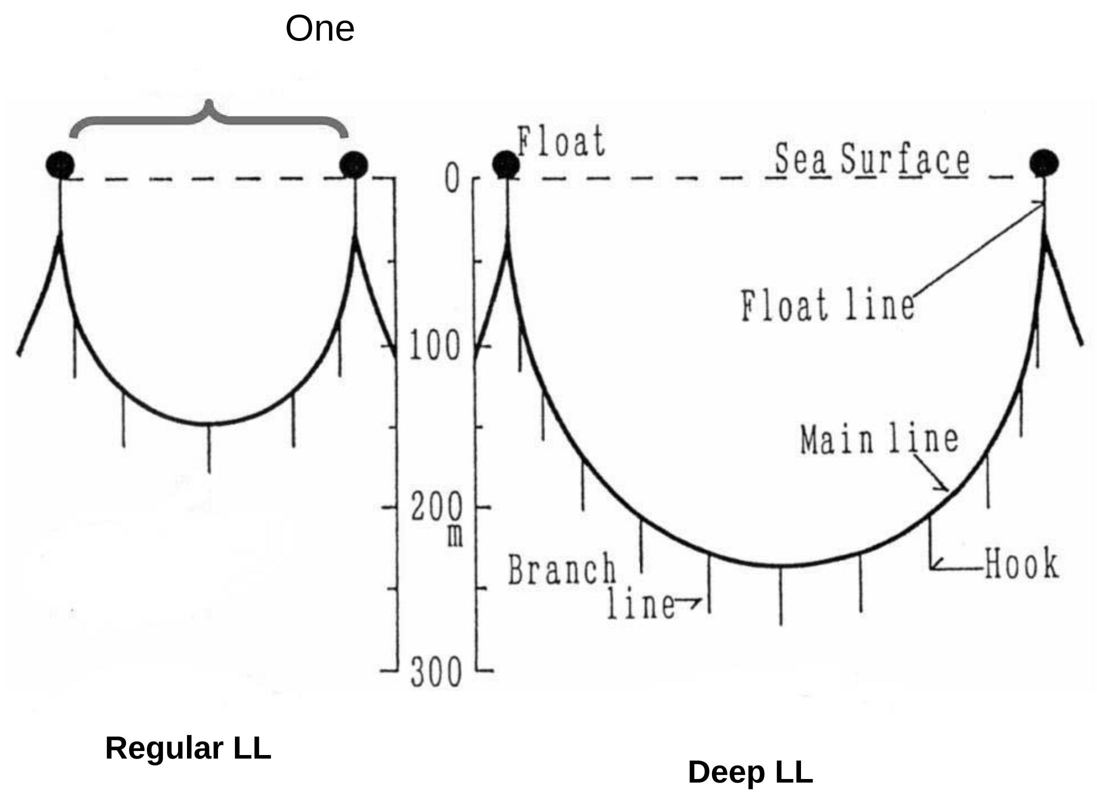


Fig. 2 Schematic diagram of regular and deep longline (LL)

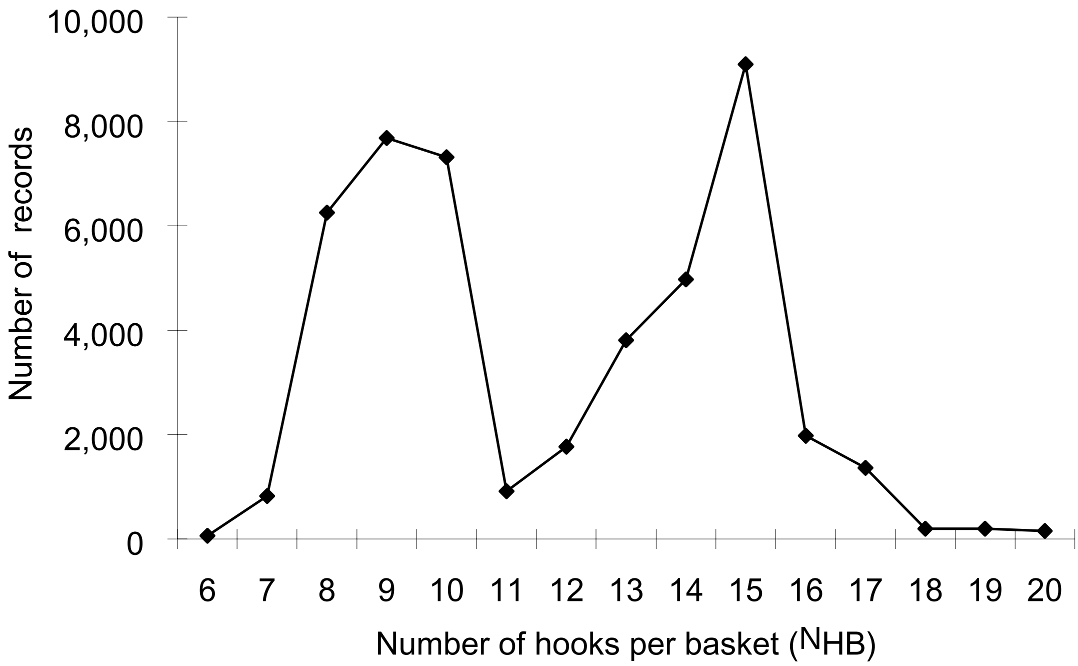
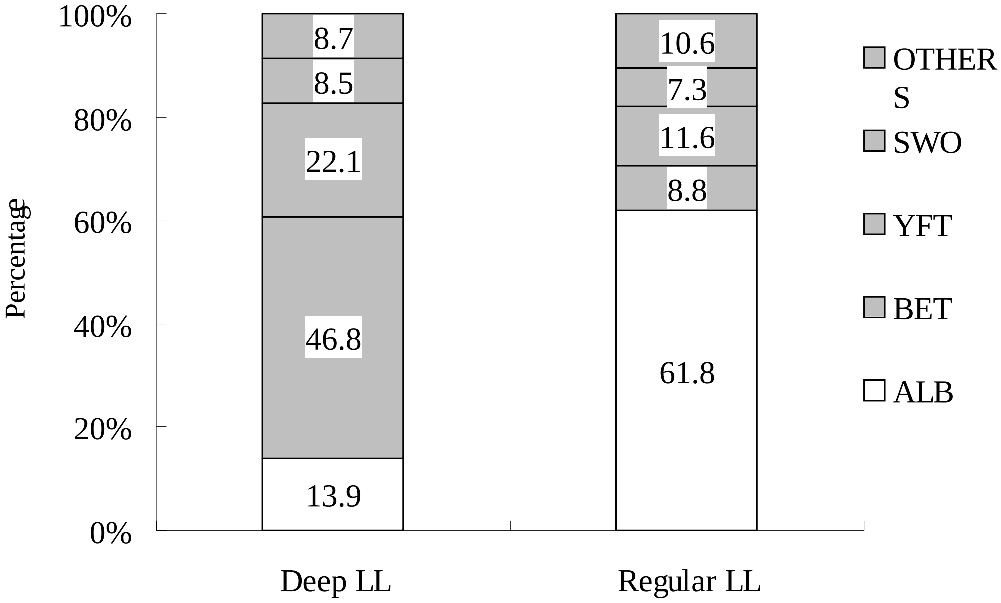


Fig 3. Frequency distribution of NHB in the leaning data set (1995-99) (n=46,590)



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ig. 4 Species compositions of deep and regular LL in the learning data set (n=46,590)

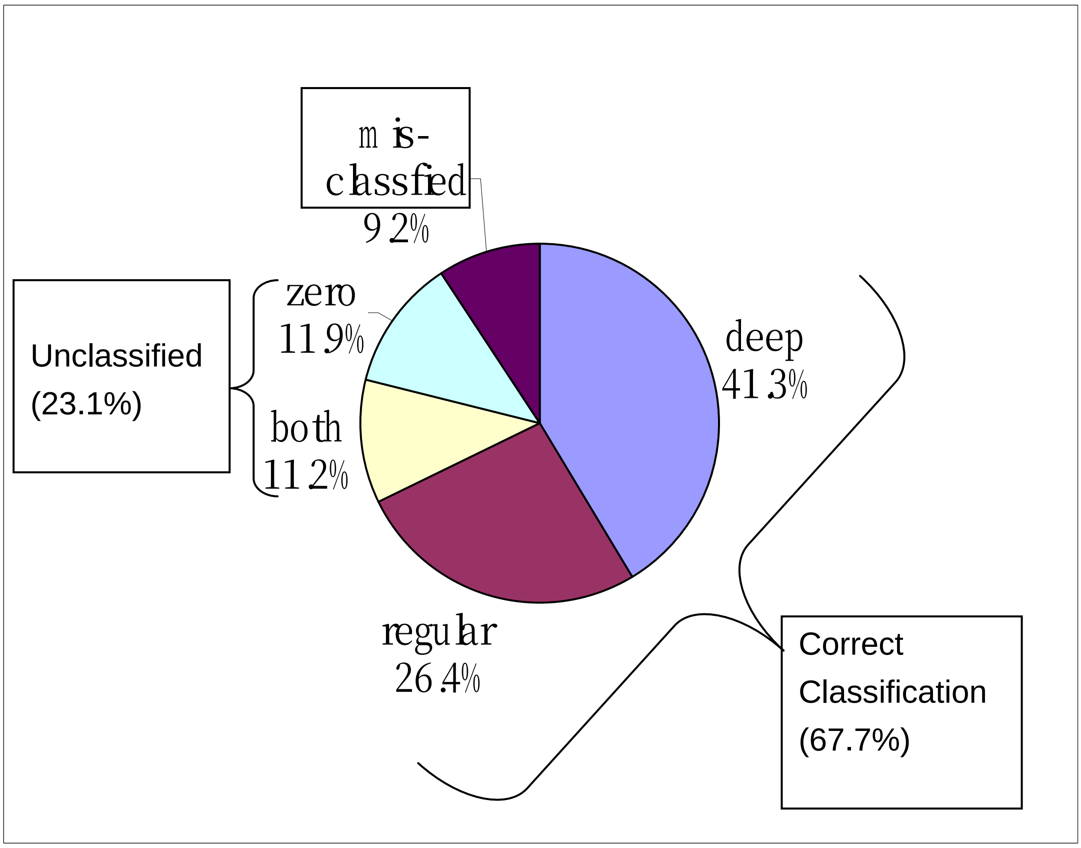

Fig. 5 Results of the classification by BET (3) & BET (4) applied to the learning data set (1955-99) (n=46,590)

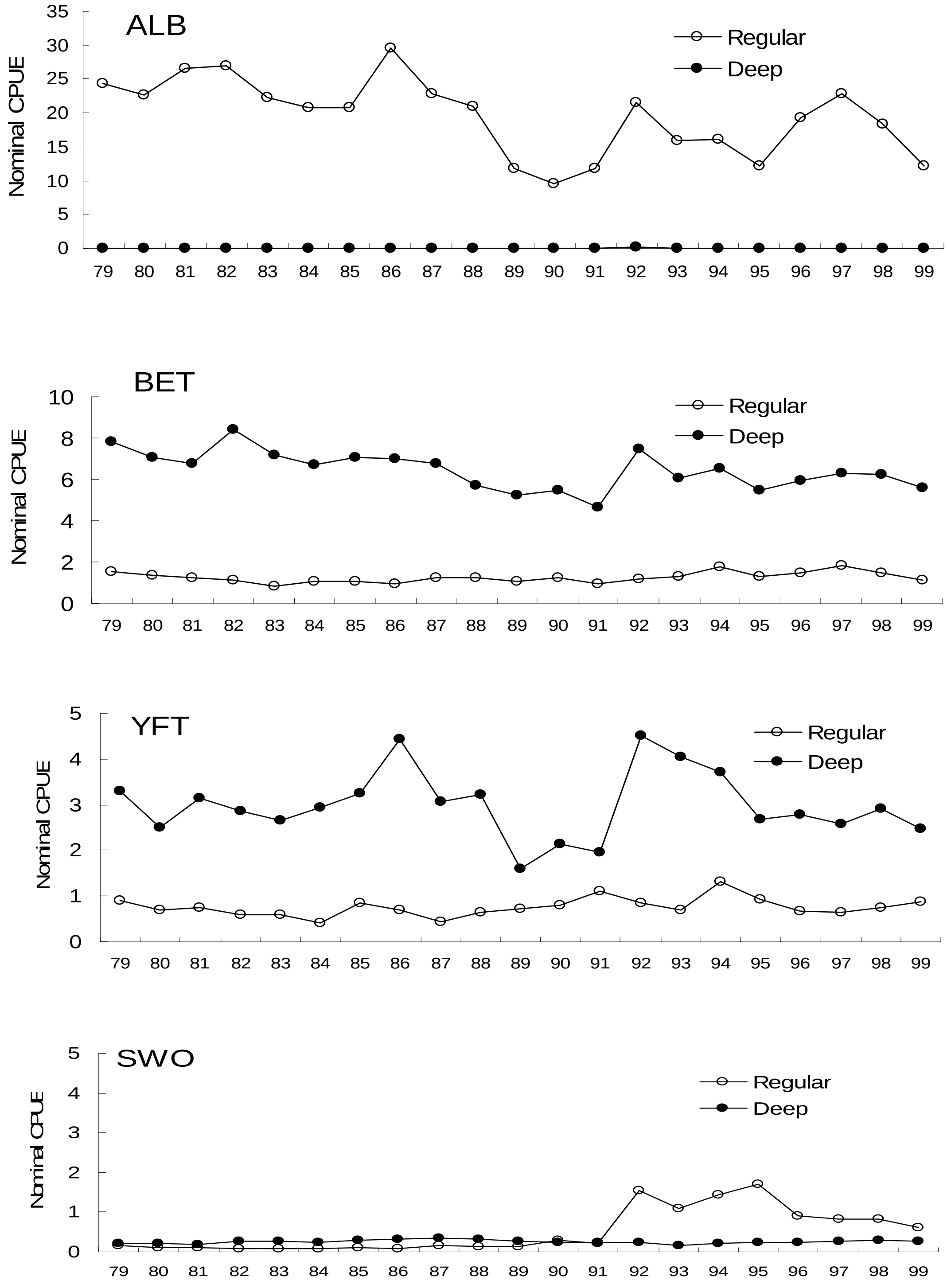

Fig. 6 Trend of nominal CPUE (ALB, BET, YFT and SWO) of unknown LL data classified into regular and deep LL types by $0.8 \leq$ *BET ratio*(3) ≤ 1 and $0 \leq$ *BET ratio*(4) ≤ 0.40. (note: the unclassified data with zero catches are excluded