

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

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ABSTRACT: Taiwanese longline (LL) fisheries operating in the Indian Ocean usually target albacore tuna (ALB), swordfish (SWO) and yellowfin tuna (YFT) using regular LL. Bigeye tuna (BET), however, is targeted using deep LL. Thus, these two types of LL are considered to be different gears as they target different tuna species. Regular or deep LL fishing is defined by number of hooks per basket (NHB): regular LL if $6 \leq \text{NHB} \leq 10$ and deep LL if $11 \leq \text{NHB} \leq 20$. However, NHB information was available in only some of the recent LL data (1995–1999). This situation had caused problems of biased results in stock analysis in the past. Thus, the objective of our study was to explore an effective method to separate the two types of LL fishing by considering species composition. Some intervals of BET catch ratios were found to be effective in separating the regular and deep LL catches, i.e. $0.0 \leq \text{BET}/(\text{BET} + \text{ALB} + \text{SWO}) \leq 0.4$ and $0.8 \leq \text{BET}/(\text{BET} + \text{ALB}) \leq 1.0$, respectively. Using these two separators, the LL known data set (1995–1999) (learning data set) was classified. Correct classification occurred in 67.7% of the data, while 23.1% of the data were unclassified (11.9% due to zero catches and 11.2% due to classification into both LL types), and 9.2% were misclassifications. Then, using the methods developed, the LL unknown data set in the historical data (1979–1999) was classified and nominal CPUE values were calculated for four species. The CPUE trends based on this study were likely to be more reliable than those of previous studies.

KEY WORDS: bigeye tuna catch ratios, Indian Ocean, regular and deep tuna longline, separators.

INTRODUCTION

The industrial tuna longline (LL) fisheries in the Indian Ocean began in 1952 (Japan), 1954 (Taiwan), 1966 (Korea), and the 1980s (Indonesia, Sri Lanka and other developing countries).¹ The total annual catches of all LL fisheries gradually increased from 20 000 t in 1952 to 170 000 t in 1967, then decreased and stabilized at 100 000–150 000 t in 1968–1991. After 1992, the total annual catches suddenly increased then stabilized at 200 000–300 000 t in 2000 (Indian Ocean Tuna Commission (IOTC) database) (Fig. 1).

The LL was composed of a mainline and many branch lines with hooks at the terminal end. There

were two types of LL, i.e. regular LL and deep LL, which were defined by number of hooks between two floating balls (NHB). The regular LL had fewer NHB, while the deep LL had more NHB. The number of NHB between regular LL and deep LL was slightly different depending on the country. The fishing depth of LL depended on the number of branch lines between two floating balls and the length of the branch lines (Fig. 2). Taiwanese fisheries refer to the number of branch lines between two floating balls as a 'basket'. Thus, the term basket is used in Figure 2. If the LL forms a 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.

Around 1986, Taiwanese longliners in the Indian Ocean equipped with super-cold storage began catching bigeye tuna *Thunnus obesus* (BET) using deep LL at an operation depth of 50–200 m.² Their target species was different from the Taiwanese tra-

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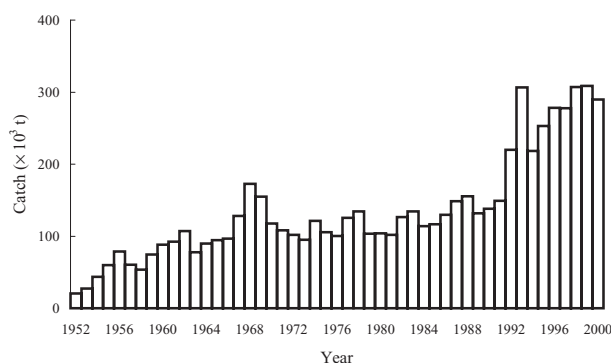


Fig. 1 Trend in tuna production from longline fisheries in the Indian Ocean (1952–2000).

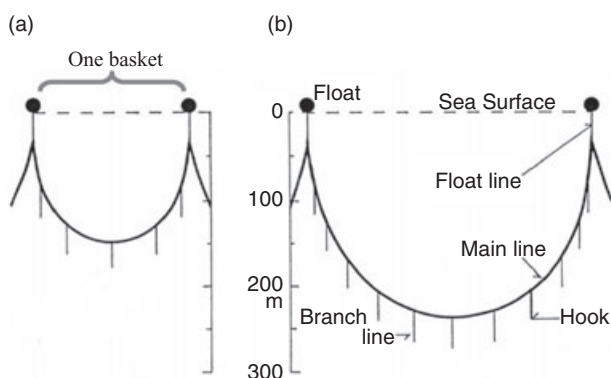


Fig. 2 Schematic diagram of (a) regular, and (b) deep longline gears.

ditional longliners (regular LL or shallow LL)² with an operation depth of 50–120 m, primarily targeting albacore *Thunnus alalunga* (ALB), swordfish *Xiphias gladius* (SWO) and yellowfin tuna *Thunnus albacares* (YFT) in the Indian Ocean.

In the past, no NHB information had caused biases on standardizing the nominal catch per unit effort (CPUE) and on 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.³ In order to conduct more realistic or unbiased tuna fisheries resource analysis, it was necessary to separate these two types of LL, regular LL and deep LL, because they targeted different species and need to be treated as different gears.

Under such circumstances, the Taiwanese government decided to collect NHB information from fishing vessel logbooks in all three oceans starting from 1995. As a result, Taiwanese fishery biologists began developing the methods to separate regular LL and deep LL in the Indian Ocean.^{4–6} NHB infor-

Table 1 Taiwanese longline data for the Indian Ocean (1967–1999)

Year	Area unit	Time unit	NHB [†] Information
1967–1978	5° × 5°	Monthly	Not available
1979–1994	5° × 5°	Daily	Not available
1995–1999	5° × 5°	Daily	available in 40% of data

[†]Number of hooks per basket.

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

mation and species compositions of the LL data were used to separate regular LL and deep LL and to estimate ALB CPUE. The results showed robust and smooth trends in both LL, but the trends without separation showed a sharp decrease in the combined (unseparated) LL, which is likely neither realistic nor accurate.^{4,5} In those studies, catch ratios of ALB/(BET + ALB) were used to distinguish between regular LL and deep LL.

However, it was necessary to take account of the BET, YFT, ALB and SWO catches with the appropriate separation method as these species were the primary species of Taiwanese LL fisheries in the Indian Ocean. Therefore, the objective of this study was to develop more general and accurate separators in considering these four species. In this study, we used exploratory data analysis to develop a separation method.

MATERIALS AND METHODS

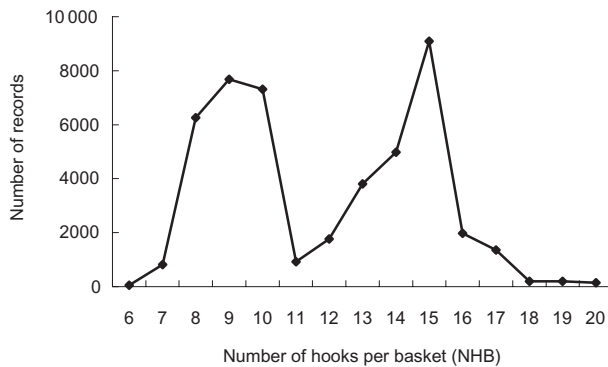
Two data sets were used in this study: (i) regular and deep LL known data set (learning data set); and (ii) regular and deep LL unknown data set. The source of these data was the Overseas Fisheries Development Council of Taiwan. Table 1 shows the types of LL data. Approximately 40% of the Taiwanese LL set-by-set data for 1995–1999 included NHB information for the Indian Ocean, which can be used as the learning data set (Table 2). The regular and deep LL unknown data set (all data for 1979–1994 and 60% of the data for 1995–1999) did not contain NHB information. The aim of this work was to develop the most effective separators to classify LL unknown data sets into regular or deep LL, using these regular and deep LL known data sets. Data on BET, YFT, ALB and SWO were collected to look at unique species compositions observed in regular and deep LL. Then, LL unknown data were separated into regular or deep LL and classification powers (accuracy) of these separators were evaluated.

Table 2 Number of operations of Taiwanese tuna longline fisheries in the Indian Ocean by regular LL, deep LL and unknown LL (1995–1999)

Year	LL type			Composition of the known (regular or deep LL) data set (%) [(A) + (B)] / [(A) + (B) + (C)]
	Regular LL [†] (A)	Deep LL [‡] (B)	(A) + (B) (C)	
1995	4 330	2 786	7 116	36.77
1996	5 929	4 955	10 884	44.44
1997	3 948	5 547	9 495	37.23
1998	4 977	5 007	9 984	41.53
1999	2 955	6 156	9 111	42.60
Total	22 139	24 451	46 590	40.59

[†]Regular LL as $6 \leq \text{NHB} \leq 10$.[‡]Deep LL as $11 \leq \text{NHB} \leq 20$.[§]Unknown LL included in the data without NHB information and a few unclassified data as $\text{NHB} \leq 5$ or $\text{NHB} \geq 21$.

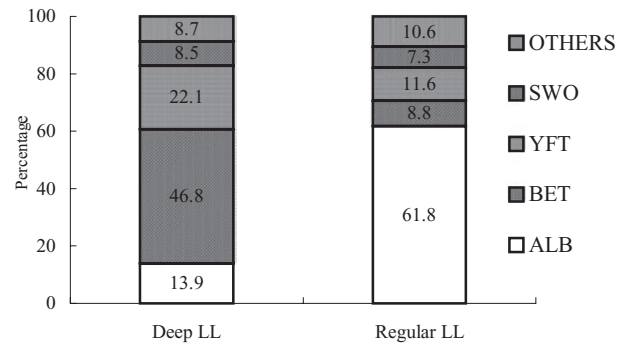
Note: (A) and (B) were used as the learning data sets in this paper.

**Fig. 3** Frequency distribution of NHB in the learning data set from 1995 to 1999 ($n = 46\,590$).

RESULTS

Using the learning data set, the definition of regular LL and deep LL by analyzing the NHB information was initially investigated. The range of NHB in this data set was 6–20, and formed a bimodal distribution (Fig. 3). The lower number of NHB denotes regular or shallow LL, while the higher number denotes deep LL. Based on the patterns of Figure 3 and also the fishing customs of Taiwanese LL fisheries, this study defined regular LL with $6 \leq \text{NHB} \leq 10$ and the deep LL with $11 \leq \text{NHB} \leq 20$.

In order to investigate the most effective separators, species compositions by regular and deep LL were further investigated using the learning data set (Fig. 4). In the regular LL, ALB was the major species (61.8%), while BET, YFT, and SWO were 8.8, 11.6 and 7.3%, respectively. In the deep LL, however, the major species was BET (46.8%), while species compositions of ALB, YFT, and SWO were 13.9, 22.1 and 8.5%, respectively. Therefore, ALB may seem to be an effective indicator to separate regu-

**Fig. 4** Species compositions of deep and regular longline in the learning data set ($n = 46\,590$).

lar and deep LL, as the compositions of these two gears were differentiated (61.8% vs 13.9%). However, ALB was exploited only in the southern part of the Indian Ocean;⁷ hence, ALB was not considered to be a useful indicator for the entire Indian Ocean. Although BET compositions were less differentiated (8.8% vs 46.8%), BET was exploited in much wider areas in the Indian Ocean. In addition, BET was distributed in deeper waters (150–400 m) and it was the target species of the Taiwanese deep LL fisheries in the Indian Ocean. Hence, BET catch ratios were considered to be more effective than ALB catch ratios in separating regular and deep LL catches. Therefore, in this study, BET catch ratios were adopted as effective separators by combining catches of the other three species. The four BET ratios are defined as follows:

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

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

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

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

BET, ALB, YFT and SWO were the catches in number of fish for bigeye tuna, albacore tuna, yellowfin tuna and swordfish, respectively. From these ratios, the best separator will be selected if the BET ratio has the highest value in the deep LL data set and if the BET ratio has the lowest value in the regular LL data set.

In evaluating these BET ratios, zero catches need to be excluded because the BET ratios cannot be calculated, i.e. $\text{BET} = \text{YFT} = 0$ for BET ratio (1), $\text{BET} = \text{YFT} = \text{SWO} = 0$ for BET ratio (2), $\text{BET} = \text{ALB} = 0$ for BET ratio (3), and $\text{BET} = \text{ALB} = \text{SWO} = 0$ for BET ratio (4).

The annual average BET ratio (3) = 0.922 was the highest and its standard error (SE) = 0.235 was the lowest in the deep LL data set, while the annual average BET ratio (4) = 0.225 was lowest and its

SE = 0.311 was lowest in the regular LL data set (Table 3). Therefore, BET ratio (3) was adopted as the best separator for the deep LL, and BET ratio (4) was adopted as the best separator for the regular LL.

Then, using the learning data set, these separators were further investigated by using a class interval of 0.1 to learn which intervals produced the most accurate classification powers as defined by correct and incorrect classification of deep and regular LL separated by BET ratios (3) and (4) (Table 4). The differences between correct and incorrect sets suggested that $0.8 \leq \text{BET ratio (3)} \leq 1.0$ and $0.0 \leq \text{BET ratio (4)} \leq 0.4$ were the most effective range intervals to separate deep and regular LL, respectively, as these intervals produced correct classifications.

Using these interval ranges of two separators, which combinations of these intervals (by 0.1 interval) produced the highest correct classifications were investigated. Eight cases as shown in Table 5 were investigated, i.e. two intervals for BET ratio (3) (0.8–1.0 and 0.9–1.0) and four intervals for

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)	1995–1999	18 908	0.594	0.399	24 065	0.712	0.280
(2)	1995–1999	19 682	0.427	0.371	24 357	0.620	0.286
(3)	1995–1999	18 322	0.357	0.400	23 183	0.922	0.235
(4)	1995–1999	19 916	0.225	0.311	23 637	0.772	0.293

$$^{\dagger} \text{BET ratio (1)} = \frac{\text{BET}}{\text{BET} + \text{YFT}}; \text{BET ratio (2)} = \frac{\text{BET}}{\text{BET} + \text{YFT} + \text{SWO}}; \text{BET ratio (3)} = \frac{\text{BET}}{\text{BET} + \text{ALB}}; \text{BET ratio (4)} = \frac{\text{BET}}{\text{BET} + \text{ALB} + \text{SWO}}.$$

Note: The following zero catch cases are excluded in the calculations: data with $\text{BET} = \text{YFT} = 0$ for BET ratio (1), $\text{BET} = \text{YFT} = \text{SWO} = 0$ for BET ratio (2), $\text{BET} = \text{ALB} = 0$ for BET ratio (3) and $\text{BET} = \text{ALB} = \text{SWO} = 0$ for BET ratio (4).

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

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
$0.0 \leq \text{ratio} \leq 0.1$	8 605	1 080	–7 525	11 043[‡]	1 704	9339
$0.1 \leq \text{ratio} \leq 0.2$	1 552	187	–1 365	2 449[‡]	532	1917
$0.2 \leq \text{ratio} \leq 0.3$	868	135	–733	1 387[‡]	451	936
$0.3 \leq \text{ratio} \leq 0.4$	738	147	–591	1 032[‡]	534	498
$0.4 \leq \text{ratio} \leq 0.5$	707	145	–562	755	829	–74
$0.5 \leq \text{ratio} \leq 0.6$	503	133	–370	367	789	–422
$0.6 \leq \text{ratio} \leq 0.7$	514	195	–319	350	1 379	–1029
$0.7 \leq \text{ratio} \leq 0.8$	455	322	–133	354	2 559	–2205
$0.8 \leq \text{ratio} \leq 0.9$	306	625[†]	319	470	3 793	–3323
$0.9 \leq \text{ratio} \leq 1.0$	4 074	20 214[†]	16 140	1 709	11 067	–9358
Total	18 322	23 183		19 916	23 637	

[†]total correct records = 20 839 and [‡]total correct records = 15 911.

Note: Two separators were applied to the regular and deep LL known learning data sets (1995–1999) to classify into two group excluding zero catch data $\text{BET} = \text{ALB} = 0$ for BET ratio (3) and $\text{BET} = \text{ALB} = \text{SWO} = 0$ for BET ratio (4).

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

Resultant classification	Type	0.8 ≤ ratio (3) ^{§§} ≤ 1.0						0.9 ≤ ratio (3) ^{§§} ≤ 1.0									
		0 ≤ ratio (4) ^{¶¶} ≤ 0.1		0 ≤ ratio (4) ^{¶¶} ≤ 0.2		0 ≤ ratio (4) ^{¶¶} ≤ 0.3		0 ≤ ratio (4) ^{¶¶} ≤ 0.4		0 ≤ ratio (4) ^{¶¶} ≤ 0.1		0 ≤ ratio (4) ^{¶¶} ≤ 0.2		0 ≤ ratio (4) ^{¶¶} ≤ 0.3		0 ≤ ratio (4) ^{¶¶} ≤ 0.4	
		Number (%)		Number (%)		Number (%)		Number (%)		Number (%)		Number (%)		Number (%)		Number (%)	
Unclassified	Zero catch [†]	5 529 (11.9%)		5 529 (11.9%)		5 529 (11.9%)		5 529 (11.9%)		5 529 (11.9%)		5 529 (11.9%)		5 529 (11.9%)		5 529 (11.9%)	
	Data with both types [‡]	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	Regular LL (A) [§]	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)	
classification	Deep LL (B) [¶]	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)	
Misclassification		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 ^{††}		46 590 (100%)		46 590 (100%)		46 590 (100%)		46 590 (100%)		46 590 (100%)		46 590 (100%)		46 590 (100%)		46 590 (100%)	
Expected probability (A + B) ^{‡‡}		28 619 (61.4)		30 441 (65.3)		31 200 (66.9)		31 525 (67.7)	highest	28 001 (60.1)		29 838 (64.0)		30 637 (65.7)		31 020 (66.6)	

[†]BET = ALB = 0, including BET = ALB = SWO = 0.

[‡]Number of the data classified into both LL types by BET ratio (3) and BET ratio (4).

[§]Number of correctly classified data into regular LL by BET ratio (4), excluding those classified into both types.

[¶]Number of correctly classified data into deep LL by BET ratio (3), excluding those classified into both types.

^{††}Number of the learning data set (1995–1999).

^{‡‡}Expected probability of correct classification.

^{§§}Abbreviation of BET ratio (3).

^{¶¶}Abbreviation of BET ratio (4).

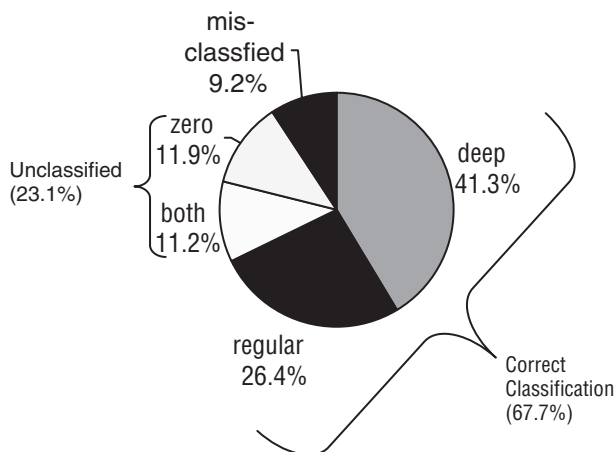


Fig. 5 Results of the classification BET ratio (3) and BET ratio (4) applied to the learning data set for 1995–1999 ($n = 46\,590$).

BET ratio (4) (0–0.1, 0–0.2, 0–0.3 and 0–0.4). The best range appeared in $0.8 \leq \text{BET ratio (3)} \leq 1.0$ and $0.0 \leq \text{BET ratio (4)} \leq 0.4$. It was suggested that 67.7% of the data were correct classifications, while 23.1% were incorrect classifications (including 11.9% due to zero catches and 11.2% due to classification into both LL types) and 9.2% were due to misclassifications (Fig. 5). This result implied that 67.7% of the unknown data can be correctly classified as regular or deep LL if the species composition of the unknown data is similar to those of the learning data set.

The nominal CPUE (number of fish per 10^3 fishing hooks) of ALB, BET, YFT, and SWO from 1979 to 1999 by regular and deep LL were calculated (Fig. 6). The nominal CPUE of ALB by the deep LL had lower values because ALB was not the target species for the deep LL, while the trend for the regular LL was higher. In addition, the nominal CPUE of YFT by deep LL showed a stable trend except during 1986–1992, which showed high variation. However, that of BET showed a long-term decreasing trend from 1979 to 1991. The values in 1992 were similar to the levels of 1980, but after that, there was a smooth decrease from 1992 to 1999. YFT and BET were not the target species for regular LL, but still some catches were listed in the logsheets. The Taiwanese LL fisheries usually caught YFT using regular or shallow LL. However, the values of nominal YFT CPUE of deep LL were higher than those of regular LL. This is because deep LL usually operated in equatorial areas, while the regular LL operated in higher latitudes in the Indian Ocean. The former area had higher YFT density than that of the latter area.¹ In addition, the regular LL targeted SWO beginning in 1992.

DISCUSSION

The CPUE trends of Indian BET based on this study were likely to be more reliable than that of a previous study⁶ because of the following reasons. The CPUE trend of Indian BET decreased from 1979 to 1999, which was similar to that of the Japanese LL in the Indian Ocean.⁸ That is, LL for both countries exploited the same stock and thus the CPUE trends of both LL should show a similar trend. However, the decrease was opposite to that of a previous study,⁶ in which BET CPUE increased from 1991 to 1999. The results of that study may show higher BET CPUE values because of the ALB ratio ($\text{ALB}/(\text{ALB} + \text{BET}))$ adopted for the studies.^{4,6} These authors separated the Taiwanese regular LL data when ALB ratio ≥ 0.82 – 0.97 for specific months in the high latitude area, ALB ratio ≤ 0.02 for all months in the equatorial area, and when ALB ratio ≥ 0.38 for all months in the south-western area; otherwise, all data were classified as Taiwanese deep LL. Among the three ALB ratios, the second one most probably misclassified many deep LL data with low BET catch as regular LL data. For example, one BET (individual only) was caught in a deep LL operation, where $\text{BET} = 1$ and $\text{ALB} = \text{YFT} = \text{SWO} = 0$. The calculated ALB ratio ($\text{ALB}/(\text{ALB} + \text{BET})) = 0$ and thus this record is misclassified as regular LL. Misclassifications are a particular problem for catch data from the equatorial area. However, BET ratio (3) ($\text{BET}/(\text{ALB} + \text{BET})) = 1$ and thus the record is correctly classified as deep LL. In another scenario, one ALB (individual only) was caught in a regular LL operation, $\text{ALB} = 1$ and $\text{BET} = \text{YFT} = \text{SWO} = 0$. The calculated ALB ratio ($\text{ALB}/(\text{ALB} + \text{BET})) = 1$ and thus this record of data is correctly classified as regular LL. In addition, BET ratio (4) ($\text{BET}/(\text{ALB} + \text{BET} + \text{SWO})) = 0$ and thus the record is also correctly classified as regular LL. Therefore, BET CPUE values of the previous study⁶ have higher values because of misclassification of many deep LL with low catch as regular LL, and it showed an increasing trend from 1991 to 1999.

Total ALB catches from the Indian Ocean were between 8300 t and 38 500 t, and the average catch was about 19 200 t from 1979 to 1999. Among the total ALB catches, the Taiwanese catches were between 5800 t and 22 500 t, and the average catch was about 13 600 t in the same period.⁵ Thus, at least half of the Indian ALB catch came from the Taiwanese LL. As the maximum sustainable yield (MSY) of ALB is approximately 25 000 t,^{4–7} the stock status of Indian ALB should be robust but it fluctuated. Still, there was a sharply decreasing trend in the late 1990s owing to the high catch rate of the Taiwanese drift gill net fishery.⁹ Therefore, the

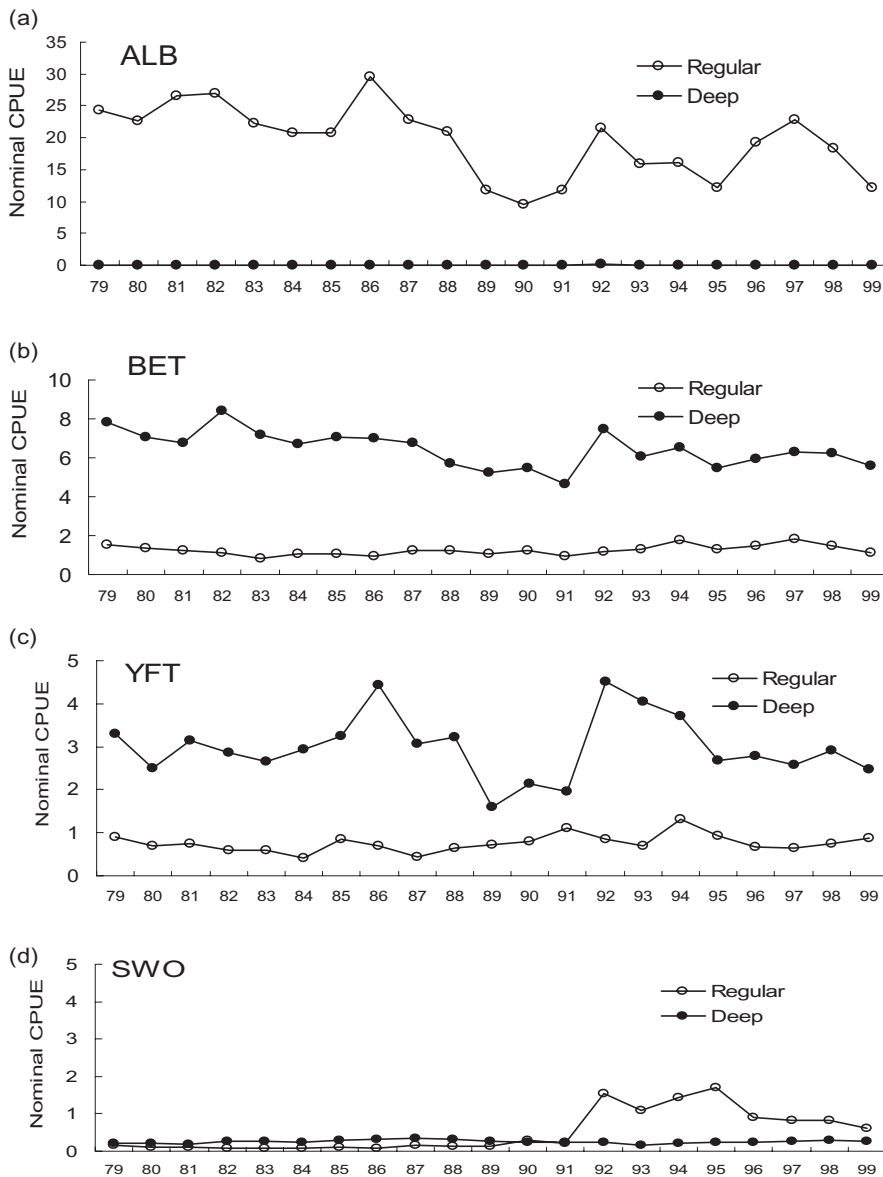


Fig. 6 Trend of nominal CPUE for (a) ALB, (b) BET, (c) YFT, and (d) SWO of LL unknown data classified as regular and deep LL types by $0.8 \leq \text{BET ratio (3)} \leq 1.0$ and $0.0 \leq \text{BET ratio (4)} \leq 0.4$. Note that un-classified data with zero catches were excluded.

applied method can effectively separate Taiwanese LL data into deep and regular LL.

There are three reasons for the 32.3% incorrect classification. First, 10–20% of BET was supposed to be exploited by the deep LL but were misclassified as regular LL, weakening the separation power of the method. Second, the LL shape was assumed to be a theoretical catenary. The depths of the deep LL should be deeper than that of the regular LL according to this assumption. However, sometimes the depths of the former may be not deeper than that of the latter underwater. Hence, if this assumption is not true, separation ability, especially for BET ratio (3), is weakened. Misclassification errors occurred because deep LL caught fewer

BET. Third, there were zero catch situations, which made the separation impossible.

A possible solution was to substitute mis- or unclassified LL data. After the daily LL data was separated into either regular LL or deep LL, resultant distributions of the two LL types were mapped. Isolated heterogeneous LL types found among the homogenous LL type on the map were considered to be misclassified data. This approach requires time to check all historical data. However, by conducting this error check, the incidence of mis- and unclassified data was minimized. Error checking was conducted by professional tuna scientists, tuna fishers, industry representatives and managers to acquire common understanding and agreement.

Alternatively, the BET ratio method was considered to be less useful in the ALB fishing area at high latitude, as there were less BET catches in these waters,^{10,11} which weakened the separation ability. Further, calculated BET ratios were probably variable because of seasons and subarea effects.

From Table 3, it is concluded that BET ratios including YFT, BET ratio (1) and BET ratio (2), were not effective. This is probably because YFT occasionally moved to waters deeper than 150 m, although it is usually distributed in regular LL depths (50–150 m),^{12,13} which probably weakened the separation ability.

For the LL unknown data set to separate into regular and deep LL in $5^{\circ} \times 5^{\circ}$ area on a monthly basis, the same criteria can be applied to separate regular and deep LL by considering the area and month as one sampling unit.

In this study, BET ratios were not considered by season and area. In the future, the seasonal and regional variations should be incorporated into the criteria in order to establish more practical separators. In addition, exploratory data analyses were used in this paper, as the first step, to search for effective separators. However, it was suggested that the statistical method (modeling approach), such as a logistic generalized linear model or neural network analysis, needed to be developed to generalize our method.¹⁴

In applying the developed methods to other LL data in different oceans and countries, the best effective separators may be obtained by examining species compositions and target species carefully as we did in our study, instead of simply applying the BET separators developed in this paper.

Finally, if regular and deep LL were separated accurately, it is expected that results of the tuna LL CPUE standardization and CPUE based stock assessments using models including virtual population analysis, age-structured production model, and a surplus production model incorporating covariates models, will become more reliable and robust.¹⁴

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