SOME CONSIDERATIONS TO SEPARATE TAIWANESE REGULAR AND DEEP LONGLINERS

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ABSTRACT

The Taiwanese Indian longline (LL) fishery usually catches albacore tuna (ALB), swordfish (SWO), and yellowfin tuna (YFT) using the regular or shallow lines, on the contrary, bigeye tuna (BET) using the deep lines. It is important separating the different gear's LL data to respond the precise fishing behavior. Based on the daily set-by-set Taiwanese LL catch and effort data including the number of hooks per basket (HPB) information from 1995-99 in the Indian Ocean, this study develops a simple and robust method to separate the Taiwanese regular and deep LL data in 1979-99. Firstly, we defined the regular LL if HPB <=10, while the deep LL if HPB => 11. Then we create four Bet ratios: BET ratio (1) = BET / (BET+YFT); BET ratio (2) = BET / (BET+YFT+SWO); BET ratio (3) = BET / (BET+ALB); and BET ratio (4) = BET / (BET+ALB+SWO).

The yearly average of BET ratios (1) and (2) did not concentrate. That is it was difficult to separate the Taiwanese regular and deep LL using these two ratios. Contrarily, the yearly averages of BET ratios (3) and (4) showed concentrated. If we defined that the BET ratio = 0.80 was the boundary, the expected probabilities of correct and mis-classification for regular LL and deep LL were estimated. If 0.8 <= BET(3) ratio, the correct probability was about 89.9% for deep LL, however, it still had 10.1% mis-classification for regular LL. If BET(4) ratio <= 0.80, the correct probability was about 89.1% for regular LL and the mis-classification probability was about 10.9% for deep LL.

Thereafter, we adopted the criteria 0.80 <= BET(3) ratio <= 1.0 for deep LL and 0 <= BET(4) ratio <= 0.80 for regular LL to separate all the catch and effort data from 1979 to 1999 into the deep LL and regular LL by years. Results showed that the yearly nominal CPUEs of ALB was very low because ALB was not the target species for deep LL. The nominal CPUE of YFT showed stable trend but that of BET showed decreasing trend for deep LL. On the other hand, the yearly nominal CPUEs of these four species of regular LL showed that the values of ALB were high and it showed a robust but high change trend. The BET and YFT were not the target species for regular LL, but still having some catch. In addition, the regular LL began to catch SWO since 1992.

INTRODUCTION

Number of hooks per basket (HPB) data of the Taiwanese longliners started to collect from 1995. Before 1995, there was no such information, which has been problems in standardizing the nominal catch-per-unit-effort (CPUE) and stock assessment for tuna and billfish resources analyses (Anonymous, 2001). The Taiwanese longline (LL) fishery primarily catches albacore (*Thunnus alalunga*) (ALB), swordfish (*Xiphias gladius*) (SWO) and yellowfin tuna (*Thunnus albacares*) (YFT) in the Indian Ocean using the regular (or shallow) lines, on the contrary, bigeye tuna (*Thunnus obesus*) (BET) using the deep lines. It is important to separate these two types (regular and deep) of LL to reflect the precise fishing behavior, so that we can perform more accurate resources analyses. Therefore, in this paper, we attempt to develop a simple method to separate the Taiwanese longline fisheries data into regular and deep one.

Using the HPB information and species compositions of the operational based data in 1995, the ALB CPUE for the regular LL was separated and estimated. Results showed the robust and smooth trend, although the trend without separation showed the sharp decrease in the previous studies (Lin 1998 and Chen 1998), which were unlikely realistic and accurate. The studies of Lin (1998) and Chen (1998) used the catch ratio between BET and ALB to separate the regular LL and deep LL using only these two species. However, the primary catch species of Taiwanese LL in the Indian Ocean are BET, YFT, ALB and SWO. Therefore, in this study we attempt to develop a simple and robust method to separate regular and deep longline using BET ratios incorporating these four species.

By applying the developed criteria, we estimated the correct- and mis-classification probabilities between two types using two types known data (1995-99) (the learning data set)(*). Then, we classified the UNKNOWN LL (1977-94) into regular and deep LL, which are assumed to include the same level of the mis-classification probabilities in the known (learning) data set. Then, based on the separation, we estimate the CPUE by regular and deep LL for ALB, BET, YFT and SWO.

Important Note: About 40% of the data have the HPB information.

DATA

Two types information are used:

(1) Regular/deep type KNOWN data set (the learning data set)

This is the set-by-set Taiwanese longline catch and effort data including HPB information from 1995-99 in the Indian Ocean. Hence, we can exactly separate into regular and deep type using the HPB information. We call this data as the learning data set. Table 1 shows number of operations by year.

Table 1. Number of operation of the set-by-set data of Taiwanese LL including HPB information (1995-1999) (IMPORTANT NOTE: About 40% of the whole data have the HPB information).

Year	Number of operations (n)
1995	7,116
1996	10,884
1997	9,495
1998	9,984
1999	9,111
Total	46,590

Regular/deep UNKNOWN data set

This is the set-by-set Taiwanese longline catch and effort data from 1979-94 and 1995-99(*) without the HPB information, which will be used to separate into two types by the learning data set (1995-99)(**).

(*) 60% of the data are UNKNOWN LL as there are no HPB data.

(**) About 40% with the HPB information are used as the learning data set.

DEFINITION OF THE REGULAR AND DEEP LL

The historical ranges of HPB is 6 - 20. The lower number of HPB is the shallower or regular LL, while the higher one is the deeper LL. Based on the Fig. 1 and also according to the Taiwanese LL fishermen, we define that the regular LL if HPB <=10, while the deep LL if HPB => 11.

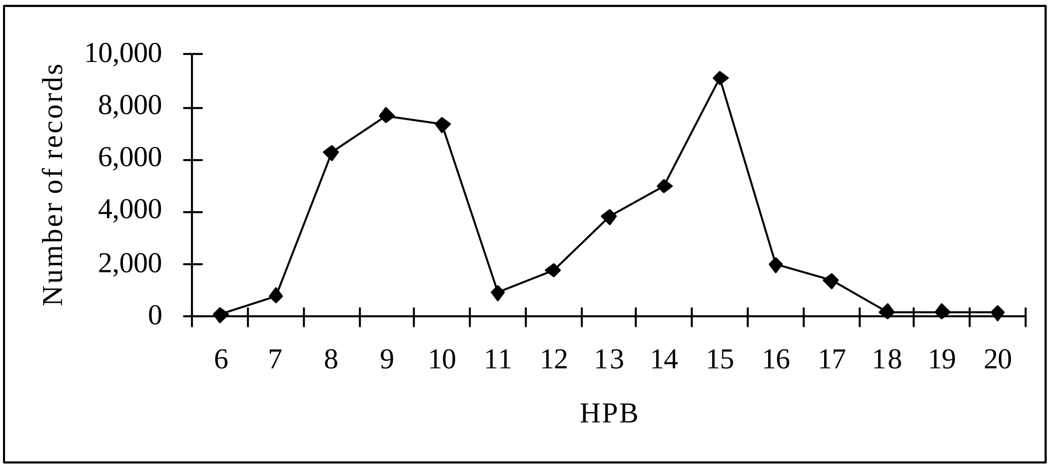

Fig. 1. The record number of HPB for the Taiwanese LL data, 1995-1999.

BET RATIOS

Bigeye tuna (BET) is the target species by the deep LL, which might be able to make separation of LL between deep and regular category. In addition, yellowfin tuna (YFT), albacore tuna (ALB), and swordfish (SWO) are targeted by the regular or shallow LL. Hence, catch of these species are considered to be the effective separators. Therefore, we combine the catches (in number) of these four species and establish following four BET ratios:

BET ratio (1) = BET / (BET+YFT)

BET ratio (2) = BET / (BET+YFT+SWO)

BET ratio (3) = BET / (BET+ALB)

BET ratio (4) = BET / (BET+ALB+SWO)

Using the Taiwanese LL data from 1995-99 including the HPB information (the leaning data set) (*), we computed four BET ratios as shown in Table 2. From Table 2, it was clearly resulted that BET ratios including only YFT were ineffective separators for the regular and deep LL. 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) (Mohri and Nishida, 2000 and Romena, 2001), which probably weaken the separation ability.

Note (*) : About 40% of the 1995-99 data have the HPB information.

On the contrary, the annual averages of BET(3) and BET(4) showed more effective separation abilities than those of BET (1) and BET(2). The best separator was the BET(3) with

0.922 (probability to classify the unknown type LL into the deep LL). The next best one was BET(4) with 0.225 (probability to mis-classify the unknown type LL into the deep LL) or 0.775 (probability to classify the unknown type LL into the regular LL).

Thus, we consider that BET(3) is the effective separator for the deep LL, while BET(4) for the regular LL.

We, then, further examined the accuracy of these two separators. Using two types known (learning) data set from 1995-99 (*), we separate them into two types by applying BET (3) and BET(4) criteria. Table 3 shows frequencies of separated regular and deep LL, while Fig. 2 shows percent frequency distributions.

Note (*) : About 40% of the 1995-99 data have the HPB information.

Based on Fig. 2, if we define 0.8< BET (3) ratio <=1 as the deep LL and 0 <= BET(4) <= 0.8 as the regular, we can compute the expected probabilities of correct and mis-classification. Table 4 shows the results. As conclusion, we can have nearly 90% of the correct classification probabilities (power). Hence, we consider that these two criteria are a simple and accurate clue to separate UNKNOWN LL into two types LL (regular or deep).

Table 2 Four types of BET ratios and relevant statistics based on the 1995-99 Taiwanese LL data.

	Year	Number of Regular LL sets	Average value	SE	Number of deep LL sets	Average value	SE
BET(1)= BET/(BET+YFT)	1995	3726	0.573	0.385	2742	0.725	0.262
	1996	5039	0.549	0.415	4802	0.719	0.308
	1997	3306	0.670	0.382	5401	0.711	0.315
	1998	4250	0.600	0.403	5019	0.661	0.272
	1999	2587	0.605	0.383	6101	0.742	0.230
	1995-1999	18908	0.594	0.399	24065	0.712	0.280
BET(2)= BET/(BET+YFT+SWO)	1995	3873	0.363	0.347	2757	0.644	0.275
	1996	5233	0.411	0.380	4864	0.623	0.318
	1997	3490	0.480	0.390	5484	0.599	0.314
	1998	4408	0.430	0.362	5073	0.578	0.272
	1999	2678	0.475	0.359	6179	0.660	0.242
	1995-1999	19682	0.427	0.371	24357	0.620	0.286
BET(3)= BET/(BET+ALB)	1995	3636	0.338	0.370	2615	0.945	0.188
	1996	4576	0.355	0.412	4502	0.900	0.267
	1997	3267	0.437	0.433	5000	0.949	0.182
	1998	4024	0.337	0.381	4949	0.882	0.293
	1999	2819	0.320	0.396	6117	0.937	0.205
	1995-1999	18322	0.357	0.400	23183	0.922	0.235
BET(4)= BET/(BET+ALB+SWO)	1995	3801	0.209	0.288	2657	0.799	0.265
	1996	4955	0.241	0.336	4615	0.750	0.320
	1997	3703	0.239	0.319	5158	0.759	0.290
	1998	4556	0.197	0.274	5023	0.743	0.321
	1999	2901	0.246	0.335	6184	0.813	0.253
	1995-1999	19916	0.225	0.311	23637	0.772	0.293

Table 3. Frequencies of separated regular and deep LL for two types KNOWN data set (1995-99) (*) by applying BET(3) and BET(4) criteria.

	BET Ratio(3) (deep LL separator)		BET Ratio(4) (regular LL separator)	
	Correct no. of regular LL sets	Correct no. of Deep LL sets	Correct no. of Regular LL sets	Correct no. of Deep LL sets
0.0 <= ratio <= 0.1	8605	1080	11043	1704
0.1 < ratio <= 0.2	1552	187	2449	532
0.2 < ratio <= 0.3	868	135	1387	451
0.3 < ratio <= 0.4	738	147	1032	534
0.4 < ratio <= 0.5	707	145	755	829
0.5 < ratio <= 0.6	503	133	367	789
0.6 < ratio <= 0.7	514	195	350	1379
0.7 < ratio <= 0.8	455	322	354	2559
0.8 < ratio <= 0.9	306	625	470	3793
0.9 < ratio <= 1.0	4074	20214	1709	11067
Total	18322	23183	19916	23637

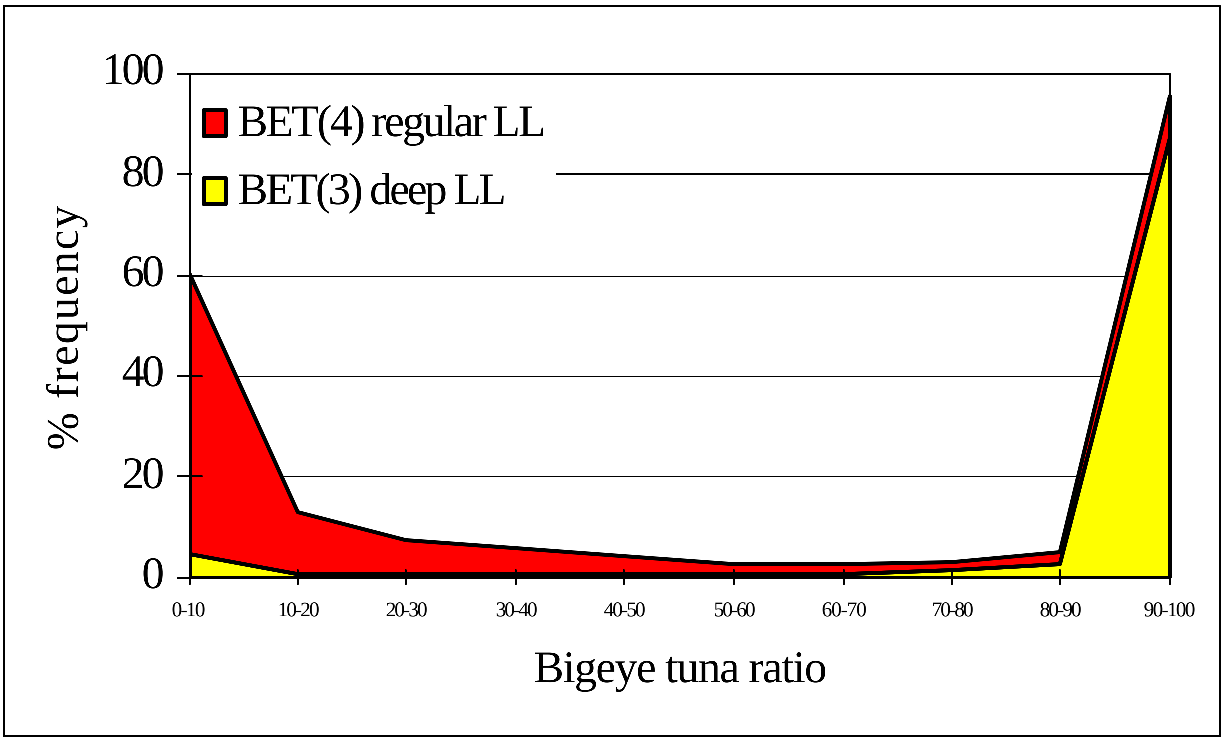

Fig. 2. Percentage frequency of separated regular and deep LL for two types KNOWN data set (1995-99) (*) by applying BET(3) and BET(4) criteria.

Note (*) : About 40% of the 1995-99 data have the HPB information.

Table 4. Probabilities of correct- and mis-classification when the criteria (0.8< BET(3) <= 1 for deep LL and 0<= BET(4) <= 0.8 for regular) are applied.

	Definition	Probability of correct & mis-calcification	
		Deep LL (true)	Regular LL (true)
Deep LL	0.80 < BET (3) <= 1	89.9 % (Prob. Correct classification)	10.9 % (Prob. mis-classification)
Regular LL	0<= BET (4) <= 0.80	10.1 % (Prob. of mis-calcification)	89.1 % (Prob. of correct classification)

5. CLASSIFICATION OF THE UNKNOWN LL DATA (1979-94 AND 1995-99*) INTO REGULAR AND DEEP LL CATEGORY

Using the developed criteria, we attempted to classify regular or deep unknown LL data (1979-94 and 1995-99*) into two types and compute the CPUE. Fig. 3 shows the results for CPUE trends of ALB, BET, YFT and SWO by the regular and deep LL.

Important note(*) : About 40% of the data have the HPB information, thus we also need to make the classification for the rest (60%) of the 1995-99 LL UNKNOWN data by this new criteria.

Fig. 3 suggested following points. The nominal CPUE of ALB by the deep LL was very low because ALB is not the target species for deep LL. The nominal CPUE of YFT by the deep LL showed stable trend but that of BET showed decreasing trend. The values of ALB by the regular LL were high and it showed a robust but high change trend. The BET and YFT were not the target species for regular LL, but we can see that there are some catches. In addition, the regular LL began to catch SWO since 1992.

DISCUSSION

Since around 1986, the Taiwanese longliners in the Indian Ocean, which had super-cold storage equipment, usually has caught BET using the deeper lines. Their target species is different from the Taiwanese traditional longliners (so-called regular longliners), which usually catch ALB with the shallower lines. In the previous assessment work for ALB and BET, there were biases because all catch and effort data of both regular & deep LL had been pooled. Therefore, how methods to separate the Taiwanese deep LL and regular LL have been developed by the fishery biologists (Lin 1998; Chen 1998; Hsu et al. 2001).

Under such circumstances, the Taiwanese Government has decided to add the HPB investigation in the logbook of vessels since 1995 in order to reduce this above mentioned problem. In this study, we developed a simple and robust method to separate the deep LL and regular LL. BET ratio criteria (3) & (4) we developed are considered to be able to separate regular and deep LL effectively. However, there are about 10 % mis-classification errors. If we omit these data, we can separate UNKNOWN LL into the regular and deep LL accurately as we have almost no errors according to Table 4, although we lose 10% of the data.

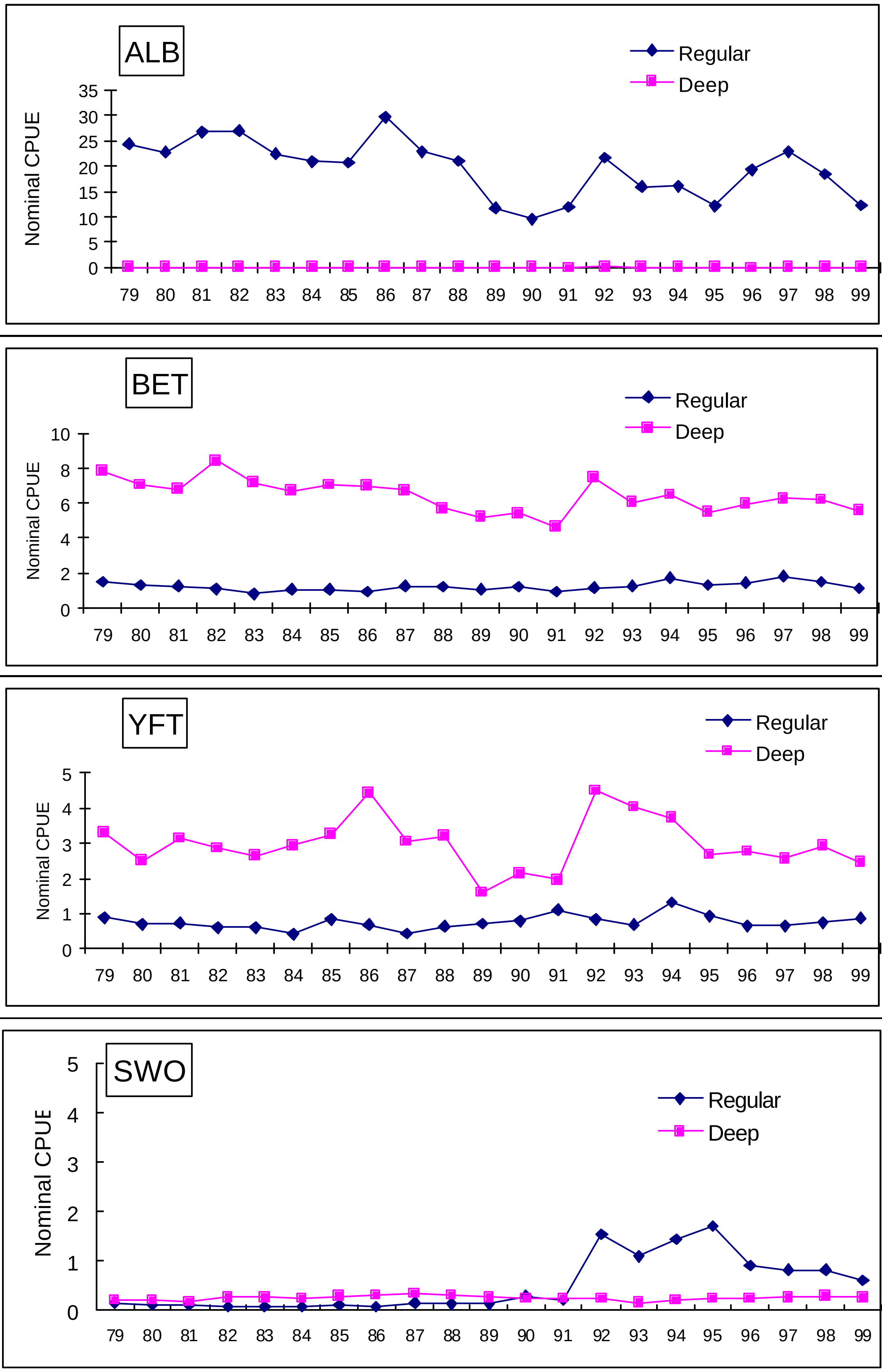

Fig. 3 Trends of CPUE by regular and deep LL separated by BET(3) & (4) criteria for ALB, BET, YFT and SWO. For 1995-99, separation were made by both HPB information (about 40%) and BET criteria (about 60%).

In the developed criteria, there is one more concern, i.e., if the catch of the three species are zero at the same operation (ALB=BET=SWO=0), these data will be excluded in the separation process. We investigated these zero catch cases by year (1979-1999) and results were showed that the percentage frequencies were about 10 % in average (Fig. 4).

Therefore, when we classify the UNKNOWN LL into regular or deep LL by the new BET criteria (3) & (4), we expect to lose about 20 % of the data set as depicted In Fig. 4.

Fig. 4 Schematic diagram of the classification result by the new BET criteria for the UNKNWON data set in some year (EXAMPLE).

Classified LL		Unclassified	Un-used data when
Regular LL	Deep LL		
30%	50%	10%	10%

Finally, in this study we apply the developed criteria for only CPUE. However, we can extend this criteria to separate catch and effort data using the proportion of the regular and deep LL for some time/area unit (for example, 5x5 and month sampling unit). This will be particularly useful for the 1967-78 which data do not have the set-by-set information and just have the 5x5/month based data.

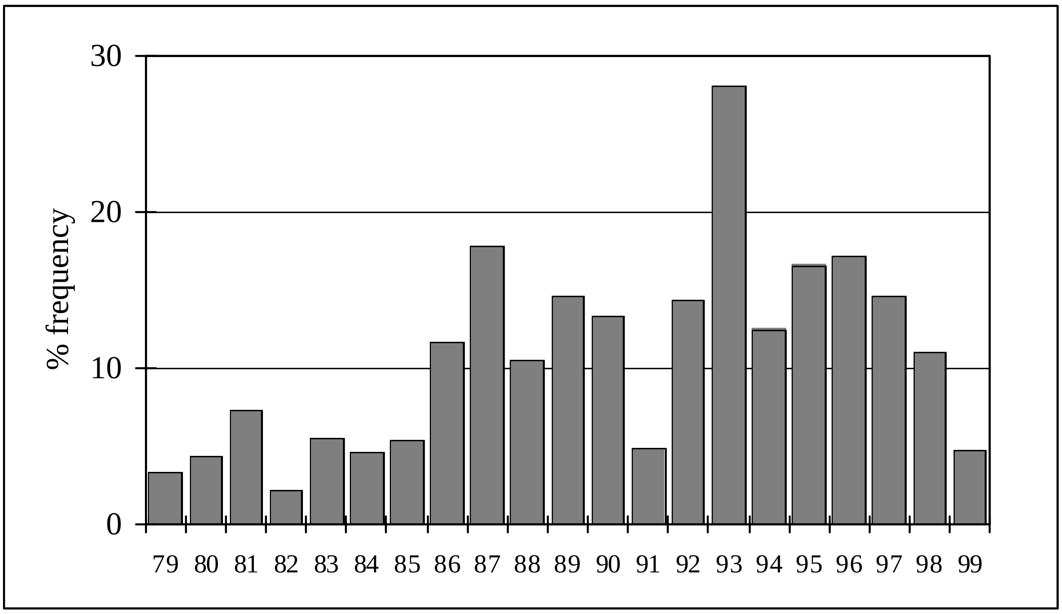

Fig. 4 Percentage frequency distribution of the LL set-by-set data when ALB=BET=SWO=0.

ACKNOWLEDGMENTS

We thank the staff of Overseas Fisheries Development Council of the Republic of China for their help in the collections of catch and effort data. We also appreciate Alejandro Anganuzzi (IOTC) who provided the BET ration information.

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