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Using Fuzzy Synthesis Approach to Extract Fishing Efforts Directed on Albacore for Taiwanese Longline Fleets in the Indian Ocean

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ABSTRACT

Indian albacore fishery is one of the most important tuna fisheries for Taiwanese longline fleets. The assessment of the Indian albacore stock is usually based on fishery-dependent data submitted from Taiwanese longline vessels. Moreover, those fishery data may contain two fishing types that are able to make standardizing catch per unit effort difficult. Therefore, in the present study, an alternative approach of fuzzy synthesis clustering is used to partition the fishing efforts from different fishing types, and the daily set catch information of logbooks from 1979 to 1997 is used as the fundamental data for this purpose. A fuzzy transformation is composed of weighting vector and membership function, in which the weighting vector used an unequal crisp value and the membership function used the distribution of percent catch of albacore in total of albacore, bigeye tuna, and yellowfin tuna under the factors of vessels' tonnage categories, fishing area, the number of hooks used and sea surface temperature. Subsequently, the result is obtained from the computation of fuzzy transformation, then, new catch, fishing effort and catch per unit effort series were obtained. The fuzzy synthesis is evidenced as one of the methods using for partitioning fishing efforts from different fishing types in preliminary.

Key words: *Albacore, fuzzy synthesis, fishing effort, longline, membership function*

INTRODUCTION

Indian albacore, *Thunnus alalunga*, is one of the economically important tunas exploited by longline. Japanese fishermen have initially involved in the exploitation for this species since early 1950s, and however, have shifted their targets from albacore to more valuable tuna species, such as bigeye tuna, *T. obesus*, yellowfin tuna, *T. albacares* and southern bluefin tuna, *T. maccoyii* since 1970s. Subsequently, Taiwanese fishermen have stepped behind to become the main exploiter of Indian albacore since 1970s, and to transfer to fish bigeye tuna since mid-1980s (Chang *et al.*, 1993; Hsu, 1994).

As usual, the transformation of longline fishing types to target different species may result in the change of fishing powers of longline fleets (Beverton and Holt, 1957; Sauthaug and Gotφ, 2001), and fishermen usually search an appropriate fishing ground and use different fishing types to catch their targets from day to day. As the result, this change would cause the accuracy of standardizing catch per unit effort as an abundance index directed to study species, if the segregation of fishing efforts is not completed for different fishing types. To evaluate the Indian albacore stock encounters the similar dilemma that the fishing efforts directed to albacore are intermingled with those directed on tropical tunas. Requirement, for standardizing catch per unit effort used as abundance index of albacore, is to solve the problem

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of partitioning longline fishing type when fishery dependent catch and effort data are applied on assessment analyses.

Fortunately, there are several studies (Suzuki *et al.*, 1977; Koido, 1985; Chang *et al.*, 1993; 1996; Lin, 1998) have reported previously to focus on the partitioning fishing effort for those longline fishing types. Those studies are based on survey census data (Suzuki *et al.*, 1977; Koido, 1985), ordination analysis (Chang *et al.*, 1993; 1996) and statistical comparison by analysis of variance on spatial and temporal catch composition (Lin, 1998). Nonetheless, an alternative approach, the fuzzy synthesis, is not found to apply on the classification of fishing efforts for the concerned fishing types.

Therefore, the objective of this study aimed at using fuzzy synthesis to partition fishing efforts resulted from different longline fishing types.

MATERIALS AND METHODS

Daily logbooks were used in the present study. Those logbooks were submitted by captains of Taiwanese longline vessels operating in the Indian Ocean from 1979 to 1997, depending on data availability. Usually longlines deploy one set per day. Fishery information of logbooks includes vessel category, fishing date, fishing area by 5x5 squared block, hooks deployed, sea surface temperature, bait used if available, catch in number and in weight by species, and size measurements for the first 30 fish. In the Indian Ocean, Taiwanese longline fleets are using two fishing types to target different species, the conventional fishing type is mainly used to target albacore and the deep fishing type is used to target bigeye tuna and yellowfin tuna. Both fishing types are different with vessel capacity, depth of lining, and fishing grounds etc. Nonetheless, fishermen usually decide fishing area by experiment, thus fishing type may be intermingled with target species day by day. Hence, the information available were used as factors to segregate the fishing efforts directed to albacore. The bait used information was not used in the present study, because the information was mostly uncompleted in the logbooks.

Further, based on fishery information mentioned above, a fuzzy transformation set was derived by

$$B_{1j} = A_{1i} \circ R_{ij} \quad (1)$$

where B_{1j} is derived from weighting average of A_{1i} and R_{ij} which are weighting vector of influencing factors and membership function matrix indicating the relationship between influencing factor and decision set, respectively for i influencing factors and j fishing types, i=1, 2, 3 (or 4 if the sea surface temperature is used), and j =1,2 for two fishing types (conventional and deep). The $\circ$ is the fuzzy operator (Klir and Yuan, 1995). The percent catch of albacore was defined as the catch of albacore in total catch of albacore, bigeye tuna and yellowfin tuna was used as decision set.

Accordingly, A_{1i} and R_{ij} should be built based on fishery information that may affect the changes of fishing power of individual longline vessels. The A_{1i} is a representative of importance of each factor on data classification. Four influencing factors are available extracting from daily logbook of Taiwanese longline fleets, those are fishing area each month, vessel category, total hooks used of daily set and sea surface temperature. The factor of fishing area each month was categorized latitudinaly by every 5° from 25° N to 45° S in the Indian Ocean with each month (Fig. 2). There are 168 subcategories in this factor. The factor of vessel was categorized by the third numeric of CT number of each vessel. The numeric represents the tonnage range of the vessel size (Fig. 3). There are 7 sublevels of this factor. The factor of hooks used of daily set was categorized from 1000 to 3800 hooks with 200 hooks interval (Fig. 4). There are 16 sublevels in this factor. The factor of sea surface temperature was categorized by Celsius scale from 12 ℃ to 36 ℃ with 2 ℃ interval (Fig. 5). There are 14 sublevels in this factor. Therefore, four A_{1i} s were

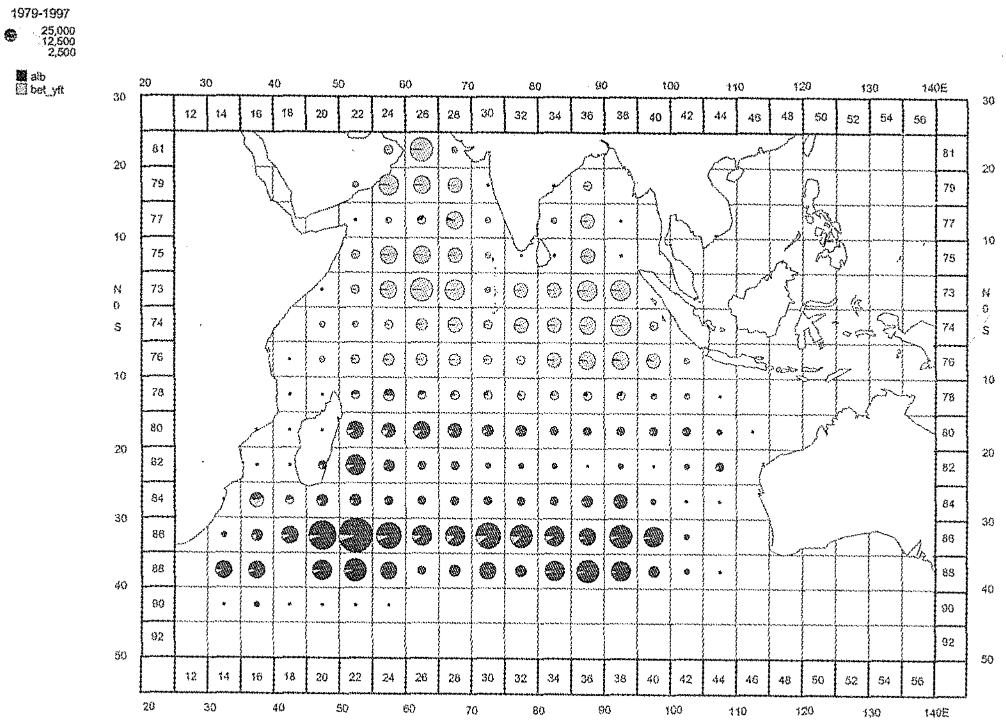

Fig. 1. Fishing area of albacore in the Indian Ocean by Taiwanese longline fishery, where the data points are averaged from catch data from 1979-1997, in which the black area of pie indicates the percentage of albacore catch in total catch of albacore, bigeye tuna and yellowfin tuna, and the hatched area indicates the catch other than albacore.

assumed in according to these influencing factors. The A_{1i} was assigned by proportion of mean square obtained from general linear model analysis (O'Brien and Kell, 1997; O'Brien *et al.*, 1998) to represent variations of each influencing factor.

A membership function can be used as a fuzzy number expressing the frequency distribution of percent catch of albacore. The triangular membership function of fuzzy number (m,α,β) can be built by taking the second, first and third quantiles of frequency distribution of percent albacore. In which m, α and β are the mean, left and right spreads of the fuzzy number (Klir and Yuan, 1995). m is the possibility of certain operation under the grouped range of the influencing factor in fuzzy sense. α and β are the variation of the possibility in fuzzy sense. Therefore, $R_{i1} = (m_i, \alpha_i, \beta_i)$ represents the fuzzy relation between the specific fishing type and the influencing factor i; and $R_{i2} = (1-m_i, 1-\alpha, 1-\beta_i)$ represents the fuzzy relation between the other type of fishing type and the influencing factors i.

Finally, catch, effort and nominal catch per unit effort directed to albacore was computed before and after fishing efforts were partitioned, and their trends were compared visually.

RESULTS

1. Weighting vector and membership function of influencing factors

The weighting vectors (A_{1i}) corresponding to influencing factors were assigned as an unequal weight, and crisp values were given as Table 1 that values were obtained from the general linear model analysis in corresponding to fishing area, vessel capacity class, hooks used of daily set and sea surface temperature factor, respectively. A high percentage weight was given to fish-

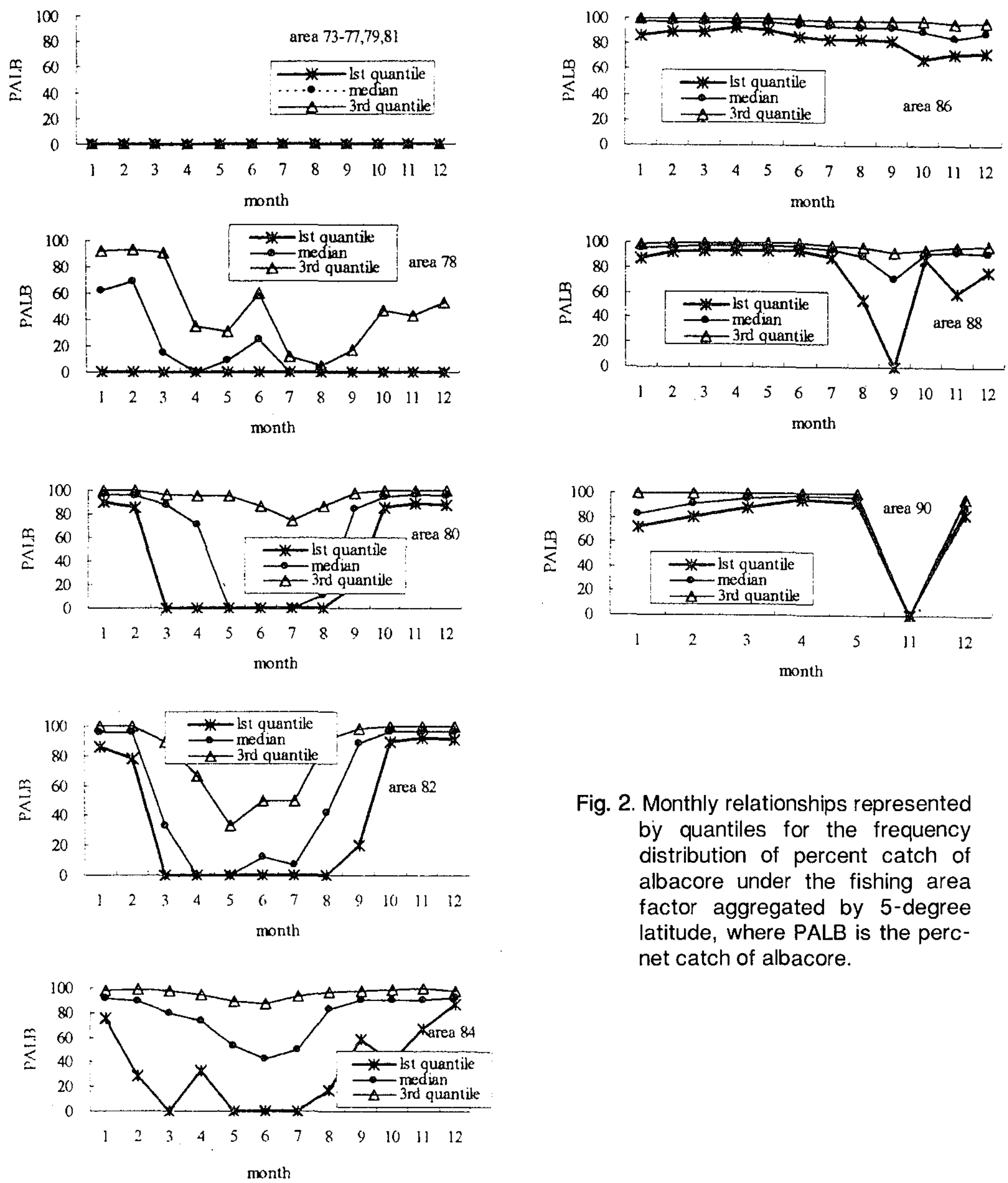

Fig. 2. Monthly relationships represented by quantiles for the frequency distribution of percent catch of albacore under the fishing area factor aggregated by 5-degree latitude, where PALB is the percnet catch of albacore.

ing area since the distribution of tuna targeted and the distribution of longline fleets operated are aggregated in the area of southern Indian Ocean (Fig. 1). Thus, it is obvious that weights for effects of fishing area and sea surface temperature are the main factors influencing the identification of fishing types. Therefore, a set of unequal weight (Table 1) was used to the following fuzzy transformation.

Membership functions are usually used for fuzzy clustering analysis, and the membership functions are built as triangular relationship of percent catch of albacore for fishing area effect (Fig. 2), vessels capacity (Fig. 3), hooks used per day per boat (Fig. 4) and sea surface temperature as available (Fig. 5). Consequently, as

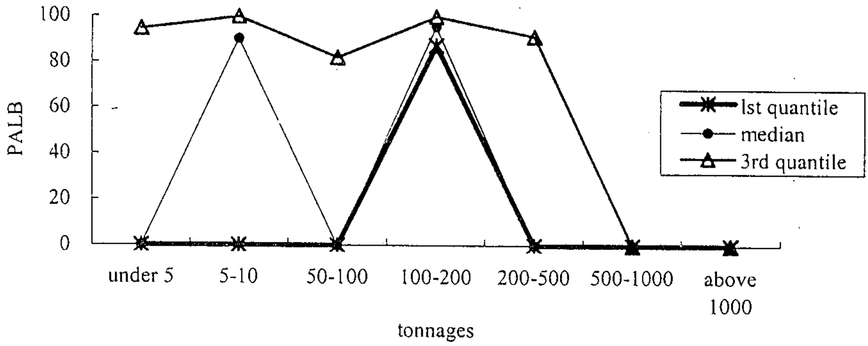

Fig. 3. Relationships represented by quantiles for the frequency distribution of percent catch of albacore under the factor of fishing vessel's tonnage classes, where PALB is the percent catch of albacore.

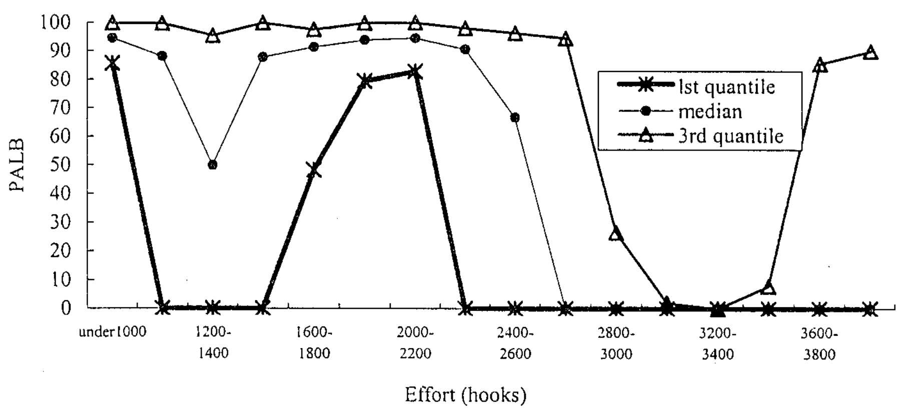

Fig. 4. Relationships represented by quantiles for the frequency distribution of percent catch of albacore under the factor of total daily hooks used, where PALB is the percent catch of albacore.

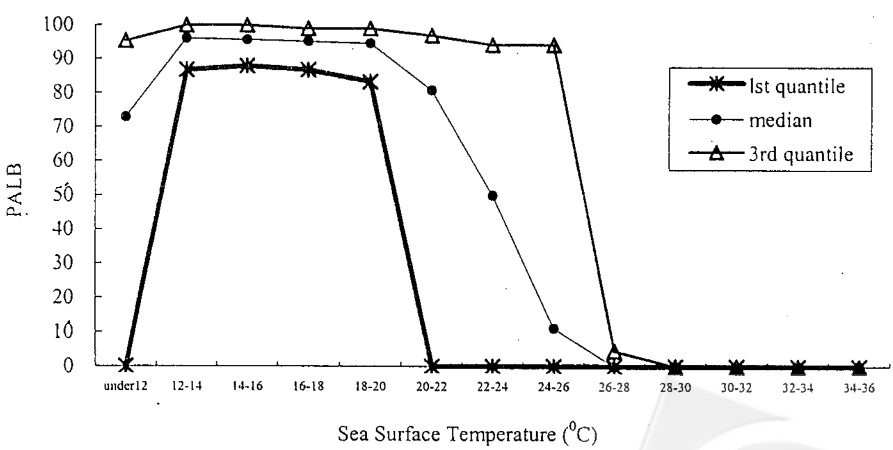

Fig. 5. Relationships represented by quantiles for the frequency distribution of percent catch of albacore under the the sea surface temperature factor, where PALB is the percent catch of albacore.

Table 1. The analysis of variance results of general linear model to fit albacore catch with four influencing factors, in which the proportion of mean square (Bold type) under each influencing factor was used as the weighting factor in the fuzzy transformation. The '***' indicates the significance test level was set at 0.0001.

Source	DF	Sume of square	Mean square	F-value	Weight
Model	194	2.18×10^{12}	1.12×10^{10}	1546***	
Fishing area	162	5.45×10^{11}	3.36×10^{9}	662.71***	40.67
Vessel category	5	3.12×10^{9}	6.24×10^{8}	85.91***	7.55
Fishing effort	15	8.12×10^{9}	5.42×10^{8}	74.52***	6.55
Sea surface temperature	12	4.49×10^{10}	3.74×10^{9}	514.47***	45.22
Error	245359	1.78×10^{12}	7.27×10^{6}		
Corrected total	245553	3.96×10^{12}	1.12×10^{10}		
R^2		C.V.	Root MSE		
0.53		123.4	2731.2		

examined the second quantile, the dispersion is larger for the area between 10°S-30 °S (coded as even numbers from 78 to 90 in Fig. 1) than the other areas (Fig. 2). The daily fishing efforts used in targeting albacore for the conventional fishing type mainly concentrated on the class of used hooks between 1800-2200 hooks (Fig. 3). The vessel tonnage class for the conventional fishing types was used between 100-200 GRT mostly, and a few vessels smaller than 100 GRT tend to be the deep longline fishing type except the vessels between 5-10 GRT. The sea surface temperature that albacore always inhabits (Nakano *et al.*, 1997) is between 12 ℃-20 ℃ (Fig. 5).

Further, a fuzzy transformation using equation (1) was computed for each daily set of longline setting. And the classification of fishing efforts into which fishing type is belonging was identified by the relationship of $\underline{B}11$ and $\underline{B}12$ as illustrated in Fig. 6. If $\underline{B}11 > \underline{B}12$, the fishing effort was classified from a conventional longline fishing type, and otherwise, $\underline{B}11 < \underline{B}12$, the fishing effort was from a deep longline fishing type.

2. Catch, fishing effort and catch per unit effort trends

Unequal weight was used to fuzzy synthesis classification of catch, fishing effort and catch per unit effort for albacore by Taiwanese tuna longline fishery from 1979 to 1997. Those trends were compared visually with the effect of classification in Fig. 7.

The resultant catch and fishing effort trends reveal that the classification is achieved. The great discrepancy was found in fishing effort trend and the similarity in catch trend (Fig. 7). The fishing effort trend obtained shows that differences occur after classification on the entire studied series, in particularly, fishing efforts directed on albacore have been reduced obviously in comparison with total fishing efforts reported since 1993. However, the fishing efforts seem fairly unreliable on 1989-1991 because of low recovery rate of logbooks (Chang and Wang, 1998). On the other hand, the catch trend for albacore shows high similarity. Correspondingly, the classified nominal trend of catch per unit effort for albacore shows high discrepancy with that of using total reported fishing efforts (Fig. 7). The result obtained from this fuzzy synthesis classification is valid as well as identified by other methods.

DISCUSSION

1. Weighting vector and membership function of influencing factors

The relationship between percent

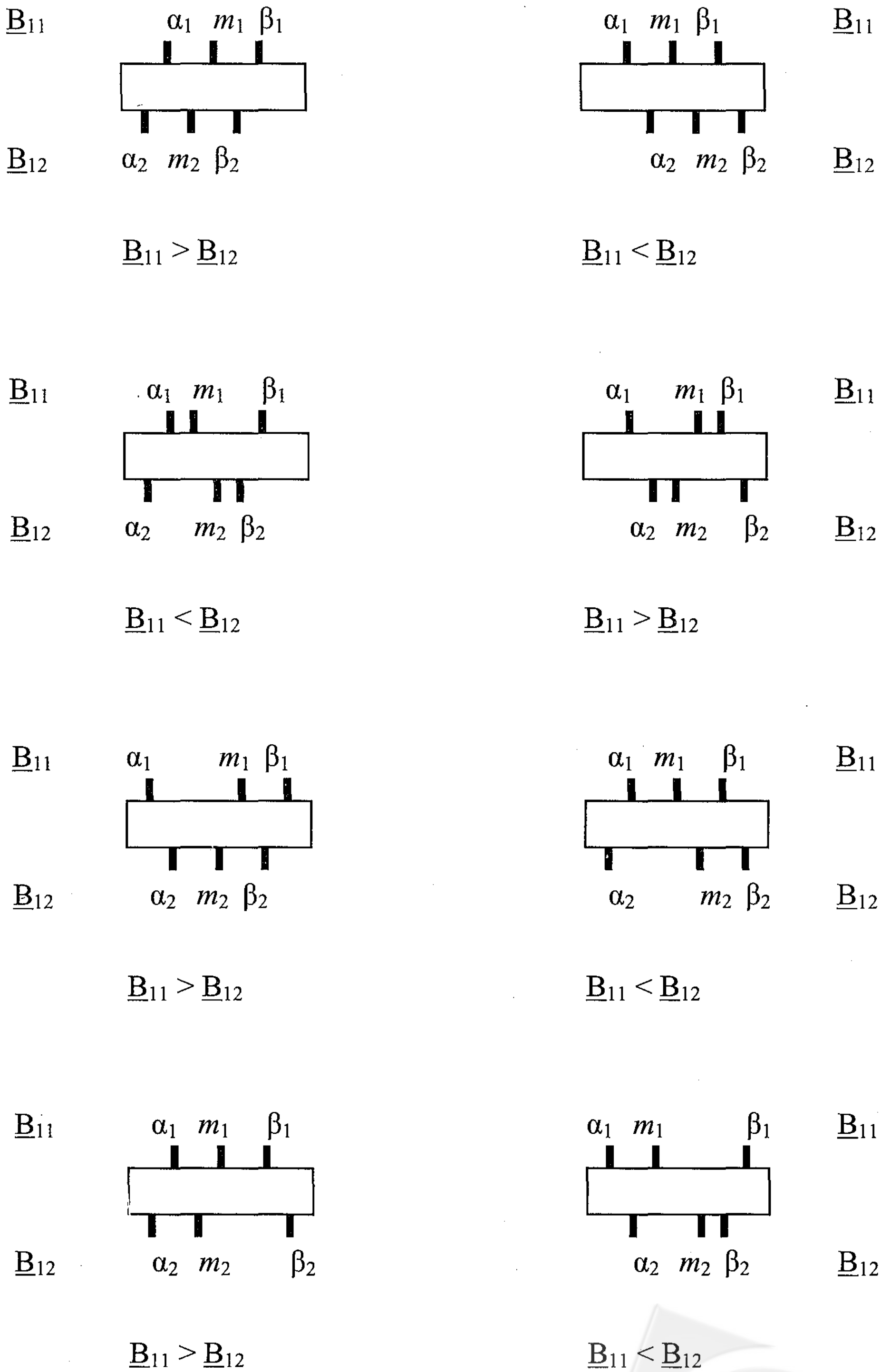

Fig. 6. Eight cases of illustration of the relationship between $\underset{\sim}{B}_{11}$ and $\underset{\sim}{B}_{12}$, those relationships are used to classify which fishing type the fishing efforts is beloging. The rectangle expresses fuzzy interval from 0 to 1 and m_j, α_j, and β_j are the mean, left and right spreads of fuzzy number $\underset{\sim}{B}_{1j}$, for j=1,2. If $\underset{\sim}{B}_{11} > \underset{\sim}{B}_{12}$, a conventional fishing type is classified, otherwise, say $\underset{\sim}{B}_{11} < \underset{\sim}{B}_{12}$, a deep fishing type is classified.

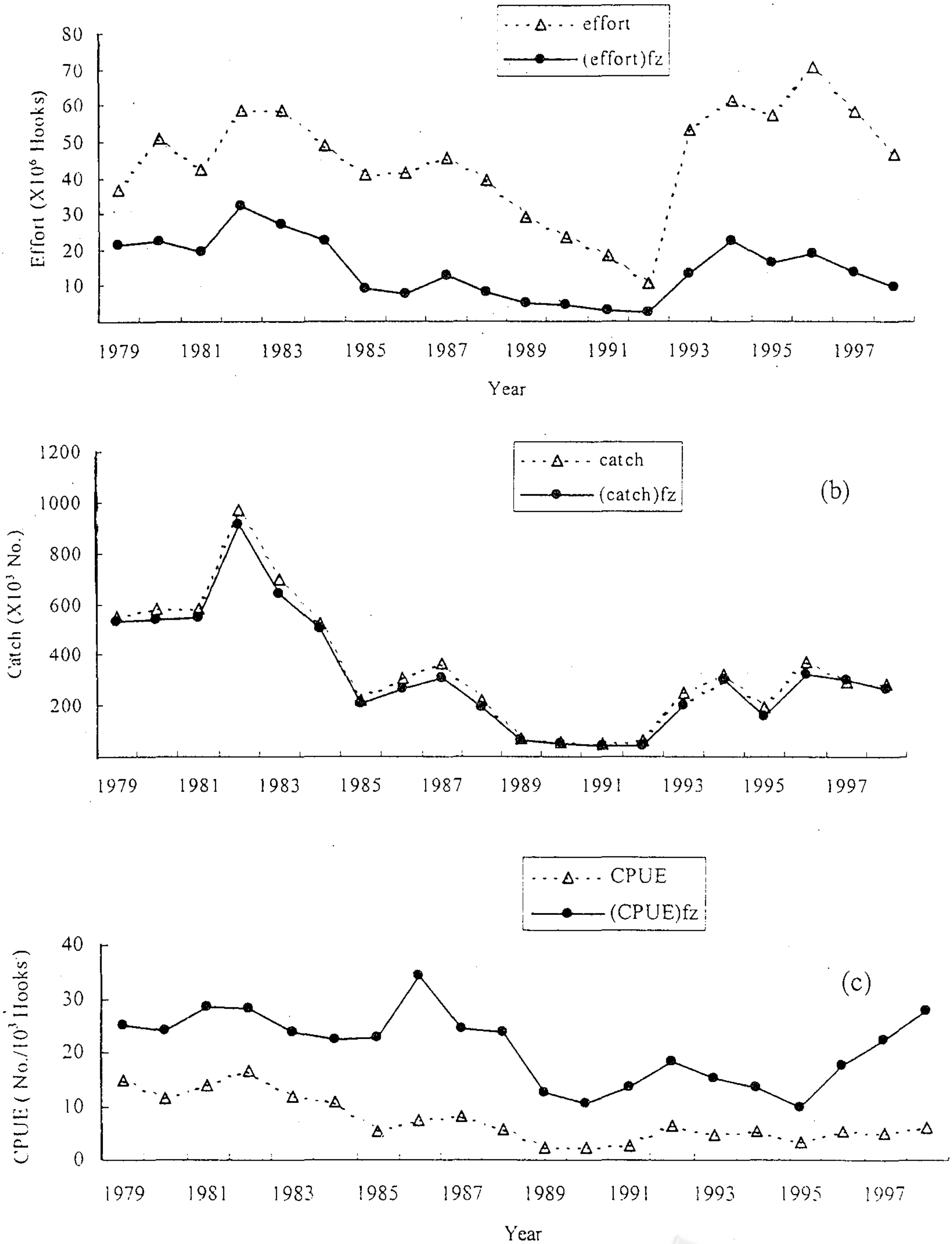

Fig. 7. Trends of catch, fishing effort and catch per unit effort of albacore in the Indian Ocean, in which the classified trends are compared with original trends to show the results of classification.

catch of albacore and each influencing factor was used as reference to set the weighting vector. Tuna longline is a species directed gear, its fishing is dependent on the distribution of how deep is the target species inhabits in the water column (Nakano *et al.*, 1997; Lin, 1998). Generally, albacore inhabits in shallow waters and bigeye tuna in deep waters usually beneath the thermocline (Suzuki *et al.*, 1977; Stequert and Marsac, 1989; Nakano *et al.* 1997). Thus, in order to distinguish the conventional longline fishing type, and to effectively target bigeye tuna, the different fishing type called deep longlining should be deployed in the area and depth of bigeye tuna inhabits. There are two ways to set lines deeper than the usual conventional fishing type that is targeting shallow species, such as albacore, swordfish and billfishes etc. One is to shorten the distance between two floats, and the other is to use more hooks between two floats or more hooks used per basket (Lin, 1998). Frequently, the latter is used, but using both alternatively in the area where fishing target species is poor and occurs seldom in one case to shift the target, and few conventional vessels with super-cold freezer fish bigeye tuna in another. Thus, to partition fishing efforts used by different fishing types is necessary before standardizing it.

Besides the waters the target species inhabits, facilities of fishing vessels also should be re-modeled to adapt the increasing hooks between floats and also the daily set and the quality maintenance of tuna caught (Hsu and Lin, 1996). Consequently, the vessel's tonnage increases to satisfy the necessary capacity. It is noted that the vessel's facility for conventional longline fishing types to target albacore is not changed at all, although an apparent change of vessel's facility for the deep longline fishing type to target bigeye tuna and yellowfin tuna.

In tradition, the number of hooks between floats is always used to identify the fishing types (Suzuki *et al.*, 1977; Nakano *et al.* 1997; Okamoto and Miyabe, 1998; Hsu and Liu, 2000). However, due to the limitation of the number of hooks between floats data available, this most important factor cannot be incorporated into the present analysis, and the daily hooks used was used to substitute this factor. The result results in lower variation for daily hooks used than any other factors used. This result reveals that daily hooks used perhaps is not an important factor to identify fishing types.

A few studies are concerning the relationship between fishing types and sea surface temperature (Chen, 2000). And the sea surface temperature whether or not a good indicator of measuring inhabits of a tuna species is not well asserted. However, the sea surface temperature was used as an influencing factor in the present study was trying to use many more factors available in the daily logbooks.

2. The validation of fuzzy synthesis

The nominal catch per unit effort segregated by three methods, the fuzzy synthesis (present study), the cluster analysis (Chang *et al.*, 1993), and hooks between two floats (Ma, 1999), were compared. They have the same nominal catch per unit effort trend (Fig. 8). Cluster analysis > fuzzy synthesis > hooks between two floats in comparing with the average level of nominal catch per unit effort of the three methods before 1990. Hooks between two floats > fuzzy synthesis in comparing with the average level of nominal catch per unit effort of the three methods after 1991.

A ratio of 7.53% of the record number of the percent catch of albacore smaller than 30% to the record number that belong to the conventional longline separated by the fuzzy synthesis. And a ratio of 2.83% of the record number of the percent catch of albacore greater than 70% to the record number that belong to the deep longline separated by the fuzzy synthesis. The small ratios mean that the strong target species effect of the tuna longline fishery make the nominal catch per unit effort trend of the three methods closely.

In order to know that the trends of the conventional and deep longline fit the real fishery change, the trends of percent catch of the target species of conventional and deep longline were calculated from the landing data. Fig. 9 shows that the trends of conventional and deep longline fit the

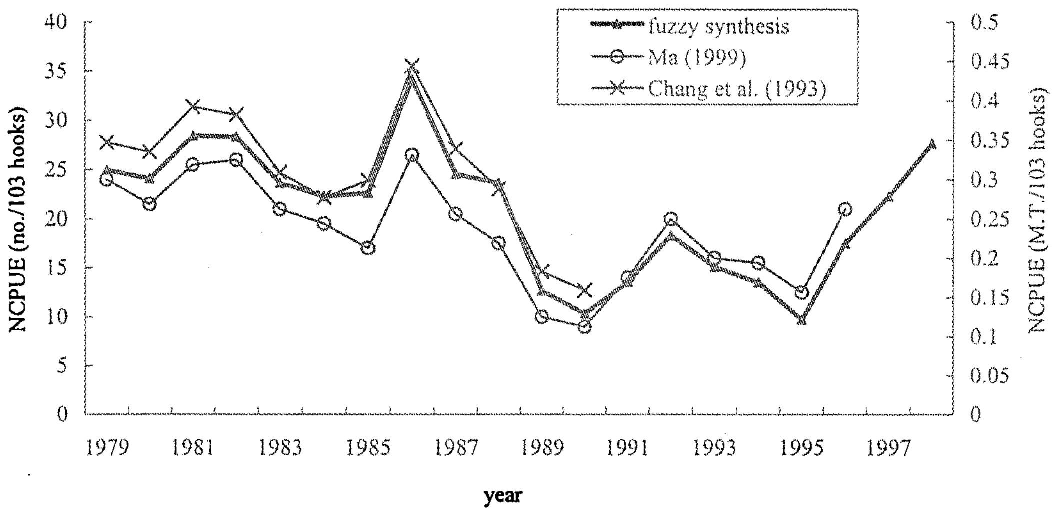

Fig. 8. The comparison of nominal catch per unit effort that segregated by fuzzy synthesis, Ma (1999), and Chang *et al.* (1993). The unit of Ma (1999) and fuzzy synthesis is number of fish per thousand hooks and that of Chang *et al.* (1993) is mt per thousand hooks.

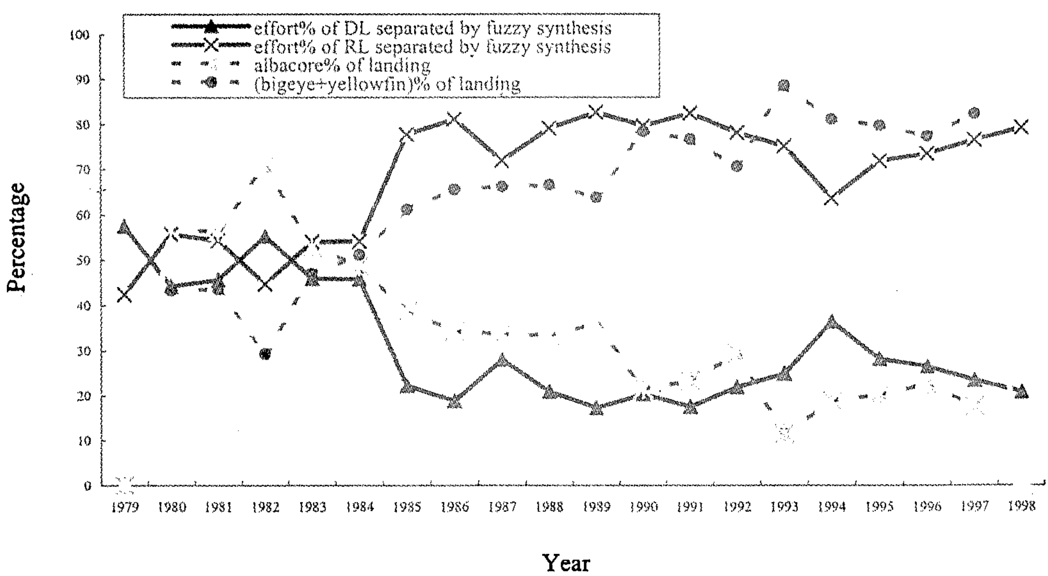

Fig. 9. The percentage distribution of target species composition of regular longline (RL) and deep longline (DL) calculated from the landings of Taiwan tuna longline in the Indian Ocean and that of effort of RL and DL separated by fuzzy synthesis.

trends of percent catch of the target species of conventional and deep longline. It means that the segregation by fuzzy synthesis fit the structure change of Taiwan tuna longline fishery in the Indian Ocean.

3. Fishery trends

As indicated in the report of the 7th expert consultation that 'the termination of large scale driftnetting in the Indian Ocean resulted in albacore catch being drastically reduced to about half the 1993 level. The longline catch and catch per unit effort have shown a steady and continuous increase for several years since then. This time lag probably reflects the recruitment of fish to the longline fishery after the cessation of the driftnet fishery. The current catch is still below the level observed when the driftnet fishery operated and the Consultation agree that the stock is probably under less fishing pressure than before'. Then the ratios of albacore juvenile fish (under 68 cm) were calculated based on the length data of logbooks from Taiwan longline fishery in the Indian Ocean. Fig. 10 shows that the ratios of juvenile fish increased from 1994 to 1997. It even reaches the highest level at 36% in 1997.

A standardized catch per unit effort is usually used as abundance index in the stock assessment (Gulland, 1956). Hence, there are many techniques used to the tuna stock standardization, such as Honma method (Honma, 1974), general linear models (Hsu, 1995; O'Brien and Kell, 1997; O'Brien *et al.* 1998) etc. However, the limited category of fishery data does not always result in the expected objective, such as the various fishing types that are used to target different species. The number of hooks used per basket (or the number of hooks between floats) is measured for different fishing types by Japanese and Taiwanese tuna longline fleets (Okamoto and Miyabe, 1998; Hsu and Liu 2000), and is used as one of the factors in standardizing catch per unit effort for Atlantic bigeye tuna. Those analyses used a knife-edged method to cut the number of hooks used between floats as two parts that one is for the conventional longline fishing type and other the deep longline one. This classification may result in losing flexibility in which, for example, Taiwanese longline fleets always change their target depending on captain's experiment (Lin, 1998). Therefore, the general linear model may not always achieve the goal of standardizing catch per unit effort as expected.

The ordination analysis can be used to reach the goal of classifying fishing types (Yeh *et al.*, 2001). Moreover, an alternative technique using fuzzy synthesis clustering in the present study could also be used to identify different fishing types incorporating with the catch composition. To investigate the result obtained in the present study, fishing efforts and catch per unit effort are two changed variables largely, in contrast, the catch is more or less maintained in original level. This result indicates the validity of the fuzzy synthesis method used in the present study. However, the set of weighting vector used in the present study seem too crisp to be a fuzzy analysis, a well-

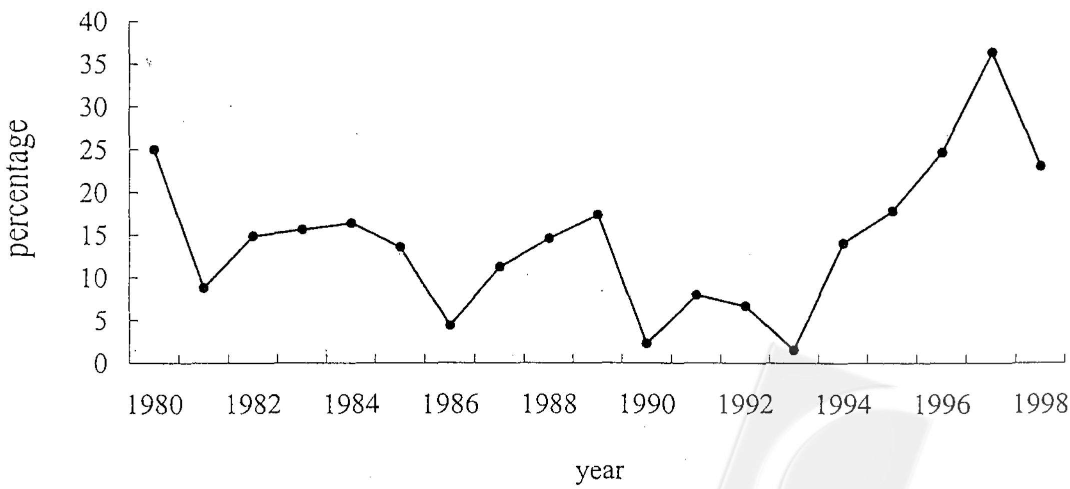

Fig. 10. The percentage of the fish length under 68 cm of albacore calculated from the length data of logbook of Taiwan tuna longline fishery in the Indian Ocean from 1980 to 1998.

defined membership function should be formulated in the advance study.

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以模糊綜合評判法分離臺灣鮪延繩釣漁船在印度洋捕撈長鰭鮪的漁獲努力量

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印度洋長鰭鮪漁業是臺灣鮪延繩釣漁船最重要的鮪漁業之一。印度洋長鰭鮪系群評估通常應用臺灣鮪延繩釣漁船所提送的漁業資料。然而，這些漁業資料可能包含有兩種造成標準化單位努力漁獲量困難的漁業型態。因此，本研究以1979-1997年的作業報表單日漁獲資訊做分析的基本資料，使用模糊綜合評判法來分離不同漁業型態的漁獲努力量。模糊轉換包含權重向量和因子函數矩陣，權重向量使用非等值眞值，和因子函數矩陣使用在漁船噸位級別、漁撈區域、使用鉤數和海表層水溫定義下之捕獲長鰭鮪、大目鮪和黃鰭鮪之長鰭鮪比值分布。由模糊轉換的運算所得到的結果，可連續獲得新的漁獲量、漁獲努力量和單位努力漁獲量序列。本研究結果可初步証實模糊綜合評判法是可以用於分離不同漁業型態的漁獲努力量方法之一。

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