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Fuzzy logic analyses for the spawner-recruitment relationship of bigeye tuna (*Thunnus obesus*) in the Indian Ocean incorporating the environmental regime shift

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ABSTRACT

The vertical sea temperature (VST) in the 0–40 m depth range for bigeye tuna (*Thunnus obesus*) inhabitation affects production of the spawning eggs. We then incorporate this VST along with regime shift into the original Ricker spawner-recruit (SR) model with two extended methods, i.e., the regime SR model and the fuzzy logic SR model. The three models are compared and evaluated using the bigeye tuna (*T. obesus*) SR data in the Indian Ocean from 1960 to 2001 obtained from the age-specific production model analyses.

In the preliminary data analyses, we searched the specific range of the VST in 0–40 m that would increase activities of spawners. Spawners are defined as the female fish with the gonad index (GI) > 3.1. Available gonad and depth-specific sea temperature data were used for the analyses. As a result, it was found that the higher average VST values in the 27.5–30.5 °C range produced higher GI values. Using its mean of 28.43 °C as a threshold value, we classified the SR data into two temperature regimes (cool or warm). Then, we applied the bigeye tuna SR data to three models. Based on Akaike Information Criteria (AIC) and r^2 (correlation coefficient) values, it was resulted that the best model was the fuzzy, then the regime and the traditional Ricker model as the last.

One of the essential problems discovered in the SR model analyses is that the time series of the SR data frequently followed the trajectories of the loops or the spirals instead of the original SR model curve. Such phenomena implied that the SR data made only apparent fitness to the SR model in many cases because the SR data could not actually satisfy the assumptions behind (the density-dependent process under the same environmental conditions). In our study, such loop was also observed in the original SR data, but after separated into two regimes, the loops were almost disappeared in each regime. This concluded that the bigeye tuna SR data in the Indian Ocean followed the density-dependent process in each homogenous environment (cool or warm regime) and the Fuzzy logic incorporating these two regimes was considered to the most appropriate method.

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1. Introduction

The objectives of our study are to compare and evaluate three types of the spawner-recruitment (SR) models by applying to the SR data of bigeye tuna (*Thunnus obesus*) (BET) in the Indian Ocean. The three models are the Ricker SR model (1975) and its two extended models incorporating the environmental regime shift, i.e., the regime-SR (Francis and Hare, 1994; Hare and Mantua, 2000) and the fuzzy logic-based model by Chen (2001) (hereafter referred as the fuzzy-SR). The primary reason that we attempted this study was that Indian Ocean Tuna Commission (IOTC) (2004) reported that the traditional SR model could not explain BET SR data well and we are interested in the performances of the environmental factors (regime) involved methods.

The SR data used in our study resulted from the age-specific production model (ASPM) (Nishida and Shono, 2004). Results of the ASPM stock assessments such as MSY, spawning stock biomass, recruitment have been officially accepted by the IOTC (IOTC, 2001–2004). However, as explained, the SR models poorly fitted to the SR data. Thus, even the results of the ASPM were officially accepted, there have been uncertain problems in the estimated SR models and results of the ASPM. Hence, the improved SR model analyses have been called for.

In the IOTC, there were less detail discussions on the causes of these uncertain phenomena in the SR relationships. According to Hisada (1979), the certain sea temperature range in their habitat (0–40 m in depth) is the key factor to produce more eggs (recruitments). Hence, in our study, we will incorporate such sea temperature to the regime model and the Fuzzy model to evaluate their performances.

2. Data

2.1. *Spawner-recruitment (SR) data*

The SR data of the Indian Ocean BET for 42 years (1960–2001) are taken from results of the ASPM analyses (Nishida and Shono, 2004) (Table 1). Fig. 1 shows its scatterplot of the SR data except 1974 data which is treated as an outlier.

Table 1 – Estimated SR data by the ASPM analyses (Nishida and Shono, 2004)

Year	Spawner fish (million)	Recruit fish (million)
1960	12.79	41.64
1961	12.50	30.37
1962	12.30	29.15
1963	12.17	45.39
1964	12.43	46.23
1965	11.92	55.57
1966	10.96	42.25
1967	11.28	53.34
1968	12.22	26.77
1969	13.23	43.79
1970	13.56	51.14
1971	14.03	21.35
1972	13.15	17.84
1973	12.61	56.39
1974	13.53	116.52
1975	12.26	17.83
1976	9.73	23.98
1977	10.62	65.40
1978	16.71	30.61
1979	16.45	35.65
1980	12.84	45.14
1981	13.49	30.31
1982	13.34	35.21
1983	11.92	76.82
1984	11.69	37.58
1985	11.05	38.86
1986	10.20	46.95
1987	12.25	43.81
1988	12.50	52.42
1989	10.98	46.81
1990	10.36	60.23
1991	9.95	40.19
1992	10.04	43.55
1993	10.21	46.83
1994	10.39	48.43
1995	9.69	59.51
1996	8.56	60.32
1997	7.70	47.15
1998	6.80	42.18
1999	6.58	44.41
2000	6.48	42.58
2001	5.93	41.59

2.2. *Gonad index (GI) data*

Female GI index data are used to examine the relationship between GI (spawning activities) and environment (average vertical sea temperature in 0–40 m). Original gonad weight data were obtained from the survey information of the Japan Marine Fishery Resources Research Center (JAMARC) and also from the database of National Research Institute of Far Seas Fisheries (NRIFSF). The former data were collected from experimental longline fishing in the Indian Ocean conducted over the period of 6 years, 1981–1986 by R/V Nippon-Maru. The latter data were taken from tuna survey cruises by R/V Shoyo-Maru, fisheries high school training vessel and prefecture fisheries experimental station vessels during 1960–2001. Total number of the GI data in the spawning area of bigeye tuna is 174,487.

We used the GI index defined by (Kikawa, 1953) as below:

$$\text{GI index} = \text{female gonad weight} \times \frac{10^4}{(\text{fork length})^3} \qquad (1)$$

We also defined the spawning area as indicated in Fig. 2, which is based on the study by Mohri and Nishida (1999). They defined the area where there are spawning bigeye tuna individuals with the gonad index (GI) more than 3.1 implying the mature fish.

2.3. *Environmental data*

We use the vertical average sea temperature between 0 and 40 m as the environmental data because such depth range is the actual habitat waters of the spawner of bigeye tuna which

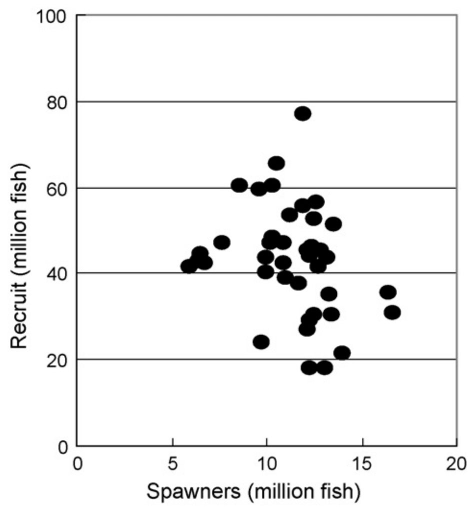

Fig. 1 – Scatterplot of the SR data based on Nishida and Shono (2004).

affect spawning activities (Hisada, 1979). The depth-specific sea temperatures (1960–2001) are taken the JEDAC database at http://acw.ucsd.edu/DATA_IMAGES/. The resolutions of the original data are by year, month, and 2° (latitude) × 5° (longitude) by depth (0, 20, 40, 60, 80, 120, 160, 200, 240, 300, 400 m). In order to match to the gonad index data (5° × 5° based data), we modified the original data to match 5 × 5 data using the area weightings in the study area in the Indian Ocean (60°S–30°N × 20°E–140°E) (Fig. 2).

The vertical average sea temperature (VST) between 0 and 40 m in the spawning area was then computed by weighted average among depths by Eq. (2):

$$\text{VST}\ (0-40\ \text{m}) = \frac{[20\ \text{m} \times \{(\text{T at 0 m}) + (\text{T at 20 m})\}/2] + [20\ \text{m} \times \{(\text{T at 20 m}) + (\text{T at 40 m})\}/2]}{40\ \text{m}} \qquad (2)$$

where T is the sea temperature.

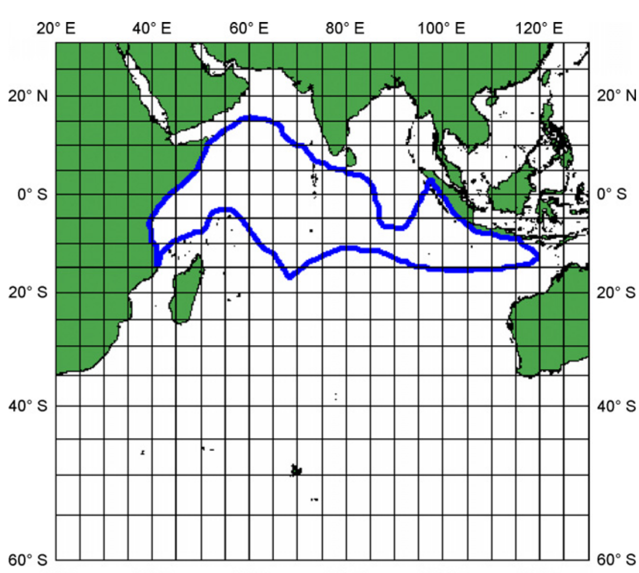

Fig. 2 – Spawning area of bigeye tuna in the Indian Ocean (after Mohri and Nishida, 1999).

Table 2 – Average GI index by vertical average sea temperature (0–40 m) in the bigeye tuna spawning waters (*n*: sample numbers)

Vertical average sea temperature (VST, °C)	*n*	Average GI index
23.0	355	1.02
23.5	119	0.57
24.0	2694	1.00
24.5	1451	1.08
25.0	3203	1.06
25.5	6932	1.40
26.0	9783	1.53
26.5	13,437	2.20
27.0	18,589	2.84
27.5	30,169	3.00
28.0	35,317	3.35
28.5	33,206	3.08
29.0	14,982	3.00
29.5	3095	3.04
30.0	986	3.33
30.5	114	1.32
31.0	19	1.39
31.5	0	na
32.0	36	1.03
Total	174,487	

3. Methods and results

3.1. *Indicators of spawning activities and the definition of the regime*

To learn how the vertical average sea temperature (VST) (0–40 m) affects the spawning activities, we investigate the relationship between GI indices and the VST data by merging them by year, month and 5 × 5 areas in the spawning area. Then, we plot the GI indices and average temperature (by 0.5 °C). Result is shown in Table 2 and Fig. 3. Female bigeye with the GI index 3.1 or over are fully mature (Kikawa, 1957). According to Table 2 and Fig. 3, the corresponding temperature range is 27.5 ≤ VST < 30.5 °C. Thus, we use the average vertical sea temperature of this range as an indicator of the spawning activities because within this range, spawning (GI index) become more active as VST becomes higher. Using this criterion, we computed the annual average vertical sea temperature (0–40 m) for the analyzing years for 42 years from 1960 to 2001, which is shown in Fig. 4. Using the mean of these values (28.43 °C) as a threshold value, we categorized the data into two regimes (cooler or warmer). Table 3 shows the list of cooler and warmer regime years. Using this classification, the SR scatter plot is re-depicted in Fig. 5.

3.2. *Ricker SR models analysis*

The traditional Ricker SR model relates the spawning biomass to the recruit biomass in the following Eq. (3):

$$R_t = S_t \exp(a - bS_t + \varepsilon_t) \qquad (3)$$

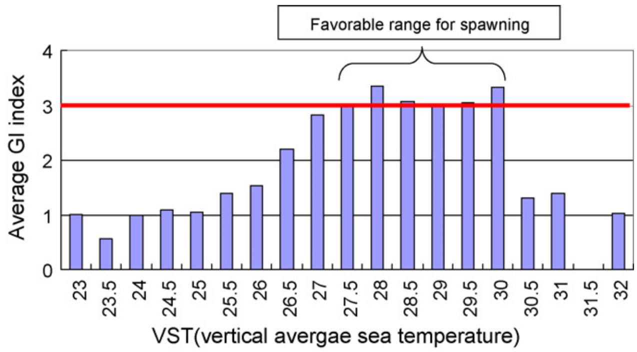

Fig. 3 – Relationship between the average GI index and the vertical average sea temperature (VST) (0–40 m) in the bigeye tuna spawning waters (n = 174,487).

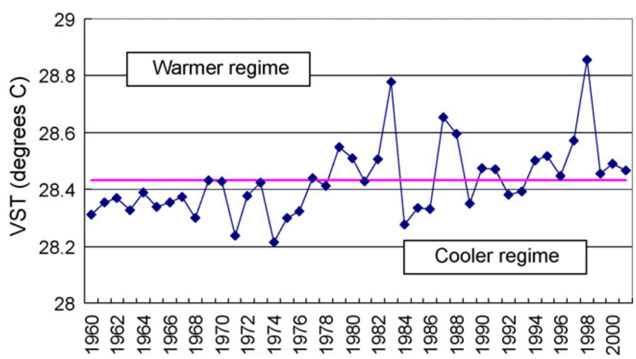

Fig. 4 – Trend of annual vertical average sea temperature (0–40 m) in the bigeye tuna spawning waters with a threshold value (28.43 °C).

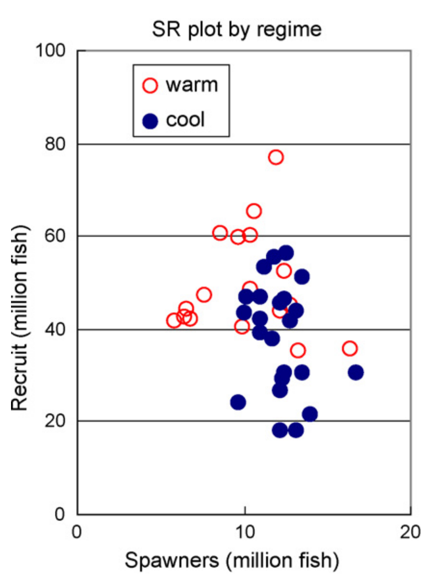

Fig. 5 – Scatterplot of the SR data by the regime.

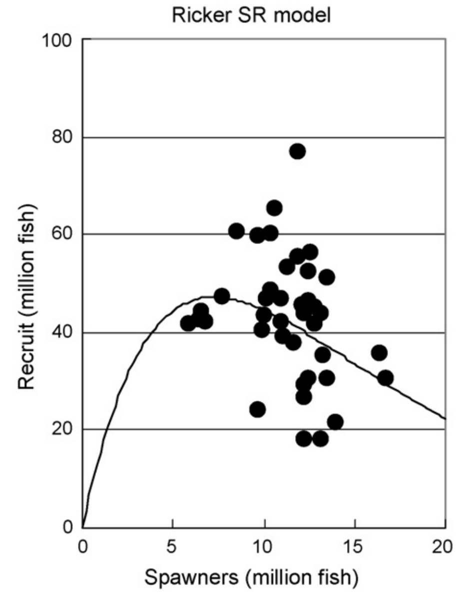

Fig. 6 – Estimated Ricker SR curve fitted for all the data ($R = S\,e^{(2.87355 - 0.13790S)}$, $r^2 = 0.5360$).

where a is the parameter measuring fish stock reproductive performance at low stock size, exp(a) the maximum recruits per spawner, b the parameter representing density-dependence in pre-recruitment, such as juvenile survival rate, and ε_t is a normally distributed error term with mean 0 and standard deviation σ. This model can be linearized as in Eq. (4):

$$y_t = \log\left(\frac{R_t}{S_t}\right) = a - bS_t + \varepsilon_t \quad (4)$$

In this form, the parameters a and b can be estimated by simple least-squares regression. Initially we estimated the Ricker SR curve for the original SR data. Fig. 6 shows the result.

3.3. *Regime Ricker model analysis*

The number of the recruitment largely depends on the number of spawners in the density-dependent Ricker SR model under

Table 3 – List of cooler and warmer regime years based on the threshold value (28.43 °C) of the VST (annual vertical average sea temperature) (0–40 m) in the bigeye tuna spawning grounds in the Indian Ocean

Regime	Years
Cooler (n = 24) (<28.43 °C)	1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970, 1971, 1972, 1973, 1975, 1976, 1978, 1981, 1984, 1985, 1986, 1989, 1992, 1993
Warmer (n = 17) (≤28.43 °C)	1977, 1979, 1980, 1982, 1983, 1987, 1988, 1990, 1991, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001

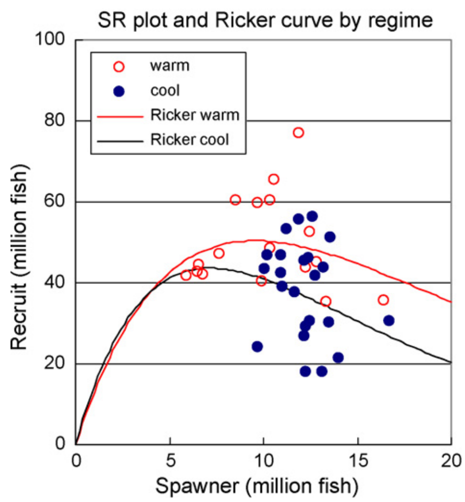

Fig. 7 – Estimated regime Ricker SR curve fitted for the SR data (r^2 = 0.61). For the warm regime: $R = S\,e^{(2.66657-0.10502S)}$. For the cool regime: $R = S\,e^{(2.80883-0.13994S)}$.

the average environmental conditions. It is known that fishery SR relationships are masked by environmental effects (Ware, 1991; Chen and Ware, 1999; Clark et al., 1999; Kaeriyama, 2004). To overcome this problem, environmental regime shift involved methods have been developed (e.g., Francis and Hare, 1994; Hare and Mantua, 2000). We call it as the regime-SR.

The regime-SR is formulated by following Eqs. (5) and (6) based on (4), where EV_t is environmental data which is the annual average vertical sea temperature (0–40 m) range between 27.5 and 30.5 °C producing fully mature BET (GI is 3.1 or larger) in this paper:

$$\text{If } EV_t \text{ is in } T_1(\text{cool}),\quad \text{then } y_t = \log\left(\frac{R_t}{S_t}\right) = a_1 - b_1 S_t \tag{5}$$

$$\text{If } EV_t \text{ is in } T_2(\text{warm}),\quad \text{then } y_t = \log\left(\frac{R_t}{S_t}\right) = a_2 - b_2 S_t \tag{6}$$

Using its threshold value (28.43 °C), we separated the SR data into two regime as in Table 3 and Fig. 5. Then we estimated two Ricker curves for each regime and results are shown in Fig. 7.

3.4. *Fuzzy-SR model*

Although the regime-SR incorporating with the environmental data seems to be the realistic and reasonable approach for the SR data, there are four fundamental problems as stated in Chen (2001): (a) the data observed for the environmental variable are a short time series of their real world representations, giving a high probability of misclassification; (b) this approach oversimplifies the natural characteristics of the environmental interventions and it is easy to misclassify those years close to the thresholds. For example, in our case, even the SR points are classified as warm or cool, they might be misclassified with a slight change, which might result from measurement error or other unknown errors; (c) this approach has the disadvantage that the information from the environmental variables is ignored in the process of fitting the data using Ricker SR model (4); (d) the SR data from the "warm years" are not used in fitting the SR model to the data from "cool years" and vice versa. In general, crisp and dichotomous classification scheme, such as "warm years versus cool years", "good years versus bad years" and "positive years versus negative years" impose subjective breakpoints on a continuously varying factor.

To overcome these problems, Chen (2001) developed the fuzzy logic-based SR analyses (fuzzy-SR). This fuzzy-SR model could handle environmental variables with linguistic categories, e.g., "cool versus warm" or "positive versus negative" without loss of generality. Chen (2001) suggested that this approach provided better and improved results than those by the crisp and dichotomous classification scheme (regime-based) approach. Generally fuzzy logic model composted of three parts, i.e., (a) fuzzy membership functions, (b) fuzzy decision rules and (c) fuzzy reasoning. These three processes applied to our BET SR data are explained as follows:

3.4.1. *Fuzzy membership function (FMF)*

VST is used as the environmental variable (EV) in our study as the input in the fuzzification process where crisp inputs are transformed into fuzzy values, i.e., values of the FMF for these crisp data. The spawning stock biomass (S) and recruitment (R) are kept as traditional variables. There are numerous choices for the FMF. For our study, we apply the simple linear model illustrated in Fig. 8 as the FMF for the cool (top diagram) and warm regime (middle diagram), respectively. As a result, we have following Eqs. (7) and (8):

$$FMF_{(warm)}(VST) = \frac{VST - \min(VST)}{\max(VST) - \min(VST)} \tag{7}$$

$$FMF_{(cool)}(VST) = 1 - FMF_{(warm)}(VST) \tag{8}$$

3.4.2. *Fuzzy decision rules*

Two fuzzy rules are decided by selecting the fuzzy membership functions defined by Eqs. (9) and (10) in our BET study. Each fuzzy rule is expressed as follows:

$$\text{Rule 1: If } EV_t \text{ is in } T_1(\text{cool}),\quad \text{then } y_t = \log\left(\frac{R_t}{S_t}\right) = a_1 - b_1 S_t \tag{9}$$

$$\text{Rule 2: If } EV_t \text{ is in } T_2(\text{warm}),\ \text{then } y_t = \log\left(\frac{R_t}{S_t}\right) = a_2 - b_2 S_t \tag{10}$$

where a_1, a_2, b_1 and b_2 are parameters to be estimated. Actually a_1 and a_2 are the parameters corresponding to the regimes, T_1 (cool) and T_2 (warm) to reflect fish stock reproductive performance at low stock size. Furthermore, $\exp(a_1)$ is the maximum recruits per spawner for the regime T_1(cool) and $\exp(a_2)$ the maximum recruits per spawner for the regime T_2(warm). The parameter b_1 and b_2 represent density-dependence in pre-recruitment survival rate in regimes T_1 and T_2, respectively. The function $y_t = \log(R_t/S_t)$, t = 1960–2001, the log-transformed stock productivity. With the rules defined in (9) and (10), the "consequent" parts (i.e., the "then-clause") of the two fuzzy rules are defined by the non-fuzzy equations of the stock spawner biomass.

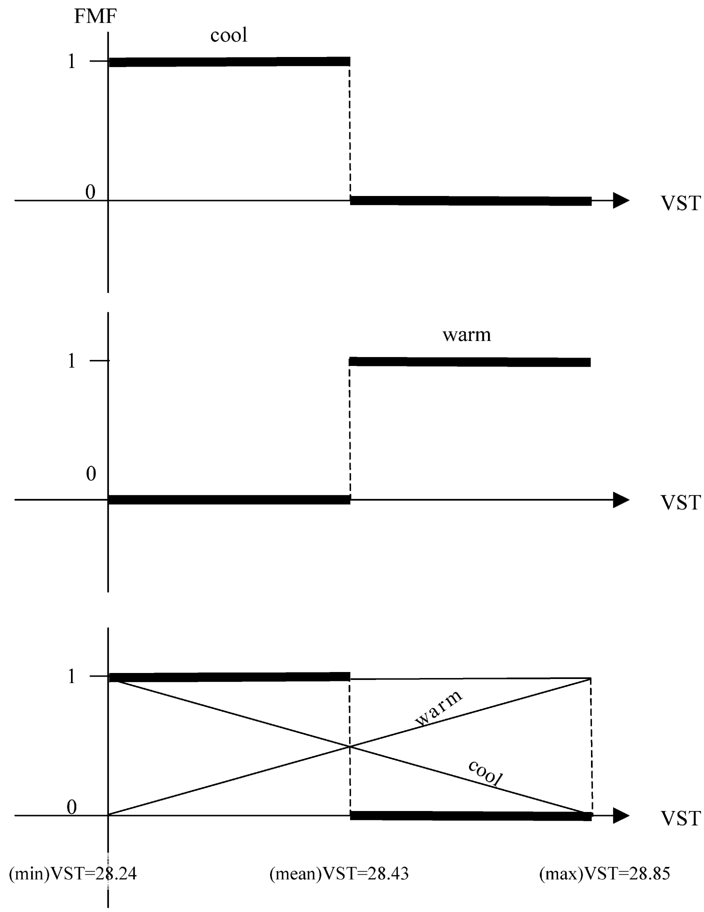

Fig. 8 – Crisp membership functions for the regime SR model (thick lines in top two diagrams) and for the fuzzy-SR model (bottom diagram). Two straight light lines present fuzzy-based warm and cool FMF, while thick lines are presented as references.

3.4.3. *Fuzzy reasoning*

With the above fuzzy logic rules defined in (9) and (10), and for any observed EV_t and corresponding S_t (fish spawner biomass), the model value of y_t is then inferred as follows:

The "firing level", a term used in fuzzy logic to refer to the FMF value for the fuzzy input and is equivalent to "weight" in Fig. 8 (bottom diagram) for each rule in (9) and (10) is computed by

$$\text{Rule 1}: \quad w_{t1} = \text{FMF}_{T_1}(\text{VST}) \tag{11}$$

$$\text{Rule 2}: \quad w_{t2} = \text{FMF}_{T_2}(\text{VST}) \tag{12}$$

For each Rule i, $\hat{y}_{ti}$ is calculated by the function defined in (9) and (10) as

$$\hat{y}_{ti} = a_i - b_i S_t \quad (i = 1, 2) \tag{13}$$

The final output of the fuzzy-SR system, $\hat{y}_t$, that is inferred from the two rules is defuzzified by computing the weighted average as

$$\hat{y}_t = \frac{w_{t1}\hat{y}_{t1} + w_{t2}\hat{y}_{t2}}{w_{t1} + w_{t2}} \tag{14}$$

Note that Eq. (14) can be simplified to $\hat{y}_t = (1 - w_t)\hat{y}_{t1} + w_t\hat{y}_{t2}$ since $w_{t1} + w_{t2} = 1$ based on Eqs. (11) and (12). With the defined fuzzy-SR model (14), the fuzzy parameters (a_1, a_2, b_1 and b_2) can be estimated by minimizing the sum of squares of errors (SSE):

$$\text{SSE}(a_1, a_2, b_1, b_2) = \sum_{t=1}^{n} (y_t - \hat{y}_t)^2$$

$$= \sum_{t=1}^{n} [y_t - \{(1 - w_t)(a_1 - b_1 S_t) + w_t(a_2 - b_2 S_t)\}]^2 \tag{15}$$

where y_t is the observed stock productivity calculated by function $y_t = \log(R_t/S_t)$, and $\hat{y}_t$ is the fuzzy-SR value from (14). The estimation of these parameters was obtained by minimizing (15) using the Gauss–Newton nonlinear method available in the SAS NLIN PROC (SAS, Version 8.0).

As a result of the first parameter estimation, b_2 (warm) was resulted to be negative, which was likely caused by high weighted warm data values in the x-value range less than 9 million fish where there are no cool data. Hence we substituted b_2 obtained in the regime SR model by assuming both are statistically not significant. Results are shown in Fig. 9. Model diagnostics for residual non-time series correlation and homogeneity are satisfied.

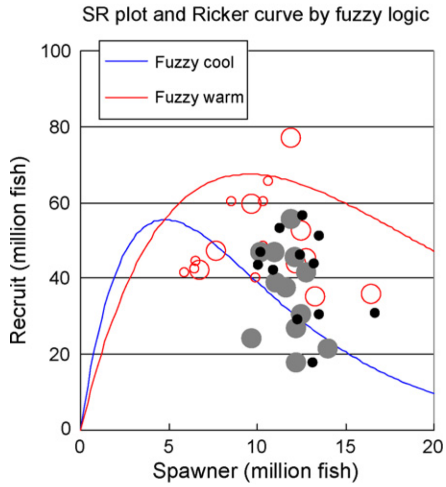

Fig. 9 – Estimated fuzzy logic-based Ricker SR curve fitted for the SR data ($r^2 = 0.69$). For the warm regime: $R = S\,e^{(2.95819 - 0.10502S)}$. For the cool regime: $R = S\,e^{(2.88220 - 0.15686S)}$. *Note*: red open circle dots represent SR data in the warm regime, while black solid and grey solid dot are for the cool regime. Sizes of these dots represent degrees of warmness or coolness.

3.5. *Comparisons*

Fig. 10 and Table 4 summarize the results of three SR model analyses. As a result, the fuzzy-SR was the best, then the regime SR and the last was the traditional SR based on the AIC and r^2 values which coincides with the conclusions from Chen (2001).

4. Discussion

4.1. *Definition of regime shift*

The regime is usually defined or separated by two time periods. But in our study, we separated the SR data by one threshold value for the warm and cool regime regardless the time period. In this way, we can conduct more realistic analyses because if we separated the data by the two time periods, we would have more misclassified points. For example, if there were many warm data in the first period (in the cooler regime) or vice versa, we will have large classification errors which weaken the performance of the fuzzy logic analyses. Hence, it is considered that separation into two regimes by the threshold value instead of two time periods would be more appropriate and reasonable approach.

4.2. *Separation of the regime*

We found that the average VST (0–40 m) is the effective parameter in order to separate the SR data into the two regimes (warm versus cool) because such temperature directly influence bigeye tuna spawning activities where they inhabited. In addition, the average temperature of the VST between 27.5 and 30.5 °C also provided the effective separation of two regimes because the temperature in this range produced more egg production (recruitment) according to Table 2 and Fig. 3.

4.3. *Evaluation of the three models*

The spawner-recruitment (SR) data have been facing difficulty to fit to the original SR models such as Ricker and Beaverton-Holt models due to the unrealistic assumptions behind, i.e., average environmental conditions and density-dependent population process. Thus, even the SR data were fit well to the models, they are likely apparent good fitness in many cases (Sakuramoto, 2004). This is because there are essentially and basically not such relationships because majority SR time series data follow the loops or the spirals and not for the original models (Sakuramoto, 2004). Fig. 11 shows some examples, i.e., in many SR model analyses, the SR data initially follow the trajectories along the original SR curves which are explainable. But at the highest point of the spawners, the trajectories of the SR data start to keep away from the SR curves and move backwards or make spirals. These phenomena cannot be explained by the SR models.

The reason for the SR trajectories to follow the loop or the spirals is that there might be some factors (mechanisms) suddenly changing the recruitment and the spawner levels

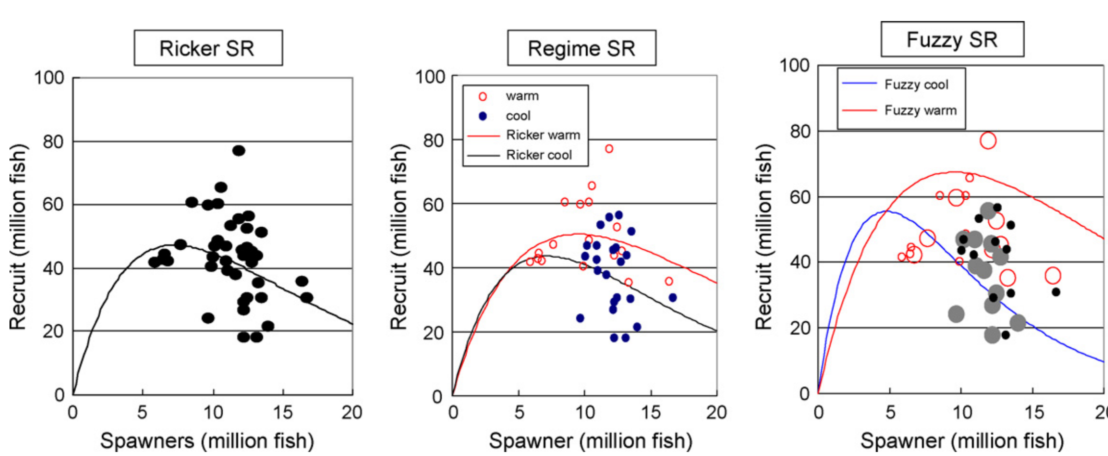

Fig. 10 – Comparisons of results of Ricker SR model analyses among the original model (left), the regime model (middle) and the fuzzy logic model (right).

Table 4 – Summary of results of three SR models

Parameters	Ricker SR (average[a])	Regime-SR		Fuzzy-SR	
		Cool[a]	Warm[a]	Cool[a]	Warm[a]
a	2.87	2.81	2.67	2.88	2.96
b	0.14	0.14	0.11	0.16	0.11
r^2	0.54	0.61		0.69	
RMSE	0.09652	0.08527		0.07648	
AIC	26.5	25.4		21.0	

[a] Environmental regime.

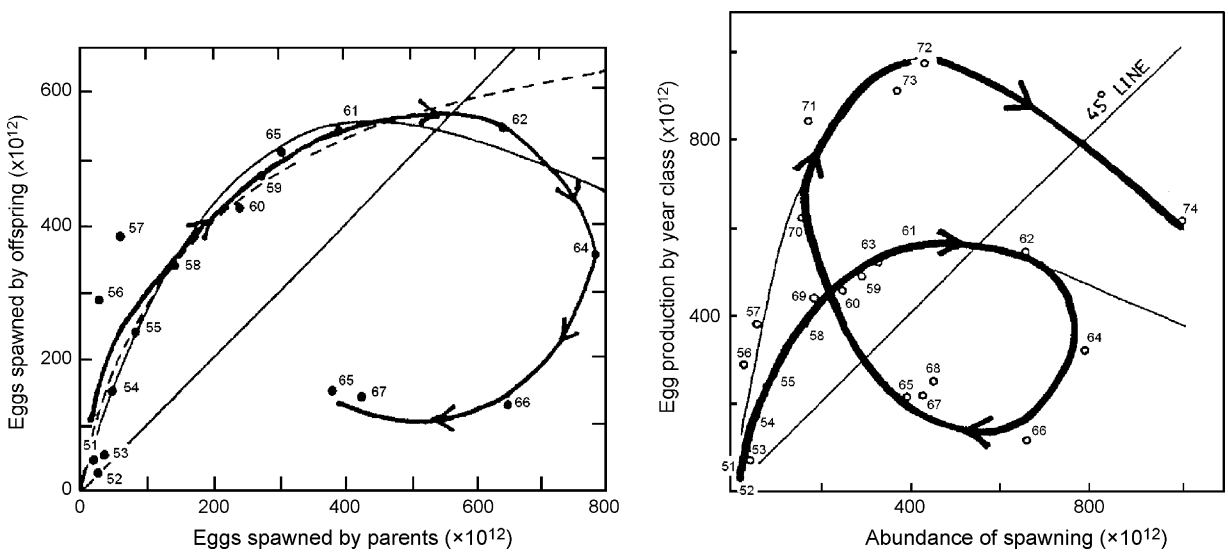

Fig. 11 – Loop and spiral observed on the SR plots and the estimated Ricker curves (Sakuramoto, 2004): (left) Japanese mackerel (original by Cushing, 1981); (right) Hokkaido herring (original by Tanaka, 1983).

dramatically. Such factors might be the regime shift of the environmental conditions, density-independent population process, strong cohort or combination of them.

In our study we consider that the regime shift of the environmental conditions play an important role to cause such phenomena, i.e., there are likely heterogeneous density-dependent process by regime. In fact, even for our cases, the original SR data shows the loop (Fig. 12). However, as a result of the fuzzy logic analyses, the loop disappeared from the SR trajectory in the warm regime while in the cool regime, there is still a minor loop. From these plots, in the cooler regime there are still likely some factor affects the intrinsic SR model, but the situation improved significantly. Although the regime-based fuzzy logic approach likely solves the looping problem but we need to prove concretely by the simulation in an extended work in the future.

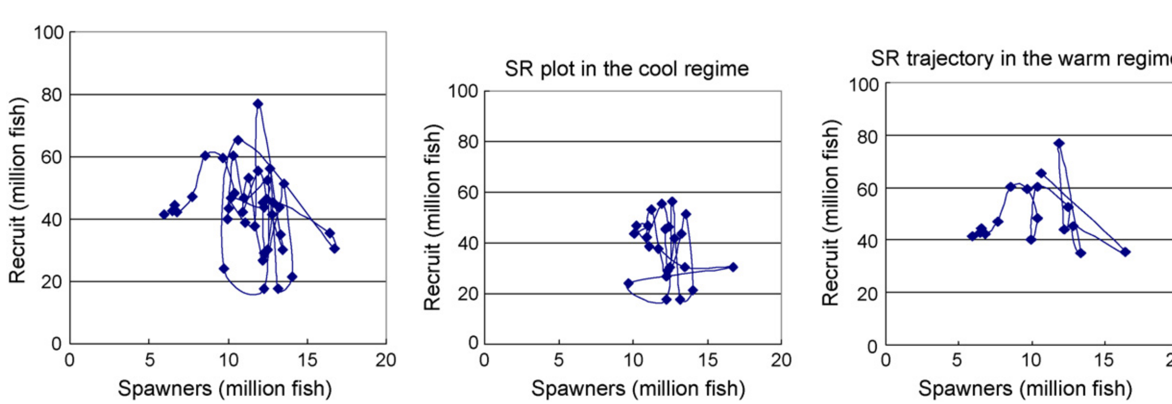

Fig. 12 – Loop observed in the original SR plot in this study (left). The loop effect is lessened in the SR plot by regime; cool (middle) and warm (right).

Thus, we consider that the environmental-based approach (regime or fuzzy model) for the bigeye SR data in the Indian Ocean can explain the density-dependent process within each regime more realistically. As the regime approach did not take account of the values of the VST while the fuzzy does, it was resulted that the fuzzy approach preformed much better than the regime approach.

5. Conclusion

In general, there are still some reservations that such good fit in many cases might be apparent as nobody proved the SR models experimentally using the real data (Sakuramoto, 2004). Nonetheless, in our case, it is likely that the fuzzy approach provided the reasonable interpretations of the SR data situation as SR plots by regime are considerably well classified and fitted well to the model which concluded that for bigeye tuna in the Indian Ocean their SR data follow the density-dependent process in each warm and cool regime.

It should be noted that we considered only the Ricker SR model with its extension in this study. It is planned that this approach will be explored in the future for other SR models such as Beaverton and Holts (1957) and other SR models discussed in Hilborn and Walters (1992) and Quinn and Deriso (1999).

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