Evolution of age determination methods for three tuna species

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Abstract

The age-based stock assessment model is the primary model used in current research on tuna stock assessment. The accuracy of age identification has a direct impact on the development of the stock assessment models. The specific application of age-identification methods for tuna varies widely across species, oceans, and historical periods, however, most methods use hard parts to infer age. There is currently no research on the development and evolution of tuna age-identification methods. Based on literature review, we used the Multinomial Logistic Regression (MLR) model to examine the differences of tuna age identification methods across species, oceans, and historical periods. We found that otoliths and dorsal fin spines analyses were most commonly used in the Pacific Ocean and the Indian Ocean than the Atlantic Ocean. Compared to albacore tuna（*Thunnus alalunga*）, otoliths analysis was more frequently used to age bigeye tuna （*Thunnus obesus*） and yellowfin tuna （*Thunnus albacores*）. As aging procedures advanced, fin spines and otoliths became the main aging materials. It is recommended that age and growth studies in the Indian Ocean should be intensified, especially for albacore tuna.

Keywords: tuna; hard parts; age determination; multinomial logistic regression

1 Introduction

Many current stock assessments are based on age-structured stock studies that estimate the maximum sustainable yield based on stock status, fishing mortality, and parent recruitment, which are used to make scientific management recommendations to keep stock in a healthy status of exploitation[1]. Accurate age identification is an important precondition for using age-structure-based stock assessment, which can provide growth data at multiple stages and investigate differences in growth patterns at various stages. Improving the accuracy and precision of age identification can refine the age differences between individuals and reduce the superposition of length groups, thus reducing observation errors in the stock assessment process and improving the accuracy of the stock assessment, as well as the subsequent recommendation of more efficient management strategies.

Tuna is a member of the Scombroidi suborder, which contains 5 genera and 15 species[2], and it is widely distributed in low and mid-latitude oceans all around the world. Among them, there are seven main commercial tuna species: Pacific bluefin tuna (*Thunnus orientalis*), Atlantic bluefin tuna (*Thunnus thynnus*), southern bluefin tuna (*Thunnus maccoyii*), albacore tuna (*Thunnus alalunga*), bigeye tuna (*Thunnus obesus*), yellowfin tuna (*Thunnus albacores*), and skipjack tuna (*Katsuwonus pelamis*), with production exceeding 5.03 million tons in 2017 and 5.3 million tons in 2019[2]. The Atlantic bluefin tuna has the longest history of fishing, with paleontological investigations revealing that hard bone tissues was discovered in caves of the Rock of Gibralta more than 30,000 years ago [3]. The growth of tuna is tightly related to its environment, with significant variances between species and even within species depending on distribution. As a result, Regional Fisheries

Management Organizations (RFMOs) divided the seven major commercial tuna species into 23 stocks based on oceans. After decades of assessment and management, 15 stocks are currently in a healthy state [4], but some species are still showing a declining trend in biomass and high fishing mortality. Most tuna species can live for up to 10 years, and bluefin tuna are up to 40 years old, with large individuals growing slowly and practically ceasing. Therefore, a proper understanding of tuna growth characteristics is essential for stock assessment.

Age identification methods include length-frequency, tag-recapture, and hard-part methods, of which hard-part identification is commonly utilized for aging tuna. Compared with length-frequency and tag-recapture, growth marks formed on hard parts provide more accurate age results[5], and the method also features cheaper sampling. The identification of Atlantic bluefin tuna by scales was the first aging study of tuna [6]. The emergence of Berry's method in the 1970s led to the maturation of vertebral age identification techniques[7, 8], while the use of otoliths made a breakthrough [7]. Besides, sampling of fin spines was simple, and the process did not damage the economic value of the fish [9], and the use rate increased throughout that period.

Differences in growth patterns, as well as catching and process, impose varied criteria on the selection of material for age identification, which is a primary factor influencing the accuracy of age identification results. Age studies of tuna have been conducted by many countries and institutions for up to a century, but the temporal and spatial changes in methods using hard parts have not been studied. The purpose of this paper is to investigate the status of hard-part aging studies for yellowfin, bigeye, and albacore tuna over time. Multinomial Logistic Regression was used to analyze the evolution of hard-part methods and their spatial and temporal changes, based on when different scholars conducted their studies, the oceans and species.

2 Materials and methods

2.1 Data sources

We searched the Web of Science database for literature on the "age and growth of tuna" as the subject in this paper, supplementing the earlier papers that are listed in previous studies as well as relevant tuna RFMOs[1, 10-13]. Besides, we searched for Chinese age studies of tuna through the China National Knowledge Infrastructure (CNKI) using the search term "age and growth of tuna". Search conducted on 9/20/2023.

123 tuna age studies using different hard parts were searched, and categorized and summarized by the ocean, species, hard parts, year of publication, and time of sampling. The year of publication represented the use of hard part age identification methods in different historical periods, and 81 studies specifically described the sampling time. If multiple hard part or tuna species were studied in the literature, they were counted separately as study samples.

2.2 Multinomial Logistic Regression (MLR)

The development and evolution of tuna hard-part age identification methods were examined in this paper. The dependent variable consisted of four levels, including scales, vertebrae, otoliths, and fin spines, and the effects of three independent variables on the dependent variable were determined: year of publication, ocean, and species. The dependent variables were multi-categorical and nonsequential, and the independent variables included two qualitative variables, oceans, and species, and one quantitative variable, so disordered MLR was used [14], and the equations were as follows:

$$\ln\left(\frac{p_i}{p_1}\right) = \alpha_i + \beta_{i1}x_1 + \beta_{i2}x_2 + \beta_{i3}x_3，\ i = 2，3，4 \tag{1}$$

where p1+p2+p3+p4=1, p1, p2, p3, and p4 are the four levels of scales, vertebrae, otoliths, and fin spines, respectively, x1, x2, and x3 are oceans, the species, and the years of publication in the literature. Respectively, i is the level of the dependent variable, α is the intercept, and β is the coefficient of the independent variable.

Unordered MLR must first set a reference level to obtain the relative parameter values under the reference level. Because this study included four levels, a single reference level cannot include the changes under all levels. Thus, different reference levels should be established to analyze the changes at the remaining levels, and the order of the use of hard parts based on the significance relationship. Oceans and species are qualitative variables, and variables need to be chosen as the reference group.

2.3 Model evaluation

Different independent variables were chosen to fit the multinominal logistic regression equation, which was tested by the Akaike Information Criterion (AIC)[15], with the minimum value of AIC indicating that it has a significant effect on the selection of hard parts and the equation is as follows:

$$AIC = -2\ln(L) + 2k \tag{2}$$

where k is the number of parameters and L is the likelihood function.

McFadden R^2 is used to evaluate the fitting effect of the logistic regression model, which belongs to the pseudo-R^2 value. When R^2 is in the range of 0.2~0.4 [16], it indicates that the model is well-suited, and the formula is as follows:

$$R^2_{\text{McFadden}} = 1 - \frac{\log(L_c)}{\log(L_{null})} \tag{3}$$

where L_c is the model likelihood and L_{null} is the corresponding value for the null model, i.e., containing only the intercept.

All computational procedures in this study were implemented through the R-4.1.3, using the nnet package for model fitting and the ggpubr package for plotting.

3 Results and analysis

3.1 Frequency analysis of hard part age studies

As shown in Figure 1, the number of studies counted by different hard parts and species in the Atlantic Ocean waters was 49, accounting for 39.8 % of the total, of which 19 used fin spines and 28 albacore tuna. There were a total of 25 studies in the Indian Ocean, with otoliths and bigeye tuna being the main subjects, and there were a total of 49 studies in the Pacific Ocean, of which otoliths and bigeye tuna were the main subjects.

In Fig. 2, otoliths were used for age identification for most years. Otoliths were employed for a long period in three oceans, and had the highest cumulative number of sampling, occupying 62.1% of the total sampling years. Fin spines were one of the main materials used for aging albacore in the Atlantic Ocean, with vertebrae and scales being the least overall.

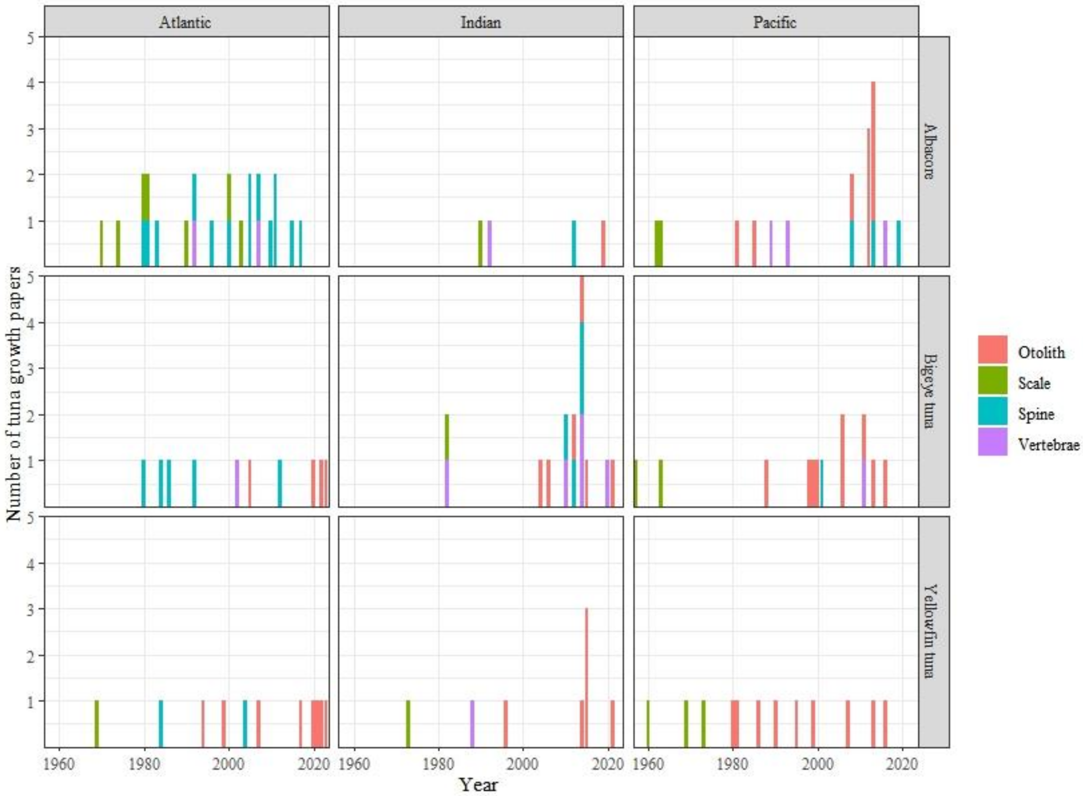

Fig.1 Frequency analysis of studies on hard parts by publication year

Fig.2 Frequency analysis of studies on hard parts by sampling year

3.2 Model evaluation

The independent and dependent variables were fitted separately to obtain the AIC and McFadden R^2 values for different reference levels as shown in Table 1. Among the three independent variables, the year of literature publication had the most significant effect on the selection of hard parts, followed by oceans and tuna species. The combination of species and years of literature publication fitted the dependent variable better among the combinations of two independent variables. When the three independent variables were functioning simultaneously, the AIC value was the lowest when compared to others, and the McFadden R^2 value was at 0.48, which was the best model.

Tab.1 AIC and McFadden R^2 of the reference group for each independent variable

Independent Variable	Scale		Vertebrae		Otolith		Spine	
	AIC	McFadden R^2	AIC	McFadden R^2	AIC	McFadden R^2	AIC	McFadden R^2
Ocean	314.19	0.07	314.19	0.07	314.19	0.07	314.19	0.07
Year	243.12	0.27	241.01	0.28	239.99	0.28	240.94	0.28
Specie	304.77	0.10	304.77	0.10	304.77	0.10	304.77	0.10
Specie + Ocean	299.38	0.15	299.38	0.15	299.38	0.15	299.38	0.15
Specie + Year	215.38	0.40	214.36	0.40	214.38	0.40	214.31	0.40
Ocean + Year	230.58	0.35	226.84	0.36	226.99	0.36	226.84	0.36
Ocean + Year	203.38	0.47	201.63	0.48	201.64	0.48	201.70	0.48

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3.3 MLR statistic

3.3.1 Differences in the use of hard parts between oceans

Differences in hard part studies between oceans are shown in Table 2, with a declining trends in using otoliths, scales, vertebrae, and fin spines in the Pacific compared to tuna age studies in the Atlantic. The Indian Ocean has the highest number of aging studies using scales, vertebrae, and otoliths, and the lowest number utilizing fin spines.

Tab.2 Relative regression statistics for the effect of the ocean on the selection of hard parts

Reference Levels	Dependent Variable	Independent Variable	Coefficient	Standard error	OR	P
Scale	Vertebrae	Pacific	-1.53	0.53	3.43	0.004
		Indian	-0.66	0.27	3.17	0.015
	Otolith	Pacific	2.41	0.48	0.06	<0.001
		Indian	0.02	0.44	1.56	0.96
	Spine	Pacific	-0.41	0.50	1.17	0.404
		Indian	-1.26	0.48	5.07	0.008
Vertebrae	Otolith	Pacific	1.25	0.40	0.28	0.002
		Indian	-1.08	0.52	2.87	0.037
	Spine	Pacific	-1.62	0.53	5.04	0.002
		Indian	-2.33	0.56	10.35	<0.001
Otolith	Spine	Pacific	-2.89	0.57	0.06	<0.001
		Indian	-1.25	0.61	0.29	0.04

3.3.2 Differences in the use of hard parts between tuna species

Table 3 shows that yellowfin tuna age studies employed otoliths more frequently than albacore tuna studies. Bigeye tuna age identification studies used otoliths, fin spines, scales, and vertebrae in a decline trend.

Tab.3 Relative regression statistics for the effect of species on the selection of hard parts

Reference Levels	Dependent Variable	Independent Variable	Coefficient	Standard error	OR	P
Scale	Vertebrae	Yellowfin tuna	-0.33	0.48	1.10	0.488
		Bigeye tuna	-1.64	0.40	3.13	<0.001
	Otolith	Yellowfin tuna	4.19	0.56	0.01	<0.001
		Bigeye tuna	2.85	0.39	0.03	<0.001
	Spine	Yellowfin tuna	0.13	0.46	0.76	0.776
		Bigeye tuna	1.00	0.46	0.24	0.029

Vertebrae	Otolith	Yellowfin tuna	4.23	0.52	0.01	<0.001
		Bigeye tuna	1.79	0.53	0.17	<0.001
	Spine	Yellowfin tuna	0.02	0.55	0.98	0.974
		Bigeye tuna	-0.11	0.46	1.11	0.810
Otolith	Spine	Yellowfin tuna	-4.24	0.75	0.01	<0.001
		Bigeye tuna	-1.92	0.51	0.15	<0.001

3.3.3 Differences in the use of hard parts between different historical periods

Differences in hard part studies from different historical periods are shown in Table 4, where the frequency of otoliths, fin spines, scales, and vertebrae used for tuna age identification decreases over time.

Tab.4 Relative regression statistics for the effect of publishing year on the selection of hard parts

Reference Levels	Dependent Variable	Independent Variable	Coefficient	Standard error	OR	P
Scale	Vertebrae	Year	-0.20	0.0003	1.15	0
	Otolith	Year	0.22	0.0002	0.75	0
	Spine	Year	0.17	0.0003	0.81	0
Vertebrae	Otolith	Year	0.08	0.0003	0.92	0
	Spine	Year	0.02	0.0002	0.98	0
Otolith	Spine	Year	-0.06	0.0002	0.94	0

4 Conclusion

The use of hard parts is directly related to tuna species, oceans, and the year in which the study was conducted. The utilization of hard parts and spatial and temporal variation have the strongest association of the three parameters. In the late 1970s, breakthroughs in dealing with otolith procedures permitted the use of this hard part, resulting in a huge increase in the number of studies and hard parts collections. Aging bigeye and yellowfin tuna favored otolith contrast to albacore tuna, and dorsal fin spines are the predominant hard part in the Atlantic. Fewer hard-part age studies of tuna in Indian Ocean have been done, with the majority of them focussing on the time following the creation of the IOTC.

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