Iran. J. Ichthyol. (2025) 12(2): 101-122
P-ISSN: 2383-1561; E-ISSN: 2383-0964
© 2025 Iranian Society of Ichthyology

ORIGINAL ARTICLE

Catch-based data-limited stock assessment of Frigate tuna (*Auxis thazard* Lacepède, 1800) in the Persian Gulf and Oman Sea (Iranian southern waters)

Seyed Ahmadreza HASHEMI*[1], Mastooreh DOUSTDAR[2], Sachinandan DUTTA[3]

[1]Offshore Fisheries Research Center, Iranian Fisheries Science Research Institute, Agricultural Research, Education and Extension Organization, Chabahar, Iran.
[2]Iranian Fisheries Science and Research Institute, Agricultural Research Education and Extension Organization, Tehran, Iran.
[3]Department of Marine Science and Fisheries, College of Agricultural and Marine Sciences, Sultan Qaboos University, Oman.

Correspondence
seyedahmad91@gmail.com
s.dutta@squ.edu.om

Article history:
Accepted 18 January 2025

Abstract
The aim of this study is to develop a framework for investigating the catch trend and estimating the optimized catch limit of Frigate tuna (FRI) stock by collecting catch data in the Iranian southern waters, including the Persian Gulf and the Oman Sea. Two methods were employed to determine the biological reference points (BRPs) of Frigate tuna in the Persian Gulf and Oman Sea. Catch data spanning 26 years (1997-2022) was utilized, and the optimized catch limit was estimated using a limited data approach. The average catch (Ct) over this period was 22,439 tons (95% confidence interval 18,299-26,638 tons), showing a significant increase over the past two decades (R= 0.9, P<0.05). The average maximum sustainable yield (MSY), current biomass to the biomass of MSY (B/B_{MSY}) ratio, the ratio of current fishing mortality to the fishing mortality rate of MSY (F/F_{MSY}), and saturation (S= B/K) ratio were obtained using the extension of Catch-MSY (CMSY) and Stochastic Surplus Production model in Continuous-Time (SPiCT). The results from different models showed that the current B/B_{MSY} ratio, F/F_{MSY} ratio, and MSY were not significantly different based on a t-test (P<0.05). The findings from the last year of the study indicated that the exploitation ratio in the Frigate tuna stock is below sustainable levels (under exploitation), our result indicating that more exploitation of FRI species is possible in the Persian Gulf and Oman Sea.

Keywords: Frigate tuna, Catch-MSY, Surplus Production model, Persian Gulf, Oman Sea

INTRODUCTION

Fisheries science assists in decision-making regarding fish management (Su et al. 2021). This guidance often involves predictions on sustainable catch levels at various fishing intensities and typically incorporates estimates of the necessary effort to maximize catch without jeopardizing population health (King 2007). Maintaining fishing activities at sustainable levels requires striking a balance between harvest rates and population replenishment through reproduction and growth (Bastardie et al. 2022). Understanding the biology of fish populations is crucial for optimizing catches while minimizing environmental and population impacts (Jennings et al. 2000). Formal stock assessments are limited by the fact that most fishery stocks in the world have limited data (Li et al. 2022). To improve stock assessment and create precautionary management plans, it is essential to determine how input data affects stock assessment (Cadrin 2020; Al Shehhi et al, 2021). The term "catch-based data-limited stock assessment" is a technique for assessing a fish stock's condition when further biological data are scarce or nonexistent and only catch data is available (Pons et al. 2020; Ovando et al. 2022). Typically, this method uses statistical models and studies of historical capture data to estimate biomass, fishing mortality, and stock size, among other important characteristics.

Even in situations where thorough biological data are absent, researchers can nevertheless evaluate the health of a fishery and make well-informed management decisions based solely on catch statistics (Gebremedhin et al. 2021).

Signs of overfishing of key fish species and other aquatic resources have become prominent in recent years. The proportion of fish caught at biologically sustainable levels (BSL) and biologically unsustainable levels (BUL) was approximately 90%

in 1974 but dropped to about 67% by 2016 (FAO 2018). Total fish capture in Iran reached nearly 800,000 tons, with more than 90% (720,000 tons) coming from southern Iranian waters (IFO 2023). Today, various methods are employed to measure and estimate fish populations and determine sustainable catch levels. These methods are utilized in fisheries worldwide, particularly in areas with limited available data. Examples include length-based spawning potential ratio (LBSPR), length-based Bayesian models (LBB), and catch-based approaches such as Maximum Sustainable Catch (Catch-MSY), Depletion-Based Resource Loss Analysis (DBSRA), and Catch-MSY (CMSY) (Wetzel & Punt 2015).

Frigate tuna (*Auxis thazard*) is one of the smallest species of the Scombridae family (the mackerel, tuna, and bonito family) that travels around the top layer of the ocean (preference of depth range not deeper than 50 meters). Cayré et al. (1993) reported the longest length for this species in the eastern Atlantic Ocean was found 65 cm of fork length (FL). Frigate tuna is a coastal species (an epipelagic and neritic fish) found circumglobally in tropical and subtropical oceans (Collette & Nauen 1983) and it has a localized migratory habit and mainly restricted to oceanic islands, continental shelves with a strong schooling behavior (Collette & Nauen 1983; *Deepti & Sujatha 2012*; Lucena-Frédou et al. 2021; Ajik & Tahiluddin 2021; Vieira *et al.* 2022). Frigate tuna is a type of fish that is often found in shallow waters and is usually caught in set nets. Surface gears and small-scale fisheries, like fishing lines, nets, and traps, can also catch it (Collette & Nauen 1983). Between 1997 and 2022, the average amount of frigate tuna caught each year was about 2240 tons (IFO 2023).

Today, the importance of forecasting and its different models in different sciences is not hidden from anyone and it is done by different methods such as Arima and neural network models. ARIMA models or integrated autocorrelation and moving average (ARIMA) models perform well in explaining changes and forecasting (Tsitsika et al. 2007). Neural networks can be called electronic models of the nervous structure of the human brain (neurons that include three parts of the body, axon and dendrite) and their learning and training mechanism is based on experience just like the human brain. Simulated neural networks are only able to simulate a small part of the characteristics of biological neural networks (Tiumentsev & Egorchev 2019*)*. The structure of the neural network includes a large number of perceptron (it is considered the simplest and oldest model of a neuron and receives a number of inputs, aggregates them and applies the activation function on them) with a functional function, and each perceptron is the output of all the perceptron due to its weighting factor. It aggregates the previous ones and transfers them to the next layer through the functional function (Skaar 2020).

Over the past two decades, there has been a notable increase in the catch of Frigate tuna. Despite its economic significance, there remains a lack of understanding regarding population measurement techniques for this species. While various authors have contributed to the literature on different aspects of Frigate tuna, including its biology and ecology (Cayré et al. 1993; Talebzadeh 1997; Deepti & Sujatha 2012; Lucena-Frédou et al. 2017; Pons *et al.* 2020; Darvishi et al. 2020; Lucena-Frédou *et al.* 2021; Ajik & Tahiluddin 2021; Vieira et al. 2022), research specifically focused on stock assessment in Iran remains limited, with only a few studies conducted by various authors in the past such as Tabatabaei et al. (2020), Haghi Vayghan et al. (2021) and Hashemi et al. (2023). The study aims to establish a framework for analyzing catch trends and determining the optimal catch limit of the southern waters of Iran's frigate tuna stock. Additionally, the analysis of catch data gathered over a 26-year period will determine the biological reference points (BRPs) of the species, and management strategies will be suggested along with an assessment of the stock's exploitation status.

MATERIAL AND METHODS

The study area covers four main Iranian fishing ports (Khuzestan, Bushehr, Bandar abbas and Chabahar) in the waters of northern Persian Gulf and Oman Sea (Fig. 1). The Frigate tuna (FRI) fishery data were

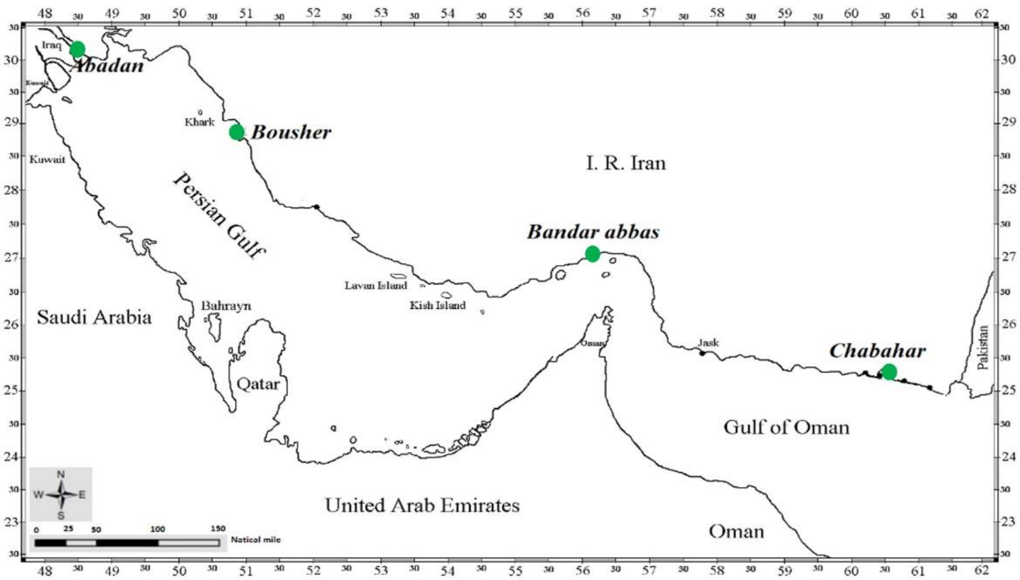

Fig.1. Location of four sites (circle with green color) in Waters of the Persian Gulf and Oman Sea.

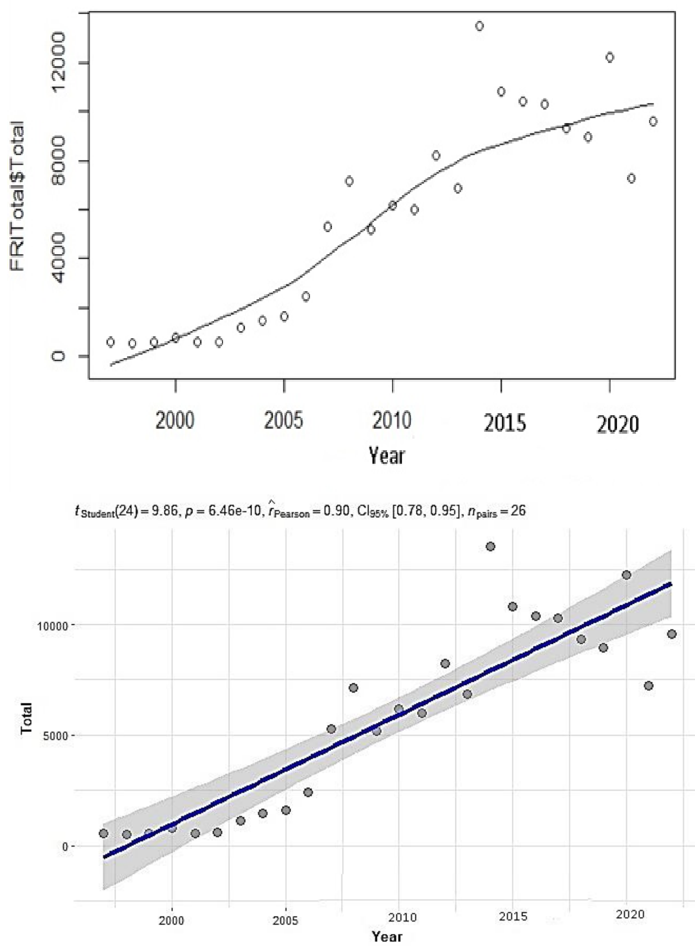

Fig.2. Fish catch quantity and trends of Frigate tuna in Waters of the Persian Gulf and Sea of Oman.

collected from the logbooks of Iranian drift gillnet fishing fleets in the southern Iranian waters, which were supplied by the Iranian fisheries organization (IFO). Data from 1997 to 2022 (26-year record of tuna catches) were gathered for calculation and inputted into the models (Fig. 2).

C-MSY (CMSY) method (Monte-Carlo algorithm): The C-MSY and Graham-Shaefer models share characteristics, and both uses catch time data to estimate maximum sustainable yield and fisheries reference points. CMSY requires prior distributions on r and k, as well as biomass at the beginning (Froese et al. 2017). Subsequent biomass is generated using a Schaefer equation (Martell & Froese 2013).

$B_{y+1} = B_y + rB_y\,(1 - B_y / k)\, es^1 - Ct\, es^2,$

This methodology uses formulas to calculate instantaneous population growth (r) and carrying capacity (K) based on depletion (d) and resource saturation (S). The maximum sustainable yield (MSY) is calculated from MSY= rk/4, and B_{MSY}= K/2. A tentative range for r is set based on the sustainability of stocks, with highly sustainable stocks assigned r values between 0.6 and 1.5. Population growth rates were calculated using the irf formula, which involves the inverse range coefficient and 3/r high – r low (Frose et al. 2016).

To achieve the desired model sampling, the prior process error variance should be 0.2 and the explanatory error must be 0.1 according to Froese et al. (2016). Exploit records for the first and last year are used, and the previous preliminary relative biomass ranges from 0.1 to 0.4, while the most recent relative biomass ranges from 0.2 to 0.65. The initial median relative biomass in 2005 was 0.5 to 0.9 over a year. See Martell & Froese (2013) and Froese et al. (2017) for CMSY details.

Stochastic surplus Production model in Continuous-Time (SPiCT): The SPiCT model is a type of model that is based on the Pella-Tomlinson model. It allows for different shapes of the production curve, not just a symmetrical one. You can find more information about the SPiCT model and its different options in the book written by Pedersen and Berg in 2017. The model has a basic structure that can include errors in the process and what is observed, as well as models that assume there are no errors in what is observed. SPiCT thinks that the numbers of fish caught might have mistaken, and it also tries to figure out how much error there is in estimating how many fish are left in the water (Mildenberger et al. 2020; Cai et al. 2023). The SPiCT can use some general guesses about the production curve and observation errors, or it can analyze the data without any guesses. (Biais 2022). The analysis was performed using the R package spict v.1.2.8 available at https://github.com/DTUAqua/spict.

Forecasting Methods

ARIMA and neural network (NN): The autoregressive integrated moving average (ARIMA) models showed that they were good at explaining and predicting things. The researchers looked at patterns in the data to make models for forecasting. The ARIMA model was used on the data, and the best model was picked by looking at the Akaike coefficient data autocorrelation functions test (Lawer 2016). The ARIMA models have a basic structure called ARIMA (p,d,q). The "p" represents the order of the autoregressive term (AR term); d is the degree of differencing involved to achieve stationarity; and q is the order of the moving average term (MA term).

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were calculated the following formula (m is that the number of the estimated parameters and n is that the number of the observations):

AIC= -2 ln (maximum likelihood) + 2m

BIC= -2 ln (maximum likelihood) + m ln(n)

The type of feed-forward neural network (FNN) used in this research include simple feedforward network that simple neural networks with a hidden layer and activation algorithm from input to output layer, without communication between neurons in a hidden layer, without backward loop and error propagation learning model) (Chen et al. 2020; Martinez et al. 2022). The difference between neural network models is the learning method, prediction algorithm and calculation of their output. In this model, the input components were seen as factors and the output layer as a dependent component. In the prediction of time series, the inputs of the artificial neural network are observations with a time series interval, and the output of the network is their future values. In fact, if the past observations are in series, then the artificial neural network approximates and projects the following function, where y is the time

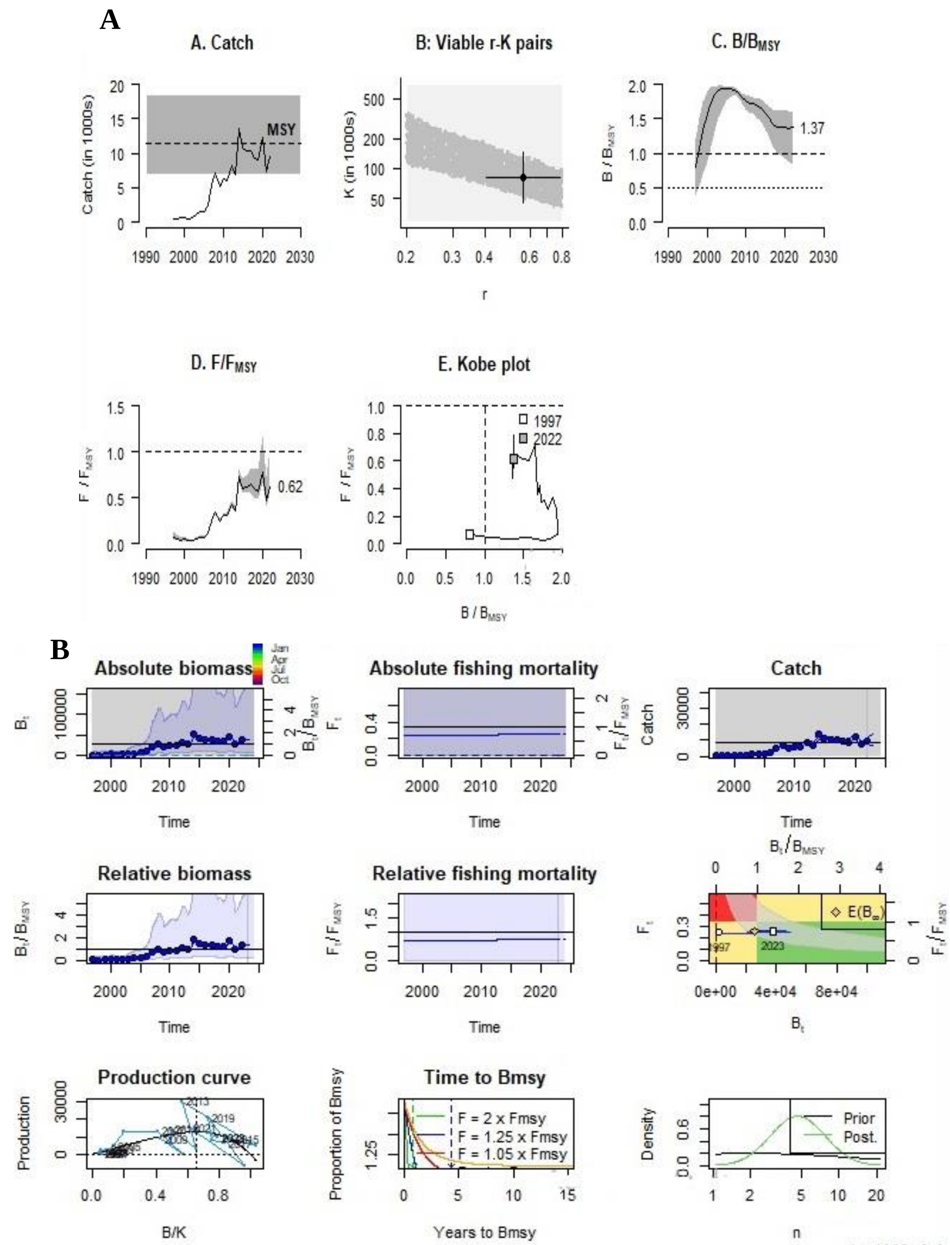

Fig.3. Comparison of averages BRP values (CMSY) (A) and SPiCT (B)) of Frigate tuna in Waters of the Persian Gulf and Sea of Oman.

observation, xi is the input of the model, yi is the output of the model, and f(n) is the functional and active function (Benzer & Benzer 2019).

$$y_{t+1}=f(y_t, y_{t-1}, \ldots, y_{t-n})$$

$$Yi = f(n) = f(\sum_{i=1}^{P} wini + b\ )$$

Statistical analyses were performed with R software (R Core Team 2022), R studio (2023.03.1-446), SPSS (26) software package and a significance level of 0.05 was adopted.

RESULTS

The amounts (1000 tons) of trend catch of frigate tuna species (FRI) showed in Fig. 2 and it has a positive and significant correlation with time (sig. 0.9 (0.78-0.95), P<0.05). The average catch (min-max) of this period was 22.4 (7-41) respectively, and the average catch was significantly increase for the twenty-six years (Figs. 2 and 3).

The software used information about how many fish were caught each year and how fast the fish grow to start making models of the fish populations (initial

Table 1. Comparison of different indices of data-limited approach for Frigate tuna in the Persian Gulf and Oman Sea. The range of the maximum sustainable yield (MSY), current biomass to the biomass of MSY (B/B_{MSY}), the ratio of the current fishing mortality to fishing mortality rate of MSY (F/F_{MSY}) and saturation (S=B/K) ratio in different method.

Indices/models	CMSY Mean (max-min)	SPiCT Mean (max-min)	Mean
MSY (1000 tons)	11.3 (9-24)	12.7 (8-32)	12±0.9
B/B_{MSY}	1.37 (0.8-1.97)	1.38 (0.5-2)	1.37±0.01
F/F_{MSY}	0.62 (0.2-0.39)	0.75 (0.3-1.2)	0.68±0.09
S=B/K	0.68	0.67	0.67±0.01

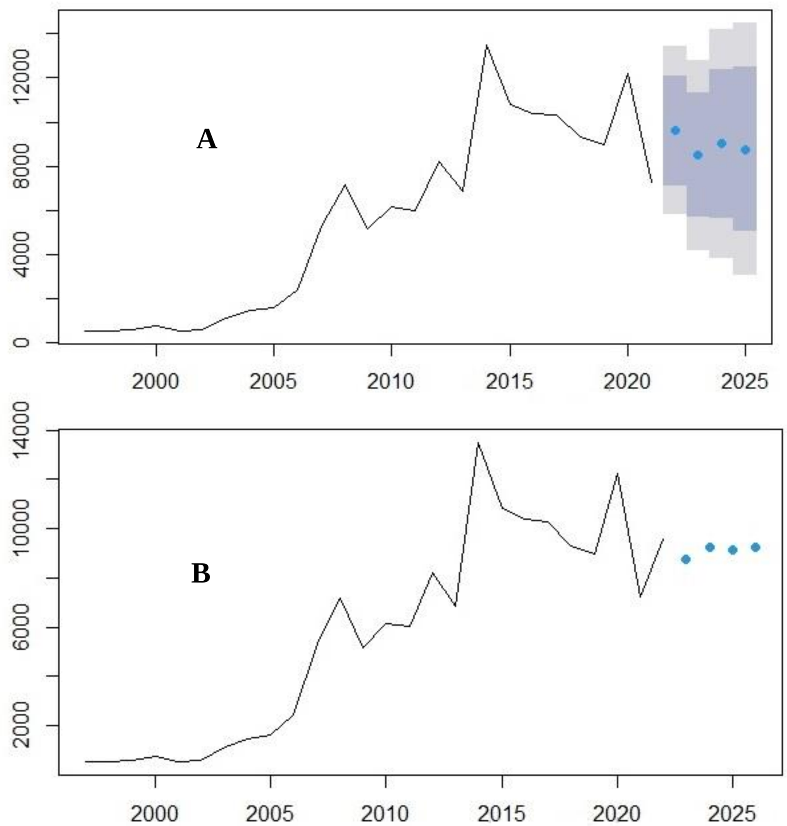

Fig.4. Predict catch values (ARIMA) (A) and NN (B)) of Frigate tuna in Waters of the Persian Gulf and Sea of Oman.

growth 0.2-0.8 per year). It used a method called CMSY and SPiCT. The starting amount of living matter was between 0. 5 to 0.9, and the ending amount was between 0. 2 to 0.6. The results from running the Monte Carlo simulation 10,000 times are shown in Table 1. The average values (95% confidence interval) of B/B_{MSY}, F/F_{MSY} and maximum sustainable yield (MSY) and saturation (S=B/K=0.5 B/B_{MSY}) ratio are shown in Table 1. Average (maximum-minimum) of maximum sustainable yield (MSY), biomass of MSY (B_{MSY}) and current fishing mortality to fishing mortality rate of MSY (F/F_{MSY}) saturation (S=B/K) ratio based on CMSY, SPiCT models were estimated and the mean reference points show significant difference by statistical tests (P<0.05), but saturation (S=B/K) ratio have no significant difference(P>0.05).

A strong and positive correlation has between the B/B_{MSY} values in CMSY, SPiCT models (P<0.05). The range of the current biomass to the biomass of MSY (B/B_{MSY}), the ratio of the current fishing mortality to fishing mortality rate of MSY (F/F_{MSY}) and maximum sustainable yield (MSY) and saturation (S=B/K) ratio in different method present in Table 1 and Figure 3.

Forecasting Methods: Various models were then fitted and compared using identified orders of ARIMA (p, d, q) based on the AIC and BIC. However, ARIMA (1, 1, 0) with drift was suitable for modeling annual *A. thazard* landings (Fig. 4) based on the selection criteria (AIC=452, BIC=455) and it predicts a decreasing trend compared to catch of 2022. Feed-forward neural network (FNN) indicates the increasing trend of catching this species in the southern waters of the country (Iran). The comparison of the two models showed that the ARIMA (1, 1, 0) model (MAE= 1821 and RMSE= 2112) has less error than the feed-forward neural network (FNN) model (MAE= 1990 and RMSE= 2283) and shows a better prediction of the catch for *A. thazard* species in this area.

DISCUSSION

This species exhibits moderate flexibility (r= 0.2-0.8) in terms of intrinsic population growth rate, which affects its ability to withstand fishing pressure and recover from declining fish stocks. The intrinsic population growth rate is a critical parameter for modeling and managing fisheries. Different flexibility classifications are assigned based on rate values: high flexibility (r= 0.6-1.5), moderate flexibility (r= 0.2-1.0), low flexibility (r= 0.05-0.5), and very low flexibility (r< 0.015-0.1) (Martell & Froese 2013; Froese et al. 2016; Zhou et al. 2017). There is a strong correlation between intrinsic population growth (r) and other life history parameters, especially natural mortality (M). The quality model gives r= 1.73M for bony fish and r = 0.76M for elasmobranchs (Zhou et al. 2017). Froese & Pauly (2015) found that the intrinsic population growth rate (r) is approximately twice the maximum fish mortality rate (F_{MSY}) for maximum sustainable catch, twice the natural mortality rate (M), 3 times the growth rate coefficient of the von Bertalanffy curve (K), 3 divided by the generation time (t_{gen}), and nine divided by the maximum age (t_{max}).

In the present analysis, mean of amount of current biomass to biomass of maximum sustainable yield (B/B_{MSY}) indicated that FRI species is under fishing (under exploitation) (Tab. 2) for catching fisheries in the Persian Gulf and Oman Sea (Iran). In addition, current level of F/F_{MSY} calculated as increasing trend and it is less than full exploitation situation (Arrizabalaga et al. 2012). Fisheries are rated using the B/B_{MSY} metric, with three categories: $B/B_{MSY} \geq 1/2$ is underexploited, 0.8-1.2 is fully exploited, 0.2-0.8 is overexploited, and <0.2 indicates collapse (Branch et al. 2011; Anderson et al. 2012).

Mean of $S=B/K=B/B_0$ ratio (biomass relative to carrying capacity) show that this species had healthy stock in the Persian Gulf and Oman Sea (Iran). Based on available resources, stocks with B/K between 0.2-0.6 are fully exploited and those with B/K over 0.6 are lightly exploited) Anderson et al. 2012). Exploitation and population biomass impact population growth and sustainable yield biomass (Zhou et al. 2017) and our result indicating that more exploitation of FRI species is possible in the Persian Gulf and Oman Sea. Rebuilding overexploited fishery stocks takes 2-3 times a species' life span (FAO 2018).

All in all, the ZBRT method calculated more saturation (B/K) than the others, but the differences between these methods were not significant. Suggested to use average of methods for less error in calculations. Estimating stock status is a first step and not a guarantee for management (Free et al. 2020).

Using careful effort-based regulations and catch methods can improve B/B_{MSY} status and reduce overfishing risks. However, this approach may result in lower yield compared to more precise determination of status (Walsh et al. 2018)

We suggest using catch-only methods as a temporary measure until more reliable options are available. Various COMs have been created to estimate stock status under data limitations; however, these models make simplifying assumptions that increase the chances of bias and uncertainty in their estimates. Using catch-only models can lead to inaccurate and biased stock status estimates, which can impede effective control efforts (Ovando et al. 2022).

FAO (1993) says that the reference points (RPs) used in fishery management, such as maximum sustainable yield, are mainly helpful for assessing individual fish populations and not very useful for highly migratory fish like tunas. Many different places catch tuna as they migrate, but they only do it for a short time each year.

In generally, nonlinear forecasting approach better than linear forecasting. Based on the results, the ARIMA model (1, 1 0) is the best model among ARIMA models, and many studies in various fields have spoken about the appropriate forecasting ability of such models (Tsitsika et al. 2007; Shabri & Samsudin 2015; Hashemi & Mirzaei 2019). Studying data about fisheries over time has been useful for making decisions about how to manage and protect them. It helps us understand the general and seasonal trends and patterns. (Koutroumanidis et al. 2006). ARIMA models have been good at predicting fishing dynamics of a wide range of species in the past.

Predicting fish production in different areas using ARIMA models has been used a lot in fisheries. Univariate and multivariate ARIMA models are helpful for making these predictions. This paper aims to create a better way to predict the number of a certain species in the Persian Gulf and Oman Sea. Those in charge of overseeing the fishing industry in the Persian Gulf and Oman Sea should focus on the current trends to improve how it is managed (Rosenberg et al. 2005).

Some studies show that the performance of time series modeling and artificial neural network (Benzer & Benzer 2019) depends on the data volume and time scale studied, and in general, the performance of neural network seems to be better than ARIMA models. forward neural networks are one of the best neural network modeling methods, and when the data volume is high, it is better than other neural network models, and when the data volume is low, the generalized regression neural network is better than other methods. It will have better output with less error (Chen et al. 2020).

In fact, the purpose of creating a neural network, rather than simulating the human brain, is to create a mechanism to solve engineering problems inspired by the behavioral model of biological networks (Azadtalaitepe et al. 2015). The reason for using neural networks in pattern recognition is because of their ability to learn and store knowledge. Currently, neural networks are widely used in pattern recognition, clustering, modeling, estimation and identification and prediction of systems due to their high ability to process information and solve complex problems (Asgharieskoui 2002).

Castellano-Mendez et al. (2004) believe that artificial neural networks are more capable in short-term forecasts because the results of their study showed that time series models perform better in monthly forecasts. Neural network forecasting studies are currently one of the most popular forecasting methods and are mainly carried out in a short period of time, because with the increase of the time period, the amount of error and uncertainty of the forecast increases and reduces its reliability (Chen et al. 2020). Therefore, it is suggested to carry out further studies in the field of comparing the efficiency of artificial neural networks and time series in forecasting aquatic catch in short time scales.

CONCLUSIONS

This study concludes that the how well catch trends and stock assessments for frigate tuna in the Persian Gulf and Oman Sea are improved by catch-based, data-limited stock assessment techniques like CMSY and SPiCT. Given the current under exploitation status of the species, as demonstrated by a mean B/B_{MSY} ratio of 1.37±0.01, rising catch levels in the southern region is considered reasonable in the context of sustainable fishing techniques. To guarantee long-term sustainability, recommendations include increasing fishing efforts and exploitation ratios while putting strong monitoring and management measures in place. In order to enable adaptive management strategies, maximize financial returns from sustainable fishing practices, and further improve future catch estimates, forecasting techniques like ARIMA models and neural networks can be combined. Fisheries authorities must work together to produce comprehensive management plans that prioritize sustainable resource use and conservation.

ACKNOWLEDGMENTS
We would like to thank Prof. Bahmani, the manager of the Iranian Fisheries Science Research Institute (IFSRI) and also very grateful the experts of the Offshore Fisheries Research Center (OFRC, Chabahar), for helping the project work. Dr. Dutta grateful to Sultan Qaboos University, College of Agricultural and Marine Sciences, Oman for research and administrative supports.

REFERENCES
Ajik, J.O. & Tahiluddin, A.B. 2021. Size distribution, length-weight relationship, and catch per unit effort of frigate tuna, *Auxis thazard* (Lacepède, 1800) in Tawi-Tawi waters, southern Philippines, caught using multiple handlines. Marine Science and Technology Bulletin 10(4): 370-375.

Al-Shehhi, A.M., Dutta, S. & Paul, S., 2021. Stock assessment of *Scomberomorus commerson* (Kingfish) fishery of Oman: Perspectives of sustainability. Regional Studies in Marine Science, 47, p.101970.

Anderson S.C.; Branch T.A.; Ricard D. & Lotze H.K. 2012. Assessing global marine fishery status with a revised dynamic catch-based method and stock-assessment reference points. Journal of Marine Science 1(2): 20-26.

Arrizabalaga, H.; Murua, M. & Majkowski, J. 2012. Global status of tuna stocks: summary sheets. Revista de Investigación Marina, AZTI-Tecnalia 19(8): 645-676.

Asgharieskoui, M. 2002. Application of neural network in time series forecasting. Iranian Economic Research Quarterly 12(1): 96-69.

Azadtalaitepe, N.; Bahmanesh, J.; Mantsari, M. & Vardinjad, V. 2015. Comparison of time series and artificial neural network methods in forecasting reference evapotranspiration (case study: Urmia). Irrigation Science and Engineering (Scientific-Research Magazine) 38(4). 85-76.

Bastardie, F.; Feary, D.A.; Brunel, T.; Kell, L.T.; Döring, R.; Metz, S.; Eigaard, O.R.; Basurko, O.C.; Bartolino, V.; Bentley, J. & Berges, B. 2022. Ten lessons on the resilience of the EU common fisheries policy towards climate change and fuel efficiency-A call for adaptive, flexible and well-informed fisheries management. Frontiers in Marine Science 9: 947150.

Benzer, S. & Benzer, R. 2019. Alternative growth models in fisheries: Artificial Neural Network. Journal of Fisheries 7(3): 719-725.

Biais, G. 2022. SPiCT runs for the northeast Atlantic porbeagle. Working document ICES WKELASMO workshop

Branch, T.A.; Jensen, O.P.; Ricard, D.; Ye, Y. & Hilborn, R. 2011. Contrasting global trends in marine fishery status obtained from catches and from stock assessments. Conservation Biology 25(1): 777-786.

Cai, K.; Kindong, R.; Ma, Q. & Tian, S. 2023. Stock Assessment of Chub Mackerel (*Scomber japonicus*) in the Northwest Pacific Using a Multi-Model Approach. Fishes 8: 80.

Cayré, P.; Amon Kothias, J.B.; Diouf, T. & Stretta, J.M. 1993. Biology of tuna. p. 147-244. In A. Fonteneau and J. Marcille (eds.) Resources, fishing and biology of the tropical tunas of the Eastern Central Atlantic. FAO fisheries technical paper 292. Rome, FAO. 354 p.

Cadrin, S.X. 2020. Defining spatial structure for fishery stock assessment. Fisheries Research 221: 105397.

Castellano-Mendez, M.; Gonzalez- Manteiga, W.; Febrero-Bande, M.; Prada-Sanchez, J. M. & Lozano-Calderon, R. 2004. Modelling of monthly and daily behavior of the run off the Xallas River using Box-Jenkins and neural networks methods. Journal of Hydrology 296: 38-58.

Chen, Y.; Song, L.; Liu, Y.; Yang, L. & Li, D. 2020. A Review of the Artificial Neural Network Models for Water Quality Prediction. Applied Sciences 10(5776): 2-49.

Collette, B.B. & Nauen, C.E. 1983. FAO species catalogue. Vol. 2. Scombrids of the world. An annotated and illustrated catalogue of tunas, mackerels, bonitos and related species known to date. FAO Fish Synopses 125(2): 137 p.

Darvishi, M.; Behzadi, S.; Salarpouri, A. & Momeni, M. 2020. Growth, mortality and exploitation ratio of *Auxis thazard* (Lacepède, 1800) in the Northern Persian Gulf and Oman Sea waters (Hormozgan Province Zone). Animal Environment Journal 12: 131-138.

Deepti, V.I. & Sujatha, K. 2012. Fishery and some aspects of reproductive biology of two coastal species of tuna, *Auxis thazard* (Lacepède, 1800) and *Euthynnus affinis* (Cantor, 1849) off north Andhra Pradesh, India. Indian Journal of Fisheries 59(4): 67-76.

Dick, E.J. & MacCall, A.D. 2011. Depletion-based stock reduction analysis: a catch-based method for determining sustainable yields for data-poor fish stocks. Fisheries Research 110: 331-341.

FAO 1993. Reference points for fishery management: their potential application to straddling and highly migratory resources. FAO Fish.Circ.,864,52p.

FAO 2018. The State of World Fisheries and Aquaculture 2018 - Meeting the sustainable development goals. Rome. Licenses: CC BY-NC-SA 3.0 IGO. 227 P.

Fisheries Statistical Yearbook, Iranian Area 2023. Fisheries Administration, Council of Agriculture, Executive Tehran. 20 P.

Free, C.M.; Jensen, O.P.; Anderson, S.; *Gutierrez*, N.L.; *Kleisner, K*.; *Longo, C*.; *Minto, C*.; *ChatoOsio, G.* & *Walsh, J.* 2020. *Blood from a stone: Performance of catch-only methods in estimating stock biomass status. Fisheries Research* 223: 1-10.

Froese, R.; Zeller, D.; Kleisner, K. & Pauly, D. 2012. What catch data can tell us about the status of global fisheries. Marine Biology 159: 1283-1292.

Froese, R.; Demirel, N. & Sampang, A. 2015. An overall indicator for the good environmental status of marine waters based on commercially exploited species. Marine Policy 51(1): 230–237.

Froese, R.; Demirel, N.; Gianpaolo, C.; Kleisner, K.M. & Winker, H. 2016. Estimating fisheries reference points from catch and resilience. Fish and Fisheries 18(3): 506-526.

Froese, R. & Pauly, D. eds. 2015. FishBase. World Wide Web electronic publication. www.fishbase.org, version. (10/2015), accessed at www.fishbase.org in November/December 2015.

Froese, R.; Demirel, N.; Coro, G.; Kleisner, K.M. & Winker, H. 2017. Estimating fisheries reference points from catch and resilience. Fish and Fisheries, 18(3): 506-526.

Froese, R.; Winker, H.; Coro, G.; Demirel, N.; Tsikliras, A. C. & Dimarchopoulou, D. *et al.* 2018. Status and rebuilding of European fisheries. Marine Policy 93: 159-170.

Gebremedhin, S.; Bruneel, S.; Getahun, A.; Anteneh, W. & Goethals, P. 2021. Scientific methods to understand fish population dynamics and support sustainable fisheries management. Water 13(4): 574.

Hashemi, S.A.R.; Doustdar, M. & Derakhsh, P.M. 2023. Stock assessment of Yellowfin tuna, *Thunnus albacares* (Bonnaterre, 1788) using the LBB and LB-SPR methods in the northern Oman Sea, Iran. International Journal of Aquatic Biology 11(4): 313-320.

HaghiVayghan, A.; Hashemi, S.A. & Kaymaram, F. 2021. Estimation of fisheries reference points for Longtail tuna (*Thunnus tonggol*) in the Iranian southern waters (Persian Gulf and Oman Sea). Iranian Journal of Fisheries Sciences 20(3): 678-693.

IFO 2023. Iran Fisheries Organization (IFO). Bureau of Statistics; Yearbook of Fisheries Statistics. 25 p.

Jenning, S.; Kasier, M. & Reynold. J. 2000. Marine Fisheries Ecology. Black well Science.391 p.

King, M. 2007. Fisheries biology, assessment and management. Fishing News Book, London, 342 p.

Koutroumanidis, T.; Iliadis, L. & Sylaios, GK. 2006. Time-series modeling of fishery landings using ARIMA models and Fuzzy Expected Intervals software. Environmental Modelling & Software 21: 1711-1721.

Lawer, E.A. 2016. Empirical Modeling of Annual Fishery Landings. Natural Resources 7: 193-204.

Li, Y.N.; Zhu, J.; Dai, X.; Fu, D. & Chen, Y. 2022. Using data-limited approaches to assess data-rich Indian Ocean bigeye tuna: Data quantity evaluation and critical information for management implications. Acta Oceanologica Sinica 41(3): 11-23.

Lucena-Frédou, F.; Frédou, T. & Ménard, F. 2017. Preliminary Ecological Risk Assessment of small tunas of the Atlantic Ocean. Collective Volume of Scientific Papers, ICCAT 73: 2663-2667.

Lucena-Frédou, F.L.; B. Mourato, T.; Frédou, P.G.; Lino, R.; Muñoz-Lechuga, C.; Palma, A. & Soares, M. Pons. 2021. Review of the life history, fisheries and stock assessment for small tunas in the Atlantic Ocean. Reviews in Fish Biology and Fisheries 31: 709-736.

Martell, S. & Froese, R. 2013. A simple method for estimating MSY from catch and resilience. Fish and Fisheries 14(4): 504-514.

Martinez, F.; Charte, F.; Frías, M. & Martínez-Rodríguez, M. 2022. Strategies for time series forecasting with generalized regression neural networks. Neurocomputing 491(1): 509-521.

Mildenberger, T.K.; Berg, C.W.; Pedersen, M.W.; Kokkalis, A. & Nielsen, J.R. 2020. Time-variant productivity in biomass dynamic models on seasonal and long-term scales, ICES Journal of Marine Science 77(1): 174-187.

Ovando, D.; Free, C. M.; Jensen, O. P. & Hilborn, R. 2022. A history and evaluation of catch-only stock assessment models. Fish and Fisheries 23: 616-630.

Pedersen, M.W. & Berg. C.W. 2017. A stochastic surplus production model in continuous time. Fish and Fisheries 18: 226-243.

Pons, M.; Cope, J.M. & Kell, L.T. 2020. Comparing performance of catch-based and length-based stock assessment methods in data-limited fisheries. Canadian Journal of Fisheries and Aquatic Sciences 77(6): 1026-1037.

R Core Team 2022. R: a language and environment for statistical computing [online]. R Foundation for Statistical Computing, Vienna. Available from https://www.R-project.org.

Shabri, A. & Samsudin. R. 2015. Fishery Landing Forecasting Using Wavelet-Based Autoregressive Integrated Moving Average Models. Hindawi Publishing Corporation Mathematical Problems in Engineering, 2015, Article ID 969450: 9.

Skaar, S. 2020. A Comprehensive Guide to Neural Network Modeling. Nova Science Pub Inc. 172 p.

Su, S.; Tang, Y.; Chen, J.; Chang, B. & Chen, Y. 2021. A comprehensive framework for operating science-based fisheries management: A checklist for using the best available science. Fish and Fisheries 22(4): 798-811.

Tabatabaei, S.N.; Abdoli, A.; Ahmadzadeh, F.; Primmer, C.R.; Swatdipong, A. & Segherloo, I.H. 2020. Mixed stock assessment of lake-run Caspian Sea trout Salmo in the Lar National Park, Iran. Fisheries Research 230: 105644.

Talebzadeh, A. 1997. Survy stocks of five species scomdride in Hormozgan Costal waters (Persan Gulf and Oman Sea). Institute research Oman sea.155 p.

Tsitsika, E.; Maravelias, C. & Haralabous, J. 2007. Modeling and forecasting pelagic fish production using univariate and multivariate ARIMA models. Fisheries Science 73: 979–-988.

Vieira, J.; Costa. P.; Braga, A.; São-Clemente, R.; Ferreira, C. & Silva, J. 2022. Age, growth and maturity of frigate tuna (*Auxis thazard* Lacepède, 1800) in the Southeastern Brazilian coast. *Aquatic Living Resources* 35: 11.

Walsh, J.C.; Minto, C.; Jardim, E.; Anderson, S.C.; Jensen, O.P.; Afflerbach, J.; DickeyCollas, M.; Kleisner, K.M.; Longo, C.; Osio, G.C.; Selig, E.R.; Thorson, J.T.; Rudd, M.B.; Papacostas, K.J.; Kittinger, J.N.; Rosenberg, A.A. & Cooper, A.B. 2018. Trade-offs for data-limited fisheries when using harvest strategies based on catch-only models. Fish and Fisheries 4: e4570-17.

Wetzel, C. R. & Punt, A.E. 2015. Evaluating the performance of data-moderate and catch-only assessment methods for U.S. west coast groundfish. Fisheries Research 171: 170-187.

Zhou, S.; Punt, A.E.; Smith, A.D.M.; Ye, Y.; Haddon, M.; Dichmont, C.M. & Smith, D.C. 2017. An optimized catch-only assessment method for data poor fisheries. ICES Journal of Marine Science 1(2): 20-26.

Iran. J. Ichthyol. (2025) 12(2): 101-112
P-ISSN: 2383-1561; E-ISSN: 2383-0964
http://www.ijichthyol.org
© 2025 Iranian Society of Ichthyology
doi: 10.22034/iji.v12i2.1026

مقاله کامل

ارزیابی ذخایر اطلاعات محدود مبتنی بر داده‌های صید ماهی تون منقوش (*Auxis thazard* Lacepède 1800) در خلیج فارس و دریای عمان (آب‌های جنوبی ایران)

سیداحمدرضا هاشمی*[۱]، مسطوره دوستدار [۲]، ساچپنندان دوتا[۳]

[۱]مرکز تحقیقات شیلاتی آبهای دور، موسسه تحقیقات علوم شیلاتی کشور، سازمان تحقیقات، آموزش و ترویج کشاورزی، چابهار، ایران.
[۲]موسسه تحقیقات علوم شیلاتی کشور، سازمان تحقیقات، آموزش و ترویج کشاورزی، تهران، ایران.
[۳]گروه علوم دریایی، دانشکده شیلات، کشاورزی و علوم دریایی دانشگاه سلطان قابوس، عمان.

چکیده: هدف از این مطالعه ایجاد چارچوبی برای بررسی روند صید و تخمین حد بهینه صید ماهی تون منقوش (FRI) با جمع‌آوری داده‌های صید در آب‌های جنوبی ایران (خلیج فارس و دریای عمان) است. برای تعیین نقاط مرجع زیستی (BRPs) ماهی تون منقوش در خلیج فارس و دریای عمان از دو روش استفاده شد. داده‌های صید شامل ۲۶ سال (۲۰۲۲-۱۹۹۷) مورد استفاده قرار گرفت و حد بهینه صید با استفاده از رویکرد داده‌های محدود و نرم‌افزار R برآورد شد. میانگین صید (Ct) در این دوره ۲۲۴۳۹ تن (۹۵٪ فاصله اطمینان ۲۶۶۳۸-۱۸۲۹۹ تن) بود که افزایش قابل توجهی را در دو دهه گذشته نشان می‌دهد (P<۰/۰۵). میانگین حداکثر محصول پایدار (MSY)، نسبت B/B_{MSY}، نسبت F/F_{MSY} و میزان اشباعیت با استفاده از مدل صید حداکثر محصول پایدار (CMSY) و مدل تولید مازاد تصادفی در زمان پیوسته (SPiCT) به‌دست آمد. نتایج حاصل از مدل‌های مختلف نشان داد که نسبت B/B_{MSY} فعلی، نسبت F/F_{MSY} و MSY براساس آزمون t تفاوت معنی‌داری نداشتند(P>۰/۰۵).یافته‌های سال آخر مطالعه نشان داد که نسبت بهره‌برداری در ذخایر ماهی تون منقوش کمتر از حد پایدار بهره‌برداری است که نتیجه ما نشان می‌دهد که امکان بهره‌برداری بیشتر از این گونه در خلیج فارس و دریای عمان وجود دارد.

کلمات‌کلیدی: ماهی تون منقوش، Catch-MSY، مدل تولید مازاد، خلیج فارس، دریای عمان