Catch-based data-limited stock assessment of Indian Ocean Frigate tuna (*Auxis thazard* Lacepède, 1800)

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Abstract

The aim of this study was 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 Persian Gulf, Oman Sea and Indian Ocean. Two methods were employed to determine the biological reference points (BRPs) of Frigate tuna in two regions. The Frigate tuna average catch (Ct) of the Iranian Waters was 22,439 tons (95% confidence interval 18,299 - 26,638 tonnes), showing a significant increase in the Iranian southern waters over the past two decades ($R = 0.9$, $P < 0.05$). The catching trend of this species in the IOTC area competence is increasing and according to the ARIMA model the growth increase is expected (AIC=1452, BIC=1455). The current biomass to the biomass of MSY (B/B_{MSY}) ratio and the ratio of saturation ($S = B/K$) were obtained using Optimized Catch Only Method (OCOM) and Zhou-Boosted regression tree models (Zhou-BRT). The results from different models showed that the current B/B_{MSY} ratio and S ratio were not significantly different based on a one-sample t-test ($P>0.05$). The findings from the last year of the study indicated that Frigate tuna stock exploitation ratio in Iranian waters (the Persian Gulf and Oman Sea) and IOTC area competence is below sustainable levels (under exploitation/green color), This suggests that the stock is close to being fished at MSY levels and that higher catches may not be sustained despite the substantial uncertainty associated with the assessment, a precautionary approach to management is recommended.

Keywords*: Frigate tuna, Persian Gulf, Oman Sea, OCOM*, Zhou-BRT, Indian Ocean

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). 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 (Ovando *et al*. 2022; Pons et al., 2020). 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).

In recent times, it has become increasingly evident that key fish species and other marine life are being overfished. The percentage of fish populations harvested within biologically sustainable limits has declined from roughly 90% in 1974 to about 67% by the year 2016, according to a report by the Food and Agriculture Organization (FAO) in 2018. Furthermore, Iran's total fishery yield neared 800,000 tonnes, with the vast majority, over 90% (equating to 720,000 tonnes), sourced from the southern waters of the country (IFO ,2023).

Currently, a range of techniques is applied to assess fish stocks and establish levels of catch that can be sustained over time. These techniques are put into practice globally in fisheries, especially in regions where data is scarce. Some of the methods used are the length-based spawning potential ratio (LBSPR), length-based Bayesian models (LBB), and various catch-based methods like Maximum Sustainable Yield (Catch-MSY), Depletion-Based Stock Reduction Analysis (DBSRA), and Catch-MSY (CMSY), as documented by Wetzel and Punt in 2015.

Frigate tuna (*Auxis thazard*) is one of the smallest species of the tribe Thunnini, 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. Frigate tuna is a coastal species (an epipelagic and neritic fish) found circumglobally in tropical and subtropical oceans (Collette and Nauen, 1983) and it has a localized migratory habit and mainly restricted to oceanic islands, continental shelves with a strong schooling behavior (Collette and Nauen, 1983; Deepti and Sujatha, 2012, Lucena-Frédou *et al*., 2021, Ajik and 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 and Nauen, 1983). 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).

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 and Sujatha, 2012; Lucena-Frédou *et al*., 2017; Pons *et al*., 2020; Darvishi *et al*., 2020; Lucena-Frédou *et al*., 2021; Ajik and 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 Hashemi *et al*., 2023; Haghi Vayghan et al., 2021; Tabatabaei et al., 2020. The study aims to establish a framework for analyzing catch trends and determining the optimal catch limit in the southern waters of Iran (Persian Gulf &Oman Sea). Additionally, the analysis of catch data gathered over a 26-year period will determine the biological reference points (BRPs) of this species, and management strategies will be suggested along with an assessment of the stock's exploitation status.

Material and Methods

Frigate tuna catch in the Indian Ocean from 1950 to 2022 (IOTC, 2023) ,and 26-year (1997 to 2022) in the Persian Gulf and Sea of Oman (Fig.1) have been compiled (IFO,2023).

Optimized Catch Only Method (OCOM)

Zhou et al. (2013) developed an optimized catch-only method that uses time series data without prior distribution knowledge. The approach employs an infinite dictionary for both r and K, where $0 < K < \infty$ and $0 < r < \infty$. The maximum K is bounded by $r = 0$ and the maximum r is bounded by the smallest possible K due to negative correlation between the parameters. The approach aims to find viable ranges for r and K, with the most likely value of r among any combination on the curve. It excludes improbable results through trials, resulting in a posterior-focused catch-based technique for estimating biological reference points (Zhou *et al.*, 2013). Based on past studies, the Natural mortality rate of this species was considered to be 0.65.

This method optimizes final biomass to estimate valid combinations of r and K values for a fixed depletion rate. 500 simulations are run without additional constraints on valid pairs. Unviable trajectories are removed. The Max K = 50 * max(C) & Min K = max(C). Initial K population is set logarithmically between these values for higher density of lower K. The depletion phase ranges from 0.05 to 0.8 in 0.05 increments while r values vary from 0.1 to 2. Biomass dynamics model is run with constraints $Bt \leq K$, $Bt > 0$, and $B > C$.

Zhou-Boosted regression tree models (Zhou-BRT)

Use Zhou-BRT model to estimate saturation (B/K) and B/BMSY time series from catch time series. Zhou-BRT is trained on RAM Legacy database and estimates saturation based on 56 catch statistics. Linear regression coefficients for whole catch time series, pre- and post-peak catch, and recent subseries are used. Saturation is predicted due to values from two BRT models with reduced bias correction (8 and 38 predictors). B/BMSY is estimated to be twice the saturation, or twice the score of Saturation (S). The upper and lower 95% confidence intervals correspond to the high and low values, respectively. Using the zBRT saturation estimate can provide a depletion prior for advanced depletion analysis, such as DB-SRA

(Dick and MacCall, 2011), DCAC (MacCall, 2009), and catch-MSY. Zhou *et al*., suggest that this can be a useful tool.

Forecasting Methods

ARIMA

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)

Statistical analyses were performed with R software (R Core Team. 2022), R studio ((2024.04.0), SPSS (26) software package and a significance level of 0.05 was adopted.

Results

The catch trend of Frigate tuna (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 increased for the twenty-six years (Fig. 2).

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 growth 0.2-0.8 per year). It used a method called OCOM and Zhou-BRT. 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 Average amount of living matter was 0.56 (0.4-0.75). 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 ($S=B/K=0.5B/B_{MSY}$) 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 OCOM, Zhou-BRT models were estimated and the mean reference points have no significant difference($P>0.05$).

The range of the current biomass to the biomass of MSY (B/B_{MSY}) and saturation (S=B/K) ratio in different method present in Table 1, Fig. 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. The catching trend of this species in the IOTC area is increasing and according to the ARIMA (2, 1,1) model the growth increase is expected (AIC=1452, BIC=1455).

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- 0.8), low flexibility (r = 0.05-0.5), and very low flexibility (r < 0.015-0.1) (Martell and Froese, 2013; Froese et al., 2016; Zhou et al., 2017)**.** A significant link exists between the intrinsic growth rate of a population, denoted as (r), and various life history traits, particularly the natural mortality rate, (M). According to a model, for bony fish, (r) is calculated as (1.73M), and for sharks and rays, known as elasmobranchs, r) is (0.76M) (Zhou *et al*., 2017). Research by Froese and Pauly in 2015 indicates that the intrinsic growth rate (r) is roughly double the maximum sustainable mortality rate (F_{MSY}), double the natural mortality rate (M), triple the growth rate coefficient (K) from the von Bertalanffy growth curve, three times the reciprocal of the generation time (t_{gen}), and nine times the reciprocal of the maximum lifespan (t_{max}).

In the present analysis, mean of amount of current biomass to biomass of maximum sustainable yield (B/BMSY) indicated that FRI species is under fishing (under exploitation) (Tab. 2) in the Persian Gulf and Oman Sea and Indian Ocean. In addition, current level of F/FMSY 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).

In addition, the OCOM method calculated more saturation(B/K) than the ZBRT model, 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.

Based on the results, the ARIMA model (1, 1 0) for Iran and ARIMA model (2, 1, 1) for IOTC 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 and Samsudin, 2015). 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. Even though we're not sure about the catch data, we should focus on them and use them in our work. 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). This suggests that the stock is close to being fished at MSY levels and that higher catches may not be sustained despite the substantial uncertainty associated with the assessment, a precautionary approach to management is recommended.

Conclusions

The results from different models showed that the current B/B_{MSY} ratio and S ratio were not significantly different based on a one-sample t-test ($P>0.05$). The findings from the last year of the study indicated that Frigate tuna stock exploitation ratio in the Persian Gulf and Oman Sea and Indian Ocean is below sustainable levels (under exploitation/green color. In order to enable adaptive management strategies, 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.

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Conflict of Interest and Ethical Statement

The authors declare no conflict of interest. This article does not contain any studies on animals performed by any of the authors.

Ethical Approval

Not applicable

Consent for publication
All of Author consent for publication

Availability of supporting data
Not applicable

Competing interests
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Seyed Ahmadreza Hashemi: Conceptualization, Validation, Investigation, Analysis, writing – original draft; **Farhad kymaram and Ali Salarpouri:** Validation, Investigation, writing – review & editing; **Mastooreh Doustdar:** Conceptualization, Validation, Analysis, writing – review & editing;

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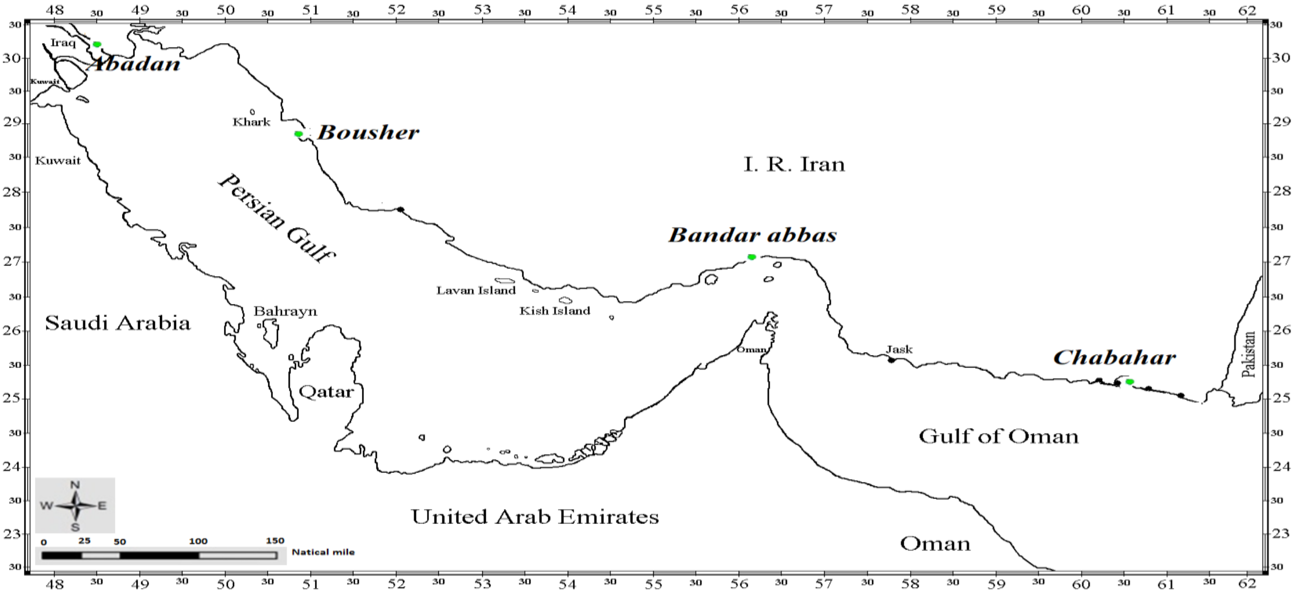

Fig 1. Persian Gulf and Sea of Oman

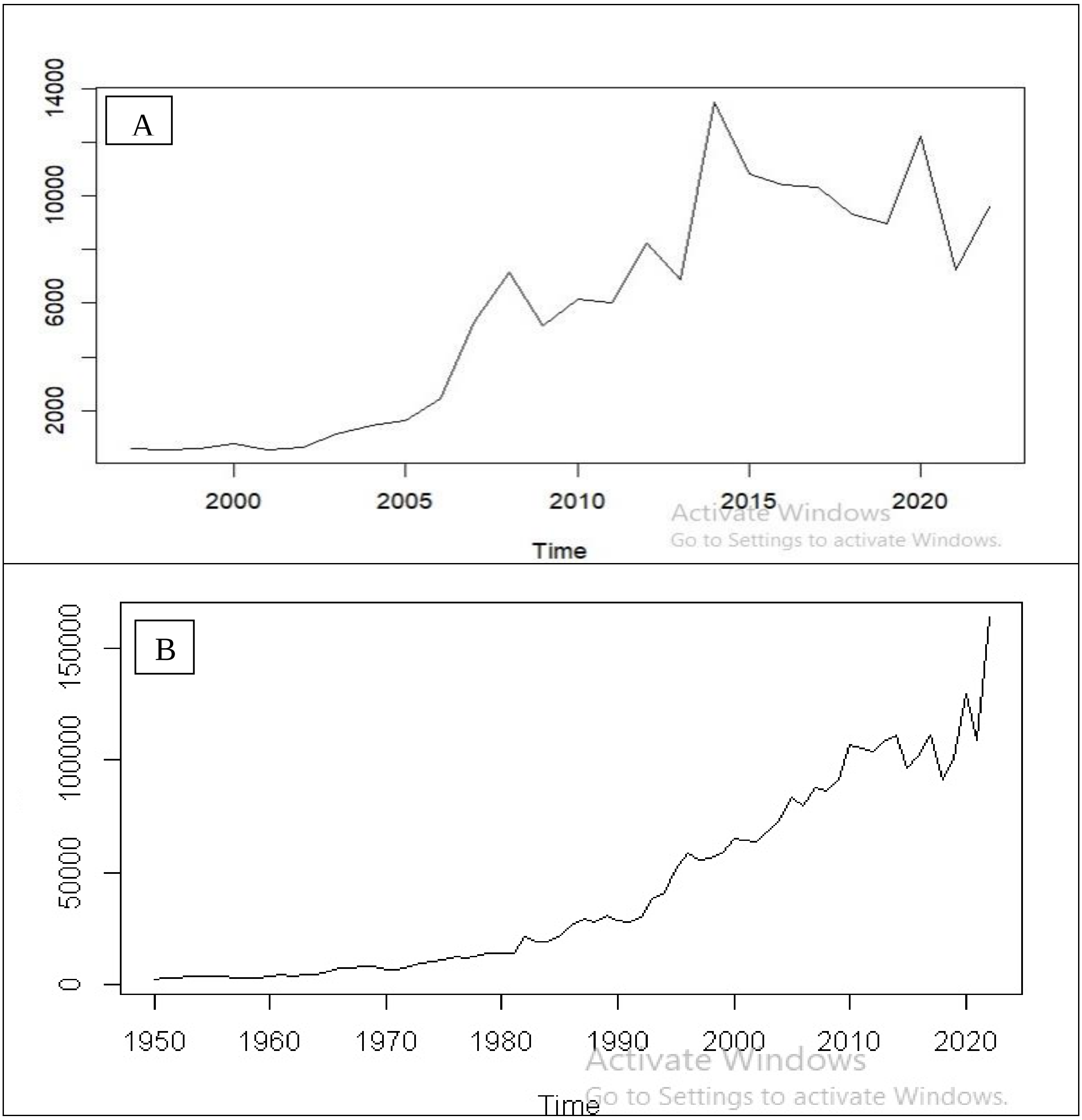

Fig 2. Catch trend of Frigate tuna in the Persian Gulf and Sea of Oman (A) and Indian Ocean (B)

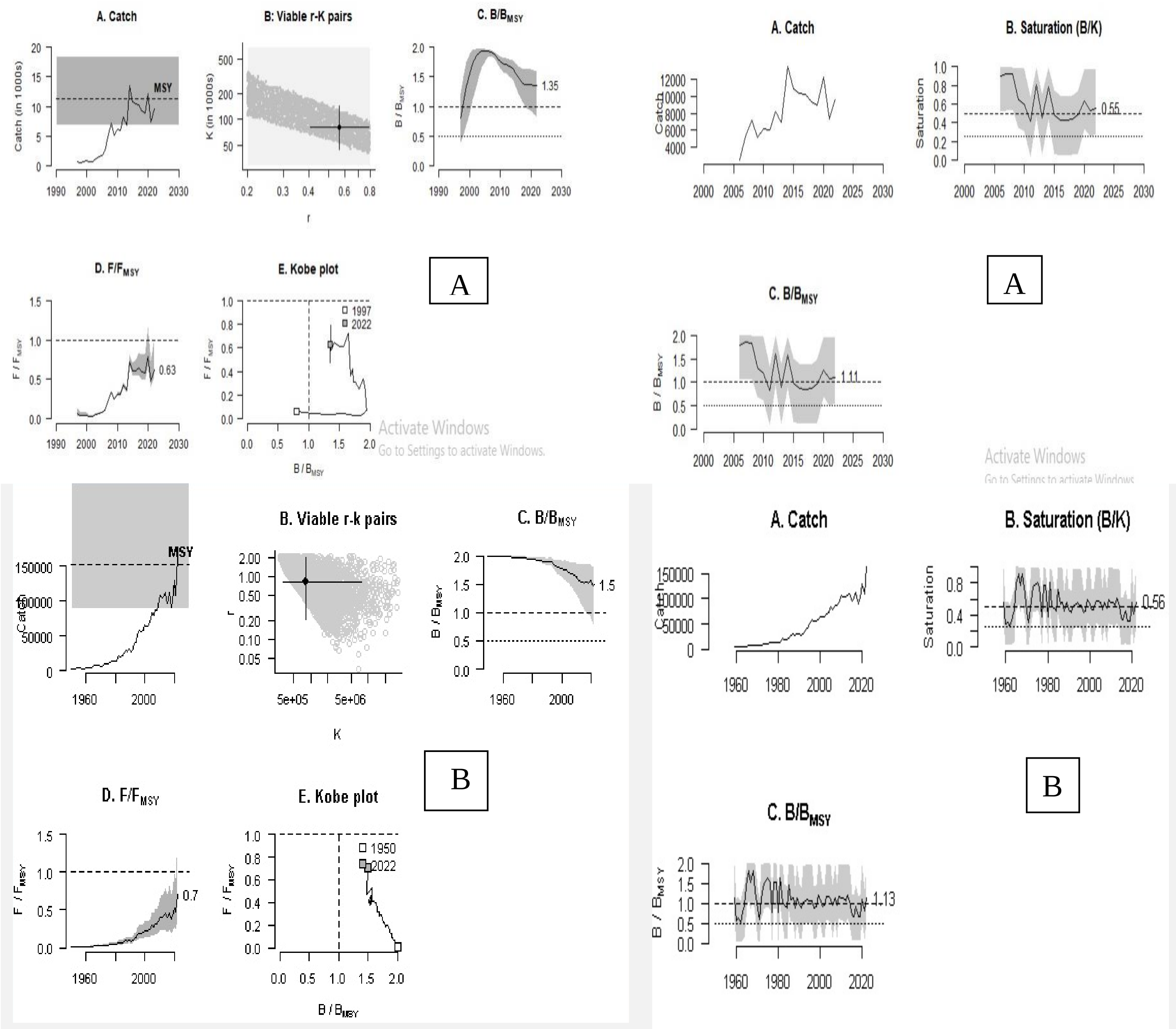

Fig 3. Comparison of averages BRP values (OCOM and Zhou-BRT) of Frigate tuna in the Persian Gulf and Sea of Oman(A) and Indian Ocean (B).

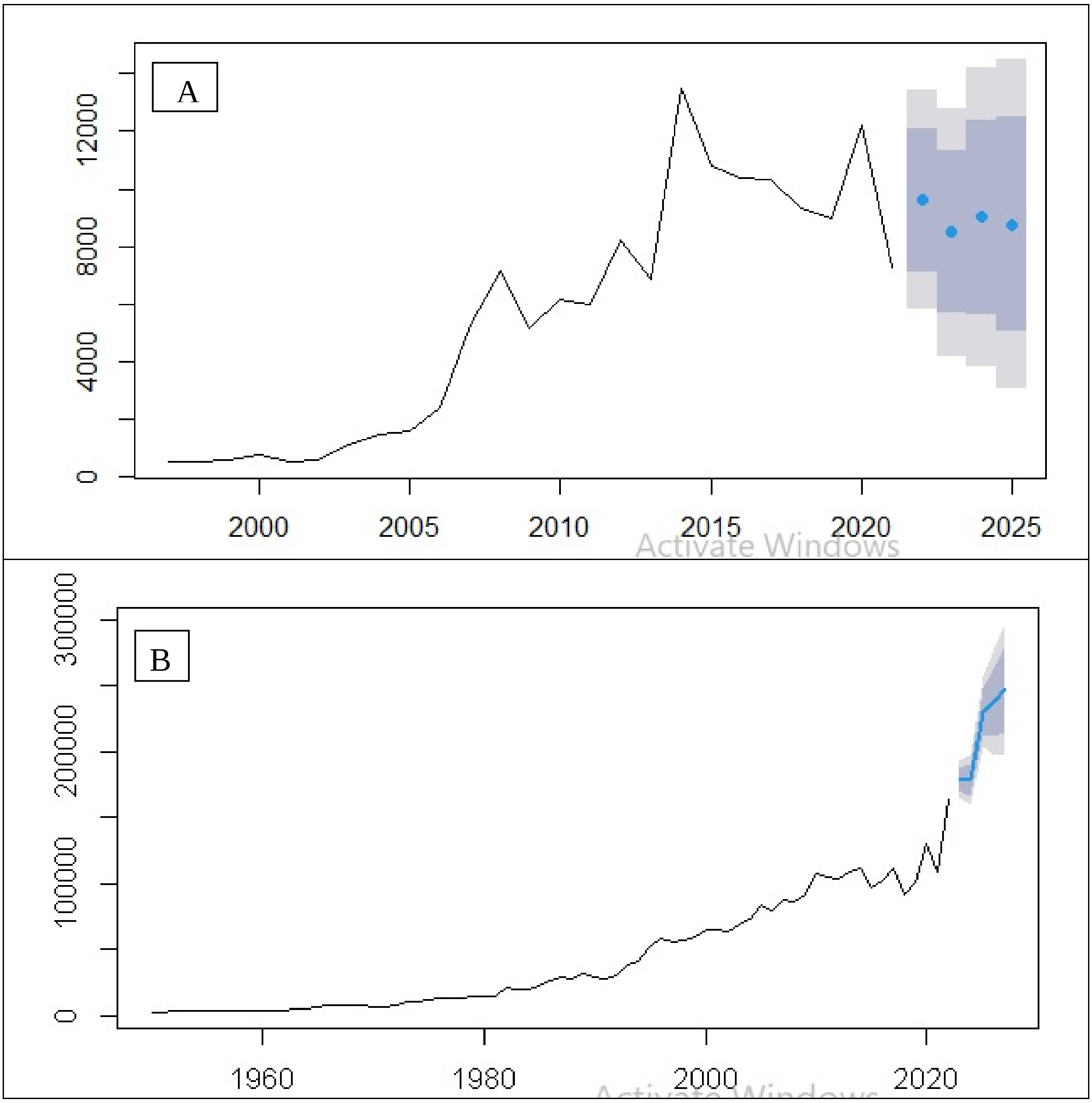

Fig 4. Predict catch values (ARIMA) of Frigate tuna in the Persian Gulf and Sea of Oman(A) and Indian Ocean (B).

Table 1: Comparison of different indices of data-limited approach for Frigate tuna in the Persian Gulf and Oman Sea & Indian Ocean. 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.

Sampling Areas	**Indices/models**	**OCOM** Mean (max -min)	**Zhou-BRT** Mean (max-min)	**Mean**	**Stock status**
Persian Gulf &Oman Sea	**MSY (1000 tons)**	11.9 (9-14)	-	-	**Under exploited/ Low depletion**
	B/B_{MSY}	1.35(0.65-1.975)	1.38(0.55-1.91)	1.36±0.01	
	F/F_{MSY}	0.63(0.2-0.69)	-	-	
	S=B/K	0.67 (0.41-0.79)	0.55 (0.27-0.79)	0.61±0.05	
Indian Ocean	**MSY (1000 tonnes)**	152 (119-229)	-	-	**Under exploited/ Low depletion**
	B/B_{MSY}	1.5 (0.65-1.975)	1.13(1.05-1.18)	1.31±0.03	
	F/F_{MSY}	0.7(0.62-0.85)	-	-	
	S=B/K	0.7(0.65-0.86)	0.56 (0.45-0.58)	0.63±0.06	