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PROOF RESEARCH PAPER

Forecasting the Anchovy Kilka Fishery in the Caspian Sea Using a Time Series Approach

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Abstract

Forecasting the status of fish landings is a major tool for fisheries managers and policy makers in order to decide on sustainable management issues. In this paper, yearly landings kilka data from 1990 to 2014 were analyzed using time series model. Autoregressive (AR), Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA) were considered through the analysis to select appropriate model for forecasting. Based on Autocorrelation function (ACF), Partial Autocorrelation function (PACF) and degree of differentiation, ARIMA (0, 2, 3) model with the lowest normal Bayesian information criterion (BIC) and Akaike information criterion (AIC) value was selected. Results showed that Kilka catch will increase gradually in the coming years. However, the hypothesis that the commercial catches have reached their zero point could not be rejected. In conclusion, results of this study revealed despite government reduced fishing mortality in the recent years, potential risk of population collapse is still remained.

Keywords: Forecasting, ARIMA, management, Kilka, Caspian Sea

Introduction

Kilka, including *Clupeonella engrauliformis*, *C.grimmi* and *C.cultriventris*, are a commercially important shoaling fish, especially in the Caspian Sea region. In addition, these species have a key role in the food chain especially for seals and sturgeon in the Caspian Sea ecosystem (Janbaz *et al*., 2012). Kilka prefers is depths greater than 30 m in the central and southern Caspian Sea that migrate central to the southern waters in autumn and winter mainly for spawning and return in spring and summer (Fazli, Zhang, Hay, Lee, Janbaz, & Borani, 2007). According to the Iran Fisheries Organization Statistics textbook (2014) kilka catch constitutes 57% of total catch in the Iranian waters of the Caspian Sea with fluctuating between 22626 and 29701 tons, since 2005. Kilka catch is performed by fishing vessels equipped conical lift net and lighting lamp. The fishing grounds of these fleets are concentrated in the southern coastal areas in the fishing seasons (mainly in early winter).

It is well known that fisheries management must applied for fish stocks in environment. Forecasting using historical time series data can provide accurate operational forecasts of annual commercial catch and planners can predict commercial landings for the next year using this method (Stergiou, Christou & Petrakis, 1997; Czerwinski, Gutiérrez-Estrada, & Hernando-Casal, 2007). Annual landings estimation can help policy-makers and fisheries managers to understand feature of stock assessment to establish goals, and as a consequent, predict, alert, and control unforeseen fluctuation in stock size and market demand (Alder, Campbell, Karpouzi, Kaschner, & Pauly, 2008).

Various methods of time series analyses, including Box–Jenkins autoregressive integrated moving average (ARIMA) model, exponential smoothing methods or and neural networks (NNs), has been applied to forecast fisheries status and annual catch in different parts of the world (Stergiou *et al*., 1997; Georgakarakos, Koutsoubas & Valavanis, 2006; Koutroumanidis, Iliadis & Sylaios, 2006; Kim, Jeong, Kim & Kang, 2015; Farmer and Froeschke, 2015; Trifonova, Maxwell, Pinnegar, Kenny & Tucker, 2017). ARIMA is the most efficient and appropriate method for forecasting the landings and catch per unit effort of many fish and invertebrate species (Koutroumanidis *et al*., 2006; Kim *et al*., 2015). Although long-term data is more effective in time series analysis, ARIMA model can also be used if the factors of series depended on short-term historical data. Therefore, this method become the most applicable and common approach for prediction in large number of scientific fields, especially aquatic science (Czerwinski *et al*., 2007).

This study applied ARIMA model to forecast the yearly landings of Kilka in the Iranian parts of the Caspian Sea. The goal of this approach was to predicting the feature catch status of Kilka and understanding its dynamics after population decline in the last decades. Results of this paper are essential to give strategic advice on potential response of the system to fishing pressure and economy.

Materials and Methods

Time Series Modeling Procedure

ARIMA was employed to assess the feature status of *Clupeonella cultriventris* (Kilka) catch rate in the Caspian Sea. Initially, time series plots were made for the catch data and differencing method applied to achieve a stationary series. Differencing was achieved using the formula below (Wei, 2006):

$$\Delta x_t = x_t - x_{t-1}$$

Were Δx_t is differenced series, x_t and x_{t-1} are time data in the time series data frame. After stationary process, Autocorrelation and Partial Autocorrelation functions were applied to assess autoregressive (AR) and moving average (MA) parameters (Wei, 2006).

The AR process of order *p* and MA process of order *q*, denoted as AR (*p*) and MA (*q*) are defined as follows, respectively:

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + W_t$$

Where $\emptyset_1$, $\emptyset_2$, … and $\emptyset_p$ are constants (parameters) and W_t is a random uncorrelated noise component (residuals) in AR and

$$X_t = \theta_1 W_{t-1} + \theta_2 W_{t-2} + \cdots + \theta_q W_{t-q} + W_t$$

Where θ_1, θ_2, … and θ_q are constants (parameters) and W_t is a random uncorrelated noise component (residuals) in MA.

Finally, the ARIMA model shown below was used after differencing:

$$x_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + W_t + \theta_1 W_{t-1} + \theta_2 W_{t-2} + \cdots + \theta_q W_{t-q}$$

Where x_t is the original data series or differenced data at time t, $\emptyset$ are the AR parameters, *p* is the autoregressive order, W_t is the white noise at time t, θ are the MA parameters and q is the moving average order. At the end, ARMA model was extended to the auto-regressive integrated moving average (ARIMA) (*p*, *d*, *q*), which *d* represent differencing order. For the purposes of evaluating the adequacy of AR, MA and ARIMA processes, various models fitting such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) were employed.

Fit statistics such as AIC, BIC, MAPE, MAE and RMSE were calculated as shown below.

$$AIC = 2k - \ln(L)$$

$$BIC = -2ln\hat{L} = k \times ln(n)$$

Where *L* is the maximum value of the likelihood function for the model and *k* is the number of estimated parameters in the model and *n* is the number of observations.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right|$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|}$$

Where Y_i and $\hat{Y}_i$ are actual observed and predicted values respectively while *n* is number of predicted values. All analyses in this study were performed using the program "R" Version 3.3.0 (Ihaka & Gentleman, 1996) and Package "forecast" (Hyndman, 2016).

Results

Identifications of Models

Differencing was performed two times in order to obtain stationary series in time series Kilka catch rate data and ARIMA model designed after. Autocorrelogram and partial autocorrelogram were plotted and the values of *p* and *q* in the ARIMA models were determined 3 for both parameters (Figure. 1). Although RMSE is the most widely used statistic to assess goodness of fit, it can be influenced by the scale of the data (Kim *et al*., 2015). Thus, to determine the statistical significance of a model along with its model parsimony, AIC or BIC, both of which consider the number of parameters, should be used instead of RMSE. However, RMSE can be determinative when AIC and BIC was identical for different models. Therefore, ARIMA (0, 2, 3) considered as best model (Table 1).

Table 1 shows various identified ARIMA models with their corresponding fit statistics. The ARIMA (0, 2, 3) model with the lowest Normal BIC and AIC value was selected.

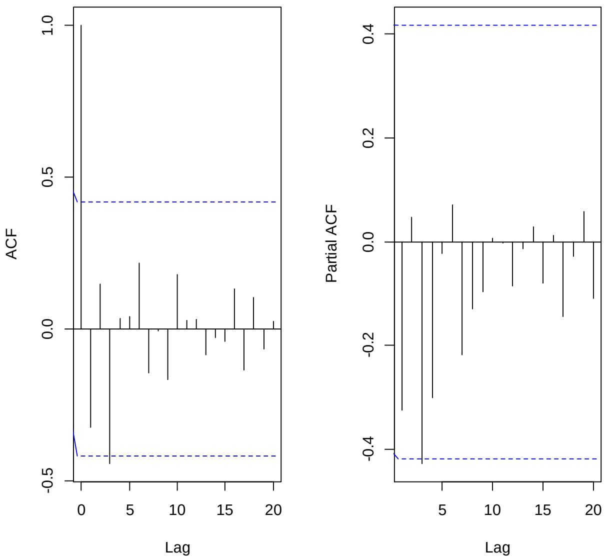

Figure 1. ACF and PACF of first order differenced data.

Table 1. Fit statistics for various competing ARIMA models

ARIMA (p, d, q)	RMSE	MAE	MAPE	AIC	BIC
ARIMA (3, 2, 0)	11343.52	7559.849	21.57007	484.18	488.55
ARIMA (0, 2, 3)	10582.37	7527.726	21.57042	**482.69**	**487.05**
ARIMA (3, 2, 3)	9046.919	6347.819	18.00079	486.11	493.75
ARIMA (1, 0, 2)	9682.577	7949.756	23.99185	521.05	526.94

Diagnostic Checks

Before forecasting, diagnostic test preformed on selected model. Residuals checked through Box-Ljung test and there was not enough evidence to reject null hypothesis (residuals have normal distribution). In addition, ACF and PACF residuals plot showed that none of autocorrelations was significantly different from zero at 95% confidence level (Figure 1 & 2). This proved that the selected ARIMA model was an appropriate model for forecasting Kilka catch from the Caspian Sea.

Forecasting

Forecasts for Kilka catch was made from the selected ARIMA model from 2015 to 2029. Figure 3 shows observed, fitted and forecasted Kilka catch rate. In order to assess the ability of the model in forecasting, actual catches were shown vis-à-vis forecast catch with 95% confidence level in Table 2. Results showed that Kilka catch will increase

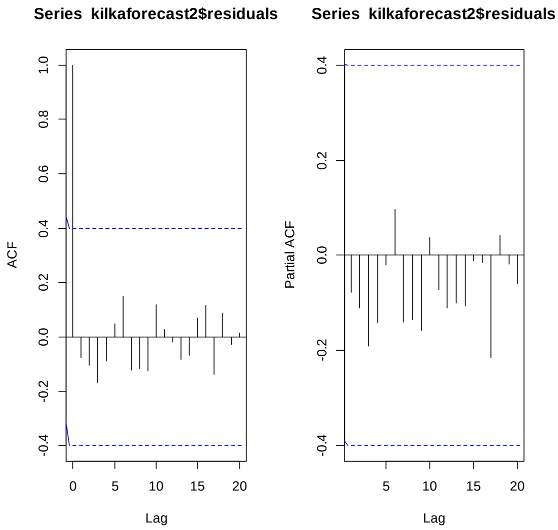

Figure 2. ACF and PACF of residuals.

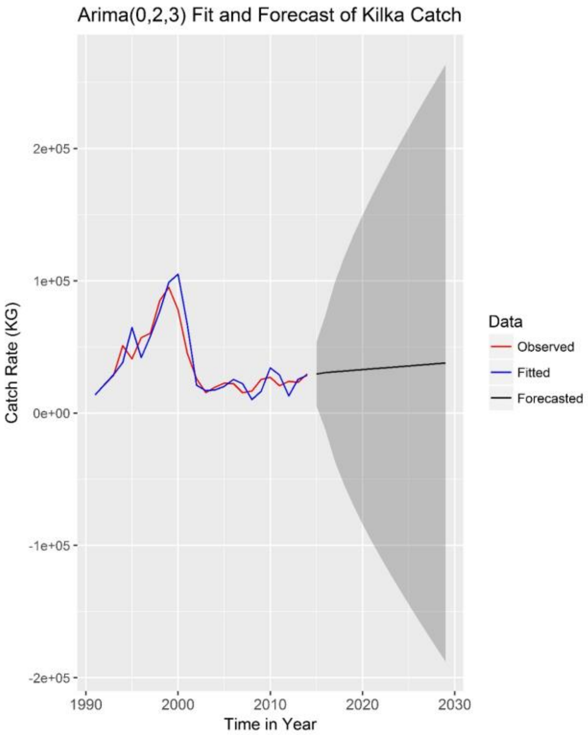

Figure 3. Actual and forecasted Kilka catch rate from Caspian Sea.

Table 2. Forecast of Kilka catch (kg) together with 95 % Confidence Interval

Year	Actual Catch	Predicted Catch	95% Confidence Intervals	
			Lower	Upper
2005	22626	20174.4	-3137.0	43485.74
2006	22303	25423.6	2112.3	48735
2007	15411	22233.7	-1077.7	45545.06
2008	16743	10196.2	-13115.2	33507.57
2009	25483	16545.3	-6766.1	39856.67
2010	27110	34159.4	10848.0	57470.73
2011	20717	28845.7	5534.4	52157.12
2012	24086	21964.5	-10346.9	36275.83
2013	23221	25580.8	2269.4	48892.14
2014	29701	28598.6	5287.2	51909.94
2015	-	29504.6	5723.6	53285.58
2016	-	30657.6	-13180.8	74496.02
2017	-	31213.3	-36301.4	98727.99
2018	-	31769.0	-54155.2	117693.2
2019	-	32324.7	-69636.2	134285.6
2020	-	32880.4	-83727.5	149488.3
2021	-	33436.1	-96898.4	163770.6
2022	-	33991.8	-109413.6	177397.2
2023	-	34547.5	-121437.8	190532.8
2024	-	35103.2	-133081.4	203287.8
2025	-	35658.9	-144421.7	215739.4
2026	-	36214.6	-155515.1	227944.3
2027	-	36770.3	-166404.2	239944.7
2028	-	37326.0	-177121.6	251773.6
2029	-	37881.7	-187693.1	263456.5

gradually in the coming years.

Discussion

Using the fitted model, forecasting was made from 2015 to 2029. In order to check the accuracy of the predicted catch, actual catch was also kept in the results (Table 2). Results revealed that forecasted and actual values were close meaning. This trend was also observed in ARIMA model for anchovy landings in Greece (Tsitsika, Maravelias, & Haralabous, 2007).

Fishing mortality has been recognized as the major problem in fish population decline in environment (Beddington, Agnew, & Clark, 2007). According to Karimzadeh, Gabrielyan, and Fazli (2010), kilka catch increased in 2005 in the Caspian Sea region due to increasing in fishing effort and declined in 2008 and 2009 as results of overfishing. In 2010, fisheries managements and limitation policy were applied for this population and Kilka catch experienced an increasing trend in the last years. The government started to reduce the number of active fishing fleets and overcapacity from 115 in 2008 to 73 in 2014 in order to decrease the fishing pressure. Results of actual catch indicates that this policy lead to increasing in Kilka landings from 16743 in 2008 to 29701 kg in 2014. Reviews of successful fishery management are of necessity to revive the Kilka fishery by 2029 in the Caspian Sea region. Daskalov and Mamedov (2007) stated that the main cause of the anchovy Kilka population collapse in the Caspian Sea is recruitment failure and the main reason in this issue is overfishing. The current fishing and natural mortality of the anchovy Kilka in the Iranian parts is 0.51 and 0.49 $year^{-1}$ respectively (Janbaz *et al*., 2012). With respect to natural mortality, it seems that fishing mortality is still considered as high risk. ARIMA model forecasted the annual catch will continue to increase approximately up to 37 ton by the year 2029. However, there are minus values in 95% confidence intervals indicating that the hypothesis that the commercial catches have reached their zero point cannot be rejected. The results are clearly showing that the Kilka fishery is in risk of collapse. This phenomenon was also observed for *Oreochromis* genus catch forecast in Malaŵi after applying ARIMA model (Lazaro & Jere, 2013). Furthermore, invasion of *Mnemiopsis leidyi* and domination of this species in the environment, induced negative effect on anchovy Kilka recruitment (Daskalov & Mamedov, 2007), and boosts natural mortality through competition.

To sum up, such natural and anthropogenic factors interacted and consequently lead to overfishing and anchovy Kilka stock collapse. However, despite the fact that cutbacks in fishing pressure policy have been applied by the government, potential risk of population collapse is still remained. Further researches on quota management and habitat destruction need to be done for recruitment revive in the Caspian Sea ecosystem.

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