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MODELLING AND FORECASTING OF CATFISH SPECIES YIELD FROM MANGOCHI ARTISAN FISHERIES OF LAKE MALAWI IN MALAWI

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ABSTRACT

Most of the wild fish stocks in Malawi either are fully or over exploited. This challenge underpins importance of forecasting using available data to support sustainable fisheries management. The study aimed at modelling and forecasting Catfish (Mlamba) species yield from artisan fishery on Lake Malawi in Mangochi District as they are becoming important food fish due to decline of more important fish species such as *Oreochromis* (Chambo). The study was based on secondary data on fish catches between1976 and 2012, collected from Fisheries Research Unit of the Department of Fisheries in Malawi. The study considered Autoregressive Integrated Moving Average (ARIMA) processes to select an appropriate stochastic model for forecasting the species yield. Appropriate models were chosen based on ARIMA (p, d, q). Autocorrelation function (ACF), Partial autocorrelation (PACF), Akaike Information Criteria (AIC), Box-Ljung statistics, correlogram of residual errors, distribution of residual errors, ME, RMSE, MAPE and MAE. Selected model was ARIMA (0, 0, 1) for forecasting artisan landings of Catfish from Lake Malawi in Mangochi District from 2013 to 2022. Based on the chosen model, forecast for artisan Catfish landings showed mean of 352 tonnes and mean of actual catches was 362 tonnes. However, catches in year 2022 are projected to be 360 tonnes, slightly below the actual catches mean but above 236 tonnes in 2010, assuming other factors remain constant. Confidence intervals of the forecasts included a zero and as such over exploitation of the species cannot be ruled out. Landings of the fishery will increase to 360 tonnes and remain stable through year 2022 necessitating fisheries management consideration to improve the trend. Policy makers should secure sustainable exploitation of Catfish species, among artisan fishery in the study area by controlling all fishing effort that lands the species such as gillnets, beach seines, open water seines among others.

Key words: Modelling, Forecasting, Lake Malawi, artisan fishery, Management, Yield

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INTRODUCTION

The fishery resource in Malawi makes a significant contribution to the Gross Domestic Product (GDP) estimated at about 4% [1, 2] and foreign exchange earnings more especially on ornamental fish trade. The fishery also provides both direct and indirect employment and supply relatively cheap animal protein to the population, thereby preventing cases of malnutrition especially in expectant women and children under five years of age [2]. Fish resource utilisation is a crucial economic activity, which provides a sustainable flow of ecosystem services to human society [3].

However, in many countries fisheries economic efficiency has significantly declined [4]. This is caused mainly by over-exploitation, which has been influenced by over population. The open access policy to the fishery resource is also blamed for the over exploitation [3] as well as weak enforcement [5]. The climatic fluctuations have also been reported to be another causative agent for the fishery resources declining [6]. This study focused on Catfish as it is becoming an important food fish due to decline of more important fish species such as *Oreochromis* (Chambo). There is need to improve management of our fisheries resources to restoration. One of the ways to do that is to provide our policy makers with an opportunity to make evidence base decisions [7, 8, 9, 10]. This is possible if the policy makers are provided with adequate and accurate information on the status of the fishery now and in the near future. The status of the fisheries stock in the future can be arrived at by forecasting. Forecasting has been used lately in fisheries to predict fish landing, fishing effort and aquaculture production on a farm. Modelling and forecasting in fisheries can as well assess if employed strategies to manage the fisheries resources in an area are efficient or not, in order to develop ways to improve them to save the collapsing fisheries.

Fisheries landings are univariate data that can be fitted and forecast by simple time series models with a stochastic process generated by unknown causes. The assumption made on the time series data is that future values of the series can be predicted as a linear combination of previously recorded values and estimates of current and previous random shocks to the fishery [11]. Linear regression, autoregressive, moving average, and Autoregressive Integrated Moving Average (ARIMA) are some of the models that have been applied to forecast the landings and catch per unit effort of different fisheries resources [12, 13, 14, 15]. The autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models are applicable where the data series is proved to be stationary. The data series that is not stationary is transformed to be stationary through different methods such as differencing. This study employed ARIMA models to forecast the artisan fish landings of Catfish for the data proved stationary or could be transformed to be stationary.

Catfish data used in this study comprised of several species from *Clariidae* family of which *Bathyclarias* species are most common in the study area; however, they are not the most studied member of suborder *Siluroidae* [16]. The diets of Catfish comprise small or young fish, zooplanktons, insect, molluscs, green algae and aquatic vegetation [17]. Catfish is an opportunistic omnivore, which can vary food according to availability [18]

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and can withstand low dissolved oxygen and highly turbid water. These characters make Catfish survive harsh condition, which very few fish species can. These have made the species to maintain their stock size relatively stable while the other fish stocks are dwindling with the current fisheries management strategies and their implementation levels.

METERIALS AND METHODS

Area covered by the study

This study covered Lake Malawi in Mangochi District on all seven (7) minor strata, namely 2.1, 2.2, 2.3, 2.4, 2.5, 2.6 and 3.1 as shown in Figure 1. The study only involved the artisan fishery and excluded the commercial fishery that is also in the area as modelling and forecasting of commercial fish landings in Mangochi had already been done [19]. The artisan fishers employ several fishing efforts that land the species such as gillnets, beach seines, open water seines among others. Mangochi district has been chosen for this study as it has the highest number of small-scale fisheries compared to any other district. The district has the most productive fishery of Lake Malawi as well. The artisan fishery has been chosen for this study because it is open access.

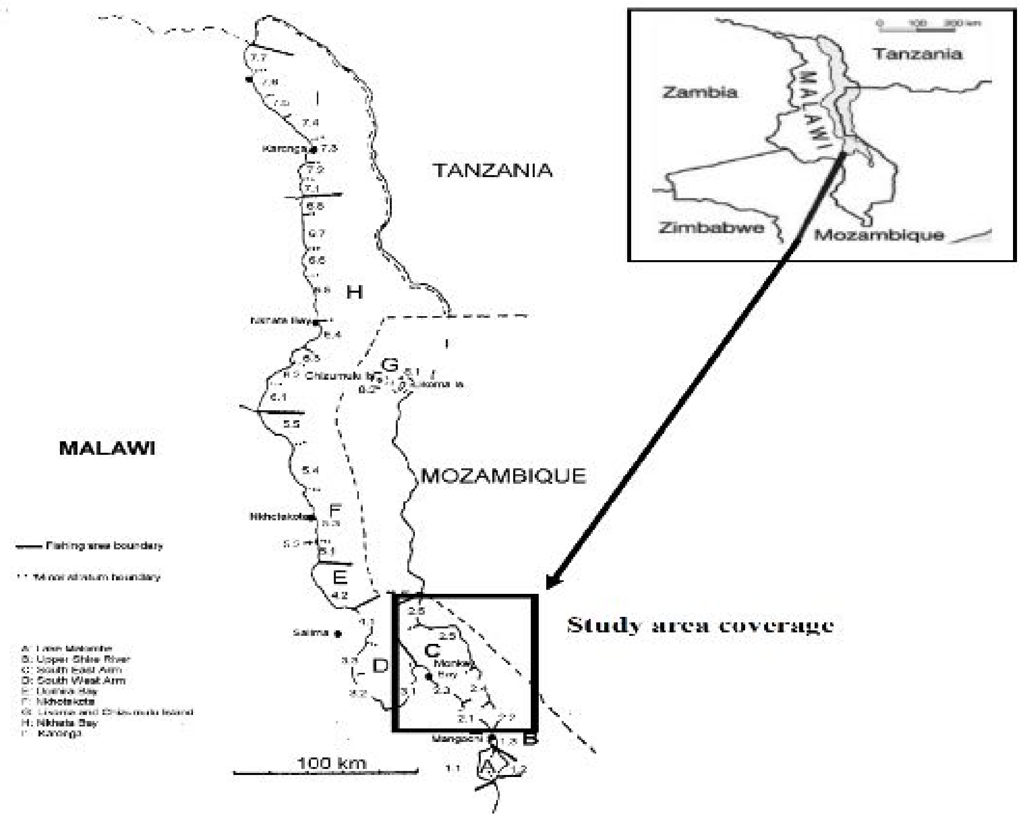

Figure 1: Map of southern part of Lake Malawi showing all minor strata 2.1 to 3.1 of Mangochi Districts

Source of data

The study used secondary data of Catfish species landings by artisan fisheries on Lake Malawi in Mangochi District from 1976 to 2012. The lake in the district is divided into major strata which are farther divided into minor strata. These minor strata have several landing sites. These divisions or sections were made to aid management of the fisheries resources. The data were collected from Fisheries Research Unit (FRU) at Monkey Bay in Mangochi District. Mangochi District has a total of seven (7) strata as shown in Figure 1. The FRU is under the Department of Fisheries in the Ministry of Agriculture, Irrigation and Water Development in Malawi.

Operationalisation of the data variable

The catch data used were measured in kilograms (wet weight) and converted to tonnage annually. The catch was recorded at the fishing landing site soon after landing. Total catch from all the seven (7) strata (Figure 1) was summed up respective of individual species to come up with specific fish species landings in a particular year.

Descriptive statistics

The data were univariate. The characteristics of the data were summarized using the descriptive statistics shown in the Table 1.

Model identification

The model identification was carried out by following the process below.

Testing for trend in the time series

Graphical analysis method and Mann Kendall test were used to detect the presence of trends in the time series data set for Catfish (Table 2 and Figure 2).

The trend was not significant in the time series for Catfish. This implied that there was no need to remove trend by transforming the data through differencing the data.

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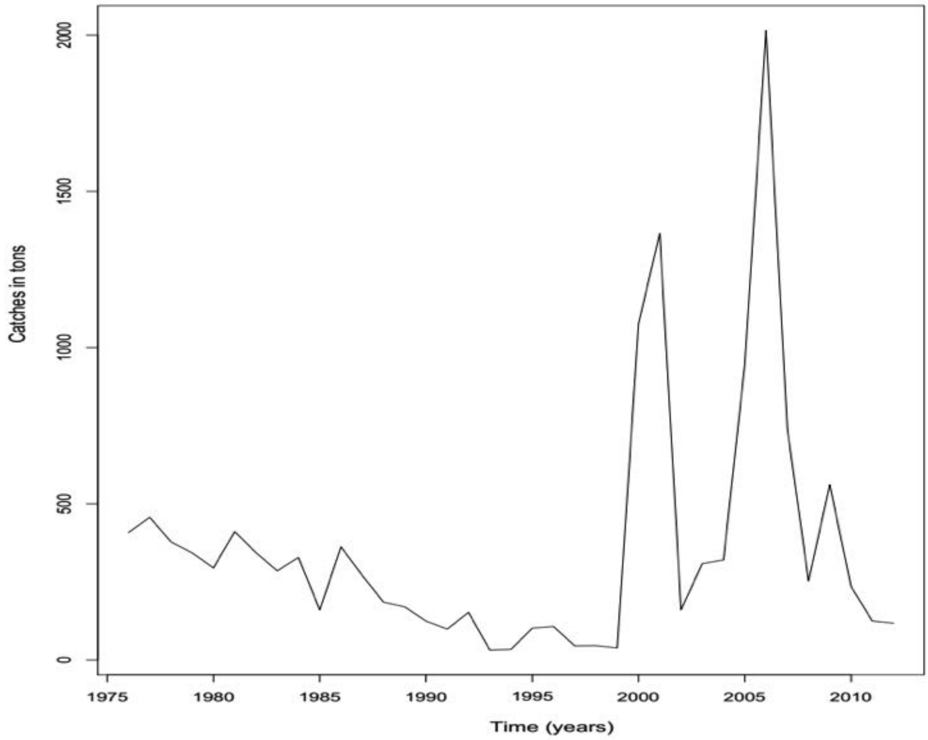

Figure 2: Annual fish catches between 1976 and 2012 for Catfish landings Autocorrelation functions (ACF)

There were significant lags in autocorrelation functions for Catfish (Figure 3). This implied that moving average parameters could be determined. The appropriate model for the time series for Catfish was the autoregressive integrated moving average (ARIMA) model with no differencing for the time series for Catfish.

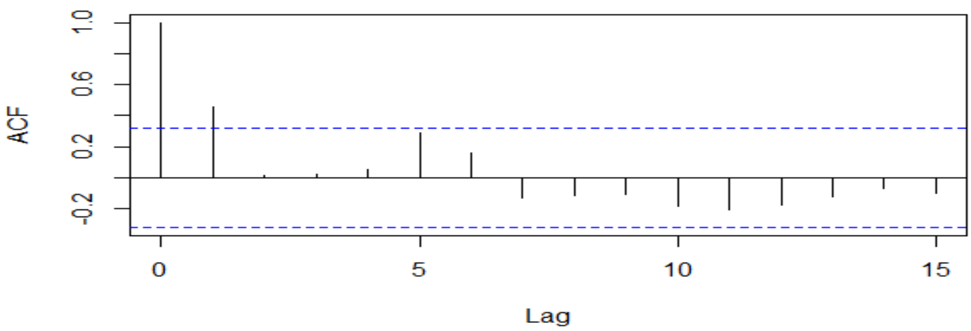

Figure 3: Autocorrelation functions (ACF) for Catfish

Partial autocorrelation functions (PACF)

There were significant lags in partial autocorrelation functions for Catfish (Figure 4). It was already determined from the ACF (Figure 3) that the appropriate model for the time series for Catfish was the autoregressive integrated moving average (ARIMA) model with no differencing for the time series for Catfish. The partial autocorrelation function

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showed that the parameters of the autoregressive (AR) part of the ARIMA model could be determined.

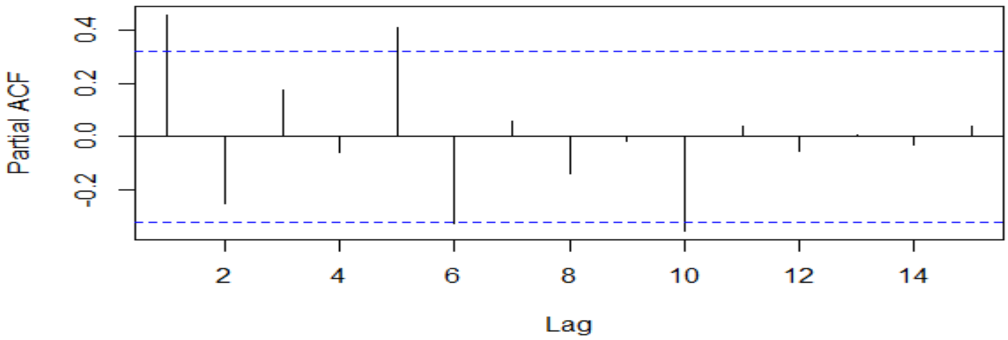

Figure 4: Partial autocorrelation functions (PACF) for Catfish

The time series data of annual fish landings for the cat fish species were subjected to stationarity test. If the data had a trend then differencing was made. Once the data were found stationary, correlograms were generated to observe if there were significant lags. For the data with significant lags on the correlogram, ARIMA modelling process was employed. The AIC was used to identify a better fitting model amongst the fitted possible models. The model with lowest AIC was chosen. The best fitting model was later subjected to a diagnosis testing to examine how best it fitted the data. If the model passed the test, forecasts were made.

The Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) were used to measure the accuracy of the fitted time series models. In addition, RMSE and MAE were used to serve as measures for comparing forecast of the same series across different models. The conclusion made was that the smaller the error, the better the forecasting power of the generated model. These were calculated as follows:

$$MAE = mean(|e_i|) \quad (1)$$

Where $e_i = y_i - \hat{y}_i$ and y_i is the *ith* observation and $\hat{y}_i$ is the forecast of y_i.

$$RMSE = \sqrt{mean(e_i^2)} \quad (2)$$

$$MAPE = mean(|P_i|) \quad (3)$$

Where $P_i = \left(\frac{e_i}{y_i}\right) * 100$

Model specification

R software version 3.1.3 (2015 – 03 – 09) was used in this study where autoregressive integrated moving average (ARIMA) was employed to model and forecast the data. However, before the modelling technique was employed, the data were tested for

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seasonality using two methods just to be sure that the data were indeed stationary before the process of modelling. The two methods for testing seasonality in this study were graphical analysis method and the Dickey–Fuller test. The graphical analysis method involved observing whether the data had a constant variance or not. If the data had no constant variance, it was regarded not stationary and vice versa. Whereas with the Dickey–Fuller test, the data with a *p-value* of < 0.05 was regarded to be not stationary and vice versa. The data were not differenced, as they were not significantly different to stationarity test, hence ready for modelling. The ARIMA modelling techniques required the data to be stationary.

The count time series of Catfish yields short term forecasts were made by employing ARIMA modelling process by Box and Jenkins [20]. The species showed that their annual yields were correlating with the yield from the previous year as proved by the autocorrelogram and partial autocorrelogram in Figure 3 and 4 respectively. Literature has shown that ARIMA has been employed successfully in modelling and forecasting fish landings, hence this study opted to employ this process. These modelling processes are also called stochastic modelling.

Forecasting using ARIMA model

Four (4) steps were followed in ARIMA model application in this study as described by Box and Jenkins [20], namely: identification, selecting a candidate ARIMA model, diagnostic checking and forecasting. The ARIMA model works where the data are stationary. The data were found not significant to non – stationarity, hence differencing was not necessary.

Selecting a candidate: the ARIMA model

The stationary data from Catfish species that were already stationary were then used to come up with correlogram and partial correlogram in order to identify an appropriate model for the fish landings. This process is called model identification. It simply involved finding the most appropriate values of p and q for an ARIMA (p, d, q) model by examining the correlogram and partial correlogram of the stationary time series.

The autocorrelation function $\rho(k)$ at lag k was denoted by:

$$\rho(k) = \frac{\gamma(k)}{\gamma(0)} \tag{4}$$

Where $\gamma(k)$ is the autocovariance function at lag k of a stationary random function {Y (t)} given by:

$$\gamma(k) = cov\{Y(t), Y(t-k)\} \tag{5}$$

Where the PACF had a cut-off at p while the ACF tails off, it gave an autoregressive (AR) of order p. Where also the ACF had a non-zero lag at q it gives a moving-average (MA) of order q. However, where there was non-zero lag(s) on both ACF and PACF, it implied that the application of the autoregressive moving-average of order p and q was possible. It also meant that since the data were not differenced, then the value of q is zero (0).

An autoregressive model (AR) of a time series $\{Xt\}$is a regression model of that time series on its previous history [1]. Autoregressive process of order (p) was found by using the following model;

$$X_t = \sum_{j=1}^{p} \emptyset_{t-j} + \varepsilon_t \tag{6}$$

A moving average (MA) model of a time series was aimed at averaging out previous error steps of a time series $\{Xt\}$to attempt to smooth the process or make the time series stationary. Moving Average process of order (q) was found by using the following model;

$$X_t = \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \varepsilon_t \tag{7}$$

The combination of linear autoregressive and moving average properties results in the autoregressive moving average (ARMA): ARMA of order (*p, q*) is,

$$X_t = \textstyle\sum_{i=1}^{p} \emptyset_i \, X_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \varepsilon_t \tag{8}$$

The general form of ARIMA model of order (p, d, q) is

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots\cdots\cdots\cdots + \phi_p x_{t-p} + w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots\cdots\cdots\cdots + \theta_q w_{t-q} \tag{9}$$

Where:

x_t is the original data series or differenced of degree *d* of the original data at time *t*;
w_t is the white noise at time *t*.
$\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive parameters.
p is the autoregressive order.
$\theta_1, \theta_2, \ldots, \theta_q$ are the moving average parameters.
q is the moving average order.

Model parameter estimation

When the model had been identified as AR, MA, ARMA or ARIMA the next step was to estimate the best possible parameters of the identified models as a way of model fitting. The best possible parameters were found using Akaike Information Criteria [21]. The best model was obtained on the basis of minimum value of Akaike Information Criteria (AIC) [22]. The AIC was found by the following model:

$$\text{AIC} = -2 \log \text{L} + 2\text{m} \tag{10}$$

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Where:

m is $p + q$

L is the likelihood function

The AIC was used to obtain a model that well represented the data on the basis of minimum value of AIC.

Model validation

Diagnostic tests were carried out to check to what extent the forecast could be trusted. The diagnostic tests were done by using method of plotting correlogram of the residual errors and the Ljung-Box test, as these were widely used and efficient in model validation.

Forecasting

Once the appropriate best candidate ARIMA (p, d, q) model was selected for yield time series data for the Catfish species then the parameters of the selected model were estimated. The fitted ARIMA models were then used as a predictive model for making forecasts for the future (next ten (10) years) of fish landings.

RESULTS AND DISCUSSION

Determining the correct parameter estimates

To determine the correct model parameter estimates, the following steps were taken:

ARIMA models for Catfish

The trend analysis by Mann Kendall of time series data of the catches of Catfish results in Table 2 showed that the original data did not have a trend (*p-value* 0.2340). The Dickey-Fuller test showed that the original data were stationary (*p-value* 0.0491) as shown in Table 2. With these results from Mann Kendal and Dickey-Fuller tests on the original data, it is implied that the original data of Catfish did not require transformation through differencing, and hence was ready for modelling with ARIMA process as it was stationary.

Since the Dickey-Fuller test on the original series proved that the series were stationary, then autocorrelogram and partial autocorrelogram were plotted to determine the values of p and q in the ARIMA models. The plotted autocorrelation function showed a first-order moving average (MA) model, while the plotted partial autocorrelation function showed tenth-order autoregressive (AR) model as shown in Figures 3 and 4, respectively in the methodology.

The ARIMA model with the lowest AIC values was selected. The value of the AIC of the selected ARIMA model was 536.56 as also shown in the Table 3. Owing to that, the most suitable model for artisan Catfish landings from Lake Malawi in Mangochi District was ARIMA (0, 0, 1) (Table 3), as this model had the lowest AIC value. The chosen model described the time series for Catfish with the following parameters estimates:

$$x_t = 0.8916w_{t-1} \tag{11}$$

This means that the current total catches of Catfish are influenced by the previous year's catch.

Validity of the model
ARIMA process
Both ACF for residual errors for the selected ARIMA model of Catfish for the forecasting of their landings had no significant lags as shown in Figure 5. The plotted forecast errors of ARIMA models shown in Figure 6 indicate that they had constant variance with a mean of zero (0). The ACF residual plot (autocorrelogram) shows that the sample autocorrelation at lag 1 exceeds the significance bounds as shown in Figure 5. However, this is probably due to chance, as we would expect one out of 20 sample autocorrelations to exceed the 95% significance bounds [23].

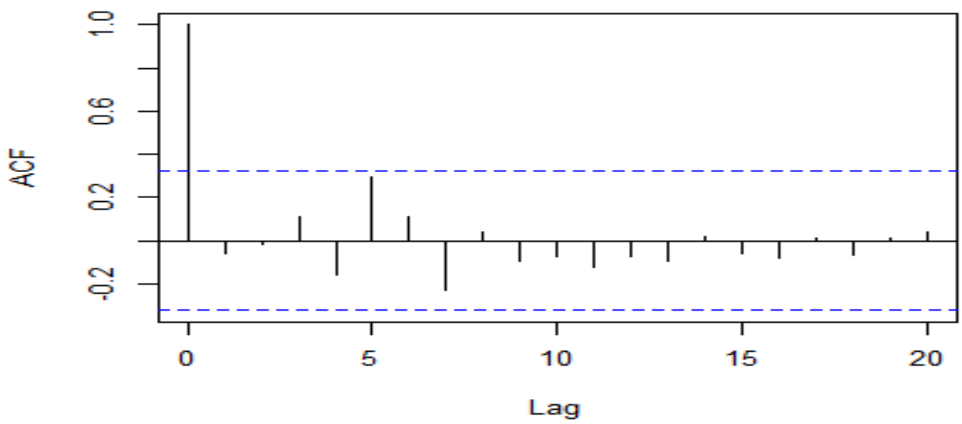

Figure 5: Autocorrelation functions (ACF) for residual errors of Catfish forecasts

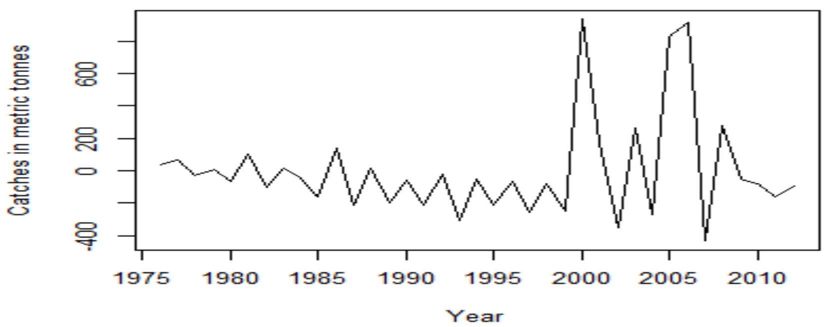

Figure 6: Plot of residual errors of Catfish forecasts

The Box–Pierce (and Ljung–Box) test results as shown in Figures 7 indicated that Catfish selected model had higher *p-values*. The Box–Pierce (and Ljung–Box) test was used to identify a best fitting model among the four most competing models. The Box–Pierce test examines the null of independently distributed residuals; it is derived from the idea that the residuals of a "correctly specified" model are independently distributed [23]. If the residuals are not independently distributed, then it shows that they come from a miss-specified model. The results of executed Box–Pierce (and Ljung–Box) test on the three most competing models, also depicted ARIMA (0, 0, 1) model as the best fitting model as shown in Figure 7.

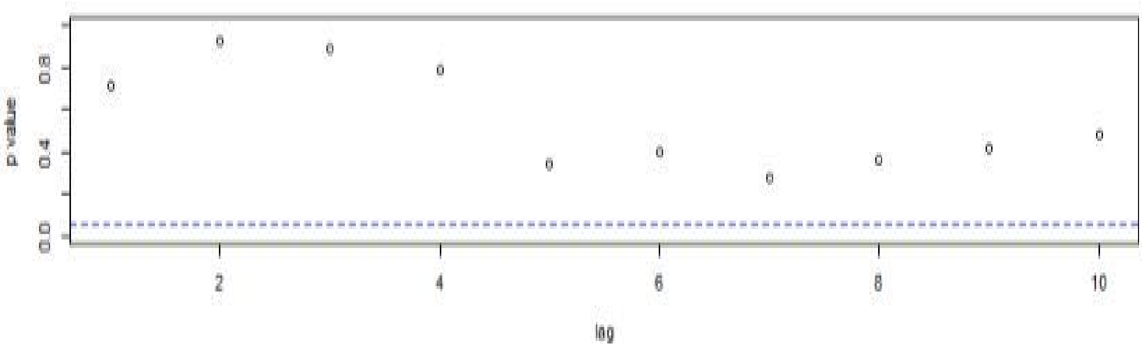

Figure 7: Box–Pierce (and Ljung–Box) test results of residual errors of Catfish forecasts

The model with significant coefficients parameters is better in terms of forecasting performance than the one with insignificant coefficients parameters [24]. The ARIMA (0, 0, 1) still came out outstanding as it has significant parameters as shown in Table 3 and was confirmed for forecasting of future artisan fishers' landings of Catfish in Lake Malawi in Mangochi District as shown in Table 4.

However, before forecasting, diagnostic checks on the proposed best fitting model were made, which involved checking the residuals of the model to see if they contain any systematic structure, which still could be removed at this stage to improve the selected ARIMA [19, 25]. This study involved several diagnostic checks such as examination of the autocorrelations of the residuals of various orders, the Box–Pierce (and Ljung–Box) test and plotting of residual errors to see if their mean was zero and are normally distributed, whose results are shown in Figures 5, 7 and 8 respectively. The ARIMA (0, 0, 1) also provided a good forecasting performance as shown by low forecast error indicators in Table 4.

In addition to this, the *p-value* for the Ljung-Box test was 0.9003 as shown in Figure 7, indicating that there is no evidence for non-zero autocorrelations in the forecast errors for lags 1-20. The Box–Pierce (and Ljung–Box) test also showed that the model fitted the series well as the *p-value* was close to one (1) as shown in the Ljung–Box statistic in Figure 7. To check whether the forecast errors have a constant variance and are normally distributed with mean zero, time plot of the forecast errors, and a histogram were made.

The histograms of plotted residuals errors for the selected ARIMA model of Catfish were normally distributed with mean zero (0) as shown in Figure 8. The histogram of residual errors in Figure 8 clearly showed that they were normally distributed with a generally constant variance and mean of zero (0). The Figure 8 showed also that the residuals errors had generally constant variance. These diagnostic tests proved that the selected ARIMA model was indeed a good model that fitted the yield time series data of Catfish from the artisan fishers of Lake Malawi in Mangochi District in Malawi, and could be used effectively to forecast the species landings. A histogram plotted out of Catfish forecast

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residual errors indicated that the residuals were normally distributed. The ACF residuals errors plots clearly showed that autocorrelation coefficients of the residuals are within 95% confidence interval and were not autocorrelating with each other. This meant that the original series trend in the landings of Catfish was successfully extracted to make a forecast.

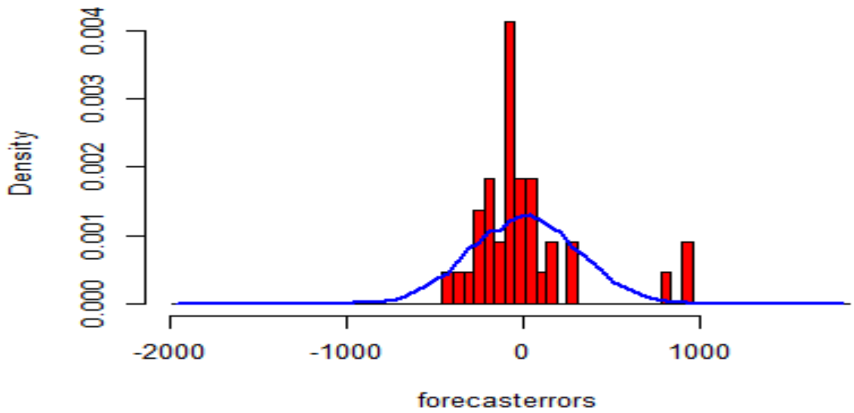

Figure 8: Histogram plot of residual errors of Catfish forecasts

Forecasting

The forecast revealed a likelihood that the species is under threat cannot be ruled out as the confidence intervals did include a zero (0) as shown in Table 4. A good model should have a low forecasting error; therefore, when the distance between the forecasted and actual values were low then the generated model had a good forecasting power [25, 26, 19] as proven by the low values of ME, RMSE, MAPE and MAE in Table 3. The forecast for artisan landings of Catfish, Catfish from Lake Malawi in Mangochi District showed a mean of 361 tonnes (rounded-up to nearest figure) and the mean of the actual catches was 362 tonnes (rounded-up to nearest figure) with 95% confidence intervals. These results are a clear demonstration that the artisan fishery of Catfish from Lake Malawi in Mangochi District will be stable as shown in Figure 9.

Table 4 shows forecasted landings of Catfish using Autoregressive Integrated Moving Average (ARIMA) model from 2013 through 2022 for Mangochi small-scale fishery. The graph in Figure 9 shows the forecasted trend and the confidence interval of 95% for same species.

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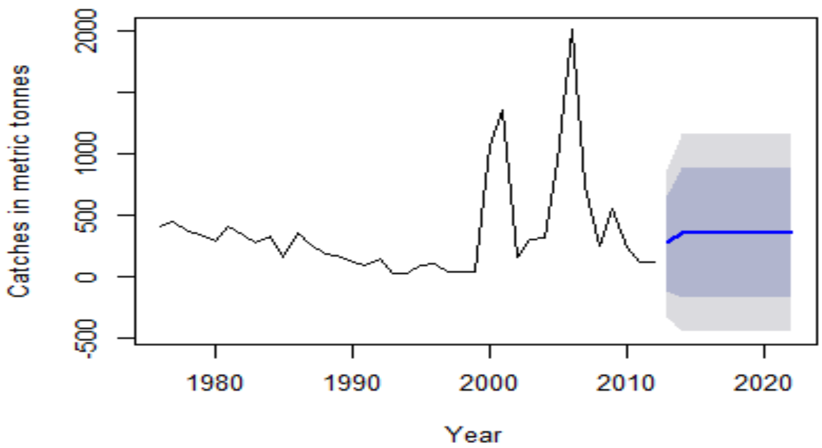

Figure 9: Ten-year forecasts for annual catches in metric tonnes of Catfish using Autoregressive Integrated Moving Average (ARIMA) models

This forecast should alert the policy makers to continue ensuring sustainable exploitation of the Catfish among artisan fishers in Lake Malawi in Mangochi District as the ecology of this fish species is directly linked to other species in the lake. Currently, Mangochi district does not have a fisheries management plan that targets Catfish. There is a need to develop the management plan to ensure that this fishery is sustainably exploited. This fisheries management plan can be coupled with area specific fisheries management in form of bylaws (which empowers local communities) that are crafted towards ensuring that the Catfish species are conserved. The forecasted trend shows that the theory of 'tragedy of commons' might be slowly setting in for the species stock as the forecast reveals the catches of Catfish will remain the same amidst increased fishers' population. As such, management of the Catfish in this fishery is very crucial to avoid the forecasted trend worsening and negatively affecting the other species in the lake.

CONCLUSION

The study showed that the artisan fishery landings of Catfish from Lake Malawi in Mangochi District would remain stable amidst increased fisher population. The government through Department of Fisheries and stakeholders should continue controlling exploitation levels of the fishery by controlling fishing efforts so as to maintain this trend of Catfish landings. As the artisan fisheries in Malawi is multi-species and multi-gear controlling Catfish exploitation levels should be controlling all fishing effort that lands the species such as gillnets, beach seines, open water seines among others. Since confidence intervals of the forecasted landings of the fishery included a zero, this implied that the possibility that the fishery is being over exploited cannot be ruled out. As such, policy makers should ensure that the fishery is sustainably exploited while maintaining the stable trend hence saving it from succumbing to the theory of tragedy of commons. This can be achieved as well by controlling entry of fishing gears landing most Catfish. However, further research should model as well fishing effort to compare the behaviour of the catch and effort in the same period of time to provide a more comprehensive picture of forecast fishery.

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Table 1: Descriptive statistics of the time series data

	Catfish
Minimum	32.29
1st Quarter	124.50
Mean	362.30
3rd Quarter.	378.20
Maximum	2015.00
Standard deviation	998.33

Table 2: Mann Kendall test for trend and Dickey-Fuller test for stationarity on time series of annual catches of Catfish

Time series	Mann Kendall test		Dickey-Fuller test	
	Tau (τ) statistic	***p*-value**	**Dickey-Fuller statistic**	***p*-value**
	-0.1380	0.2340	-3.5676	0.0491

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Table 3: Competing ARIMA models for the time series of annual catches of Catfish from 1976 to 2012

	ARIMA(10,0,1)		ARIMA(6,0,1)		ARIMA(1,0,1)		ARIMA(0,0,1)	
Parameter	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
AR10	0.7752	0.2626						
AR9	-0.6234	0.2716						
AR8	0.5097	0.2819						
AR7	-0.6292	0.2701						
AR6	1.0431	0.2581	1.4879	0.1218				
AR5	-0.5927	0.2779	-1.0134	0.2279				
AR4	0.2605	0.2999	0.8282	0.2561				
AR3	0.2979	0.2715	-0.7558	0.2491				
AR2	0.3271	0.2281	0.8556	0.2192				
AR1	0.6139	0.1604	-0.6061	0.1250	-0.0944	0.1788		
MA1	0.0962	0.3358	-1.0000	1.1040	0.9085	0.0831	0.8916	0.0797
Intercept	316.5569	45.5670	312.5438	22.3744	361.3612	87.0580	360.4622	94.5480
σ^2	48819		61628		94036		947.27	
Log likelihood	-256.29		-259.84		-265.14		-265.28	
AIC	538.59		537.69		538.28		536.56	
ME	0.3762256		-12.46281		-0.4619485		-0.319132	
RMSE	220.5072		248.2405		134.7127		180.6979	
MAPE	104.5796		134.7127		127.6727		123.1608	
MAE	146.0011		180.6979		202.5072		204.07	

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Table 4: Ten-year forecasts for annual catches in metric tonnes of Catfish using Autoregressive Integrated Moving Average (ARIMA) models

Year	Catfish Mean (MT)	95 % CI
2013	273.846	(-329.396, 877.088)
2014	360.462	(-447.712, 1168.637)
2015	360.462	(-447.712, 1168.637)
2016	360.462	(-447.712, 1168.637)
2017	360.462	(-447.712, 1168.637)
2018	360.462	(-447.712, 1168.637)
2019	360.462	(-447.712, 1168.637)
2020	360.462	(-447.712, 1168.637)
2021	360.462	(-447.712, 1168.637)
2022	360.462	(-447.712, 1168.637)

Confidence Interval (CI)
Metric Tonnes (MT)

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