Modeling and Forecasting of *Engraulicypris sardella* (*Usipa*) Yields from Mangochi Artisanal Fisheries of Lake Malawi using Holt Exponential Smoothing Method

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Abstract

This study was aimed at modelling and forecasting *Engraulicypris sardella* (*Usipa*) species yield from artisanal fishery on Lake Malawi in Mangochi District. The study was based on secondary count time series data on fish catches during the years of 1976 through 2012 provided by Fisheries Research Unit of the Department of Fisheries in Malawi. The study considered Holt exponential smoothing method to select an appropriate stochastic model for forecasting the *Usipa* species yields. Appropriate model was chosen based on Holt's exponential parameters α (alpha) and β (beta). Box – Ljung statistics and distribution of residual errors among others were estimated. The Holt's exponential smoothing method showed that the artisanal fishery landings of *Usipa* would increase to 22,849.4 tonnes in year 2022 which is 2,135.76 tonnes more than the landings in the year 2010 of 20,713.64 tonnes assuming that the biological and ecological factors remain the same. The forecast mean for *Usipa* is predicted to be 22,849.4 tonnes through the year 2022. The study observed that *Usipa* fisheries is being exploited sustainably. The confidence interval of 95% does not include a zero meaning that the likelihood that *Usipa* fishery might be under extinction currently or anytime soon might be very low. The increase of

Usipa, could be as a result of a decline in population of competing species in the ecosystem. The *Usipa* Management Strategy for Southeast and Southwest Arms of Lake Malawi and Lake Malombe developed by the USAID/FISH Project will ensure continued effective and sustainable management of exploitation of the fishery.

Keywords: *Engraulicypris sardella, landings, Holt exponential smoothing method, artisanal fishery, Lake Malawi.*

1 INTRODUCTION

Catch per unit effort (CPUE) has been used for many years to manage data limited fisheries such as in Malawi by assessing catch trends for different fish stocks (Maunder et al., 2006; Bordalo-Machado, 2006; Lazaro & Jere, 2013). However, over the past years, the use of time series models has been recommended as the best in determining both trends and forecasts in other countries (Lazaro & Jere, 2013; Tolimieri et. al., 2017; Ryan & Meyer, 2019). Ryan & and Meyer (2019) in Austraria successfully employed the time series analysis technique to model and predicting catch per unit effort from a multispecies commercial fishery in Port Phillip Bay. The time series analysis technique is cheap, provide an indicator of a stock (Ryan & Meyer, 2019), easy to interpret, allows a detailed assessment of seasonal effects and adequately forecast production trends and seasonal fluctuations (Lazaro & Jere, 2013). Time series analysis is a well-developed scientific method of analysis that has been extensively and successfully used in fisheries studies around the world as well as other fields such as econometrics and meteorology (Craine, 2005).

As the fisheries resources in Malawi continue to decline amidst population increase and climate change there is a need to enhance our fisheries management strategies to be more efficient than before. Literature shows that there are very few attempts to model and forecast timeseries fisheries data (landings, effort or CPUE) in Malawi. As such fisheries managers and policy makers may not have been provided with adequate information regarding the future state of the fisheries resources (Raman, 2018). The forecasts are very important for policy makers to make informed decisions as regards to which fisheries management option will be more appropriate for the resources (Coro et. al., 2016).

It is of paramount importance that the trend of the species of economic importance and those becoming important such as *Usipa* be modelled and forecasted to provide a picture of how the fishery will behave in the years to come. Of late catch species composition has shifted from large cichlids, catfish, and cyprinids to small pelagic species such as *Usipa*, Kambuzi (*Haplochromine* species) and Matemba (*Barbus* species) (Torell et al., 2020). *Usipa* has recently become the dominant fishery in Lake Malawi, however, uncertainty exists about short and long -term ecosystem responses. The species is currently contributing over 70% of total landings in Malawi though not fully managed (Christophe and Damien 2014; Fisheries Integration of Society and Habitats ((FISH), 2018). Prediction models are necessary for fisheries administrators to foresee in advance the evolution of the resource abundance (Berachi, 2003). This is very important for fisheries managers and policy makers to device tools to sustainably manage the fishery resources for the benefit of the nation. In Malawi fish constitutes about 27% of the total animal protein intake (FAO, 2010). However, increasing population, overfishing, dwindling in catches as well as rising of real fish prices have reduced per capita fish consumption from 12-18 kg/person/year in 1970s to 9.4 kg/person/year in 1990, to 5.4 kg/person/year in 2008 and 5.6 kg/person/year in 2011 (Yaron et al. 2010, GoM, 2012). The decline from 14 kg/person/year in 1970s to 5.6 kg in 2011 represent a 60% decrease of per capita consumption of fish in Malawi (GoM, 2012). This decline in the fish per capita is a serious indicator of a threat of national food security and may have serious nutritional implications for the nation more especially the poor, under-five children, expectant women, the elderly and those affected or infected by HIV/AIDS.

Brown (1959 & 1962) and Holt (1960) founded the exponential smoothing forecasting methods in the 1950'with formulation of forecasting models for inventory control systems (Fomby, 2008). Holt's exponential smoothing method is basically an extension of the Moving Average (MA) process and generate forecasting by weighted moving average. The smoothing concept assumes that more recent values are more important than oldest values when it comes to forecasting. As such Holt's exponential smoothing method uses a weighting scheme that has decreasing weights as the time series observations become older (Fomby, 2008). Kisang-Ryu (2002) reported that in their research which compared different forecasting methods, the Holt's exponential smoothing method performed better than the other forecasting methods by generating better accuracy than moving average model (MA), double moving average model (DMA), single exponential smoothing method (SES), double exponential smoothing method (DES) and linear regression (LR). Taylor (2008) reported also that the overall accuracy of forecasts made with the exponential smoothing method are very good hence the forecast of Holt's exponential smoothing method can be trusted. This is consistent with al-Salam (2013) who reported that best forecasting model for fish product and supply series in Sudan were the Quadratic Trend Model and Winter's Exponential Smoothing model, respectively. Yugui et al. (2016) reported as well that the single exponential smoothing and ARIMA (1, 1, 1) models were best for predicting sea cucumber short-term catches, and the predictive powers of both models are good. The Holt's exponential smoothing method is known to provide very low forecasting errors. This is in agreement with Kahforoushan et al. (2010) who reported that Holt-Winters model had the lowest mean absolute percent error in both model fitting and model validation stages when predicting value addition of agricultural subsections using artificial neural networks.

It is for this reason that this study seeks to generate more forecasts on the fish landings on *Usipa* using Holt's exponential smoothing method to assist the policy makers in strengthening or revisiting the current species management strategies to ensure that the stocks are sustainably exploited.

2 MATERIALS STUDY AREA AND METHODS

2.1 *Usipa* Biology

Lake Malawi has a single biological stock of *Usipa* (Figure 1) which is a very significant cyprinid species in the lake economically and ecologically (Maguza-Tembo & Palsson, 2004). *Usipa* is a small shoaling zooplankton feeder which forms an important component of the pelagic ecosystem in the lake (Turner, 2004). Morioka & Kaunda (2004) reported that growth rate of *Usipa* in the rainy season was greater than 0.70 mm TL per day but less than 0.50 mm TL per day in the dry season. *Uispa* can reach a maximum length of 13 cm TL for adults although most of them are less than 10 cm (Eccles, 1992).

Figure 1: *Engraulicypris sardella (Usipa).*

2.2 Study area

This study covered artisanal fishery of 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 2.

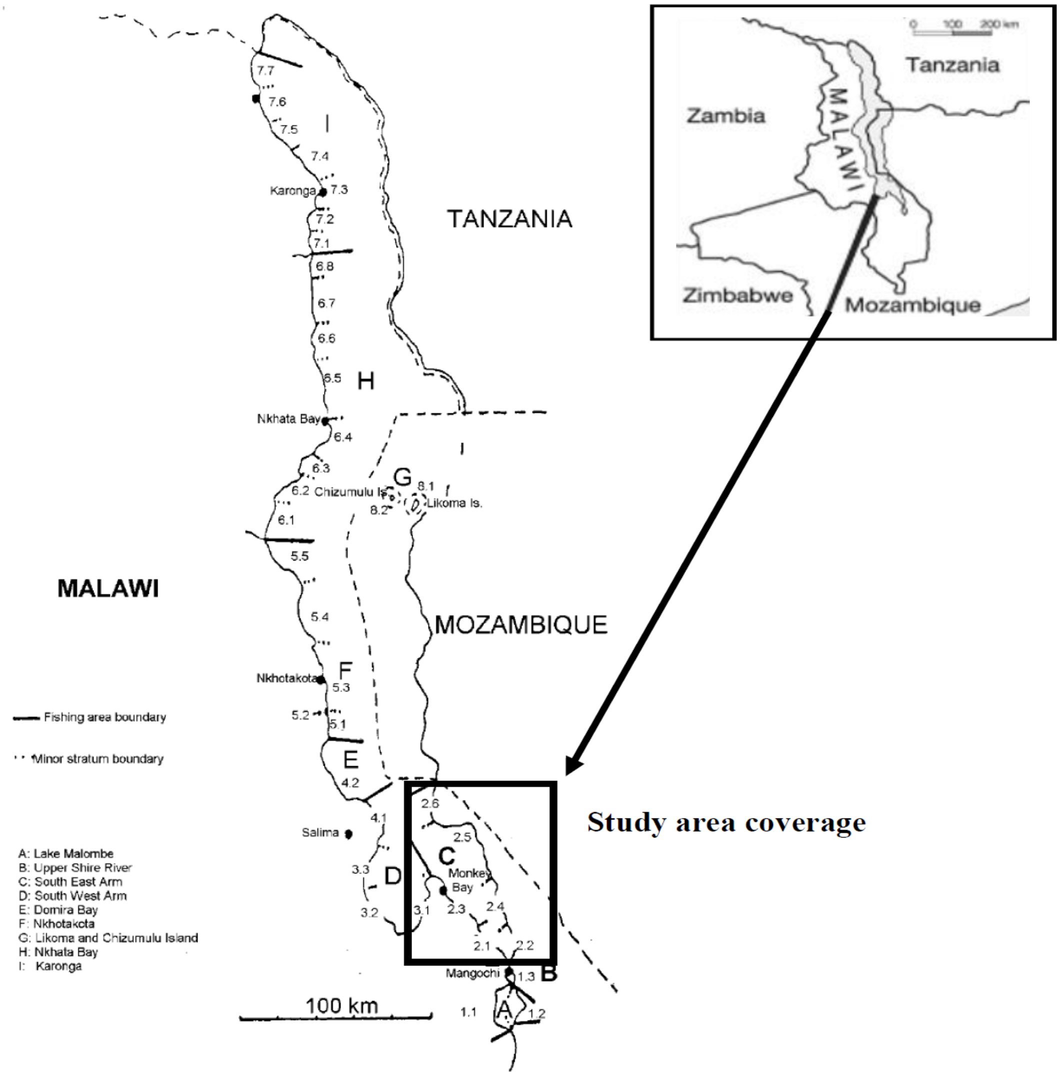

Figure 2: *Map of southern part of Lake Malawi showing all minor strata 2.1 to 3.1 of Mangochi Districts.*

2.3 Data

The study used secondary data of *Usipa* landings by artisanal fisheries on Lake Malawi in Mangochi District. The data was univariate time series of total fish catches of *Usipa* from 1976 to 2012 collected from the Department of Fisheries in Malawi. The unit of measurement of the data was metric tonnes and refers to the weight of fish at the time it was landed. The descriptive statistics characteristics of the data are mean of 4841 tons, standard deviation of 6310.34 tons, range of 42.13 to 2399 tons and, first and third quantile of 562.3tons and 5158tons respectively. The artisanal fishery in the area is more complex than the rest of the lake as it has high number of fishers, fishing gears and crafts. The part of Lake Malawi in the district is the most productive area of the lake.

R software version 3.6.0 (2019 – 04 – 26) was used in this study in which modelling technique, Holt's exponential smoothing method was employed to model and forecast the data. Holt's exponential smoothing method is very useful when forecasting data which is stationary and has no non-zero lags (Coghlan, 2015). As such it fitted very well the data of *Usipa* yield which had no significant lags on their correlogram. The study took the following steps to forecast using Holt's exponential smoothing model namely estimating parameters, model validation and forecasting within the time series and the future.

2.4 Estimating parameters

The study used Holt's exponential smoothing modelling process to estimate the level and slope at the current time point of *Usipa* data according to Coghlan (2015). Smoothing was later on done by estimating the level at the current time point denoted by α (alpha) as shown in model (1) and estimating the slope b of the trend component at the current time point denoted by β (beta) as shown in model (2).

2.5 Model validation

The study tested the trustworthy of the developed model by using a Ljung-Box test. With the Ljung-Box, the study passed models with *p-values* of > 0.05. The study also tested the trustworthy of the developed model by checking that the forecast errors were normally distributed with a mean of zero and had constant variance over time. This was done by making a time plot of forecast errors, and a histogram of the distribution of forecast errors with an overlaid normal curve according to Coghlan (2015). The developed model with its forecast errors that are normally distributed with a mean of zero and a constant variance was passed for being making accurate forecasts.

Once alpha and beta were estimated, then the original time series was plotted together with the forecasted values (fish landings) at a time point in different colours to be easily traced. This was aimed at checking to what extent the fitted Holt's exponential smoothing model best fitted the original time series. This was done by ensuring that the forecasted trend was responding positively to the trend of the original time series data (close enough to the original trend) of the species. Once the results were satisfying for a best fit of the Holt's exponential model, the model was used to forecast short term in the future.

2.6 Forecasting for future catches

The parameters generated during parameter estimation stage were used to get the forecasted value (*Ft + m*). The Holt's exponential smoothing method was represented by a set of models as follows:

Level: $$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + b_{t-1}) \quad (1)$$

Trend: $$b_t = \beta(L_t - L_{t-1}) + (1 - \beta) b_{t-1} \quad (2)$$

Forecast: $$F_{t+m} = L_t + b_t m \quad (3)$$

Where:

F_{t+m} represents the forecast m periods ahead

L_t denotes an estimate of the level of the series at time t

b_t is an estimate of the slope of the series at time t.

The first model (1) directly adjusted L_t for the last smoothed value (L_{t-1}) by adding it to the trend of the previous period (b_{t-1}). The second model (2) updated the trend, which is expressed as the linear difference between the last two smoothed values.

3 RESULTS AND DISCUSSION

3.1 Model identification

3.1.1 Testing for trend in the time series

Graphical analysis method of the *Usipa*, *Usipa* plotted series showed that there was a general increase in landing of *Usipa* from the fishery especially from the years 2005 to 2012 as shown in Figure 3 hence the series was visibly found not stationary and required transformation for modelling. The Mann Kendall test also showed that the *Usipa* original series had a significant trend (*p*-value of 0.0000) which necessitates differencing to detrend it as shown in Table 1. The Dickey-Fuller test also showed non-stationarity of the original *Usipa* series by providing a *p*-value of 0.8456 (Table 1) which implied the series was indeed not stationary. The transformation was made by differencing the series in order to be able to model and forecast.

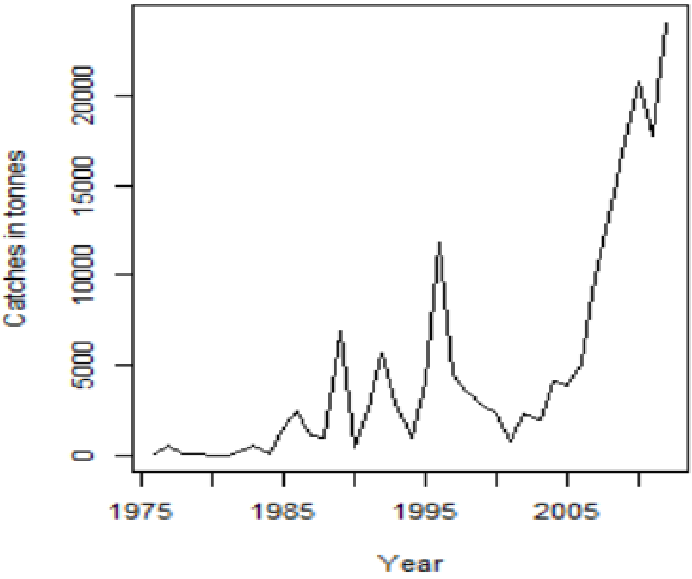

Figure 3: *Annual fish catches between 1976 and 2012 for Usipa.*

Table 1: *Mann Kendall test for trend and Dickey-Fuller test for stationarity on time series of annual catches of Usipa.*

***Usipa* time series**	**Mann Kendall test** **Tau(τ) statistic**	***p*-value**	**Dickey-Fuller test** **Dickey-Fuller statistic**	***p*-value**
Original series	0.6370	0.0000	-1.3016	0.8456
After differencing	0.1620	0.1689	-7.327	0.0000

3.1.2 Removing the Trend

The Dickey-Fuller test results in Table 2 showed that the differenced series had a *p-value* of 0.0000 resulting into failure to reject the alternative hypothesis of the differenced series being stationary. The Mann Kendall test on the differenced series showed that the series did not have a trend by giving a *p*-value of 0.1689 as shown in Table 1. Graphical analysis of the differenced *Usipa* plotted series (Figure 4) showed that the series was stationary and ready for modelling.

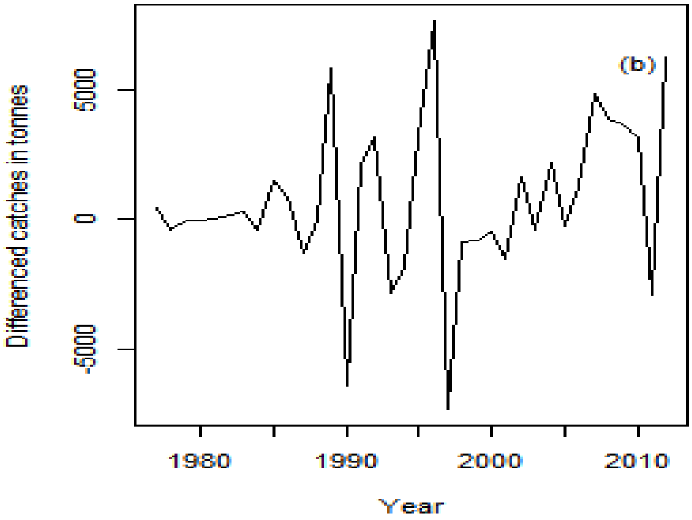

Figure 4: *Annual fish catches between 1976 and 2012 for usipa.*

The autocorrelogram and partial autocorrelogram were carried out on the difference series. However, the autocorrelogram and partial autocorrelogram plotted both showed that the new *Usipa* series did not have non- zero lags as shown in Figure 5 and 6 respectively hence its values were not autocorrelating nor partially autocorrelating with each other. The ACF non-zero lag at zero (0) was disregarded as it was correlating with itself.

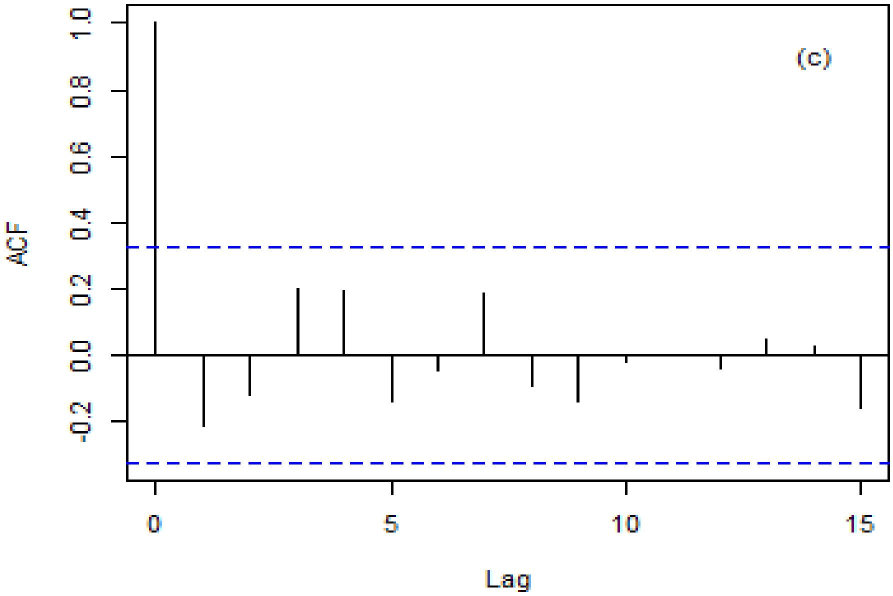

Figure 5: *Autocorrelation functions (ACF) for usipa. Dashed horizontal lines are the limits of 95% Confidence Interval.*

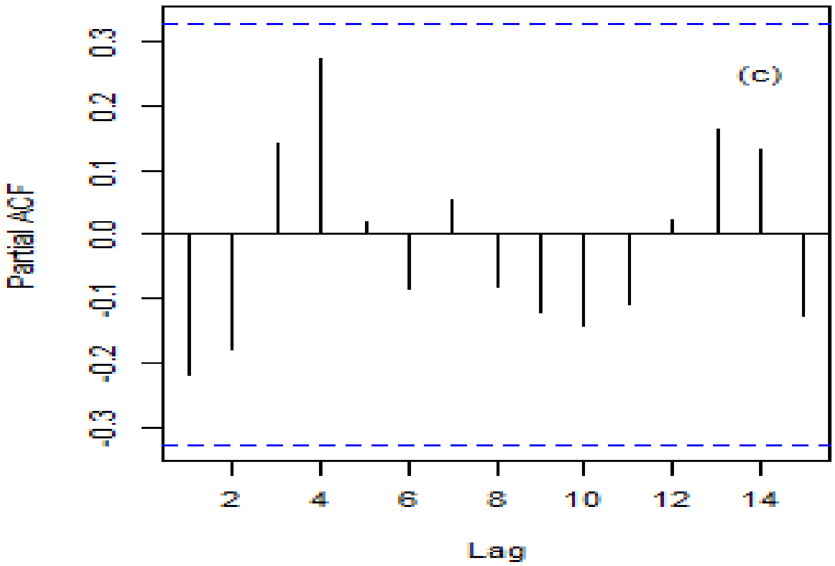

Figure 6: *Partial autocorrelation functions (PACF) for usipa.*

The absence of non-zero lags in both autocorrelogram and partial autocorrelogram indicated that it was not possible to find order of autoregressive (AR) model and order of moving average (MA) model on the differenced series. This meant that AR, MA, ARMA and ARIMA modelling were not suitable for the original *Usipa* artisanal fishery catches time series from Lake Malawi in Mangochi District. As such, Holt' exponential smoothing model was suggested to be used to model and forecast the *Usipa* landings series from artisanal fishery of Lake Malawi in Mangochi District. The Holt winters model that fitted very well the *Usipa* landing series from artisanal fishery of Lake Malawi in Mangochi District was Holt's exponential smoothing model as the series could be described by an additive model, had a trend with no seasonality.

3.2 Determining the correct Holt Winters Smoothing Models for *Usipa*

The Holt's exponential smoothing model with the parameters and coefficients as shown in the Table 2 was developed and used to successfully forecast the future artisanal fishers' landings of *Usipa* in Lake Malawi in Mangochi District shown in Table 6 and Figure 9.

Table 2: *Parameters and coefficients of developed Holt's exponential smoothing model generated from annual Usipa catches*

	Smoothing parameters	**Coefficients**
Alpha	0.8036248	
Beta	FALSE	
A		22849.4
ME	786.5682	
RMSE	1102.998	
MAPE	105.8794	
MAE	2218.943	

The smoothing parameter, α (alpha) for *Usipa* series was found to be 0.8036 while the trend component β (beta) was assumed to be false at the current time point where as *a* was found to be 22849.4.

3.3 Validity of the Models

The fitted model made forecasts that were very close to the actual values. The plotted forecast errors correlogram of *Usipa* showed no significant lags hence the errors were not significantly autocorrelating as shown by a *p*-value of 0.9586 and x-squared of 10.482 in Table 3 from the Box-Ljung test. The time plot of residual errors showed that the errors have a mean of zero with constant variance over time as shown in Figure 7 which meant that the model had successfully extracted the trend in the landings from *Usipa* fishery among artisanal fishers of Lake Malawi in Mangochi District.

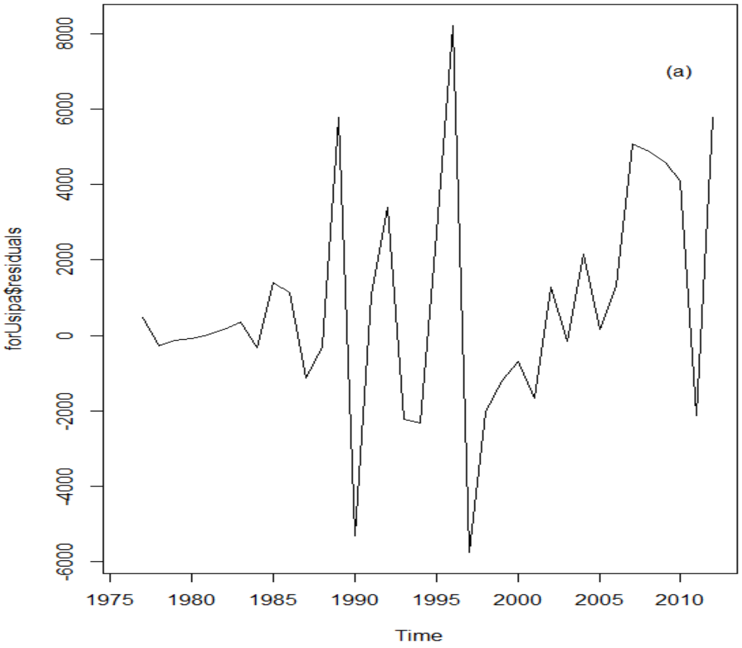

Figure 7: *Plot of residual errors of usipa forecasts.*

Table 3: *Box-Ljung test of usipa forecast errors of the developed holt's exponential smoothing models generated*

Fish species	**X-square**	**Df**	***P*-value**
Usipa	10.482	20	0.9586

p-value < 0.05 is significantly different.

The histogram of the forecasted errors showed a mean of zero, constant variance over time and normally distributed as shown in Figure 8. This implies that Holt's exponential smoothing method provided an adequate forecast model for *Usipa* catches of Lake Malawi artisanal fisheries in Mangochi District, which probably cannot be improved upon. This indicated that the assumptions of 95% predictions intervals were based upon, are probably valid. The generated model also displayed good precision as shown by the lower values of forecast error measuring indicators; ME, RMSE, MAPE and MAE in Table 4 hence the forecast from this model can be trusted. The forecasted and actual values were close implying that the forecasted errors were very low. This meant that the model is a good model according to Shitan et al. (2008). Czerwinski et al. (2007), Singini et al. (2012) and Lazaro & Jere (2013) argued that a good model should have a low forecasting error implying that the distance between the forecasted and actual values should be low depicting that the developed model have a good forecasting power.

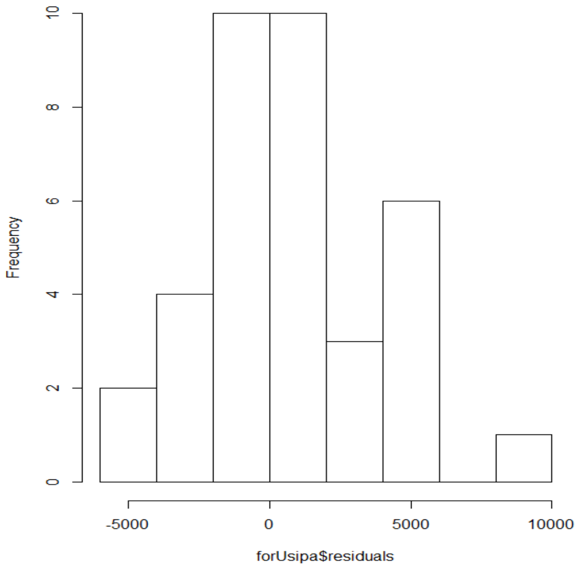

Figure 8: *Histogram plot of residual errors of engraulicypris sardella (usipa) forecasts.*

3.4 Forecasting

The forecast for artisanal landings of *Usipa*, from Lake Malawi in Mangochi showed a mean of 22,849.4 tonnes and that in the year 2022 the fishery will be 22,849.4 tonnes which is 2,135.76 tonnes more than the landings in the year 2010 of 20,713.64 tonnes as shown in Table 4. These forecasted results compare very well with what DoF (1999) management reports which indicated that *Usipa* stock is well-managed. The *Usipa* is also known to breed throughout the year and have generally long breeding periods and different stocks adapt to different optimum temperatures for breeding (Morioka & Kaunda 2004).

Table 4: *Ten-year forecasts for annual catches in metric tonnes of Usipa using Holt-Winters Smoothing models.*

Year	Mean	95 % CI
2013	22849.4	(16934.07, 28764.72)
2014	22849.4	(15260.67, 30438.12)
2015	22849.4	(13894.71, 31804.08)
2016	22849.4	(12711.15, 32987.64)
2017	22849.4	(11652.00, 34046.79)
2018	22849.4	(10684.72, 35014.07)
2019	22849.4	(9788.88, 35909.91)
2020	22849.4	(8950.666, 36748.13)
2021	22849.4	(8160.204, 37538.59)
2022	22849.4	(7410.159, 38288.63)

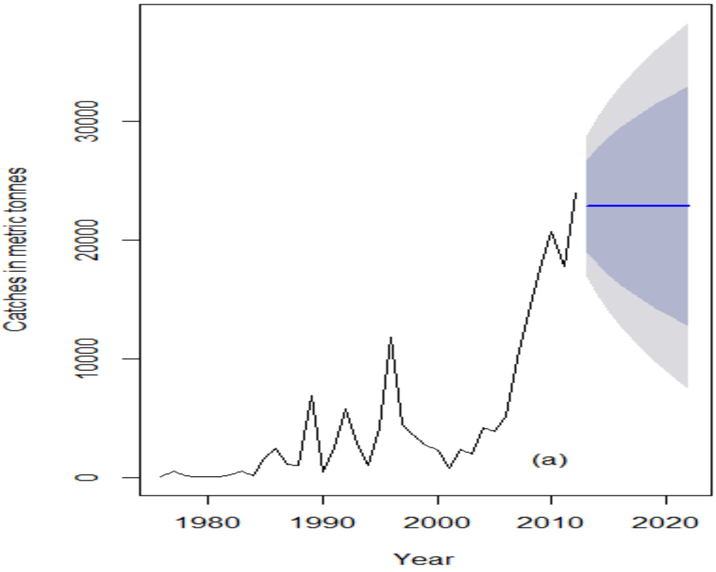

Figure 9: *Ten-year forecasts for annual catches in metric tonnes of Usipa using Holt-Winters Smoothing models*

This could be as a result of what Thompson, 1996 reported that *Usipa*, *Usipa* had a lower mortality of larvae which coincides with the windy mixed period when primary and secondary production were at a maximum, and correlated with an increased food supply at this time. These same windy season causes strong waves on the Lake Malawi which limit fishers' entry to exploit the *Usipa* during their breeding season unlike the other fish species which are more vulnerable during their breeding season. *Usipa* has a high reproductive output but with a high natural mortality rate outside the windy mixing period (Thompson & Allison, 1997).

The populations of *Usipa* fluctuate due to their adaptation to feed low in the trophic level (phytoplankton and zooplankton) hence are heavily influenced by environmental conditions which influence as well their food availability and have short vital cycle (Marshall 1987). The population of *Usipa* fluctuates even in the absence of fishing as their recruitment and feeding is affected by short-term environment changes (Maguza-Tembo & Palsson, 2004). The fluctuation behaviour of the population of *Usipa* makes inclusion of its forecasted catches very useful in its fishery management. The trend forecasted for *Usipa* catches in this study is not surprising as Marshall (1987) reported that the species are r-selected species; fast-growing with short life-spans and high rates of reproduction.

The current fisheries management though crafted towards management of *Oreochromis* species (Chambo) may be working for the sustainable exploitation of the *Usipa* fishery, implying the fisheries management are successfully managing the commons in as far as this fishery is concerned. The confidence interval of 95% as shown in Table 6 did not include a zero meaning that the likelihood that *Usipa* fishery might be collapsing currently or anytime soon might be very low. However, the years of high abundance may be immediately followed by years of low abundance of *Usipa* landings as the survival of the species larvae may be influenced by density-dependent effects (Thompson 1996). For years, *Usipa* was not managed until in 2018 when *Usipa* Management Strategy for Southeast and Southwest Arms of Lake Malawi and Lake Malombe was developed by the USAID/FISH Project. *Usipa* from the rest of the Lake Malawi still remain unmanaged (FISH, 2018). However, like the *Chambo Restoration Strategic Plan* whose existence is not stopping decline of *Chambo* species, if not properly implemented and enforced, *Usipa* will still remain unmanaged even in Southeast and Southwest Arms of Lake Malawi and Lake Malombe.

The increase of *Usipa* forecasted catches as shown in Figure 9, could be also as a result of decline in population of competing species in the ecosystem. For instance, the decline of predators or food competitors of *Usipa* will directly lead to an increase in the population of the species in this fishery. This scenario if not properly controlled may lead to trophic cascade. However, at every point the fishery ecosystem must be balance hence the increase of this species will affect the ecosystem of other species as well hence causing some to even decline more in population especially their food competitors. This scenario on the other hand might boost the declined stocks of predators of *Usipa*, as the increase in population of

Usipa will mean increase in food for the predators such as *Rhamphochromis* (*Ncheni*) species.

Although previous fisheries management system aimed at managing *Chambo* on Lake Malawi seem to be effectively and sustainably managing the exploitation of the fishery, a fisheries management plan in place for Southeast and Southwest Arms of Lake Malawi and Lake Malombe will ensure continued sustainable exploitation of the fishery in the area. The implementation of the strategy should take advantage of the management instruments in place such as devolution of management of natural resources such as the decentralized fisheries management approach. This is being operationalized as Participatory Fisheries Management (PFM) (FISH 2018). There is a need to reduce climate change (erratic rainfall and wind patterns) impacts, habitat destruction such as removal of submerged aquatic vegetation (SAV) and changes in water quality among others. Further research must be done to assess size of the *Usipa* stock in this fishery to make sure that the fishery is not under exploited. The important management parameters should be generated such as maximum sustainable yield, maximum economic yield among others for the whole Lake Malawi to sufficiently equip the policy makers to take the best options in employing ecosystem approach to managing the fishery.

4 CONCLUSIONS

The artisanal fishery landings of *Usipa* from Lake Malawi in Mangochi district may increase by the year 2022 to 22849.4 tonnes, slightly above the landings in the year 2010, which was at 20713.64 tonnes. The current fisheries management system on Lake Malawi in the case of this species shows that may be effectively and sustainably exploiting the fishery. There is a need however to adequately monitor and control the exploitation levels of the fishery by employing a logical participatory approach which should be sufficiently policed to limit effort.

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