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Modelling and forecasting Lake Malawi water level fluctuations using stochastic models

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ABSTRACT

Fluctuations of water level in Lake Malawi has become a big concern among stakeholders owing to its hydro-ecological and socio-economic implications. The study was aimed at modelling and forecasting patterns of Lake Malawi water levels in Malawi to provide a likely trend in the future. The study used Seasonal Autoregressive Integrated Moving Average (SARIMA) processes to select an appropriate stochastic model for forecasting the monthly data for water levels in Lake Malawi for the period 1986 to 2015. The appropriate model was chosen based on SARIMA (p, d, q) $(P, D, Q)^S$ process. The SARIMA (1, 1, 0) $(2, 1, 1)^{12}$ model was selected to forecast the monthly data of water levels for Lake Malawi from August, 2015 to December, 2021. The plotted time series data showed that water level in Lake Malawi has been decreasing since 2010 to date, but not as much as was the case between 1995 and1997. The forecast of water level in Lake Malawi until 2021 showed a mean of 474.45masl ranging from 473.93 to 475.04masl with a confidence interval of 95% against registered mean of 473.40masl in 1997 and 475.48masl in 1989, which were the lowest and highest water levels on the lake respectively since 1986. The forecast implies that by the year 2021, water level in Lake Malawi will fall below the actual recorded mean by 0.15masl and 0.69masl from the maximum ever recorded. It is however unlikely to be lower than the level recorded in 1997.

Key words: Anthropogenic activities, climate change, Lake Malawi, SARIMA

RÉSUMÉ

Les fluctuations du niveau d’eau dans le lac Malawi sont devenues une préoccupation importante pour les acteurs en raison de leurs implications hydro-écologiques et socio-économiques. La présente étude visait à modéliser et à prévoir les tendances des niveaux d’eau du lac Malawi afin de sortir des tendances pour le futur. L’étude a utilisé les processus de la moyenne mobile intégrée saisonnière autorégressive (SARIMA) pour sélectionner un modèle stochastique approprié permettant de prévoir les données mensuelles des niveaux d’eau du lac Malawi pour la période de 1986 à 2015. Un modèle approprié basé sur SARIMA (p, d, q)$(P, D, Q)^S$ processus a été choisi. Le modèle SARIMA (1, 1, 0) $(2, 1, 1)^{12}$ a été sélectionné pour simuler les données mensuelles des niveaux d’eau du lac Malawi d’août 2015 à décembre 2021. Les données chronologiques tracées ont montré

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que le niveau d'eau dans Le lac Malawi a diminué depuis 2010 jusqu'à maintenant, mais pas autant qu'entre 1995 et 1997. Selon les prévisions, le niveau d'eau dans le lac Malawi jusqu'en 2021 indiquait une moyenne de 474,45 masl allant de 473,93 à 475,04 masl avec un intervalle de confiance de 95% contre une moyenne enregistrée de 473,40 masl en 1997 et de 475,48 masl en 1989, qui étaient respectivement les plus bas et plus élevés niveaux d'eau du lac depuis 1986. Selon les prévisions, d'ici 2021, le niveau d'eau du lac Malawi sera réduit de 0,15 masl et de 0,69 masl par rapport à la moyenne actuelle enregistrée. Il est toutefois peu probable qu'il soit inférieur au niveau enregistré en 1997.

Mots-clés: activités anthropiques, changement climatique, lac Malawi, SARIMA

INTRODUCTION

Malawi has a total surface area of 118,484 km^2 of which 20% is covered by surface water (Department of Fisheries, 2012), and Lake Malawi alone has a surface area of 29,000 km^2. The lake has a drainage system made up of rivers such as Shire, Lithipe, Bua, Dwangwa, Songwe, North Rukuru and South Rukuru, among others. The Lake Malawi is the third largest lake in Africa with an average depth of 292m. It is bordered by three countries Malawi, Mozambique and Tanzania and is situated in the Great African Rift Valley between 9^{0}30'S and 14^{0}30'S (Patterson & Kachinjika, 1995). The most productive areas on the lake are the shallow areas found in the southeast and southwest arms of the lake (Kanyerere, 2001). The depth of Lake Malawi is influenced by the activities of its basement tectonics and climatic factors. The climate influence is due to the long dry seasons caused by subtropical climate and the small dimensions of the hydrological catchment area. The lake dried out almost completely at the beginning of the Pleistocene due to stable tectonic conditions and dry climate. It is reported that the tectonic lowering of the overflow sill, through subsidence of the rift floor, combined with erosional incision currently being accelerated by anthropogenic activities lowered the water level by 40m since Pleistocene era. Of late, climate change and anthropogenic activities in the catchment areas have been linked to fluctuation of the water levels in Lake Malawi as the case with other water bodies in Africa. However, there is a level at which these two factors can be controlled, unlike the stability of the tectonic conditions. This challenge underpins the importance of modelling and forecasting water level in Lake Malawi using the available data to appreciate the future trends in the face of c;limate change . This is very crucial to policy makers and different user-groups of Lake Malawi for the purpose of developing strategies that address the impacts of climate change and anthropogenic activities on water levels of the lake. The study employed stochastic models to simulate water level in Lake Malawi using available time series data from 1986 to 2015. Given the time-series nature, autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models (Craine, 2005) have been used to model such data. However, this study has employed seasonal ARIMA (SARIMA) models to forecast the Lake Malawi water levels as the available data was seasonal. The SARIMA is a particular form of ARIMA process (Potier and Drapeau, 2000). In the SARIMA approach the variation in the time series X(t) is modelled by a combination of ARIMA with seasonal operators, and the seasonal component is allowed to behave as an ARIMA process.

MATERIALS AND METHODS

Data analysis. All the analyses of the time series data in this study were performed using R software version 3.3.1 (2017-06-21). The study used secondary data of water level for Lake Malawi which was collected by the Water Resources Department in the Ministry of

Agriculture, Irrigation and Water Development in Lilongwe, Malawi. The data on water levels were recorded on Lake Malawi every day in the morning and afternoon and, later summarized to monthly mean water levels. The data had a mean of 474.6 masl, a standard deviation of 0.67 and a range of 473.0 to 476.1 masl. The data covered a period from 1986 to 2015 and did not have gaps. The period of 30 years was found to be sufficient enough to reliably forecast water levels in the Lake. Graphical analysis method and Dickey-Fuller test on the original series of water level in Lake Malawi showed that the original data was not stationary (p= 0.1937) and required transformation.

The removal of the non-stationarity was by seasonal differencing of the data at every 12 months (Figure 1) and the resultant time series was found fit for SARIMA modelling. The graphical analysis of the plotted differenced time series data showed stationarity with a constant variance and a mean of zero. The Dickey-Fuller test proved the stationarity in the differenced time series data (p= 0.00). As such autocorrelogram and partial autocorrelogram were plotted to determine the values of p, q, P and Q in the SARIMA models. The plotted autocorrelation function showed second-order moving average (MA) model as shown in Figure 2, while the plotted partial autocorrelation function showed second-order autoregressive (AR) model as shown in Figure 3. The autocorrelogram and partial autocorrelogram in Figures 2 and 3 were used to identify various competing models.

METHODS

Various statistical modelling methods can be applied to forecast such as Garch, STL, averaging, exponential smoothing and ARIMA (Potier and Drapeau, 2000). ARIMA models are developed from historical time series analysis and based on well-articulated statistical theory (Box and Jenkins, 1976). These models capture the historic autocorrelations of the data and extrapolate them into the future, while while SARIMA is simply the seasonal ARIMA. The approach underlying the Box-Jenkins

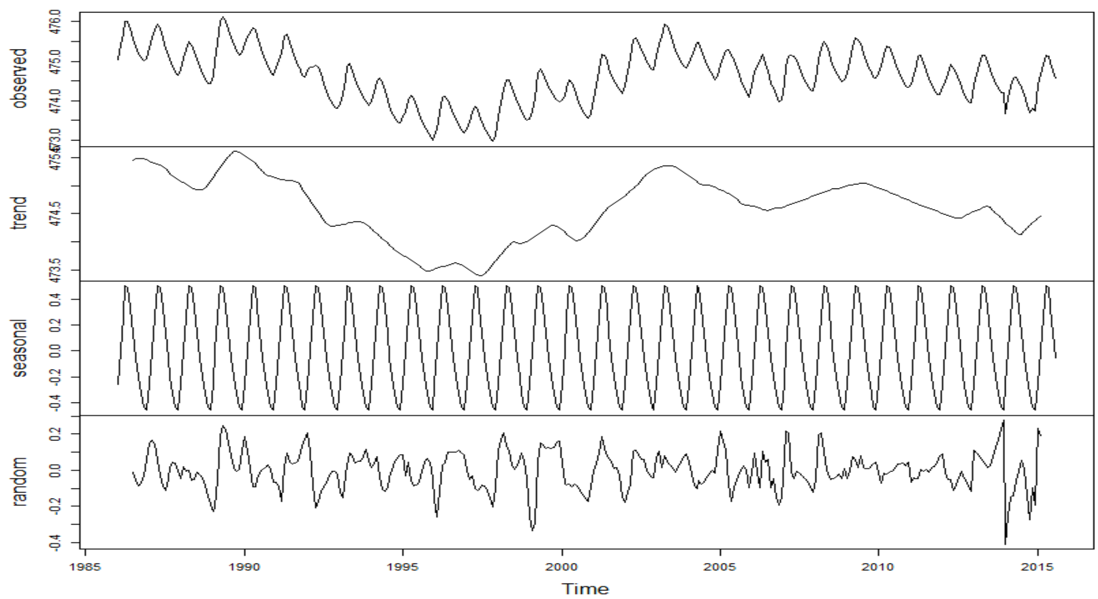

Figure 1. Decomposed Lake Malawi water levels time series

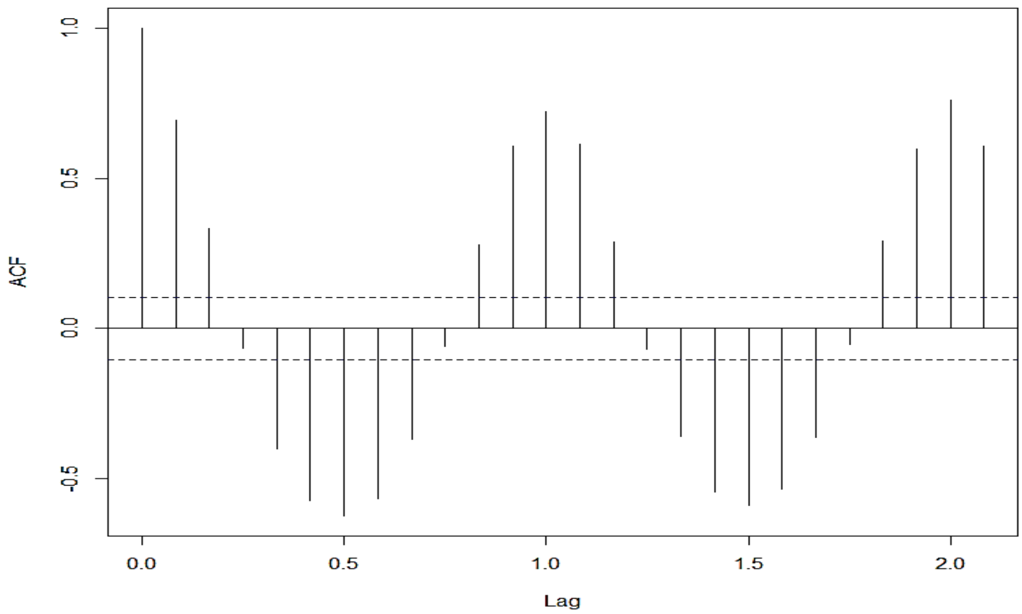

Figure 2. Autocorrelation function of differenced Lake Malawi water levels showing second-order moving average (MA) generated from monthly Lake Malawi water levels

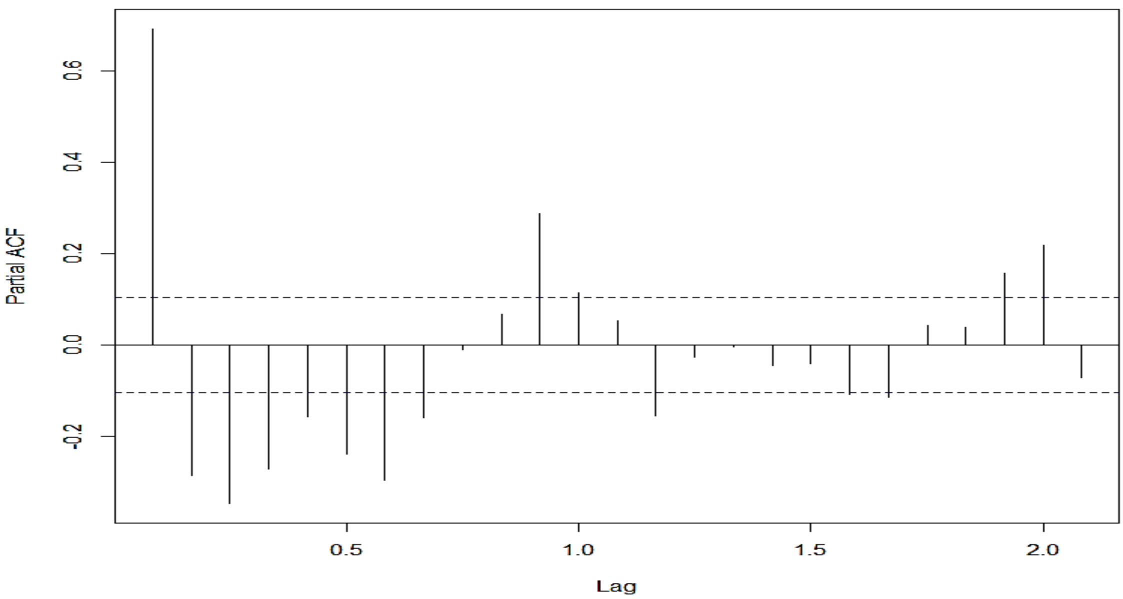

Figure 3. Partial autocorrelation function of differenced Lake Malawi water levels showing second-order autoregressive (AR) model generated from monthly Lake Malawi water levels

models (Box and Jenkins, 1976) is to empirically remove as much structure from the data as possible, with the ultimate goal of having the residuals as 'white noise' as empirical representation of the response variable time series which is desirable for forecasting (Potier and Drapeau, 2000). The SARIMA model works where the data are or made stationary and deseasonalised. Therefore, in this study, Lake Malawi water levels were tested for stationarity using two methods namely graphical analysis method and the Dickey – Fuller test (Dickey and Fuller, 1979). The data were found to be non-stationarity hence were differenced to make them stationary. Afterwards differencing correlograms were generated to observe if there were significant lags. Since the data had significant lags on the correlogram and had seasonality, SARIMA modelling process was employed.

Selecting a appropriate SARIMA model. The stationary differenced data for Lake Malawi water levels was used to generate correlogram and partial correlogram in order to fit the most appropriate values of p and q for an ARIMA (p, d, q).

Then, the general form of SARIMA model (p, d, q)(P,D,Q)s is expressed as:

$$\Phi(B^S)\varphi(B)\nabla^D{}_S\nabla^d X_t = \Theta(B^S)\theta(B)\varepsilon_t$$

Where: X_t = value of variable at time t; $\Phi(B^S)$ = seasonal autoregressive coefficients; $\Theta(B)$ = seasonal moving average; $\nabla^D{}_S$ = seasonal d-fold difference operator; $\varphi(B)$ = Non-seasonal component; $\theta(B)$ = Non-seasonal moving average

Model variable estimation. After identifying AR, MA, ARMA, ARIMA or SARIMA models, model fitting was performed to estimate the best possible variables of the identified models using Akaike Information Criteria (Akaike, 1973). The best model is obtained on the basis of minimum value of Akaike Information Criteria (AIC) (Satya *et al.,* 2007). 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. The conclusion made was that the smaller the error, the better the forecasting power of the generated model.

Diagnostic checks. After a best fitting model was identified, diagnostic tests were carried out to check to what extent the model was reliable.

The diagnostic tests were performed using methods of autocorrelation of the residuals and the Ljung-Box test (Figure 4) (Ljung and Box, 1978). A good forecast should come from a SARIMA model with forecast errors that have a mean of zero, with no significant correlations between successive forecast errors and have constant variance. Once the model was found to be inappropriate, the process was restarted through the four steps in the SARIMA modelling process until the diagnostic checks validated the model as fitting.

Forecasting. Once the appropriate SARIMA (p, d, q) (P, D, Q_s model for Lake Malawi water levels time series data was selected and validated, the variables of the selected SARIMA model was estimated. The fitted SARIMA model was then used as a predictive model for making forecasts of water level in Lake Malawi for next seven (7) years.

RESULTS AND DISCUSSION

The time series used in the study covered a period 29 years (1986 to mid-2015) with 356 data points. SARIMA process fitted very well and was used to forecast the water level for Lake Malawi. The model in the SARIMA family with the lowest AIC values was selected. The model with significant coefficients variables with least AIC is better in terms of forecasting performance than the one with insignificant coefficients variables with large AIC (Guti´errez-Estrada *et al.,* 2004, Czerwinski *et al.,* 2007). The value of the AIC of the selected SARIMA model was -661.93 as shown in the Table 1. The SARIMA (1, 1, 0) (2, 1, 1)$_{12}$, was therefore selected as the most suitable model for forecasting Lake Malawi water levels given that it had the lowest AIC values. The most competing models identified together with their corresponding fit statistics are shown in Table 1.

The Box–Pierce (and Ljung–Box) test also showed that model (1, 1, 0) (2, 1, 1)$_{12}$ was among the best fitting models as it had its p-value close to one (1) as shown in Figures 4. The Box–Pierce test basically examines the null of independently distributed residual errors, derived from the idea that the residual errors of a "correctly specified" model are independently distributed. In a case where the residual errors are not independently distributed, then it indicates that they come from a miss-specified model. All these tests and examinations proved that the SARIMA (1, 1, 0) (2, 1, 1)^{12} model is the best model to forecasting of the future of water level in Lake Malawi.

After selecting SARIMA (1, 1, 0) (2, 1, 1)^{12} as the best fitting model, several diagnostic checks were made on the identified model before the actual forecasting such as examination of the residuals of the model to identify any systematic structure still in it requiring improvement (Singini *et al.,* 2012; Lazaro and Jere, 2013). The diagnostic checks were done by examining the autocorrelations of the residual errors of various orders. In this regard, the Box–Pierce (and Ljung–Box) test and residual errors plots were performed to see if the residual errors had a mean of zero. ACF for residual errors was plotted as shown in Figures 9 and showed that there was

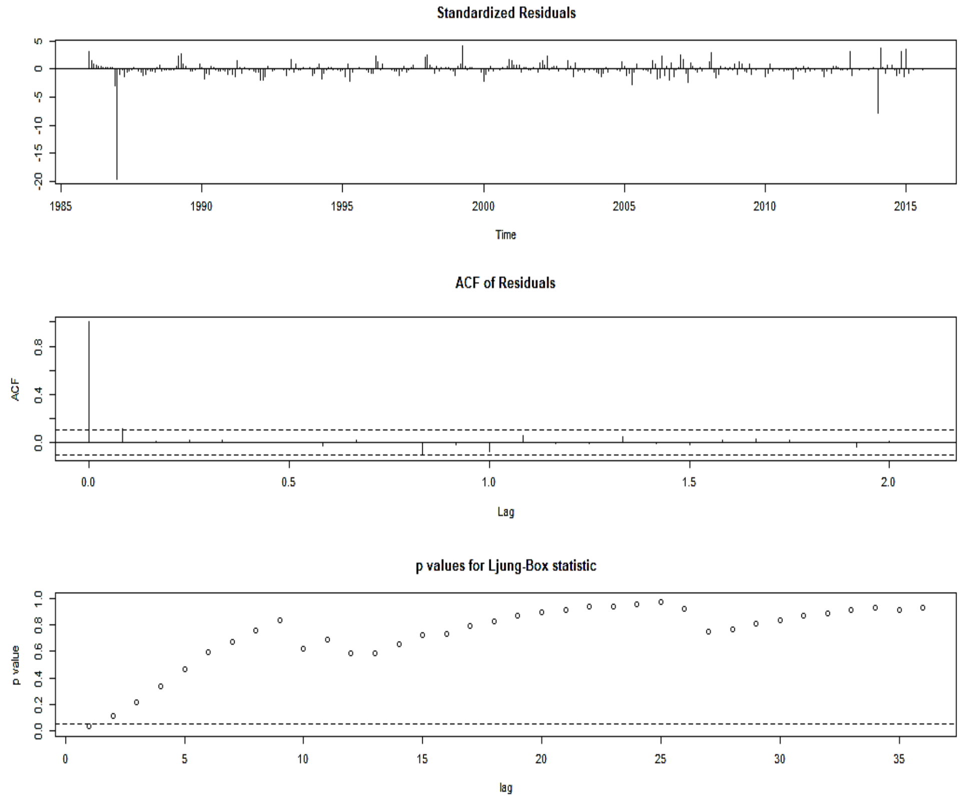

Figure 4. The Box–Pierce (and Ljung–Box) test out-put for SARIMA (1, 1, 0)(2, 1, 1)12 generated from monthly Lake Malawi water levels

no non-zero lags. This indicated that there were no significant autocorrelations among the residual errors to exceed the 95% significance bounds. The Box–Pierce (and Ljung–Box) test also showed that the model fitted the series very well as the p-value was close to one (1) as shown in the Ljung–Box statistic in Figure 4. The time plot of the forecast errors shown in Figures 4 proves that the forecast errors has a constant variance. These diagnostic tests proved that the selected SARIMA (1, 1, 0) $(2, 1, 1)_{12}$ model was indeed an appropriate model for forecasting Lake Malawi water levels. The ability of the model to forecast the water levels was tested to check the level of accuracy on the post sample forecasting. The selected model had good forecast precision as shown by the lower values of ME, RMSE, MAPE and MAE presented in Table 1, hence showing the reliability of the forecast from this model. The graph in Figure 5 also shows actual catches and the forecasted trend being within the confidence interval of 95%. Czerwinski *et al.* (2007), Singini *et al.* (2012) and Lazaro and Jere (2013) reported that 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. Consequently, the selected model was used to forecast Lake Malawi water levels as shown in Figure 5.

The forecast showed that the water level in Lake Malawi will likely have a mean of 474.45 masl by the year 2021, while mean of the actual recorded data was 474.6 masl, which is below the actual recorded mean by 0.15 masl and 0.69 masl from the maximum (475.14 masl) ever recorded water level in Lake Malawi. Figure 5 shows the forecasted trend of Lake Malawi through 2021.

These results demonstrate that the water levels in Lake Malawi might drop below the long-term mean recorded for the lake. This corroborates the personal observations at Senga Bay Fisheries Research Centre in Salima District that indicate that the shore line of the lake has receded by about 35m into the lake since 2010. Other lakes in the tropical region are reportedly experiencing fluctuations in water levels due to climate change and upstream dam construction as is the case of Lake Victoria. The fluctuation and drop of water level of Lake Malawi could be due to the climate change and tectonics of the lake bed. It is therefore crucial that all direct and indirect water users take into consideration the result of this study to inform sustainable use of the water resource. The declining water levels in the lake has a potential of reducing aquatic plants (more especially the macrophytes) around the lake. This is in line with what Logez *et al.* (2016) reported that as the water level decrease significantly, habitat conditions tend to be much more homogeneous and the proportion of sites with a thin substrate and low slope increase, while submerged vegetation and riparian shade may disappear. The loss of aquatic vegetation negatively affects fisheries resources as they act as breeding grounds for some of the economically import fish species such as the *Oreochromis* spp. The same vegetation provides a good habitat and nursery ground for the juvenile fish which migrate into the lake after growing. The receding of the lake due to drop in water level may as well affect fish breeding grounds (nests) of the shallow dwelling species especially in the long term. In the long run, the drop in lake water levels may negatively affect fish populations. Logez *et al.* (2016) made a similar observation that the habitat effect on assemblage structure was strongest when the water-level conditions were high and very high, and weaker for low and very low water-level conditions. Lake water level fluctuations (recession and refilling) have provided numerous opportunities for the Mbuna to establish different founder population leading to speciation (Owen *et al.,* 1990). There are over 200 rock dwelling species (Mbuna) in Lake Malawi whose mitochondrial DNA differentiation shows that their whole flock is extremely of recent origin. Water-level fluctuations affect the ecological processes and patterns of lakes in several ways (Wantzen *et al.,* 2016). Laë (1994) reported that

Table 1. Selected competing models' variables with their AIC generated from monthly Lake Malawi water levels

	SARIMA (0, 1, 1) $(1, 1, 1)_{12}$	**Se**	**SARIMA** (0, 1, 2) $(1, 1, 1)_{12}$	**Se**	**SARIMA** (1, 1, 0) $(1, 1, 1)_{12}$	**Se**	**SARIMA** (1, 1, 1) $(1, 1, 1)_{12}$	**Se**	**SARIMA** (1, 1, 0) $(2, 1, 1)_{12}$	**Se**
Constant										
L1. AR					0.2720	0.0522	0.2661	0.1834	0.2752	0.0522
L1. MA	0.2544	0.0493	0.2727	0.0544			0.0063	0.1905		
L2. MA		0.0776	0.0545							
L1. SAR	-0.2438	0.0567	-0.2317	0.0577	-0.2324	0.0562	-0.2327	0.0574	-0.2180	0.0568
L2. SAR						0.1061	0.0657			
L1. SMA	-0.9991	0.0625	-0.9990	0.0665	-0.9990	0.0662	-0.9990	0.0661	-0.9994	0.0480
ME	-0.5549746		-0.5179501		-0.3476219		-0.5113396		-0.3457697	
MAE	0.6126432		0.580155		0.4196812		0.5737838		0.4139066	
MAPE	423.8729		395.0768		282.5719		389.518		279.1434	
RMSE	0.800835		0.7553016		0.5309216		0.7471556		0.524839	
AIC	**-659.44**		**-659.46**		**-661.31**		**-659.31**		**-661.93**	

Model with the lowest AIC is the best fit

The fitted model was used to forecasts for Lake Malawi water levels from September, 2016 to 2021 at a confidence interval of 95% and they included a zero (0).

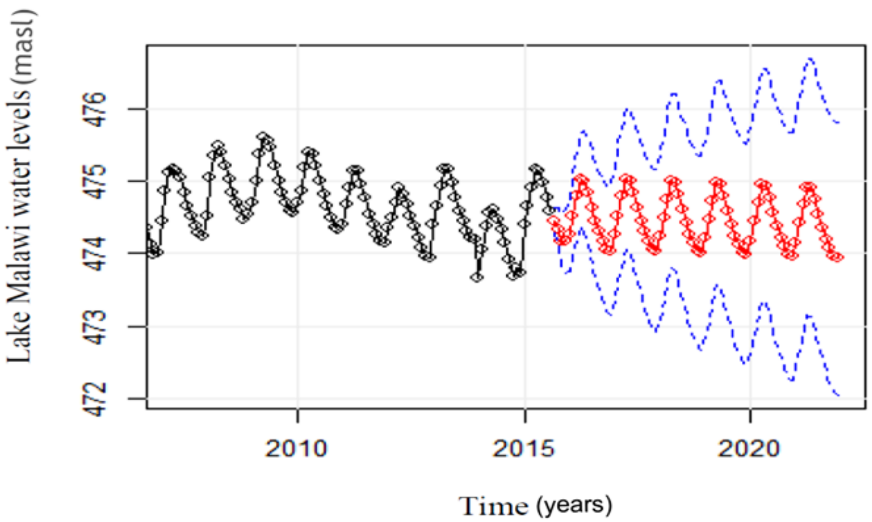

Figure 5. Forecasted Lake Malawi Water levels using SARIMA (1, 1, 0) (2, 1, 1)[12]

lowest flood years resulted in decline in fish landings by 40,000 metric tons in Mali.

The forecasted trend of dropping water levels is likely to affect, for instance, the hospitality operators such as lodges, guest houses, hotels, among other users that rely on water from the lake. These operators and the those involved in irrigation might require to extend their extraction pipes from time to time as they follow the receding water of the lake. The user groups of Shire river are expected to be negatively affected by the forecasted dropping of Lake Malawi water levels as the river draws most of its water from the Lake Malawi. The potential effects of the dropping lake water levels in the lake can be grouped into long term and short term impacts. Hofmann *et al.* (2016) reported that large-scale shore line displacements change the habitat availability for organisms adapted to terrestrial and aquatic conditions over long time scales. Short-term water level fluctuation, in contrast, do not significantly displace the boundary between the aquatic and the terrestrial habitat, but impose short-term physical stress on organisms. There is therefore need to put in place strategies to counteract the impacts of climatic and anthropogenic activities on the lake's water level fluctuations. Poor crop husbandry practices in the catchment areas are increasingly silting rivers hence cause them to flood and spill most of the water instead of conveying adequate water to the lake. Afforestation and reforestation programme should be encouraged in the catchment areas to enhance ground water recharge. The release of water at Liwonde barrage on Shire river should be regulated to maintain the water level on Lake Malawi for extended period. Parry and Burton (2009) recommended several options for controlling water levels in Lake Malawi, among them, refurbishment of Kamuzu Barrage and construction of a high dam at Kholombidzo to stabilize water level in the Lake and Shire river while in turn stabilizing hydropower generation.

CONCLUSION

A relatively extensive literature base already exists for shallow lakes, demonstrating that excessive water level fluctuations impair ecosystem functioning, ultimately leading to shifts between clear-water and turbid states. Lake Malawi water levels is notably fluctuating posing an increasing worry to some of the lake water users. The forecast for Lake Malawi water levels showed that the water levels will relatively drop by 0.15 masl as compared to the mean water levels recorded in the previous years. This is likely to have negative implications over use of Lake Malawi and Shire river that flow out of it for irrigation, pumping of water for domestic use and hydroelectric power generation among others. This calls for practices and policies that promote watershed approach to land and water resource conservation to ensure sustainable resource management and enhance water recharge to the lake.

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STATEMENT OF NO-CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in this paper.

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