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Long-term Estimates of Reservoir Evaporation Using ARIMA Model and Impact on Water Supply: A Case Study of Erinle Dam, Osun State, Nigeria

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Abstract: It is common practice in water resource management to estimate evaporation of water from reservoirs using nearby measurements of pan evaporation. With the emergence of water supply and food security issues as a result of increasing population and climate change pressures, the need for efficient use of available water supplies is paramount. Management of available resources and improved efficiency require accurate knowledge of evaporation, which is a major water loss pathway. This study used Autoregressive Integrated Moving Average (ARIMA) models to forecast pan-evaporation data. The historical data on pan evaporation (1982 – 2012) at Osogbo, southwest Nigeria, was initially subjected to a regression analysis which showed that the data has an increasing trend, while the plot of autocorrelation function indicated that the data is not stationary. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), as well as diagnostics of residuals confirmed that $ARIMA_{(3,4,3)}$ is a good fit for both short term data forecast and data generation for pan-evaporation. Estimated long term reservoir evaporation series (2013 – 2062) was applied to the reservoir capacity curve and compared to the water demand curve. The results showed that with the increasing evaporation trend the reservoir will not be able to serve the various benefitting towns after year 2038. This implies that new water sources would be needed to meet the increasing water demand due to increasing population.

Keywords: Evaporation, ARIMA, Water Supply, Forecasting, Reservoir, Management

1. Introduction

The rapidly growing population of the world is putting increasing pressure on fresh water supplies. Adding to this pressure is the potential changes to rainfall timing and amount due to climate change. These threats to water supply mean that management of water resources through quantification of uses and improvements to water use efficiency are essential. Evaporation from water storage reservoirs represents one of the major water loss pathways. Evaporation in reservoirs plays a prominent role in water resources planning, operation, and management because a considerable amount of water is lost through evaporation, especially in large reservoirs. Estimating evaporation from surface water usually requires sample data that are not easily measurable.

In the last decades, both local and global climate hadve undergone tremendous changes. This is not unconnected with the increased human activities on the environment ranging from deforestations to air pollution resulting from the fast growing industrial activities. In view of this, all climate variables (rainfall, sunshine hours, temperature, relative humidity, wind speed, etc.) have equally undergone commensurate modification. The cumulative effect of the above is responsible for the increased concentration of greenhouse gases released into the atmosphere which is impacting the environment. Douville et al. (2001) observed that the mean average global temperature has increased by $0.6^{0}C$ over the twentieth century. The global hydrological cycle is not left out in the global climatic changes because it had already been predicted that there would be an intensified hydrological cycle in response to increasing trend in temperature. Evaporation is an important component of the hydrological cycle and has great effect on the water balance of the earth surface. Higher evaporation rate creates more arid environment while downward trend of evaporation results in a more humid environment.

Throughout history much of the world has witnessed ever-greater demands for reliable, high-quality and inexpensive water supplies for domestic consumption, agriculture and industry. In recent decades there have also been increasing demands for

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hydrological regimes that support healthy and diverse ecosystems and provide for water-based recreational activities. Water managers are challenged to meet these multiple and often conflicting demands. Added to all these management challenges are the uncertainties of natural water supplies and demands due to changes in our climate, changes in people's standards of living, changes in watershed land uses and changes in technology.

Water scarcity is a major challenge facing a lot of nations especially the third world countries in the present time (Adeboye, et. al. 2009). This can be attributed to climate change, increasing demand for freshwater by the competing users in different sectors and more importantly the environmentally induced problems such as desertification and overexploitation of the existing water resources (Pereira, 2005). Sadoff and Muller (2009) revealed that weather and climate data information are valuable inputs in planning and decision-making processes. Weather data and information primarily affect short-term decisions, for example, operational decisions that involve daily fieldwork or irrigation scheduling for the next several weeks. Climate data and information, however, are used in many long-term planning processes.

Climate is a principal factor in determining the water resources of a region (Woudenberg, 2002). Climate strongly influences both the supply of and demand for water. Precipitation for example is the major input to a watershed. Climatic factors, such as temperature, humidity, and wind, govern water loss through evaporation and transpiration. Infiltration and runoff are determined by soil type, soil condition, and weather variables, such as antecedent precipitation (as it affects soil moisture), temperature, and rainfall intensity. In addition, water quality depends on amounts of both water and pollutants. The distribution of pollutants is strongly influenced by climatic conditions, such as wind and type and frequency of precipitation (Clarvis et al., 2013)

A wide variety of methods for estimating open water evaporation have been reported in literature. Finch and Hall (2001) categorized the methods into seven types; pan evaporation, mass balance, energy budget models, bulk transfer models, combination models, the equilibrium temperature method and empirical factors. Babu et al. (2011) compared auto regression, Markov chain and the ARIMA model for the prediction of rainfall time series for Vellore in Tamil Nadu metrological station in India. Rainfall series from 2008 to 2010 was used for the study. The future prediction of possible rainfall flow was done using the ARIMA model. The comparison of the observed rainfall flow and the synthetically generated data shows that the statistical characteristics were satisfactorily preserved. The statistical tools used for the study were the mean, standard deviation and the serial correlation coefficients. These statistical parameters were integrated in the different model for the analysis. It was observed that ARIMA approach gave a more appropriate prediction for the future meteorological parameters compared with the probability Markov chain models.

Time series analysis and forecasting has become a major tool in different applications in hydrology and environmental management fields. Among the most effective approaches for analyzing time series data is the model introduced by Box and Jenkins, popularly known as ARIMA models (Naill and Momani, 2009). In their work, Box-Jenkins methodology was used to build ARIMA model for monthly rainfall data taken at Amman airport station for the period from 1922-1999 with a total of 936 readings. ARIMA (0, 1, 1) model was developed and the model was used to forecast the monthly rainfall for the upcoming 10 years to help decision makers establish priorities in terms of water demand management. It was recommended that an intervention time series analysis could be used to forecast the peak values of rainfall data. This study used Autoregressive Integrated Moving Average (ARIMA) model to estimate the evaporation series for Osogbo and its environs in southwest Nigeria.

2. Study Area

Erinle reservoir in Ede, southwest Nigeria (Figure 1) lies between Latitude 7^0 44' 30.44" – 7^0 57' 00.79" N and Longitude 4^0 26' 21.71" – 4^0 41' 23.48"E. The dam and its impounded reservoir on Erinle River is designed to improve water supply to some towns and villages in Osun State, Nigeria. These include Osogbo, Ede, Ife, Ifon Osun, Ilobu, Gbongan, Ode Omu, and a host of other semi-urban areas. Table 1 shows the details of Erinle Dam.

3. Materials and Methods

3.1 Data collection

The required meteorological (Pan-evaporation) data was obtained from Nigeria Meteorological Agency (NIMET) Ido-Osun, Osun state. According to NIMET Ido-osun branch where the data was

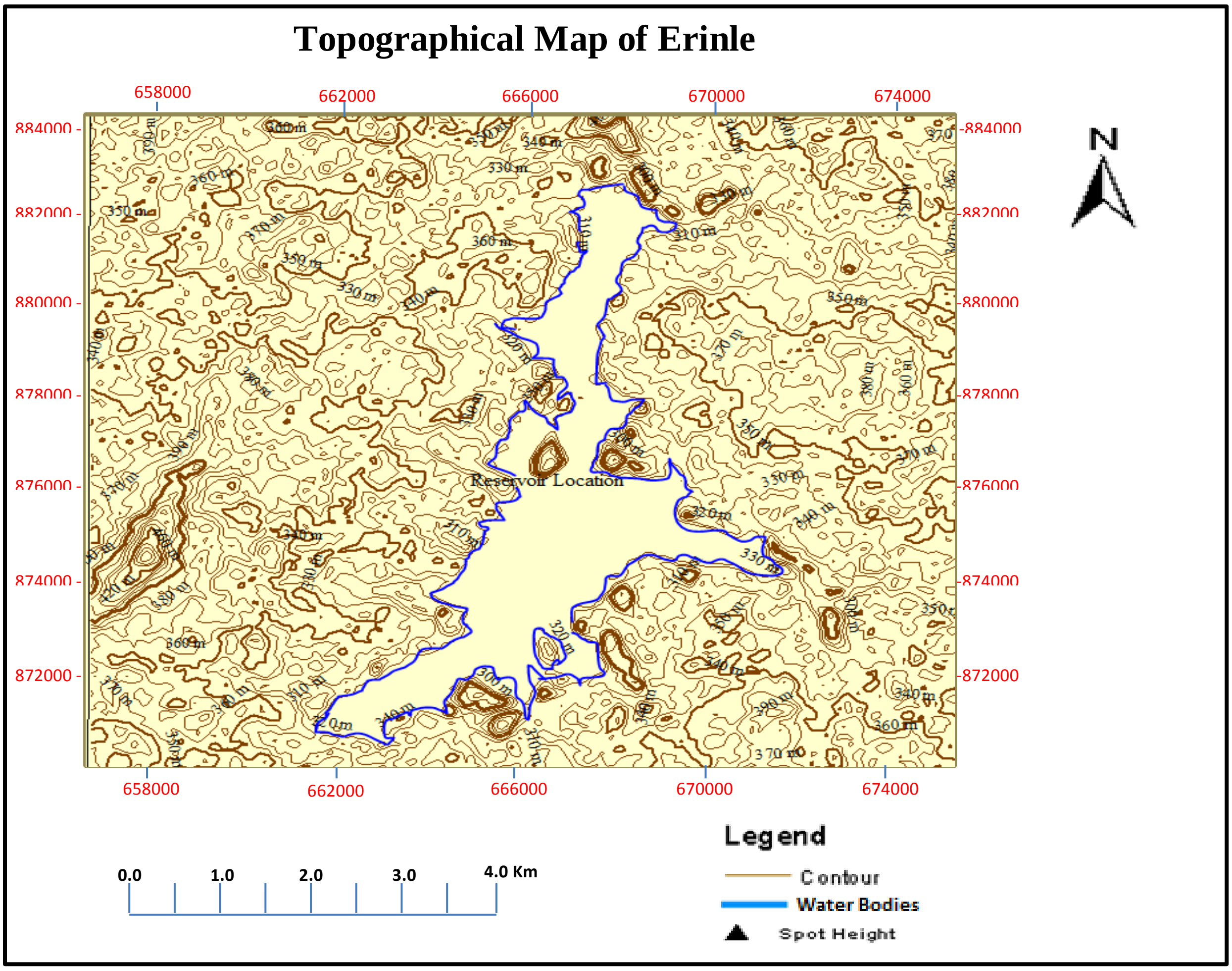

***Figure 1:** Topographical Map of Erinle Reservoir Area (**Source:** Author's Global Mapper & GIS Analysis)*

Table 1 : Details of Erinle Dam, southwest Nigeria

S/No.	Parameters	Values/Details
1	Surface Area	19.0 Km^2
2	Dead Storage	7.0 x 10^6 m^3
3	Total Capacity	94.0 x 10^6 m^3
4	Height	28.0 m
5	Length	600.0 m
6	Crest Width	8.0 m
7	Elevation	333.5 m a.s.l
8	Slope of Embankment	Upstream – (1:3) Downstream – (1:2.5)
9	Serving Communities	Osogbo, Ede, Ife, Ilobu, Erin-Osun, Gbongan, Ifon Osun, Ode Omu, Awo, Ara, Iragberi, and Oogi

Source: Osun State Water Corporation (OSWC)

collected, the data have been quality - controlled for data reduction errors and original data input errors (such as typographical errors) and combined with existing digital monthly pan-evaporation data. The data at the station is also periodically updated to reflect additional data. The duration of the data was from 1982 to 2012. Data on dam attributes, characteristics, and serving communities were obtained from Osun State Water Corporation (OSWC), Osogbo; the population data of the communities was collected from National Population Commission (NPC), Osogbo.

3.2 Autoregressive Integrated Moving Average ARIMA (p,d,q) Modeling

Typically, various statistical tools are applied to auto-correlated time series of data for modeling and predicting future values of monthly meteorological series. In general, autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models are applied to time series of meteorological data. A model which depends only on previous outputs of a system to predict an output is called an autoregressive (AR) model while a model which depends only on inputs to the system to predict an output is called a moving average (MA) model. The model derived from autoregressive and moving average processes may be a mixture of these two and of higher order than one as well, which is termed as a stationary ARMA model with its random shocks independent and normally distributed with zero mean and constant variance. An ARMA model can be denoted as ARMA(p,q) where p is the number of AR parameters and q is the number of MA parameters. One major attribute of this type of model is that it is applicable to only stationary dataset, that is, the dataset for which residuals are independent for all time periods. It is understood that all hydrologic datasets are not stationary in real life (Milly et. al. 2008). Some datasets follow some sort of persistence or autocorrelation which is inherently present in it and which cannot be removed, while some sorts of trend and cycle are also associated with such datasets. Modeling of non-stationary datasets with ARMA model looks difficult. Non-stationary datasets can be modeled through autoregressive and moving average processes through differentiation, that is the dataset is differentiated until it becomes stationary. ARIMA model is an extension of ARMA model in the sense that including autoregressive and moving average has an extra part of differencing the time series. If a dataset exhibits long term variations such as trend, seasonality and cyclic components, differencing of dataset in ARIMA allows the model to deal with such long term variations.

In general, an ARIMA model is characterized by the notation $ARIMA_{(p,d,q)}$ where p, d and q denote orders of autocorrelation, integration (differencing) and moving averages respectively. In ARIMA parlance, time series is a linear function of the past actual values and random shocks. For instance, given a time series process (Y_t), a first order auto-regressive process is denoted by ARIMA (1, 0, 0) or simply AR (1) and is given by;

$$Y_t = \mu + \phi_1 y_{t-1} + \varepsilon_t \qquad (1)$$

And a first order moving average process is denoted by ARIMA (0, 0, 1) or simply MA (1) and is given by;

$$Y_t = \mu - \theta_1 \varepsilon_{t-1} + \varepsilon_t \qquad (2)$$

Alternatively, the model ultimately derived may be a mixture of these processes and of higher orders as well. Thus, a stationary $ARMA_{(p,q)}$ process is defined by the equation below;

$$Y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (3)$$

Where $\varepsilon_t's$ are independently and normally distributed with zero mean and constant variance σ^2 for t=1, 2…, n.

Also, a dependent time series that is modeled as a linear combination of its own past values and past values of an error series is known as a (pure) ARIMA model.

The first stage in building the model is the identification of the appropriate ARIMA models through the study of the autocorrelation and partial autocorrelation functions. The next stage is to estimate the parameters of the ARIMA model chosen. The third stage is the diagnostic checking of the model. The Q statistic is used for the model adequacy check. If the model is not adequate, then an alternative model is chosen and this is tested for adequacy and if adequate then the fourth and final stage of the process is forecasting.

3.3 Model Identification

The foremost step in the process of modeling is to check if the series is stationary, as the estimation procedures are available only for stationary series. The cursory look at the graph of the data and structure of autocorrelation and partial autocorrelation coefficients may provide clues for the presence of stationarity. If the model is found to be non-stationary, stationarity could be achieved mostly by differencing the series or go to Dickey Fuller test. Stationarity in variance could be achieved by some modes of transformation, say, logarithmic transformation. This is applicable for both seasonal and non-seasonal stationary series.

Thus, if Y_t denote the original series, non-seasonal difference of first order is;

$$X_t = Y_t - Y_{t-1} \qquad (4)$$

Where t=1, 2 …, n

The next step in identification process is to find the initial values for the orders of the autoregressive and moving average terms (that is, p and q). This could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients. Table 2 below summarizes how we use the sample ACF/PACF for model identification.

Table 2: How to determine the model by using ACF and PAC pattern

Process	ACF	PACF
AR(p)	Spikes decay towards zero	Spikes cutoff after lag q
MA(q)	Spikes cutoff after lag p	Spikes decay towards zero
ARMA(p,q)	Spikes decay towards zero	Spikes decay towards zero

Source: Amadi and Aboko (2013)

Other tools for model identification includes Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AIC_C), Bayesian Information Criterion (BIC), and a hosts of others.

Akaike Information Criterion (AIC)

$$AIC = \log \sigma_k{}^2 + \frac{n+2k}{n} \qquad (5)$$

Where $$\log \sigma_k{}^2 = \frac{SSE_k}{n} \qquad (6)$$

k is the number of parameters in the model, and

n is the sample size.

The value of k yielding the maximum AIC specifies the best model. That is, given two or more competing models, the one with the smallest AIC will be selected.

Corrected Akaike Information Criterion (AIC_C)

$$AIC_C = \log \sigma_k{}^2 + \frac{n+2k}{n-k-2} \qquad (7)$$

Where $\sigma_k{}^2$, n and k are as defined in Equation (19) and (20).

The model with the smallest AIC_C value is considered to perform best and therefore will be selected

Bayesian Information Criterion (BIC)

$$BIC = \log \sigma_k{}^2 + \frac{k \log n}{n} \qquad (8)$$

Where $\sigma_k{}^2$, n and k are as defined above

BIC is also called the Schwarz Information Criterion (SIC). Various simulation studies have tended to verify that BIC does well at getting the correct order in large samples, whereas AIC_C tends to be superior in smaller samples where the relative number of parameters is large. One of the problem of the information criteria approach is the enormous work involved in computing maximum likelihood estimates of several models which is time consuming and expensive. However, this problem has been overcome by the introduction of computers since there are software's like R, SPSS etc. which can compute several of these information criteria.

3.4 Estimation of Model Parameters

At the identification stage, one or more models are tentatively chosen that seem to provide statistically adequate representation of the available data (that is, models that behaved reasonably well). Then estimates of the parameters of the models are next obtained by least square as advocated by Box and Jenkins. Although there are several numbers of algorithms available in most statistical toolboxes for the estimation of parameters in ARIMA models, this study used "armax" toolbox in MATLAB software to estimate the parameters of the model.

3.5 Model Diagnostic Stage

Different models can be obtained for various combinations of AR and MA individually and collectively. The best model is obtained by test of significance of the coefficients. For each coefficient

$$t = \frac{estimated\ coefficients}{standard\ error} \qquad (9)$$

If $|t| \geq 2$, the estimated coefficient is significantly different from 0, then the model coefficient is statistically significant. If not, the model should probably be simplified, say, by reducing the model order. For example, an AR (2) model for which the second-order coefficient is not significantly different from zero might be discarded in favor of an AR (1) model. After selection of the best model the diagnostics of the residuals are made with time plot of the residuals, normal Q – Q plot, plot of ACF of residuals, etc.

3.6 Reservoir Evaporation

Since pan-evaporation is a measurement that combines or integrates the effects of several climate elements: temperature, humidity, rainfall, drought dispersion, solar radiation, and wind; the model built was applied to forecast several months of pan-evaporation series data which was thereafter used to estimate future (50 years) evaporation data series of the study area. After an ARIMA model has been carefully selected for the long term monthly data generation of the pan-evaporation data, the monthly evaporation data series was estimated with the formula

$$E = K_p\, E_{pan} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (10)$$

Where K_P is the pan coefficient, and E_{pan} is the pan evaporation. Marvin (2010) suggested using 0.65 as pan coefficient.

3.7 Water demand

The water demand and active reservoir storage needed to meet demand are expected to increase with the population growth. In this study, the geometric growth projection method according to Jarabi (2012) was adopted

$$P_t = P_o(1+r)^t \dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (11)$$

Where P_O = Initial Population; P_t = Population in "t" years later; t = year(s); r = growth rate

Majority of the reservoir serving communities are semi-urban areas, hence, the daily per-capita water demand of 90 litres/capita/day was adopted. The average population growth rate was taken as 2.38% (NPC, 2016). Table 3 shows the population of benefitting communities and the estimated water demand in 2062.

Table 3: Population data of the reservoir servicing communities

S/No.	Name	*Population *(2006 Census)*	Population Projected to *2016*	Population Projected to *2062*	Water Demand *(2062)* Mm^3/year
1	Osogbo	155,507	196,744	580,493	18.804
2	Orolu	103,077	130,392	384,777	12.468
3	Irepodun	119,497	151,164	446,071	14.448
4	Ede North	83,831	106,046	312,941	10.140
5	Ede South	76,035	96,184	283,839	9.192
6	Ife Central	167,254	211,576	624,359	20.232
7	Ife East	188,087	237,930	702,129	22.752
8	Ife North	153,694	194,423	573,740	18.588
9	Ife South	131,761	166,678	491,864	15.936
10	Ayedaade	150,392	190,246	561,413	18.190
TOTAL		1,329,135	1,681,353	4,961,666	160.747

***Source:** National Population Commission (NPC, 2016)

4. Results and Discussion

4.1 Time Plots of Meteorological Data

The time plots of the pan-evaporation from 1982 – 2012 is as shown in Figure 2. The x – axis indicates the months while the y – axis indicates the observed monthly values. The time plot indicates that there are systematic changes known as (increasing) trend. Also, the plot shows that there are some irregularities in the series, and with this information, it is suspected that the data is non-stationary based on trend and there may be some periodicities present in the data.

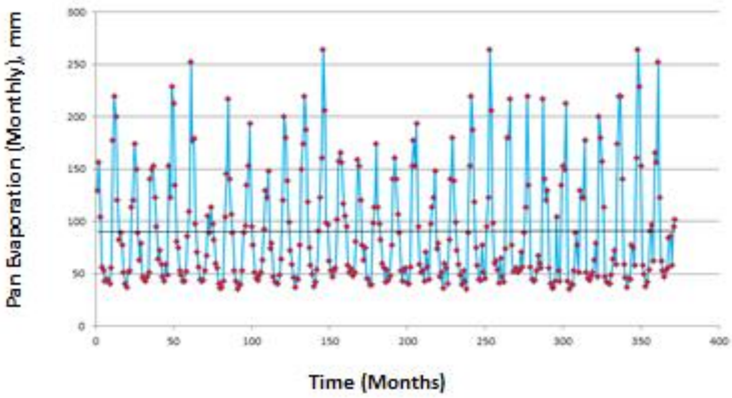

Figure 2: Time Plot of Monthly Pan Evaporation Data from 1982 – 2012

4.2 Test for Stationarity

Figure 3 represents the Auto-Correlated Function (ACF) plot of the observed data series. It cab be observed that there are several significant lags on the ACF plots far above the significant band of $\pm 1.96/\sqrt{N}$; therefore, the considered meteorological data is not stationary when considering the original series. Since the non stationarity of the data has been suspected, there is need to stationarize the data by standardization or trend difference.

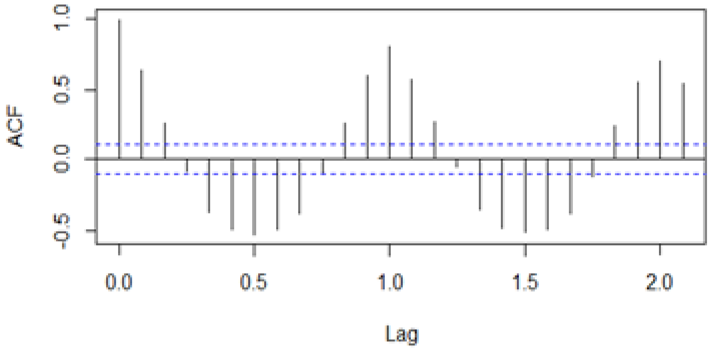

Figure 3: ACF Plot of Observed Pan Evaporation Data

4.3 Trend Differencing

Trend difference was performed on all the data series until stationarity is observed. The data looked to be approximately stable after the fourth order of differencing, hence, stationarity was achieved.

4.4 Model Identification and Diagnostics of $\text{ARIMA}_{p,d,q}$

Model identification is important in time series analysis since there are infinitely many possible models. In general, Okunlola and Folorunsho (2015) recommended that AR parameters of order up to 6 and MA parameters of order up to 3 serve the purpose in most hydrologic applications. To select the best model for forecasting into the future, this study assessed several candidate models of Auto-Regressive Integrated Moving Average (ARIMA) family. The best models for forecasting and representing meteorological data are selected using the criteria of Akaike Information (AIC), Corrected Akaike Information (AIC_C), as well as Bayesian Information (BIC) values as discussed earlier. The corresponding results of different information criteria are shown in the Table 4 with respective candidate models. The AIC, AIC_C, and BIC are good for most of the candidate models but they favour model highlighted in Table 4. Therefore, $\text{ARIMA}_{(3,4,3)}$ seems to perform better and also satisfied all the necessary conditions indicated in the ARIMA modeling building process.

Table 4: Computed Values of AIC, BIC, and AIC_C used for Model Identification

Criteri-on	ARMA(p,q)											
	(1,2)	(2,2)	(3,2)	(4,2)	(5,2)	(6,2)	(1,3)	(2,3)	(3,3)	(4,3)	(5,3)	(6,3)
AIC	54.18	51.04	49.23	47.87	47.35	46.79	46.79	47.65	45.65	46.37	45.65	47.37
BIC	54.34	51.23	49.46	48.14	47.66	47.14	47.14	47.88	45.96	46.64	45.96	47.76
AIC_C	54.18	51.04	49.23	47.87	47.35	46.80	46.80	47.65	45.66	46.37	45.66	47.38

NOTE:
- All values ($\times 10^2$)
- Highlighted column indicates the selected ARMA model

4.5 Parameter Estimates

The estimates of the parameters (AR and MA), obtained for the chosen model is shown in Table 5.

Table 5: Parameter Estimates Results

Data Type	Model	Test on Parameters				
		Parameter	Estimate	Std Error	t-value	Sig. if |t| ≥ 2
Pan-Evaporation	ARIMA (3,4,3)	AR1	-1.7054	0.0073	-233.6	Significant
		AR2	-1.402	0.028	-50.1	Significant
		AR3	-0.5033	0.0054	-93.2	Significant
		MA1	-2.9460	0.0048	613.75	Significant
		MA2	2.9230	0.0055	531.45	Significant
		MA3	-0.9767	0.0018	542.61	Significant

The t-statistic is a ratio of the departure of estimated parameters from its notional value and its standard error; it is used here in hypothesis testing for the significant of the estimated coefficients. The test results in Table 5 show that the parameters for autoregressive and moving averages (AR and MA) are all significant.

4.6 Diagnostics of the Residuals

Figures 4 – 8 show the plot of standardized residual, autocorrelation plots of residuals, P-values of Ljung-Box statistics, Normal Q – Q plot, and histogram of residuals for the pan evaporation series (1982 – 2012)

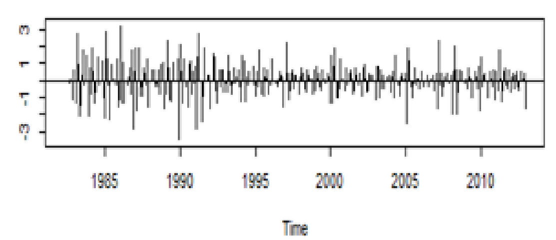

Figure 4: Standardized Residual Plot (Pan Evaporation)

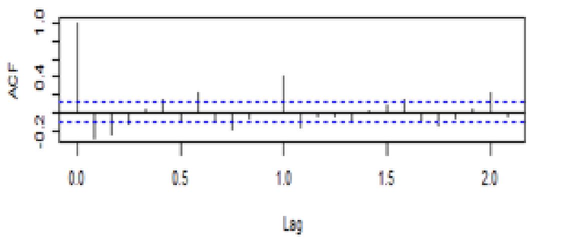

Figure 5: ACF of Residuals (Pan Evaporation data)

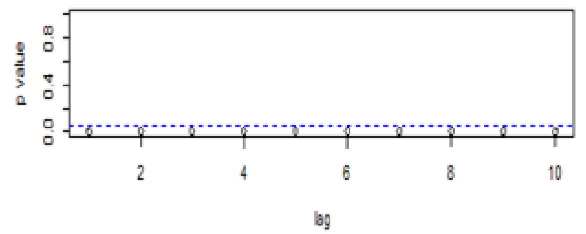

Figure 6: P-values for Ljung – Box Statistic (Pan Evaporation data)

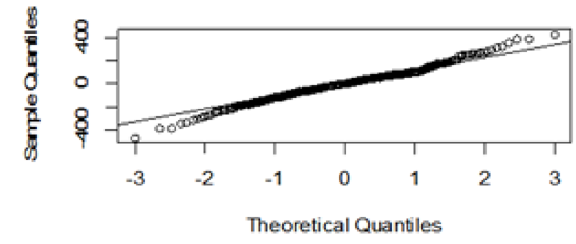

Figure 7: Normal Q – Q Plot (Pan Evaporation data)

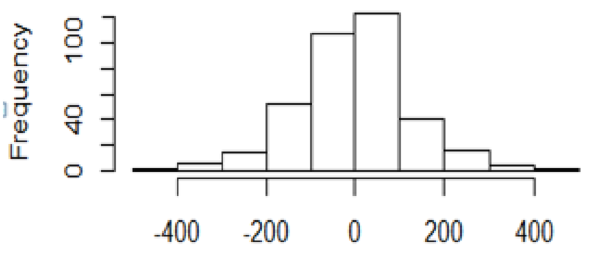

Figure 8: Histogram of Residuals (Pan Evaporation data)

A critical examination of the standardized residual plot of the selected model show that the residuals are independently and identically distributed with mean zero and some few outliers. There is no evidence of significance at any positive lag in the autocorrelation functions (ACF) of the residuals. The residuals appear to be normally distributed as shown in Figure 8. Similarly, all the p-values of the Ljung – Box statistic are not significant at any positive lag, since most of p-values are less than 0.05. The normal Quantile – Quantile (Q – Q) plot of the standardized residuals of the selected model (Figure 7) indicates that most of the residuals are located on the straight line except for some few residuals deviating from normality. The histogram plot (Figure 8) of the residual also appears to be normal, therefore the normality assumption is satisfied and hence, the residual of the selected model seems to be normally distributed.

4.7 Evaporation

The time plot of the (forecasted) evaporation series was plotted as shown in Figure 9, while Figure 10 shows the estimated monthly reservoir evaporation at Erinle dam, southwest Nigeria.

Understanding the magnitude of evaporation from water supply reservoirs is an important component of water resource management. The effect of evaporation is usually considered during the design of water supply reservoirs and subsequent reservoir yield investigations. During the operation of a water supply system, the losses due to evaporation should be taken into account before water is allocated to consumptive users.

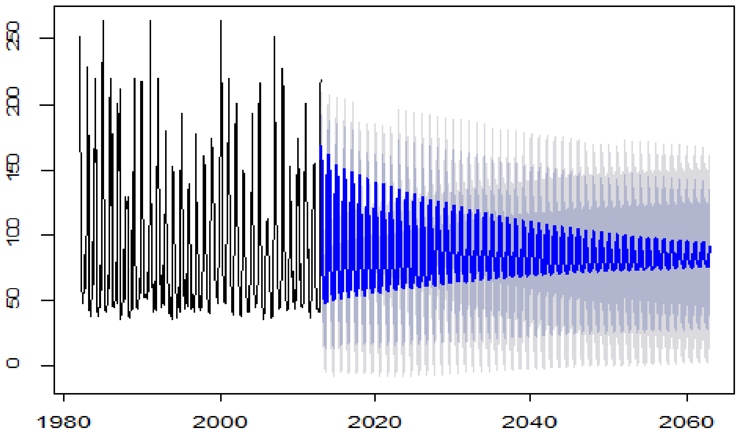

Figure 9: Plot of Pan Evaporation forecast from ARIMA(3,4,3) Models

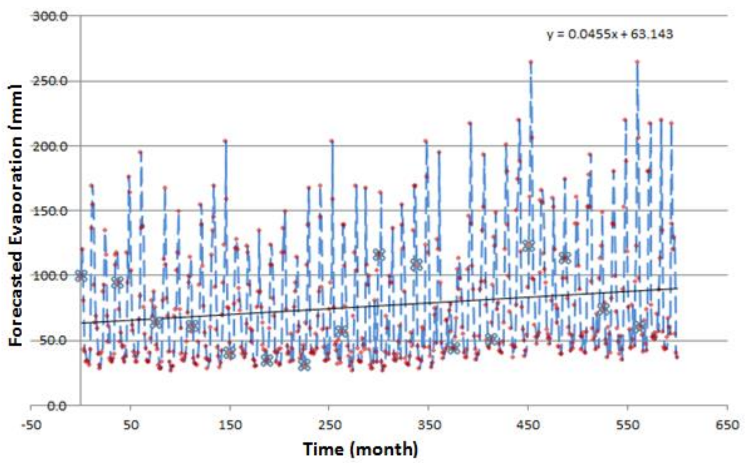

Figure 10: Time Plot of 50years Estimated Monthly Evaporation Series (2013 – 2062)

The effects of the estimated evaporation rate on Erinle reservoir is compounded by increase in water demand of the reservoir serving communities due to an increasing population. Figure 11 shows the reservoir capacity versus water demand curve. It can be seen that the increasing evaporation trend which is largely due to climate change will impact negatively on the storage available to service the benefitting communities. The reservoir will become inadequate as a major supply source to the communities after 2038.

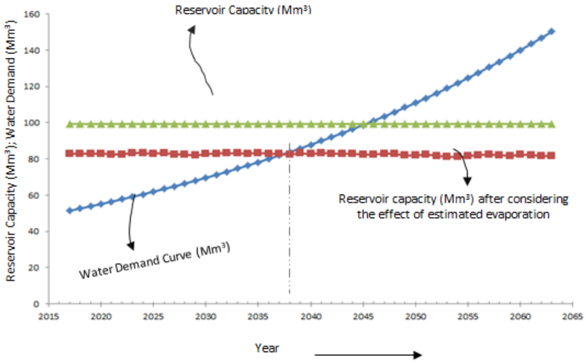

Figure 12: Erinle Reservoir Capacity – Demand Curve

5. Conclusion

The choice of the right model for a given hydrological series is an important aspect of modeling process. The statistical model that is best suited for pan-evaporation data collected from Ido-Oshun meteorological station was investigated herein. The data was analyzed for trend, autocorrelation, partial autocorrelation, and several autoregressive integrated moving average models considered. The selected model was used for the forecast of the pan-evaporation data which was later used to forecast a monthly series (50 years) of reservoir evaporation for the Erinle dam, Oshun sate, Nigeria. The time plot of monthly estimated evaporation series showed an overall increasing trend which could affect the safe yield of Erinle water supply reservoir, especially as the water demand increases due to increase in population rate. The reservoir would not be able to adequately serve the various communities after 2038. It is therefore recommended that new sources of water are needed to cater for water demand in the study area beyond 2038.

References

1. Adeboye, O. B., Jimmy A.O., Kenneth O. A., and David A. O. (2009) Evaluation of FAO-56 Penman-Monteith and Temperature Based Models in Estimating Reference Evapotranspiration Using Complete and Limited Data, Application to Nigeria, Agricultural Engineering International: the CIGR E-journal, Manuscript Number 1291. Volume XI, Pg. 1 – 25
2. Amadi, I. U. and Aboko, S. I. (2013); The Fitting of ARIMA Model in Forecasting Nigeria Gross Domestic Product (GDP), Journal of Physical Science and Innovation, ISSN: 2277-0119, Volume 5, No. 2, pg. 79 – 90.
3. Arora KR (2004) Irrigation, Water Power and Water Resources Engineering, 4th Edition, Standard Publishers Distributors, Delhi.
4. Babu, S.K., Karthikeyan, K., Ramanaiah, M.V., and Ramanah, D. 2011. “Prediction of Rain-fall Flow Time Series using Auto-Regressive Models”. *Advances in Applied Science Research*. Vol. 2, Issue 2, pp 128-133.
5. Clarvis, M. H, Fatichi, S., Allan, A., Fuhrer, J., Stoffel, M., Romerio, F., Gaudard, L., Burlando, P., Beniston, M., Xoplaki, E., and Toreti, A. (2013), Governing and managing water resources under changing hydro-climatic contexts: The case of the upper Rhone basin, Environ. Sci. Policy. http://dx.doi.org/10.1016/j.envsci.2013.11.005
6. Douville H, Chauvin F, Planton S, Royer J, Salas-Melia D, Tyteca S (2001); Sensitivity of the hydrological cycle to increasing amounts of greenhouse gases aerosols, Climate Dynamics 20: Page 45 - 68
7. Finch J. W. and Hall R. L. (2001); Estimation of Open Water Evaporation – A Review of Methods, Environment Agency, Rio House Waterside Drive, Aztec West, Almondsbury, Bristol, BS32 4UD
8. Jarabi, B. (2012); Population Projections – Background & First Steps, Population Studies and Research Institute, University of Nairobi, Nairobi, Kenya
9. Marvin E. J. (2010); Estimating Evaporation from Water Surfaces, CSU/ARS Evapotranspiration Workshop, Fort Collins.
10. Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., and Stouffer, R. J. (2008), “Stationarity Is Dead: Whither Water Management?” Policy Forum, Science Vol. 319, pg. 573 – 574.
11. Mohammad K., Ferenc S., and Banafsheh Z. (2003), Water Resources System Analysis, a CRC Press Company, London.
12. Naill P. E., and Momani, M. (2009), Time Series Analysis Model for Rainfall Data in Jordan: Case Study for using Time Series Analysis, American Journal of Environmental Sciences 5 (5) ISSN 1553-345X: pg. 599-604
13. National Population Commission, NPC (2016), Osogbo, Nigeria
14. Okunlola O. A., and Folorunso S. (2015), Modelling Rainfall Series in the Geo-Political Zones of Nigeria, Journal of Environment and Earth Science, ISSN 2225-0948, Vol.5, No.2, Pg. 100 – 111
15. Osun (state). (2016, February 14). In *Wikipedia, The Free Encyclopedia*. Retrieved 13:09, April 2, 2016, from https://en.wikipedia.org/w/index.php?title=Osun_(state)&oldid=704863518
16. Pereira, L. S. (2005); Water and Agriculture: Facing Water Scarcity and Environmental Challenges. Agricultural Engineering International: the CIGR E-journal, Vol. 7, Pg. 1-26.
17. Sadoff, C. W., and Muller, M. (2009), Better water resources management – Greater resilience today, more effective adaptation tomorrow, A Perspective Paper contributed by the Global Water Partnership through its Technical Committee.
18. Woudenberg, D. L., (2002); "The Role of Climate in Modern Water Planning and Related Decisions: Nebraska Case Study". *OpenAccess* Master's Theses from the University of Nebraska-Lincoln,* Paper 7