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Application of Seasonal Autoregressive Integrated Moving Average (SARIMA) For Flows of River Kaduna

L. Mamudu[1], A. Yahaya[2], S. Dan'azumi[3]

[1]Department of Civil Engineering, Bayero University Kano
[2]Department of Agric and Bio-Environmental Engineering, Nuhu Bamalli Polytecnic Zaria, Kaduna.
[3]Department of Civil Engineering, Bayero University Kano.

[1]lawalagim@gmail.com, [2]sdanazumi.civ@buk.edu.ng, [3]alyahaya14@nubapoly.edu.ng

Research Article

Abstract

Using 25 years monthly discharge data (1988 to 2013), the discharge of River Kaduna was investigated for the possibility of accurate forecast. With the aid of ADF (Augmented Dickey-Fuller) test, auto-correlation and partial auto-correlation functions the discharge was found to exhibit a stochastic non-stationary seasonal time series behavior which becomes stationary after first seasonal differencing. Based on this, the study predicted the discharge of the river from 2014 to 2018 using seasonal autoregressive integrated moving average model and validates this with the actual discharge of the river for the corresponding period. Hence, the study concluded that SARIMA (1, 0, 1) (0, 1, 1)12 mode is the most appropriate based on the selection criteria, and could adequately predict the discharge of River Kaduna with minimal errors.

Keywords
Auto-correlation; Discharge; SARIMA; River Kaduna; Time series.

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1. Introduction

Water management decision making process requires accurate forecasts of the short-term water demand (Oliveiraa, *et al.*, 2017). This short-term water demand forecast can be used in the areas of water reservoir design, future studies, and quality distribution problems (Oliveiraa, *et al.*, 2017). River Kaduna which is the main tributary of River Niger (Garba, *et al.*, 2013) is the main source of domestic, agricultural and industrial water use for a large proportion of rural and urban populations in Kaduna state. Any unusual adjustment or extreme events on this river will have dangerous consequences for not only the people of Kaduna State but the country at large. It is therefore necessary to use available scientific means to predict, based on past records, as accurate as possible the future flow of the River to aid forecasting and decision making by relevant water management agencies and authorities.

Seasonal auto regressive integrated moving average (SARIMA) model has proven to be a suitable candidate for this (Oliveiraa, *et al.*, 2017), several scientists and researchers have used it to predict a wide varieties of seasonal time series. Other models that have been used to predict river flows include artificial neural network (Oluwatobi, *et al.*, 2018), multi-linear regression (Patel, *et al.*, 2016), genetic programming and M5 (Londhe & Charhate, 2010; Patel, *et al.*, 2016; Oluwatobi, *et al.*, 2018). Autoregressive integrated moving average (ARIMA) models have the ability to predict using data with any form or pattern, irrespective of the existence of autocorrelations, with linear or not linear relationship (Manoj & Madhu, 2013; Zupan, 1994). A SARIMA model is an auto regressive integrated moving average (ARIMA) that has incorporated seasonal component into the model (Goh & Law, 2001; Sankaran, 2014).

The ARIMA model was first presented by Box and Jenkins in 1970, hence it is also referred to as the Box-Jenkins Model which is used to predict a single variable (Manoj & Madhu, 2013). A 12 seasonal ARIMA is in the general form SARIMA(p,d,q)(P,D,Q)$_{12}$, where (p,d,q) is the non-seasonal component and (P,D,Q) is the seasonal component of model, with non-seasonal and seasonal autoregressive order AR(p) and AR(P), non-seasonal and seasonal moving average order MA(q) and MA(Q), non-seasonal and seasonal differencing order of d and D respectively (Box & Jenkins, 1970; Bowerman & O'Connell, 1993) this can also be represented mathematically as;

$$(1-B)^d(1-B^s)^D\varphi_p(B)\Phi_P(B^s)X_t = \theta_q(B)\Theta_Q(B^s)e_t \qquad (1)$$

Where B is the backward shift operator, $(1-B)^d$ is the non-seasonal difference operator, $(1-B^S)^D$ is the seasonal difference operator and can also be represented by ∇^d and ∇^D respectively, φ_p, Φ_P, θ_q, Θ_Q are polynomials of order p, P, q, Q respectively, e_t denotes a purely random process (Box & Jenkins, 1970; Bowerman & O'Connell, 1993; Gijo, 2011). The method of estimating the model parameters is maximum likelihood probability (MLE), this selects the set of values for the model parameters which maximizes the likelihood function given below (Hurlin, 2013);

$$max\left\{f(z;\theta) = \frac{1}{\sigma\sqrt{2\pi}}e^{\left(-\frac{(z-m)^2}{2\sigma^2}\right)}\right\} \quad (2)$$

$\forall\ z \in R$, and $\theta = \binom{m}{\sigma^2}$, where θ is the parameter to be estimated; m is mean; σ^2 is variance.

2. Materials and Methods

2.1 Data collection and analysis

Daily time series data of the discharge of River Kaduna were collected from Nigeria Hydrological Service Agency (NIHSA) from 1988 to 2018 at its Goni-Gora Bridge station. The study used 25 years (1988-2013) as training or calibration set, and 5 years (2014-2018) as validation set. These data were converted to monthly averages in m^3/s, some of the software for the research data analysis include; IBM-SPSS used for running the SARIMA Model and carrying out the Ljung-Box test, Eviews used for the Augmented Dickey-Fuller (ADF) and Microsoft excel for plotting some of the graphs.

2.2 Data testing

The data were tested for stationarity and seasonality to ascertain the applicability of SARIMA. A stationary time series is one that has a constant statistical properties over time (savit, 1996). Data can be stationarized by one or more seasonal or/and non-seasonal differencing, the number of these differencing determine the seasonal or/and non-seasonal order D and d respectively. Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979; Montgomery, *et al.*, 1990; Gijo, 2011) was used to test for stationarity and hence, determined the order of differencing of the time series, the null (H_o) and alternative (H_a) hypotheses for the ADF test are; H_o (The time series is non-stationary), H_a (The series is stationary).

The ADF test equation for a flat time series turning around with a mean $\neq 0$ is;

$$\Delta Xt = \propto_0 + \theta X_t - 1 + \sum_{i=1}^{p}(\alpha_i \Delta X_{t-i}) + Z_t \quad (3)$$

Where α_o is the constant, Z_t is a white noise and θ and α_i are coefficients, the t statistic was performed on the θ to determine if the series stationarity is at level (means the original data without differencing) or if it requires differencing. The SARIMA model will only be applicable if the H_o (null hypothesis) is rejected, the hypothesis was first tested on the original data by applying the ADF test without differencing. The two conditions that must be met before rejecting the H_o are; the p value soul be significant at 0.05 ($p < 0.05$) and the t statistics should be more negative (less) than ADF test statistic at 1% level of significance (ADF test < t statistics at 1% level) (Dickey & Fuller, 1979; Mingda Z., 2018). If this occurred without differencing it implies that H_o is rejected at 0 differencing order if not a difference is applied and the test is conducted again until stationarity is achieved (Mingda Z., 2018).

Seasonality can be tested by ranking events below or above a specific median number (Nwogu, *et al.*, 2016). Hewitt, et al., (1971) consider seasonality as six month peak followed by six months trough, even though, other scholars like Nwogu, *et al.*, (2016) consider lower periods acceptable. Beside the regular peak and the trough as measure of seasonality the study also adopted the autocorrelation function (ACF) and partial-autocorrelation function (PACF) plots to determine seasonality, moving average and autoregressive orders (Dickey & Fuller, 1979; Gijo, 2011).

2.3 Model structure and parameterization

The data pattern determines the structure of model applied, and river flows normally follow a seasonal time series pattern. The order of seasonal and non-seasonal differencing 'D' and 'd' is determined by the number of seasonal and non-seasonal differencing applied to the data before stationarity is achieved (Chatfield, 1996; Gijo, 2011). The ACF plots for the original and differenced data determine the presence and the order of a seasonal and non-seasonal Moving Average model, while the corresponding PACF plot determines that of the Autoregressive Model (Chatfield, 1996; Gijo, 2011; Manoj & Madhu, 2013)

2.4 Model selection

The accuracy of the forecasting model needs to be evaluated in order to determine the model with the smallest error (Goh & Law, 2001). There are different ways of measuring and interpreting models forecast errors, the most commonly used are the Mean Absolute Percentage Error (MAPE), the Mean-Squared Error (MSE), Mean-Absolute Error (MAE) and the Root-Mean-Squared Error (RMSE) (Goh & Law, 2001), other model accuracy evaluation criteria include; coefficient of determination (R^2), Akaike information criteria (AIC or AIC_C), Bayesian information criteria (BIC) (Mamudu, *et al.*, 2020), the expression of some of which are shown below. While R^2 tends to reward more parameters in model (favours model complexity), BIC penalized more parameter (penalized model complexity) and AIC strike a balance between the two (Kuha, 2004) and hence more accurate in measuring the fits accuracy for statistical models in econometrics. At higher lag AIC and AICc tend to have the same value.

$$AIC = 2k + n\ ln\left\{\frac{RSS}{n}\right\} \quad (4)$$

$$AICc = 2k + n\ ln\left\{\frac{RSS}{n}\right\} + \frac{2k(k+1)}{(n-k-1)} \quad (5)$$

$$BIC\ (\text{Schwartz's}\ BIC) = k\ ln(n) + n\ ln\left\{\frac{RSS}{n}\right\} \quad (6)$$

$$Normalized\ BIC = \frac{k\ ln(n)}{n} + ln\left\{\frac{RSS}{n}\right\} \quad (7)$$

$$R^2 = 1 - \frac{\left\{\sum_i^n (A_i - F_i)^2\right\}}{\left\{\sum_i^n (A_i - \bar{A}_i)^2\right\}} \quad (8)$$

$$k = p + q + P + Q + 1 \quad (9)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{N}\left(\frac{|A_i - F_i|}{A_I}\right) \times 100 \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\left\{\sum_{i=1}^{n}(A_i - F_i)^2\right\}} \quad (11)$$

$$MAE = \frac{1}{n}\left\{\sum_{i=1}^{N}|A_i - F_i|\right\} \quad (12)$$

Where k is the number of parameters or repressors, n is the number of time series database and RSS is the residual sum of square, p, q, P, Q, are the non-seasonal and seasonal AR and MA orders. Where A_i is the actual value, F_i is the forecast value $\bar{A}$ is the mean actual value. (Mamudu, *et al.*, 2020). In selecting the best model, consideration is given to the one that has the least AIC, AICc, BIC (both Normalized and Schwartz), coupled with the smallest errors and the highest R^2. The Ljung-Box test is used to test model fitness; the H_o is that the model does not show lack of fit while H_a is that the model shows lack of fit, hence a significant p value means the null hypothesis is ejected and hence the model is ejected for lack of fit.

2.5 Model evaluation (model performance, validation and forecasting)

2.5.1 Model performance

As a means to measure the accuracy of the different possible models the study evaluated and compare; the Mean Absolute Percentage Error (MAPE), Mean-Absolute Error (MAE) and the Root-Mean-Squared Error (RMSE), and coefficient of determination (R^2) for the shortlisted models. These are all acceptable criteria for measuring model accuracy (Mamudu, *et al.*, 2020).

2.5.2 Model validating and forecasting

The forecast values for 2014 to 2018 were used to validating the accuracy of the selected model, since the model was built with values from 1988 to 2013.

3. Result and Discussion

3.1 Model structure, parameterization and selection

Figure 1 is the plot of the average monthly discharge of River Kaduna from 1988 to 2018 at level, that is, without differencing. The graph shows a seasonal pattern; supporting the possibility of using seasonal auto-regressive integrated moving average (SARIMA) for the forecast.

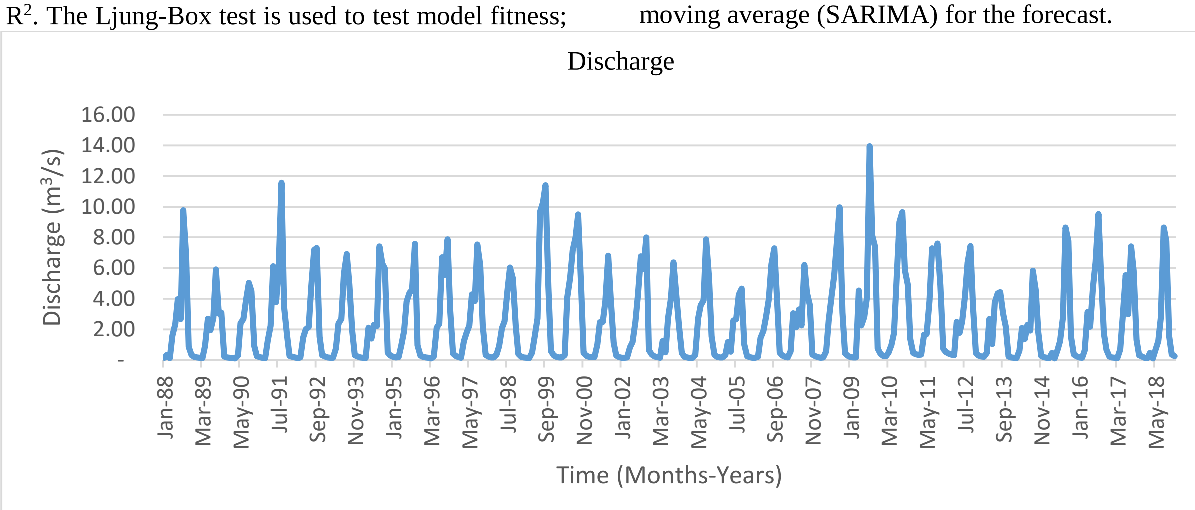

Figure: 1 Time series discharge data of River Kaduna at level (d = 0)

3.1.1 Test for stationarity and seasonality

ADF test was carried out on the original data without differencing, the results are shown in Table 1. The ADF test statistics is -2.96052, while the t statistics is -3.448943 and therefore not significant at 1% level of significance but significant at 5% indicating that the series is stationary with 95% confidence (Mingda Z., 2018). The p-value is 0.0434, significant at (0.05); both the p value and ADF test have 95% confidence, however, stationarity is needed with 99% confidence, but since stationarity is at 95% only seasonal differencing is required to bring it to 99%.

Table 1: Lag Length: 11 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.926052	0.0434
Test critical values:	1% level	-3.448943	
	5% level	-2.869629	
	10% level	-2.571148	

The study further carried out the ADF test of the first seasonal differencing; the plot of this new series is shown in Figure 4 while the result of this second ADF test is shown in Table 2. The result shows ADF statistics = -5.30552, more negative than the t-statistics = -3.449738 significant at 1% level of significance. (The $\nabla^0\nabla_{12}^1$ series is stationary with 99% confidence) and the p value is 0.00 which is also significant at 0.05.

Table 2: Lag Length: 12 (Automatic - based on SIC, maxlag=16)

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-5.305552	0.0000
Test critical values:	1% level		-3.449738	
	5% level		-2.869978	
	10% level		-2.571335	

Source: Eviews

Therefore, zero non-seasonal differencing and first seasonal differencing the data become stationary, hence the study rejects H_o based on both criteria. On the other hand, for the seasonality test the ACF and PACF plot is employed. A close inspection of the ACF and PACF plot in Figures 2 and 3 show an exponential decay and a continuous swing from positive to negative this is an indication of seasonality (Gijo, 2011). This is coupled with the fact that the data reflect a six month peak followed by six months trough as suggested by Hewitt *et. al*. (1971).

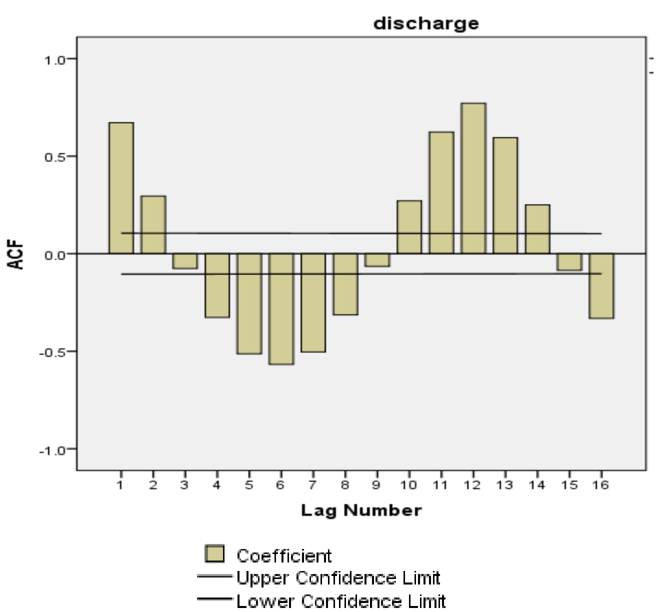

Figure 2: Autocorrelation function (ACF) for average monthly discharge

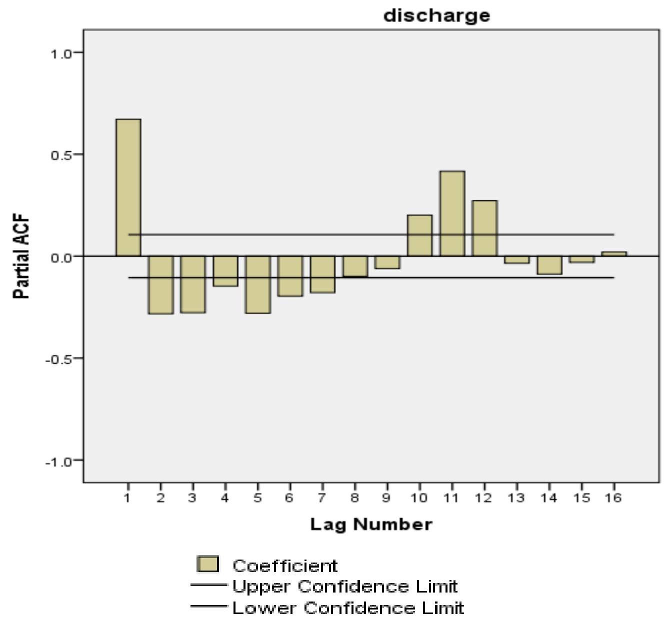

Figure 3: Partial autocorrelation function (PACF) for average monthly discharge

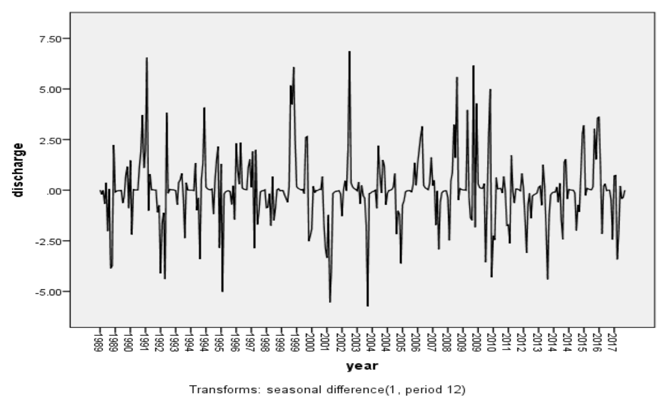

Figure 4: Discharge at level and first seasonal difference ($\nabla^0\nabla_{12}^1$)

3.1.2 Model identification and parameterization

Based on the above, the model is identified as SARIMA(p,0,q)(P,1,Q)$_{12}$, where values for p, q, P and Q which represent the order of the seasonal and non-seasonal components of AR and MA are to be determined. Based on the ACF plot the study observed that the autocorrelation coefficient decreased significantly after lag 2. This shows the presence of a non-seasonal MA(2) model, while the PACF value drop significantly after lag 1, indicting the presence of a non-seasonal AR(1) (Manoj & Madhu, 2013; Gijo, 2011). The available options for the non-seasonal component of the model will be SARIMA(1,0,2)(P,1,Q)$_{12}$ or SARIMA(1,0.1)(P,1,Q)$_{12}$, however, by using the principle of parsimony (Manoj & Madhu, 2013) the models, SARIMA(1,0,1)(P,1,Q)$_{12}$ was chosen.

Regarding the seasonal part, the ACF and PACF at first seasonal differencing were examined to determine the non-seasonal order of MA(Q) and AR(P) respectively, these plots are as shown in Figure 5 and 6. The ACF of the first seasonal differencing show a sharp decrease in auto correlation after lag 2 and become non-significant, indicating a seasonal MA(2). The significant correlation at lag 12 may be due to error. There are no positive seasonal autocorrelation for the PACF for the first 3 lags, this has two implications; firstly, no further seasonal differencing is required and secondly, no seasonal AR part in the model (Sankaran, 2014). Hence, the following models are possible candidates for the forecast; $SARIMA(1,0,1)(0,1,2)_{12}$, $SARIMA(1,0,1)(0,1,1)_{12}$, $SARIMA(1,0,1)(0,1,0)_{12}$,

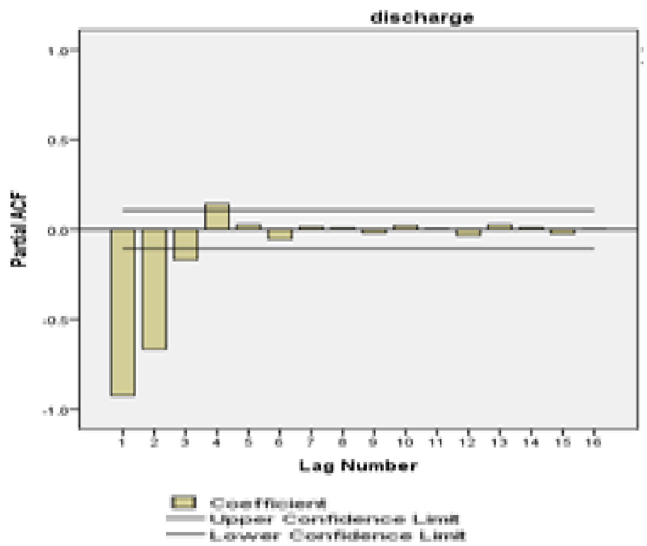

Figure 5. Autocorrelation function for 1st seasonal difference

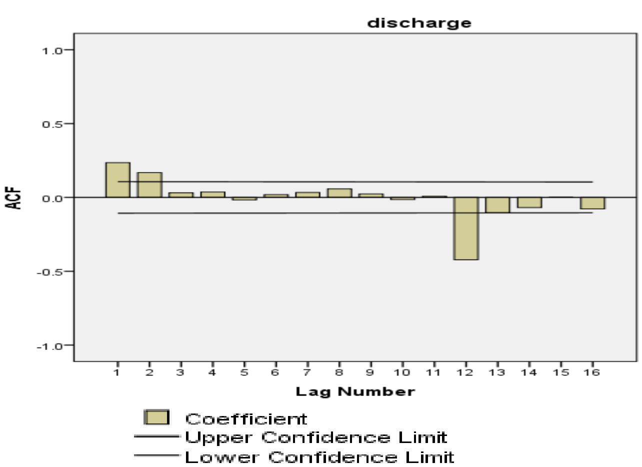

Figure 6. Partial Autocorrelation function for 1st seasonal difference

3.1.3 Model selection

In selecting the best model, consideration is given to the model with the least errors from the different error measurement criteria stated above and as well as having the least AIC, AICc, BIC (both Normalized and Schwartz) and the highest R^2. Table 3 shows all the selection criteria, and $SARIMA(1,0,1)(0,1,1)_{12}$ prove to be the best, it has the least normalized BIC, BIC, AIC, AICc, while having the same R^2 value of 0.765 and MAE value of 0.806 with $SARIMA(1,0,1)(0,1,2)_{12}$. SARIMA(1,0,1)(0,1,1) also has lower RMSE of 1.325 against 1.327 of the $SARIMA(1,0,1)(0,1,2)_{12}$. This model, $SARIMA(1,0,1)(0,1,2)_{12}$ performed well with MAPE of 57.035 as against 57.23 of the selected model. However, $SARIMA(1,0,1)(0,1,0)_{12}$ has the least BIC while falling short in every other criteria, hence this can be considered an abnormality which may have resulted from the few model parameters in $SARIMA(1,0,1)(0,1,0)_{12}$. Moreover, this mode is actually not in contention because it fail the Lung-Box Q test with a significant p-value of 0, where the two contending models both have non-significant p-values.

Table 3: Models Fit Summary

Model		SARIMA (1,0,1)(0,1,0)	SARIMA (1,0,1)(0,1,2)	SARIMA (1,0,1)(0,1,1)
Number of Predictors		1	1	1
Model Fit statistics	Stationary R-squared	0.06	0.437	0.437
	R-squared	0.608	0.765	0.765
	RMSE	1.708	1.327	1.325
	MAPE	62.524	57.035	57.23
	MAE	1.049	0.806	0.806
	MaxAPE	681.145	477.219	481.19
	MaxAE	6.554	6.911	6.94
	Normalized BIC	1.147	0.679	0.657
Ljung -Box Q(18)	Statistics	78.205	9.248	9.384
	DF	16	14	15
	Sig.	0	0.815	0.857
Number of Outliers		0	0	0
BIC		9.81	22.61	16.71
AIC		355.98	176.7	175.4
AICc		356.01	176.81	175.47

Source: IBM SPSS

The software result for the different SARIMA models are shown in Appendix 1A to. Based on the overwhelming evidence from these Results, the model $SARIMA(1,0,1)(0,1,1)_{12}$ was selected as the best fit model for the forecast. Table 4 shows the model parameters from which the forecast equation below is obtained;

$$(1 - B^{12}) \times 0.652BX_t = 0.388B \times 0.938B^{12} \times e_t \quad (13)$$

Table 4: Model parameters

					Estimate	SE	t	Sig.
Discharge-Model_1	**Discharge**	No Transformation	**Constant**		0.005	0.029	0.161	0.872
			AR	Lag 1	0.652	0.127	5.135	0.000
			MA	Lag 1	.388	.154	2.516	.012
			Seasonal Difference		1			
			MA, Seasonal	Lag 1	.938	.058	16.208	.000
	MONTH, period 12	No Transformation	Numerator	Lag 0	.002	.003	.651	.516

Source: IBM SPSS

3.2 Model evaluation (model performance, validation and forecasting)

3.2.1 Model performance and validation

Figure 7 is a plot of the actual discharge, fit values from the model (calibration period) of Jan. 1988 to Dec. 2013 and five years forecast period of Jan. 2014 to Dec. 2018. The model's RMSE, MAPE and the MAE are 1.325, 57.23 and 0.806 respectively with an R^2 of 0.765 (calibration period). This SARIMA model was able to replicate the seasonality and trend of the discharge, replicating the peak and trough for all the five years.

Figure 8 shows the comparison of the forecast results from 2014 to 2018 with the actual discharge for the same period, while figure 9 is a scattered plot of actual discharge against forecast. The model's RMSE, MAPE and the MAE are 1.2995, 0.764 and 1.01 respectively with an R^2 of 0.8016 (validation period).

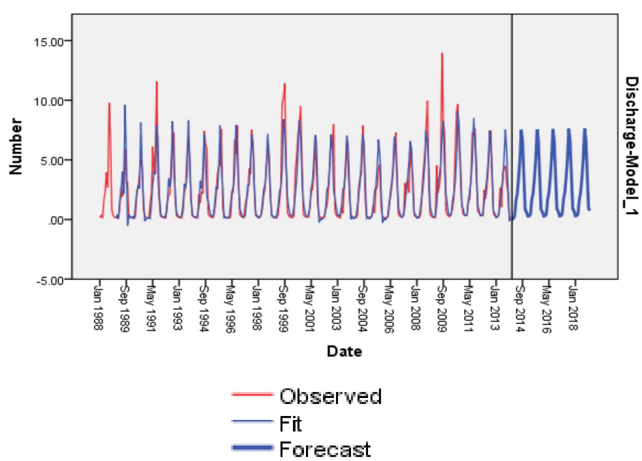

Figure 7: Observed, fit and 5 years forecast graph.

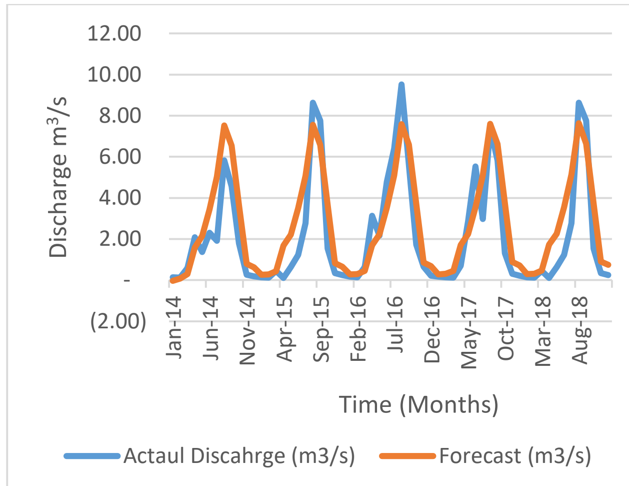

Figure 8: Forecast discharge for 2014 to 2018.

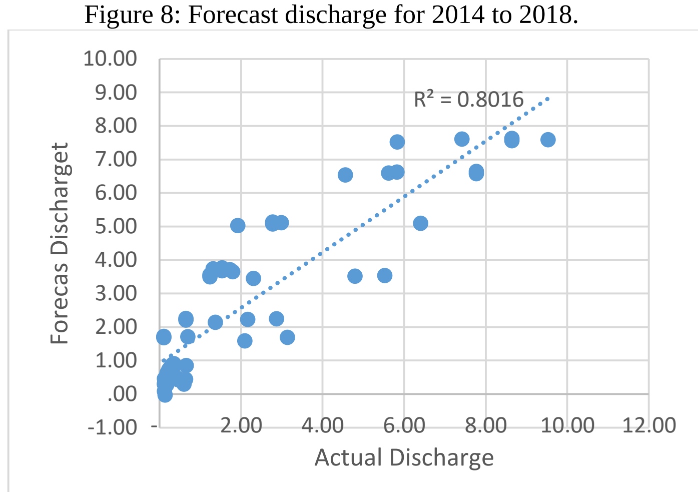

Figure 9: Actual and forecast discharges against time

3.3 Model future forecast

Figure 8 shows the forecast result from Jan. 2014 to Dec. 2018, from the graph the highest average monthly discharge occurred always in the month of August. The highest predicted average monthly discharge between 7.5m^3/s to 7.6 m^3/s always occurs in August.

4. Conclusion

The monthly discharge of River Kaduna at GoniGora Bridge exhibits stochastic seasonal time series behaviour which becomes stationary after first seasonal differencing, hence, it could therefore be predicted with certain time series models. Selecting the right model for accurate forecasting requires both adequate knowledge of time series and a good understanding of the theoretical frame work involved in time series models. It was observed that SARIMA $(1,0,1)(0,1,1)_{12}$ could accurately predict the discharge of River Kaduna with minimum errors. Even though the study predicted 5 years discharge (2014-2018), it is advisable to always review the accuracy of the model as more recent data becomes available, reliability should always be placed on short term forecast. The study recommends the construction of flood control reservoirs in flood prone areas to control excess runoff during the periods of July, August and September and compensate for low flow period around December and January. The application of artificial neural network (ANN) or a hybrid of ARIMA and other autoregressive model to test for more efficient forecast should also be considered

References

Bowerman, B., & O'Connell, R. (1993). Forecasting and Time Series: An applied approach, 3rd ed. California: Duxbury Press,.

Box, G., & Jenkins, G. (1970). Time Series Analysis, Forecasting and Control. HoldenDay, San Francisco .

Chatfield, C. (1996). The Analysis of Time Series: An Introduction, 5th ed. London: Chapman and Hall.

Dickey, D., & Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root', . Journal of the American Statistical Association, Vol. 74, pp.427–431.

Garba, H., Ismail, A., Batagarawa, R. L., Ahmed, S., Ibrahim, A., & Bayang, F. (2013). Climate Change Impact on Sub-Surface Hydrology of Kaduna River Catchment. Open Journal of Modern Hydrology, vol. 3, pp. 115-121.

Gijo, E. (2011). Demand forecasting of tea by seasonal ARIMA model. Int. J. Business Excellence, Vol. 4, No. 1, .

Goh, C., & Law, R. (2001). Modeling and forecasting tourism demand for arrivals with stochastic nonstationary seasonality and intervention. Hong Kong: Department of Hotel and Tourism Management, The Hong Kong Polytechnic University, Hung Hom, Kowloon.

Hewitt, D., Milner, J., Csima, A., & pakula, A. (1971). On Edward's criteria of seasonality and non-paramtric alternative. British Journal of Preventive Social medicine, 25, 174-176.

Hurlin, C. (2013). Maximum Likelihood Estimation Advanced Econometrics. University of Orleans: HEC Lausanne.

Kuha, J. (2004). AIC and BIC: Comparisons of Assumptions and Performance. Sage Journals: Socologica Mehod and Research , 599-624.

Londhe, S., & Charhate, S. (2010). Comparison of data-driven modelling techniques for river flow. Hydrological Sciences Journal – Journal des Sciences Hydrologiques, 55(7), pp. 1163-1174.

Mamudu, A., Khan, F., Zendehboudi, S., & Adedigba, S. (2020). Dynamic Rist Assessment of Reservior Production Using Data-Driven Probabilistic Apprach. Journal of petroleum science and engneering, 184(106486).

Manoj, K., & Madhu, A. (2013). AN APPLICATION OF TIME SERIES ARIMA FORECASTING MODEL FOR PREDICTING SUGARCANE PRODUCTION IN INDIA . Studies in Business and Economics , 81-93.

Mingda Z. (2018). Time Series: Autoregressive models AR, MA, ARMA, ARIMA, . University of Pittsburgh : mzhang@cs.pitt.edu.

Montgomery, D., Johnson, L., & Gardiner, J. (1990). Forecasting and Time Series Analysis. New York: McGraw-Hill.

Nwogu, E. C., Iheanyi, S., & Nlebedim, V. U. (2016). Some for seasonality in Time Series data. Journal of Modern Applied Statistical Methods; Vol. 15 Iss. 2 Article 24, 382-399.

Oliveiraa, P. J., Steffenb, J. L., & Cheungb, P. (2017). Parameter Estimation of Seasonal Arima Models for Water Demand Forecasting using the Harmony Search Algorithm. Procedia Engineering 186, pp. 177-185.

Oluwatobi, 1. 2., Gbenga, O., Joy, A., & Oluwole, A. (2018). MODELING AND SIMULATION OF RIVER DISCHARGE USING ARTIFICIAL NEURAL NETWORKS. Ife Journal of Science vol. 20, no. 2 , 363-370.

Patel, S., Hardaha, M. K., Seetpal, M. K., & Madankar, K. K. (2016). Multiple Linear Regression Model for Stream Flow Estimation of Wainganga River. American Journal of Water Science and Engineering, 2(1), 1-5.

Sankaran, S. (2014). Demand forecasting of fresh vegetable product by seasonal ARIMA model. Int. J. Operational Research, Vol. 20, No. 3, , 315.

savit, R. M. (1996). Stationariy and nonstationarity in time series analysis. Physica D Nonlinear Phoomena, 134-161.

Zupan, J. (1994). Introduction to Artificial Neural Network (ANN) Methods: What They Are and How to Use Them. Acta Chimica Slovenica, 327-352 Francis.