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MODELLING MONTHLY RAINFALL IN OWERRI, IMO STATE NIGERIA USING SARIMA

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ABSTRACT

The paper considers modelling of monthly rainfall pattern in Imo state using seasonal autoregressive integrated moving average (SARIMA) model. The univariate monthly rainfall data set used covered the period of 1981M1-2017M12. The ADF and NP unit root tests showed that rainfall data is integrated order zero. But the ACF plot exhibits evidence of seasonal effect and the PACF plot reveals periodic peaks at lags 12 and 24, which indicates the need for seasonal differencing in the model. Sum of square deviation forecast criterion (SSDFC) was used to compare nine (9) different sub-classes of $SARIMA(p,d,q)\times(P,D,Q)_{12}$ *models identified. And the result indicates that* $SARIMA(0,0,0)\times(1,1,1)_{12}$ *is preferred to the other sub-classes of* $SARIMA(p,d,q)\times(P,D,Q)_{12}$ *models. This model choice was also supported by AIC. The diagnostic tests indicate the adequacy of the fitted model. However,* $SARIMA(0,0,0)\times(1,1,1)_{12}$ *is recommended to predict seasonality of rainfall water for agriculture and hydrological purpose in Imo state. The model can also be useful in creating short term awareness against flood and control strategy in the state.*

KEYWORDS: *Rainfall, SARIMA, SSDFC and seasonality.*

1.0 INTRODUCTION

Rainfall is one of the major components of the water cycle and is responsible for depositing most of the fresh water on the earth. Several methods have been proposed by various researchers for modelling rainfall data. The paper focuses on the sub-classes of seasonal autoregressive integrated moving average (SARIMA) model that is most appropriate for fitting monthly rainfall in Owerri, Imo state. Nigeria Imo State is one of the five states in the South eastern Nigeria with Owerri as the capital,. located at 5.4850N latitude and 7.0350E longitudes. .Owerri as the capital consist of 3 Local Government Areas including Owerri Municipal, Owerri North and Owerri west having estimated population of about 400,000 based on 2006 census figure and it is approximately 40 square miles (100km2) Its topography ranges from flat plains, with a network of two rivers around it; Otamiri River to the east and Nworie River to the South.

Rainfall is generally seasonal, as well as heavy, and occurs between the months of March and October through November. The wet season peaks in July, lasting more than 290 days. The only dry months are December and January with February having little or no rainfall. Moreover, Rainfall is one of the most important natural factors that determine the agricultural production in and across the globe, particularly in Nigeria. The variability of rainfall and the pattern of extreme high or low precipitation are very important for agriculture as well as the economy of the state.

2.0 LITERATURE REVIEW

A lot of researchers have paid considerable attention towards modelling and forecasting the amount of rainfall pattern in various places. For instance, Nimarla and Sundaram (2010) fitted a SARIMA(0, 1, 1)x(0, 1, 1)$_{12}$ model to monthly rainfall in Tamilnadu, India. Adejuwon(2011) studied Power spectral analysis of annual rainfall for Edo and Delta States (formerly Mid-Western Region) in Nigeria using data for 1931 – 1997 in order to identify any regular periodicities which may be present. The Hanning filter was employed for the purpose of smoothing the power spectral. Irregular short-term periodicities were evident with significant cycles of between 3 and 6 years.

Yusuf and Kane (2012) fitted the SARIMA models of orders (1, 1, 2)x(1, 1, 1)$_{12}$ and (4, 0, 2)x(1, 0, 1)$_{12}$ respectively for monthly rainfall in Malaaca and Kuantan in Malaysia. Abdul-Aziz et al. (2013) examined rainfall data pattern in Ashanti region of Ghana and fitted a SARIMA(0, 0, 0)x(2, 1, 0)$_{12}$ to it. Etuk et al (2013) modelled monthly rainfall in Port Harcourt, Nigeria, using seasonal ARIMA (5, 1, 0)x(0, 1, 1)$_{12}$ model. The time-plot shows no noticeable trend. The known and expected seasonality is clear from the plot. Seasonal (i.e. 12-point) differencing of the data is done, then a nonseasonal differencing is done of the seasonal differences. The correlogam of the resultant series reveals the expected 12-monthly seasonality, and the involvement of a seasonal moving average component in the first place and a nonseasonal autoregressive component of order 5. Hence the model mentioned above. The adequacy of the modelled has been established. Osarumwese (2013) modelled quarterly rainfall in Port Harcourt, Nigeria, as a SARIMA(0, 0, 0)x(2, 1, 0)$_4$ model.

Edwin and Martins(2014) examined the stochastic characteristics of the Ilorin monthly rainfall in Nigeria using four different modelling techniques (Decomposition, Square root transformation-deseasonalisation, Composite and Periodic Autoregressive) where they compared the results from the various methods employed. Again, Akpanta et al(2015) modelled the frequency of monthly rainfall in Umuahia, Aba state, Nigeria. They found that the plots of the ACF and PACF show spikes at seasonal lags respectively, suggesting SARIMA (0,0,0) (1,1,1)$_{12}$. Though the diagnostic check on the model favoured the fitted model, the Auto Regressive parameter was found to be statistically insignificant and this led to a reduced SARIMA (0, 0, 0) (0, 1, 1)$_{12}$ model that best fit the data and was used to make forecast.

Alawaye and Alao (2017), examined the Time Series Analysis on Rainfall in Oshogbo Osun State, Nigeria, using monthly data of rainfall between 2004-2015. The time plot reveals that the rainfall data show high level of volatility characterized by seasonal and irregular variations. And the logistic model applied showed to be better and then used to forecast the rainfall for the next 2 years. Amaefula(2018) examines the modelling of mean annual rainfall pattern in Port Harcourt, Nigeria using ARMA(p,q) model.. The data on rainfall used covered the period of 1981 to 2016. Sum of squares deviation forecast criteria (SSDFC) was adopted to select the best performing sub-classes of ARMA(p, q) that fits the data. Among ARMA(1, 1), ARMA(1, 2) ARMA(2, 1) and ARMA(2, 2) models estimated, SSDFC chose ARMA(1, 2) as the best performing model. The selected model were supported by AIC and BIC respectively..And concluded that ARMA(1, 2) can be used to predict long term quality of water for agriculture and hydrological purpose and to create long term awareness against flood and control strategy for Port Harcourt.

3.0 MATERIALS AND METHODOLOGY

This section highlights the methods and sources of data collection, variable measurement, and method of unit root test, model specification, and model identification, method of data analysis, model comparison techniques and diagnostic checks.

3.1 Source of Data and variable measurement

The monthly rainfall data was obtained from central bank of Nigeria (CBN) (2018) statistical bulletin. The univariate time series data collected covered the period of 1981M1-2017M12 (432 observations of monthly rainfall data). Rainfall is usually measured in millimetre using rain gauge.

3.2 Model Specification

An integrated order one time series $\{X_t\}$ is said to follow an autoregressive moving average model of orders p and q denoted by ARMA(p, q) if it satisfies the difference equation

$$x_t = \delta + \alpha_1 x_{t-1} + \cdots + \alpha_p x_{t-p} + u_t - \beta_1 u_{t-1} - \cdots - \beta_q u_{t-q}$$

$$\left(1 - \alpha_1 L - \cdots - \alpha_p L^p\right)x_t = \delta + \left(1 - \beta_1 L - \cdots - \beta_q L^q\right)u_t \qquad (1)$$

where x_t is the original series, δ is the mean of the series, u_t is a sequence of random variables with zero mean and constant variance, called *a white noise process,* and the α_j's and β_j's are constants. Equation (1) can be summarized as follows;

$$\left(1 - \alpha_1 L - \cdots - \alpha_p L^p\right)x_t = \delta + \left(1 - \beta_1 L - \cdots - \beta_q L^q\right)u_t \qquad (2)$$

$$A(L)x_t = \delta + B(L)u_t \qquad (3)$$

where $A(L)$ is the autoregressive (AR) operator, given by $A(L) = 1 - \alpha_1 L - \cdots - \alpha_p L^p$ and $B(L)$ is the moving average (MA) operator, given by $B(L) = 1 - \beta_1 L - \cdots - \beta_q L^q$. For L denotes the backshift operator defined by

$L^k x_t = x_{t-k}$. If $X_t = x_t - \delta$ and u_t is the shock at time t, then Equation(3) can be rewritten as presented in Equation (4) below;

$$A(L)X_t = B(L)u_t \tag{4}$$

The process is stationary if , with stochastic initial conditions – the stability conditions of the AR term are fulfilled, i.e. if $A(L)$ only has roots that are larger than 1 in absolute value. If, likewise, all roots of $B(L)$ are larger than 1 in absolute value, the ARMA(p,q) process is also invertible. A stationary and invertible ARMA(p,q) process may either be represented as an $AR(\infty)$ or as an $MA(\infty)$ process.

If the time series $\{X_t\}$ is nonstationarity due to the presence of one or several of five conditions: outliers, random walk, drift, trend, or changing variance, it is conventional that first or second differencing (d) is necessary to achieve stationarity. Hence, the original series is said to follow an *autoregressive integrated moving average model or orders p, d and q* denoted by ARIMA(p, d, q). For nonstattionary series, Equation(4) can be of the form

$$A(L)\nabla^d X_t = B(L)u_t \tag{5}$$

If the series $\{X_t\}$ exhibits seasonal patterns of nonstationarity, this may be detected using time plot, correlograms or even unit root test. And according to Box and Jenkins(1976) Seasonal ARIMA models sometimes called SARIMA models has the general form $SARIMA(p,d,q)\times(P,D,Q)_S$ and it is given as

$$A(L)\Phi(L^s)\nabla^d\nabla_s^D X_t = B(L)\Theta(L^s)u_t \tag{6}$$

where $\Phi(L^s)$ and $\Theta(L^s)$ are lagged seasonal AR and MA operators of order P and Q respectively. The operator ∇^d denotes the difference operator defined by $\nabla^d = 1-L$ and $d \le 2$. The ∇_s^D represents the seasonal difference operator defined by $\nabla_s = 1 - L^s$ and D is the seasonal differencing order. The seasonal differencing $(1-L^s)$ is called the simplifying operator, insofar as it renders the residual series stationary and amenable to further analysis.

3.3 Unit Root Test

The unit root test here, is based on Augmented Dickey Fuller (ADF) test and is of the form

$$\nabla y_t = \alpha + \alpha_1 t + \beta y_{t-1} + \sum_{i=1}^{k} \xi_i \nabla y_{t-i} + a_t \tag{7.1}$$

$$\nabla y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \xi_i \nabla y_{t-i} + a_t \tag{7.2}$$

$$\nabla y_t = \beta y_{t-1} + \sum_{i=1}^{k} \xi_i \nabla y_{t-i} + a_t \tag{7.3}$$

where k is the number of lag variables. In (7.1) there is intercept term, the drift term and the deterministic trend. The non deterministic trend term removes the trend term as seen in (7.2) And (7.3) removes both the constant and deterministic trend term in the above regression. ADF unit root test null hypothesis $H_0 : \beta = 0$ and alternative $H_a : \beta < 0$. According to Dickey and Fuller(1979), if the ADF test statistic is greater than 1%, 5% and 10% critical values, the null hypothesis of a unit root test is accepted. NP unit root test will used to consolidate the result provided by ADF test. See the technical details in Ng Perron(2001).

3.4 Model Identification

The ACF of an MA(q) model cuts off after lag q whereas that of an AR(p) model is a combination of sinusoidals dying off slowly. On the other hand, the PACF of an MA(q) model dies off slowly whereas that of an AR(p) model cuts off after lag p. The AR and MA models are known to exhibit some duality relationships. Parametric parsimony consideration in model building entails the use of the mixed ARMA fit in preference to either the pure AR or the pure MA fit.

3.5 Model Comparison

There are several model selection criteria in literature such as; Bayesian information criterion(BIC),Aikaike information criterion(AIC), residual sum of squares and so on. If n is the sample size and RSS is the residual sum of squares, then, BIC and AIC are given as follows;

$$BIC = 2k + \ln(RSS / n) + k(\ln n / n) \quad (8)$$

$$AIC = 2k + n\ln(RSS / n) \quad (9)$$

where, n is the sample size, k is the number of estimated parameters (for the case of regression, k is the number of regressors) and RSS is the residual sum of squares based on the estimated model. However, it is good to note that both BIC and AIC are affected by the number of parameters included to be estimated in a model. For the case of BIC, it penalizes free parameters while AIC becomes smaller as the number of free parameters to be estimated increases. But for this study, sum of squares deviation forecast criterion introduced by Amaefula(2011) will be used for model selection. And it is of the form;

$$SSDFC = \frac{1}{m}\sum_{i=1}^{m}\left(y_{t(l,i)} - \hat{y}_{t(l,i)}\right)^2 \quad (10)$$

Where l is the lead time, m is the number of forecast values to be deviated from the actual values (m should be reasonably large), $y_{t(l,i)}$ is the actual values of the time series corresponding to the i^{th} position of the forecast values and $\hat{y}_{t,(l,i)}$ is the forecast values corresponding to the i^{th} position of the actual values. In comparison, the model with the smallest value of SSDFC is the best fitted model that can describe, to the closest precision, the behaviour of the underlying fitted model.

3.6 Model Estimation

The coefficients are estimated using an iterative algorithm that calculates least squares estimates. At each point of iteration, the back forecasts are computed and sum of squares error (SSE) is calculated. For more details, see Box and Jenkins(1994).

4.0 DATA ANALYSIS AND RESULTS

This section presents the time series plot of monthly rainfall data, results of ADF unit root test, , plots of ACF and PACF and estimates of $SARIMA(p,d,q)\times(P,D,Q)_S$ model.

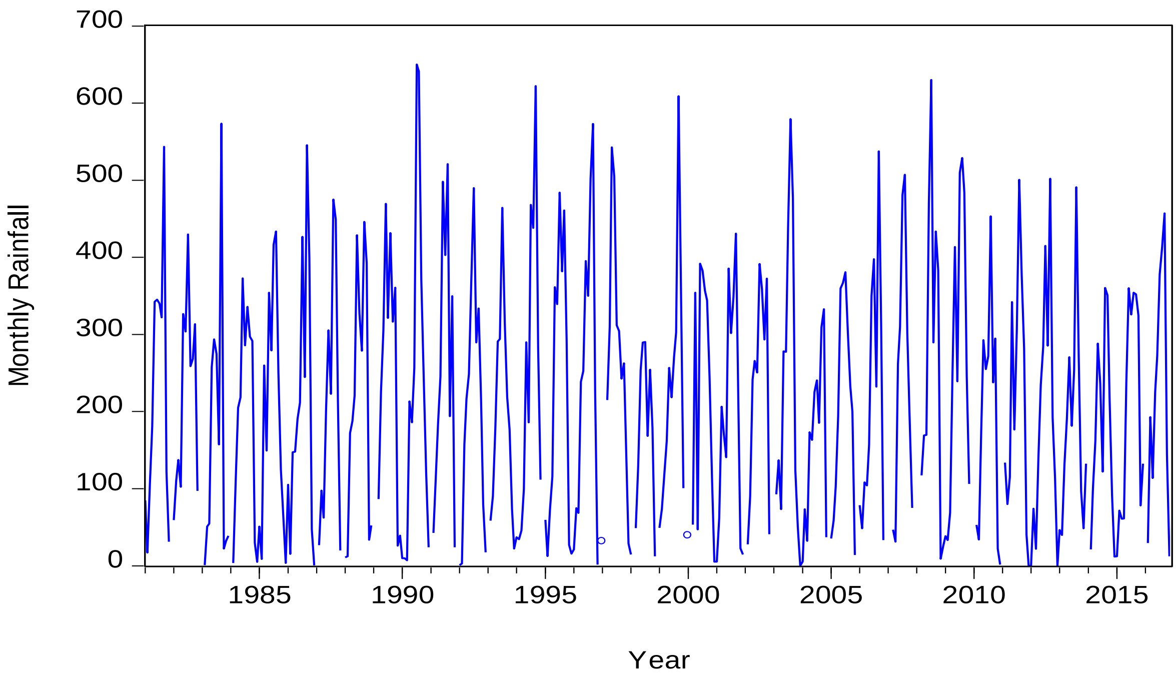


Figure1. Plot of Monthly Rainfall in Owerri, Imo State, Nigeria(1981 – 2017)

The plot of monthly rainfall in Figure1 exhibits seasonality. It is also observable that the time series plot lacks trend.

4.1 ADF Unit Root Test

In order to check the order of integration of the variables under study, ADF and NP unit root tests are carried out and the results are presented in Table1 and Table2 below;

Table 1. Analysis of order of integration using ADF unit root test

Null Hypothesis: RAINFALL has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.17991	0.0000
Test critical values:	1% level	-3.456950	
	5% level	-2.873142	
	10% level	-2.573028	

*MacKinnon (1996) one-sided p-values.

The result of ADF unit root test in Table1 specifies that monthly rainfall variable is integrated order zero I(0) since the p-value is significance under 1% level. Hence, the monthly rainfall under investigation is stationary. Having the monthly rainfall variable exhibiting stationarity, the variable will be model using seasonal autoregressive moving average $SARIMA(p,d,q)\times(P,D,Q)_S$.

Table 2 Analysis of order of integration using Ng Perron unit root test

Null Hypothesis: RAINFALL has a unit root
Exogenous: Constant
Lag length: 0 (Spectral GLS-detrended AR based on SIC, maxlag=16)
Sample (adjusted): 1981M01 2016M11
Included observations: 371 after adjustments

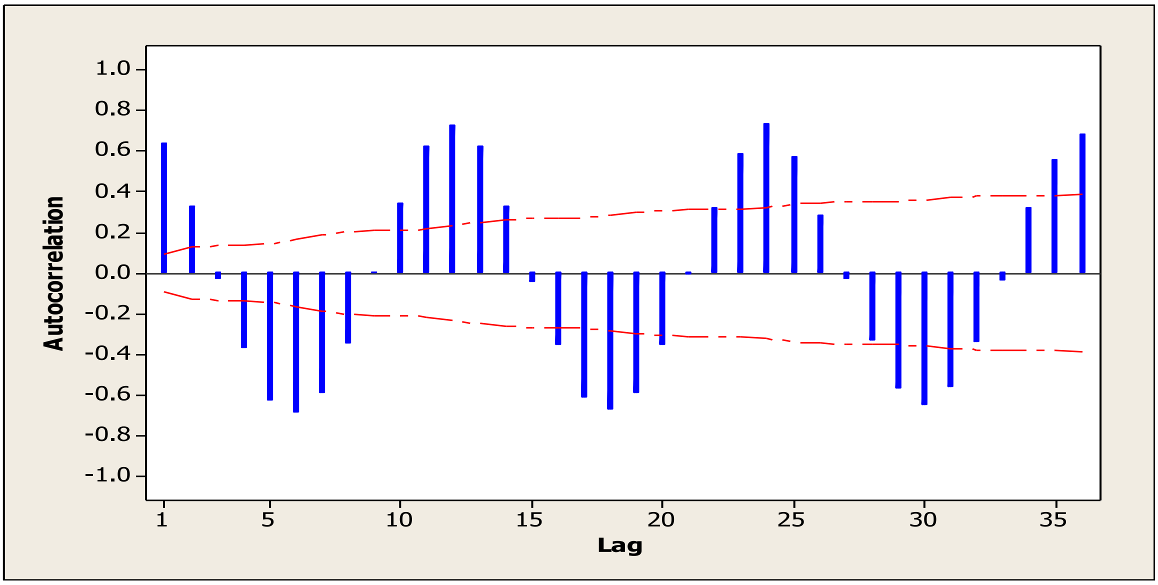
		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-86.4988	-6.57330	0.07599	0.28961
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

*Ng-Perron (2001, Table 1)

The NP test values in Table 2 are all less than asymptotic critical values at 1%, 5% and 10% significant levels. This indicates that rainfall variable is integrated order zero as reported by ADF test. Hence, the rainfall variable is stationary..

4.2 Correlogram

The correlogram presents the plots of autocorrelation function (ACF) and the partial autocorrelation function (PACF) for model identification as presented in Figure2 and Figure3 below.



Figures2. ACF of monthly rainfall in Owerri, Imo State, Nigeria(1981 – 2017)

The plot of autocorrelation in Figure2 exhibits presence of seasonal effect. The result indicates the need for seasonal differencing in the model. The time plot revealed seasonality in the series. But where this is not too clear via time plot, the autocorrelation function (ACF) could reveal the value of s, as the significant lag of the ACF. The differencing operators d for nonstationary series could be atmost 2 and the seasonal difference D may be chosen to be at most equal to 1. The nonseasonal and seasonal AR orders p and P are estimated by the nonseasonal and the seasonal cut-off lags of the partial autocorrelation function (PACF) respectively. Similarly the nonseasonal and the seasonal MA orders q and Q are estimated respectively by the nonseasonal and seasonal cut-off points of the ACF.

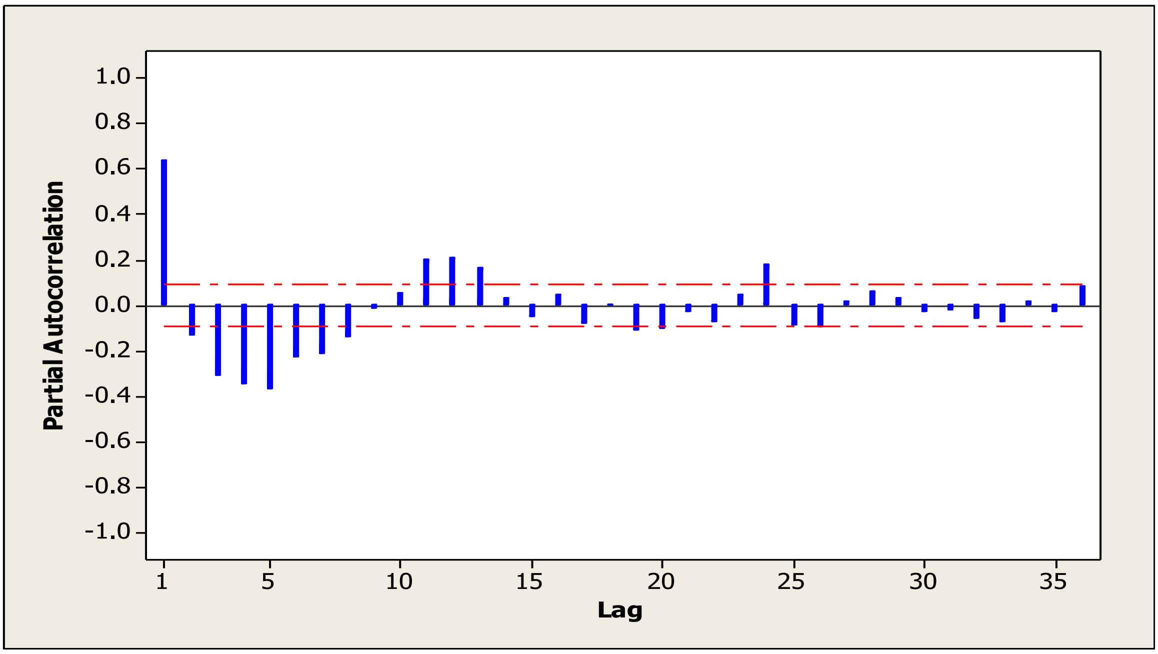


Figure3. PACF of monthly rainfall in Owerri, Imo State, Nigeria (1981 – 2017)

There appear to be annual or 12-month spikes in the ACF and PACF correlograms. The ACF in Figure2 clearly exhibits this prima facie evidence of seasonal nonstationarity. The PACF in Figure3 reveals the seasonal spikes as well. Slow attenuation of the seasonal peaks in the Figure2 ACF signifies seasonal nonstationarity. The 12-month PACF periodicity can be seen in the periodic peaks at lags 12 and 24, suggestive of seasonal differencing at lag 12.

4.3 Model Comparison

This section presents compared 9 possible models using SSDFC as presented in Table3 below;

Tabel3. Model comparison using SSDFC

S/N	Model	RSS	AIC	BIC	SSDFC
1	$SARIMA(1,0,0)\times(1,1,0)_{12}$	3879279	3938.38	15.1449	72015.5
2	$SARIMA(0,0,1)\times(0,1,1)_{12}$	2747666	3789.39	14.8000	291.039
3	$SARIMA(1,0,1)\times(1,1,1)_{12}$	2735451	3791.46	18.8236	563.123
4	$SARIMA(0,0,0)\times(1,1,1)_{12}$	2757893	3787.46	14.7955	5.25123*
5	$SARIMA(0,0,0)\times(0,1,1)_{12}$	2766268	3790.30	12.7927	12.2040
6	$SARIMA(0,0,0)\times(1,1,0)_{12}$	3910010	3939.79	13.1387	70370.9
7	$SARIMA(1,0,0)\times(1,1,1)_{12}$	2736086	3789.56	16.8098	204.175
8	$SARIMA(0,0,1)\times(1,1,1)_{12}$	2736605	3789.64	16.8100	177.149
9	$SARIMA(2,0,0)\times(2,0,0)_{12}$	3739102	3926.48	19.1362	22411.1

The model comparison using SSDFC in Table3 indicates that $SARIMA(0,0,0)\times(1,1,1)_{12}$ is preferred to the other sub-classes of $SARIMA(p,d,q)\times(P,D,Q)_{12}$ models since it has the smallest value of SSDFC. This model choice is also supported by AIC.

Table 4. Estimates of $SARIMA(0,0,0)\times(1,1,1)_{12}$ model

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
SAR 12	-0.0571	0.0513	-1.11	0.266
SMA 12	0.9567	0.0242	39.54	0.000
Constant	-0.2418	0.2825	-0.86	0.393

Differencing: 0 regular, 1 seasonal of order 12
Number of observations: Original series 432, after differencing 420
Residuals: SS = 2757893 (backforecasts excluded)
MS = 6614 DF = 417

Table 5 Model diagnostic using Ljung-Box Test

Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag	12	24
Chi-Square	15.7	29.7
DF	9	21
P-Value	0.074	0.098

The result of Table5 shows that the probability of Modified Box-Pierce (Ljung-Box) Chi-Square statistic is greater than 5% significant level, this indicates that the residuals of the $SARIMA(0,0,0)\times(1,1,1)_{12}$ are not correlated. Hence the model is adequate.

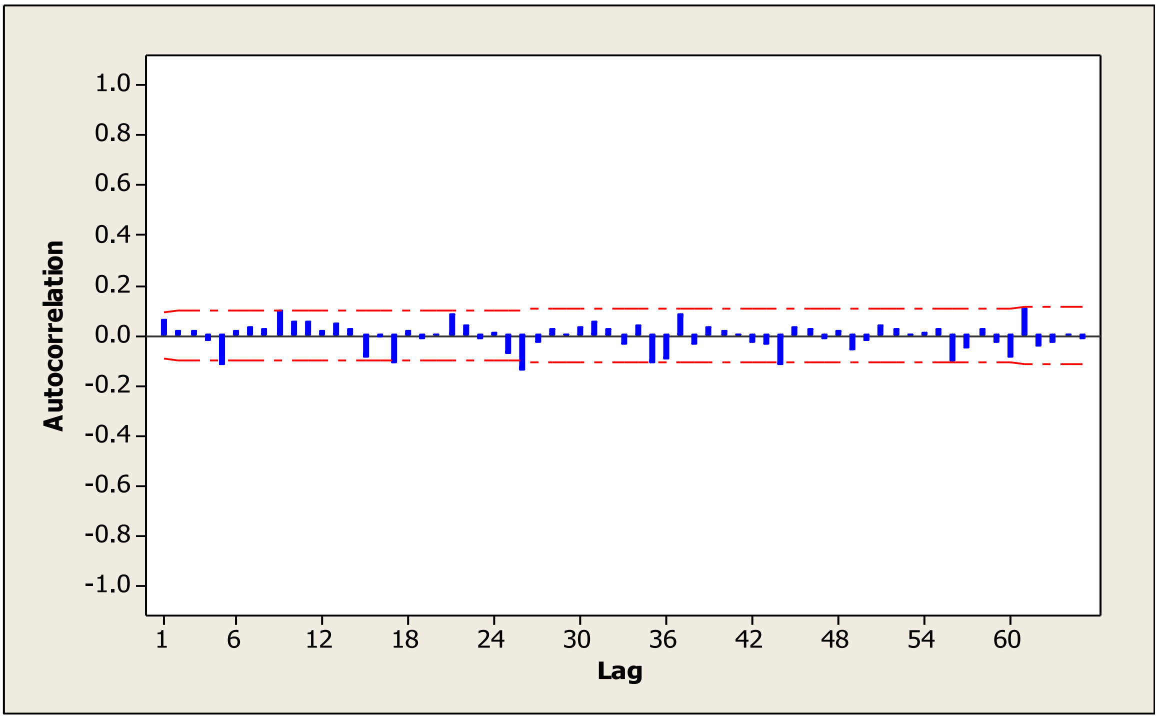


Figure4. Plot of ACF of residuals for $SARIMA(0,0,0)\times(1,1,1)_{12}$ fitted for Imo rainfall

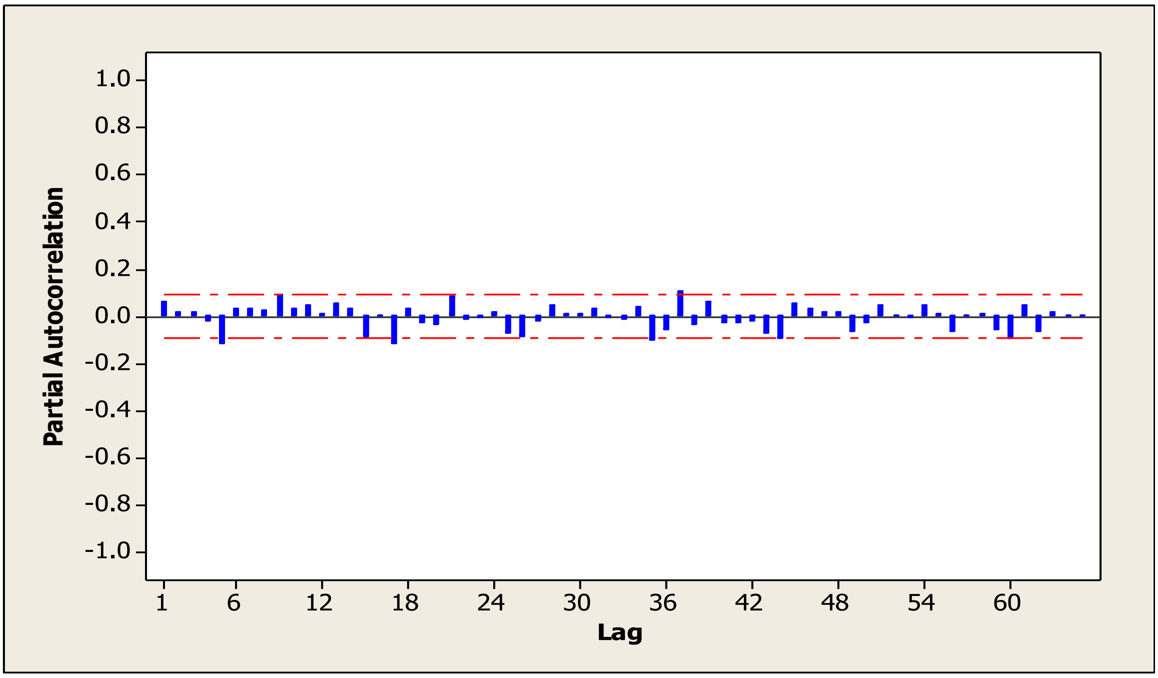


Figure5. Plot of PACF of residuals for $SARIMA(0,0,0)\times(1,1,1)_{12}$ fitted for Imo rainfall

The ACF and PACF of residuals in Figure4 and Figure5 for the Imo rainfall data show nonsignificant spikes (the spikes are within the confidence limits) indicating that the residuals seem to be uncorrelated. Therefore, the $SARIMA(0,0,0)\times(1,1,1)_{12}$ model appears to fit well and can be used to make forecasts.

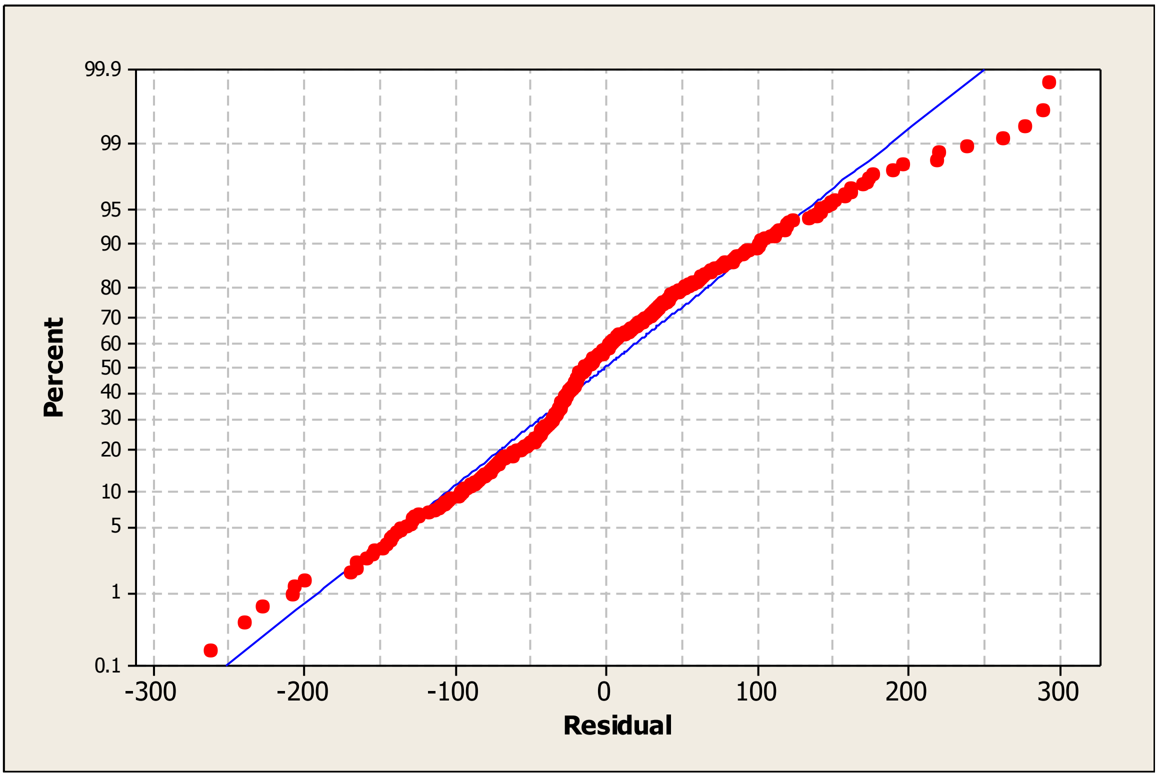


Figure6. Normal Probability Plot of residuals for $SARIMA(0,0,0)\times(1,1,1)_{12}$ model fitted

The diagnostic test using normal probability plot of residuals in Figure6 above indicates that the model residuals are normally distributed. Hence, the model fitted is adequate.

4.4 DISCUSSION OF RESULTS

The monthly rainfall variable in Imo state is integrated order zero as reported by ADF test and confirmed using NP test. Hence, the rainfall variable is stationary. But the correlogram exhibited presence of seasonal effect. The results indicate the need for seasonal differencing in the model. The periodic peaks at lags 12 and 24 observable in Figure3 indicates the need for seasonal differencing at lag 12. And the model comparison in Table3 using SSDFC favoured the choice of fitting $SARIMA(0,0,0)\times(1,1,1)_{12}$. This fitted model agrees with that of Akpanta *et al*,(2015) who modelled the frequency of monthly rainfall in Umuahia, Aba state, south eastern Nigeria suggesting SARIMA (0,0,0) x$(1,1,1)_{12}$. And fitted model differs with that of Etuk et al (2013) who modelled monthly rainfall in Port Harcourt, River State Nigeria, the closest State nearest to Imo in the south-south using seasonal ARIMA (5, 1, 0)x$(0, 1, 1)_{12}$ model.

The Modified Box-Pierce (Ljung-Box) Chi-Square statistic in Table5 is not significant indicating that the residuals of the fitted $SARIMA(0,0,0)\times(1,1,1)_{12}$ are not correlated. Hence the model is adequate. The ACF and PACF of the model residuals in Figure 4 and Figure 5 respectively showed that the residuals are uncorrelated. The probability plot in Figure 6 reveals that the residuals are normally distributed; hence, the fitted model is adequate.

5.0 CONCLUSION AND RECOMMENDATIONS

The paper examines monthly rainfall pattern in Imo state using $SARIMA(p,d,q)\times(P,D,Q)_S$ model. And nine(9) different sub-classes /order of $SARIMA(p,d,q)\times(P,D,Q)_S$ models were identified and compared using model information criteria, specifically the SSDFC introduced by Amaefula(2011). The model comparison showed that $SARIMA(0,0,0)\times(1,1,1)_{12}$ is preferred. This choice was also supported by AIC and all the diagnostic tests indicated that the model is adequate.

However, the $SARIMA(0,0,0)\times(1,1,1)_{12}$ can be recommended to predict seasonality of rainfall in Imo state and seasonal quality of water for agriculture and hydrological purpose.. The model may also be useful in creating short term awareness against flood and control strategy in the state.

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