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Application of Sarima Models in Modelling and Forecasting Monthly Rainfall in Nigeria

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Authors' contributions

This work was carried out in collaboration among all authors. Author ASA designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors AMA, MOA managed the literature searches. All authors read and approved the final manuscript.

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Abstract

Application of SARIMA model in modelling and forecasting monthly rainfall in Nigeria was considered in this study. The study utilizes the Nigerian monthly rainfall data between 1980-2015 obtained from World Bank Climate Portal. The Box-Jenkin's methodology was adopted. SARIMA (2,0,1) (2,1,1) [12] was the best model among others that fit the Nigerian rainfall data (1980-2015) with maximum p-value from Box-Pierce Residuals Test. The study forecasts Nigeria's monthly rainfall from 2018 through 2042. It was discovered that the month of April is the period of onset of rainfall in Nigeria and November is the period of retreat. Based on the findings, Nigeria will experience approximately equal amount of rainfall between 2018 to 2021 and will experience a slight increase in rainfall amount in 2022 to about 1137.078 (mm). There will be a decline of rainfall at 2023 to about 1061 (mm). Rainfall values will raise again to about 1142.756 (mm) in 2024 and continue to fluctuate with decrease in variation between 2024 to 2042, then remain steady to 2046 at approximately 1110.0 (mm). Nigerian Government should provide a more mechanized and drier season farming methods to ease the outage of rainfall in future that may be caused due to natural (or unpredictable) variation.

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Keywords: Rainfall; time series analysis; SARIMA (Seasonal Autoregressive Integrated Moving Average) model; monthly rainfall.

1 Introduction

Rainfall is very important for the economic growth and development of Nigeria. As a country whose citizens actively participate in rain fed agricultural practices (crop production, animal husbandry and plantation), rainfall is the most important natural factor that determines the agricultural production 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 country. It is well established that rainfall is changing on both the global and the regional scales due to global warming [1,2]. As the government is making effort to encourage agriculture and ensure food security continues to gain ground and acceptability, information on rainfall probabilities is vital for the design of water supply and supplemental irrigation schemes and the evaluation of alternative cropping and of soil water management plans. Such information can also be beneficial in determining the best adapted plant species and the optimum time of seeding to re-establish vegetation on deteriorated rangelands. Rainfall records are mostly available in many countries, little use is made of this information because of the unwieldy nature of the records [3].

It has become important that Nigerian government and stakeholders need information about the future rainfall to make informed decisions. Farmers and other agribusiness managers need forecast about future rainfall in order to make investment decisions. Hence, there is a need to understand the rainfall pattern and forecast future rainfall in Nigeria, through time series analysis.

Time series models such as AR (Auto Regression), MA (Moving Average), ARMA (Autoregressive Moving Average) and ARIMA (Autoregressive Integrated Moving Average) can be used to model annual rainfall pattern in a specific geographical area. However, Seasonal time series models like SARIMA (Seasonal Autoregressive Integrated Moving Average) can be used to model monthly amount of rainfall. Seasonal ARIMA (SARIMA) models are models of time series that take into consideration the seasonal effect present in a time series data.

This study identifies the best SARIMA model that fit the Nigerian monthly rainfall data and predict future monthly rainfall in Nigeria. The motivations of this study are to:

- i Identify patterns in the Nigerian rainfall data – stationarity/non-stationarity and seasonality.
- ii Identify the best SARIMA model that fit the Nigerian rainfall data.
- iii Predict future monthly rainfall using the best estimated SARIMA model.

2 Brief Review of Literature

This study reviewed the following literatures. They include:

Ekpoh [4] carried out analysis using long time series rainfall data from Katsina, Zaria and Kano meteorological stations, testing for trend and the results showed a decrease in mean annual rainfall for the three stations.

Enete and Ebenebe [5] study showed a downward trend of rainfall in Nigeria, which suggested a general decline in rainfall values in recent times. This supports the findings of Olaniran & Summer [6,7], where they found that there was a progressive early decline of rainfall in Nigeria. Following the pattern, they reported a noticeable and significant decline of rainfall frequency in September and October which coincide with the end of rainy season in almost every parts of the country especially in the Northern and Central parts of Nigeria.

Obot et al. [8] considered rainfall series in each of the six geopolitical zones in Nigeria by examining the trend over the period between 1978 and 2011 and found that Maiduguri in the Northeast zone showed an increasing trend among other rainfall towns in other zones.

Ekpoh and Nsa [9] considered the rainfall in the North-Western Nigeria using monthly data between periods 1968 and 2008. Their study identified four drought episodes for about three decades within the sampled period, and the shifts could be temporary since possible recovery was also suspected in sub-sample closer to 2008.

Akinsola and Ogunjobi [10] studied the rainfall variability in Nigeria using observations from 25 stations from 1971 to 2000, analyzing temporal and spatial trends. They found evidence of significant increase in rainfall anomaly in most of the stations and these stations include Lokoja, Kaduna, Bida, Bauchi and Warri.

3 Methodology

3.1 Source of data

The data used for the analysis of this study was sourced from World Bank Climate Portal, http://sdwebx.worldbank.org/climateportal. The dataset contains the mean monthly rainfall (mm) in Nigeria from 1980 to 2015.

3.2 Model specification

A Seasonal Autoregressive Integrated Moving Average (SARIMA) model of the form $SARIMA(p,d,q)\times(P,D,Q)_{[m]}$ was fitted for the Nigerian monthly rainfall data. The model is given by:

$$(1-B)^d(1-B^m)^D\varphi(B)\Phi(B)X_t= \theta(B)\Theta(B)\varepsilon_t \qquad \text{………… (1)}$$

Where,

P and p = orders of seasonal and non-seasonal Autoregression.
Q and q = orders of seasonal and non-seasonal Moving Average (MA) respectively.
D and d = seasonal and non-seasonal difference.
m = order of seasonality.

X_t is the time series value at time t and φ, θ, Φ and Θ, are polynomials of order of p, q, P, and Q respectively. B is the backward shift operator and white noise process is denoted by ε_t.

We set $m = 12$ since the rainfall series is made of monthly observations. Thus;

$$(1-B)^d(1-B^{12})^D\varphi(B)\Phi(B)X_t= \theta(B)\Theta(B)\varepsilon_t \qquad \text{………… (2)}$$

3.3 Modelling procedure

The Box Jenkin methodology was employed to identify the best seasonal ARIMA model for the Nigerian Rainfall data. When fitting an ARIMA model to a set of time series data, the following procedure provides a useful general approach [11]:

1. Plot the data. Identify any unusual observations.
2. If necessary, transform the data (using a Box-Cox transformation) to stabilize the variance.
3. If the data are non-stationary: take first differences of the data until the data are stationary.
4. Examine the ACF/PACF: Is an AR (pp) or MA (qq) model appropriate?
5. Try your chosen model(s), and use the AICc to search for a better model.
6. Check the residuals from your chosen model by plotting the ACF of the residuals, and doing a multiple test of the residuals. If they do not look like white noise, try a modified model.
7. Once the residuals look like white noise, calculate forecasts.

3.3.1 Model selection criteria

In choosing the model that best describe a time series data, attention is given to the RMSE, AIC, BIC and AICc. Smaller values indicate better model.

2-log Likelihood: The -2 log likelihood is the most basic measure for model selection. It is the basis for the AIC and BIC.

$$L = -Nln(\sigma^2{}_a) - \frac{SSQ'}{2\sigma^2{}_a} - \frac{2Nln(2\pi)}{2}$$

AIC: Akaike's Information Criterion (AIC) adjusts the -2 Restricted Log Likelihood by twice the number of parameters in the model.

$$AIC = -2L + 2N_p$$

AICc: The Akaike information criterion, corrected (AICc) is a measure for selecting and comparing models based on the -2 log likelihood. Smaller values indicate better models. The AICc "corrects" the Akaike information criterion (AIC) for small sample sizes. As the sample size increases, the AICc converges to the AIC. The AIC "penalizes" over parametrized models.

BIC: The Bayesian information criterion (BIC) is a measure for selecting and comparing models based on the -2 log likelihood. Smaller values indicate better models. The BIC also penalizes over-parametrized models, but more strictly than the AIC because the BIC accounts for the size of the dataset as well as the size of the model.

$$BIC = -2L + \ln(N)N_p$$

Where;

N = Total number of observations
L= -2 log likelihood,
$\sigma^2{}_a$=variance of residuals
N_p= Number of parameters $(N_p = p + q + d + P + Q + D + m)$
SSQ = residuals sum of squares

3.4 Data analysis

R-software (version 3.4.0) was used for analysis in this study with the help of “forecast”, “teseries”, “lmtest” and “ggplot2” packages. The Arima function from forecast package was used to fit the best model for the data. Model diagnostic check was carried out using ACF and PACF of residuals and various tests including the Box-Pierce test and Ljung-Box test of residuals, and normal Q-Q plot.

4 Results and Discussion

This section provides detail analysis of the rainfall data collected for this study and discussion of results.

4.1 Results

Table 1 presents the summary statistics of the Nigerian monthly rainfall data from 1980-2015. There were 432 data points and no missing observation. The minimum and maximum rainfall observed over the time period are 0.0523 (mm) and 315.0 (mm). The average rainfall over the time period is 93.1 (mm). There is more than one mode in the dataset, the least observed value was 0.0523 (mm). The coefficient of skewness (0.493) indicates the rainfall series is moderately skewed right.

Table 1. Descriptive statistics

Statistics	Estimate	Statistics	Estimate
N	432	Minimum	0.0523
Missing	0	Maximum	315.0
Mean	93.1	Skewness	0.493
Std. error mean	4.12	Std. error skewness	0.117
Median	75.4	Kurtosis	-1.11
Mode	0.0523*	Std. error kurtosis	0.234
Sum	40239	25^{th} Percentile	9.59
Standard deviation	85.5	50^{th} Percentile	75.4
Variance	7316	75^{th} Percentile	166
Range	315		

**More than one mode exists, only the first is reported*

4.2 Time-plot and model identification

To get an insight from the data, it is decomposed to unveil different components of the time series (or metric charts) – raw data, seasonality, trend and remainder.

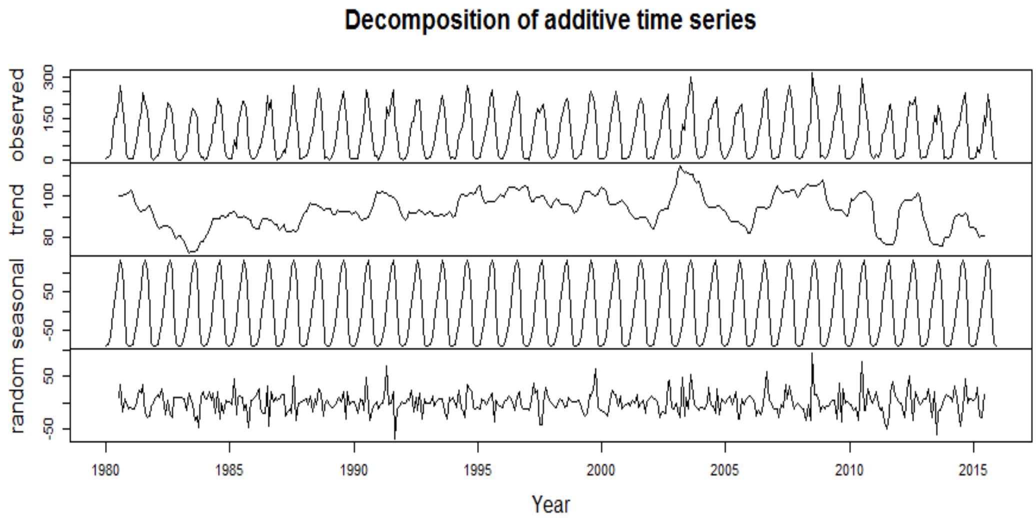

Fig. 1. Decomposition of Nigerian monthly rainfall data (1980-2015)

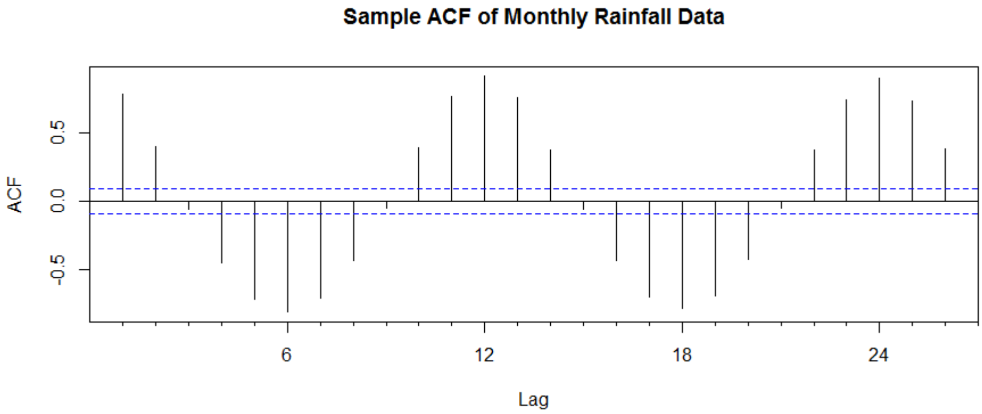

Fig. 2. Sample ACF of Nigerian monthly rainfall data (1980-2015)

Fig. 2 is the sample ACF of the monthly rainfall data, it shows there is seasonality in the data – a regular raise and fall meeting at the seasonal lags. It shows the presence of autocorrelation in the rainfall series.

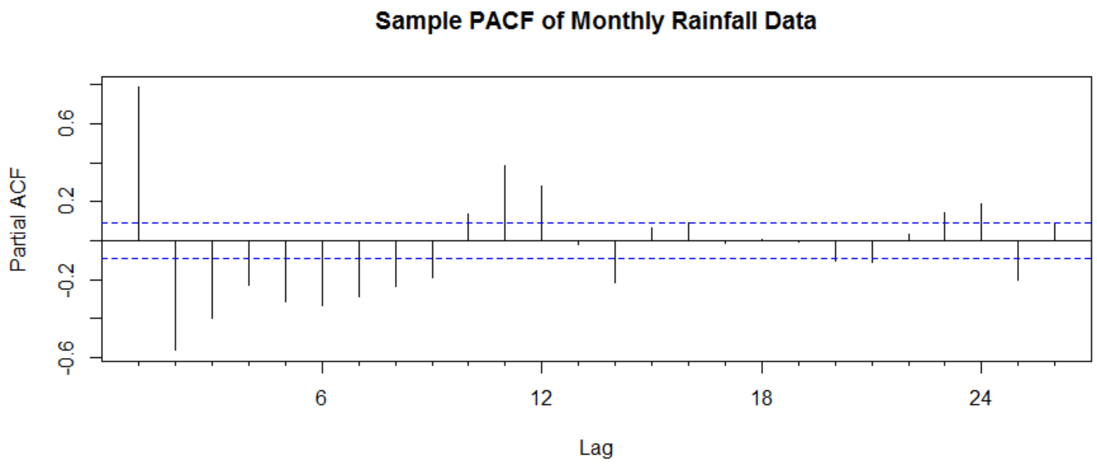

Fig. 3. Sample PACF of Nigerian monthly rainfall data (1980-2015)

Fig. 3 shows the partial autocorrelation function of the rainfall data. The significant peak at a lag of 12 in the partial autocorrelation function confirms the presence of an annual seasonal component in the data.

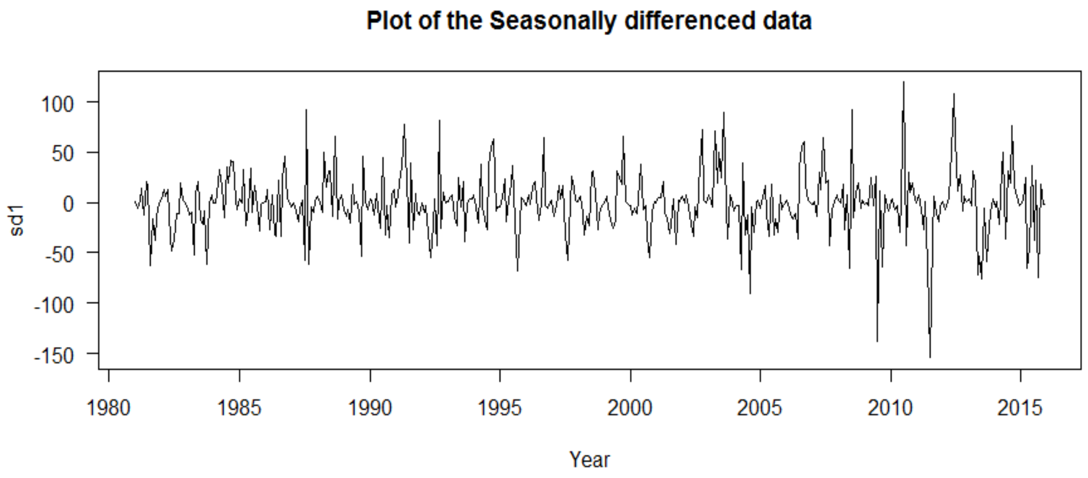

Fig. 4. Plot of seasonal differenced data

Fig. 4 provides the plot of the seasonally differenced data. The plot suggests the series is now approximately stationary. And the Augmented Dickey-Fuller (ADF) test confirms it.

Table 2. Augmented dickey-fuller (ADF) test for rainfall data

Dickey-Fuller	Lag order	p-value	Alternative hypothesis
-6.6849	7	0.01	stationary

Warning: p-value smaller than printed p-value

The p-value of 0.01 from the ADF test prove that the series is stationary. If the series were to be non-stationary, it would have been differenced the series one more time to make it stationary.

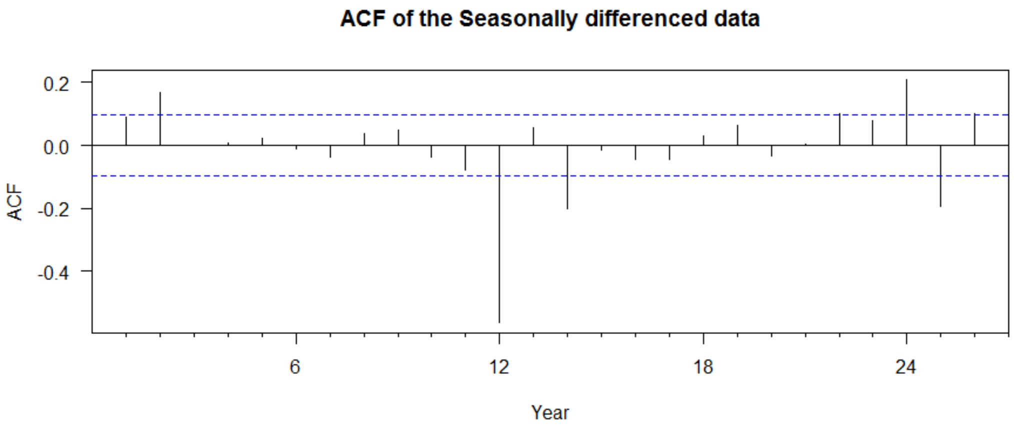

Fig. 5. ACF of the seasonal differenced data

From Fig. 5, there are perhaps three significant spikes in the non-seasonal lags of the ACF. This may be suggestive of a non-seasonal MA (3) model. Two significant spikes are seen at seasonal lags 12 and 24. This suggests a seasonal MA (2) model.

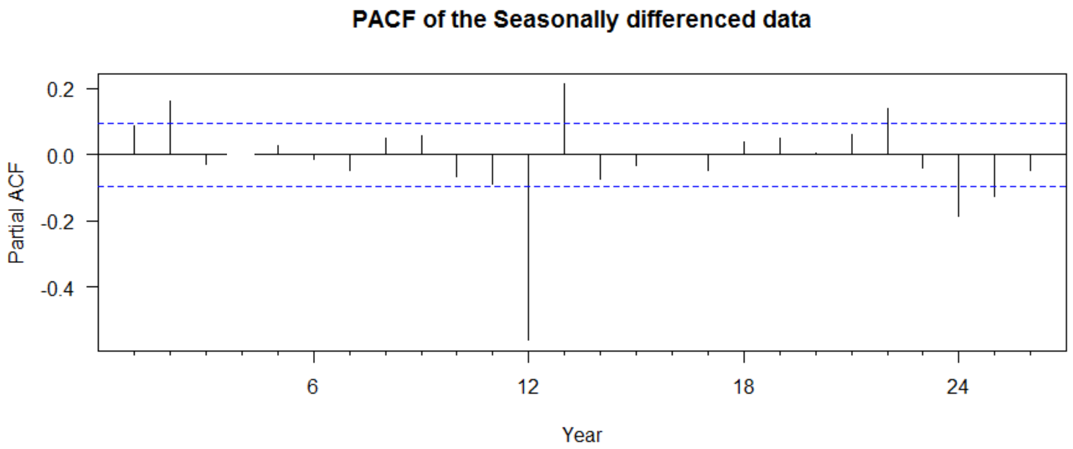

Fig. 6. PACF of the seasonal differenced data

Fig. 6 provides the PACF of the seasonal differenced data. From the figure, there are perhaps two significant spikes in the non-seasonal lags of the PACF. This suggests a non-seasonal AR(2) model. Two significant spikes are seen at seasonal lags 12 and 24. This suggests a seasonal AR(2) model. Hence, this initial analysis suggests that a possible model for the data is SARIMA(2,0,3)(2,1,2) [12].

Table 3. Different combinations of SARIMA models by several metrics

SARIMA Model	AIC	AICc	RMSE
(2,0,3)(2,1,2)[12]	3812.48	3813.02	21.28065*
(2,0,3)(2,1,1)[12]	3814.45	3814.89	21.28065
(2,0,2)(1,1,1)[12]	3826.38	3826.65	21.86938
(2,0,2)(2,1,2)[12]	3812.70	3813.05	21.37913
(2,0,1)(1,1,1)[12]	3823.80	3824.01	21.85137
(2,0,1)(1,1,2)[12]	3811.29	3811.56	21.36171
(2,0,1)(2,1,2)[12]	3808.98	3809.34	21.29681
(2,0,1)(2,1,1)[12]	3810.85	3811.12	21.38643
(2,0,0)(2,1,1)[12]	3808.87	3809.08	21.38811

SARIMA Model	AIC	AICc	RMSE
(2,0,0)(2,1,2)[12]	3807.01*	3807.28*	21.29797
(2,0,0)(0,1,3)[12]	3809.89	3810.09	21.42644
(2,0,0)(0,1,4)[12]	3811.25	3811.52	21.42378
(2,0,0)(1,1,3)[12]	3808.14	3808.41	21.34269
(2,0,0)(1,1,2)[12]	3809.29	3809.49	21.36386
(1,0,3)(1,1,1)[12]	3825.74	3826.01	21.85181
(1,0,3)(1,1,2)[12]	3813.26	3813.61	21.36011
(1,0,2)(1,1,1)[12]	3823.72	3823.92	21.85053
(1,0,2)(1,1,2)[12]	3811.27	3811.54	21.36358
(1,0,3)(1,1,0)[12]	3879.83	3880.03	23.69538
(1,0,3)(1,1,3)[12]	3812.15	3812.59	21.34300
(1,0,3)(2,1,1)[12]	3812.78	3813.13	21.38640
(1,0,1)(2,1,1)[12]	3810.49	3810.69	21.42769
(1,0,1)(1,1,1)[12]	3824.38	3824.52	21.92029
(1,0,1)(2,1,2)[12]	3807.64	3807.91	21.31130

**The minimum of AIC, AICc and RMSE*

The model SARIMA(2,0,3)(2,1,2)[12], along with some variations of it are fitted and their accuracy measures (AIC, AICc and RMSE) are computed as seen in Table 3. Of these models, SARIMA (2,0,0)(2,1,2)[12] proves to be the best model, as it has the minimum of AIC, AICc and RMSE.

Table 4. SARIMA (2,0,0)(2,1,2)[12] compared with its alternative models: Box-pierce residual test

SARIMA Model	AIC	AICc	MASE	p-value
(2,0,0)(2,1,2)[12]	3807.01	3807.28	0.7173631	0.9821
(2,0,0)(2,1,1)[12]	3808.87	3809.08	0.7257475	0.9792
(2,0,0)(1,1,3)[12]	3808.14	3808.41	0.7172852	0.9826
(2,0,1)(2,1,1)[12]	3810.85	3811.12	0.72583	0.9912*
(1,0,1)(2,1,2)[12]	3807.64	3807.91	0.7149352	0.9034

**the residuals from this model best resemble white-noise*
The best model (fit) has the highest p-value

Based on the above comparative analysis (Table 4), the SARIMA(2,0,1)(2,1,1)[12] model is now the best (final) model to be fitted to the monthly rainfall data.

4.3 Estimation of model parameters

Table 5. Parameter estimate for SARIMA(2,0,1)(2,1,1)[12]

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
AR(1)	0.1012	0.4032	0.2963	0.7670
AR(2)	0.1252	0.0827	1.3892	0.1648
MA(1)	0.0511	0.4061	0.0930	0.9259
SAR(1)	0.0318	0.0581	0.6317	0.5276
SAR(2)	0.221	0.0568	3.9732	7.092e-05 ***
SMA(1)	-0.9373	0.0383	-27.5131	<2.2e-16 ***
Sigma ^2 estimated as 477.3		Log likelihood= -1898.43		
AIC=3810.85		AICc=3811.12	BIC=3839.13	

*Sig. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Table 5 present the estimate and test of significance of the parameters of SARIMA(2,0,1)(2,1,1)[12]. Only SAR(2) and SMA(1) are significant.

The model can be written as:

$$(1-B)^d(1-B^{12})^D\varphi(B)\Phi(B)X_t = \theta(B)\Theta(B)\varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where d (non-seasonal difference) = 0, and D (seasonal difference) =1.

Substituting the model parameters give rise to:

$$(1-B^{12})(1+\varphi_1 B)(1+\varphi_2 B)(1+\Phi_1 B^{12})(1+\Phi_2 B^{12})X_t = (1+\theta_1 B)(1-\Theta_1 B^{12})\varepsilon_t$$
$$(1-B^{12})(1+0.1012B)(1+0.1252B)(1+0.0318B^{12})(0.221B^{12})X_t = (1+0.0511B)(1-0.9373B^{12})\varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

4.4 Model diagnostic checks

ACF, PACF and Residuals plot

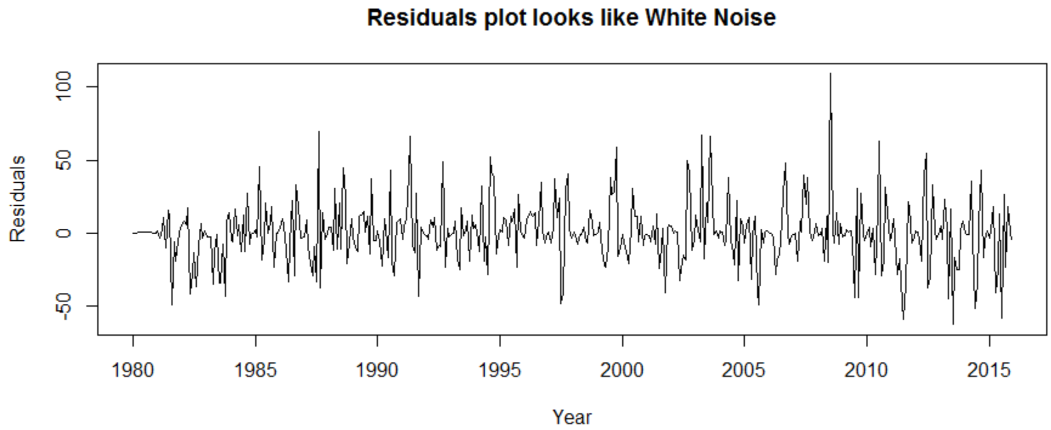

Fig 7. Residuals plot of SARIMA (2,0,1)(2,1,1) [12]

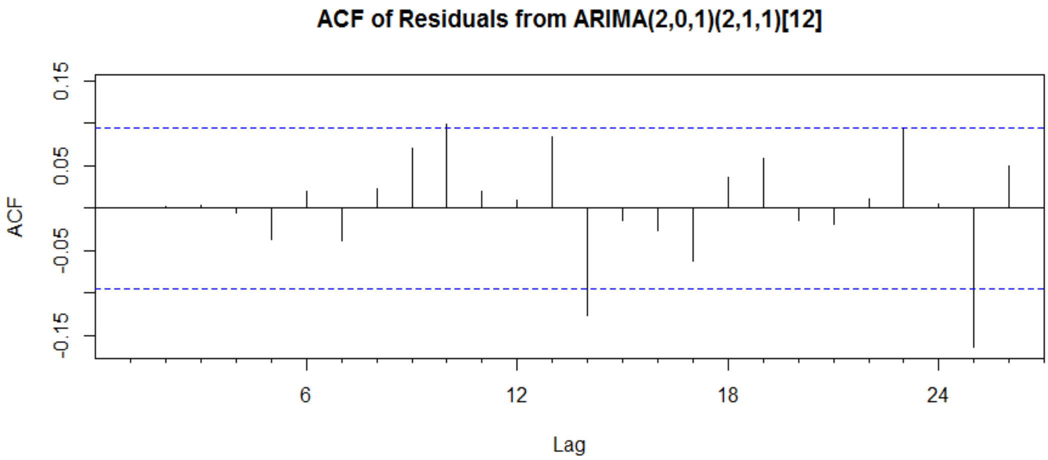

Fig. 8. ACF of residuals

The plot of residuals from SARIMA(2,0,1)(2,1,1)[12] (Fig. 7) shows the residuals look similar to the original rainfall series and are approximately stationary. This shows that the fitted model is doing good. The ACF of the residuals is presented in Fig. 8. The aim is to keep the spikes within the confidence limit. From the plot, only two significant spikes at the non-seasonal lags, hence the fitted SARIMA (2,0,1)(2,1,1)[12] provides adequate information about the rainfall data. Also, from the PACF of the residuals (Fig. 9), there are no significant spikes at the seasonal lags, this shows that the seasonal effect has been taken care of by the fitted model. Only two significant spikes at the non-seasonal lags, and this residuals PACF plot looks similar to the ACF plot, this shows that the model is good.

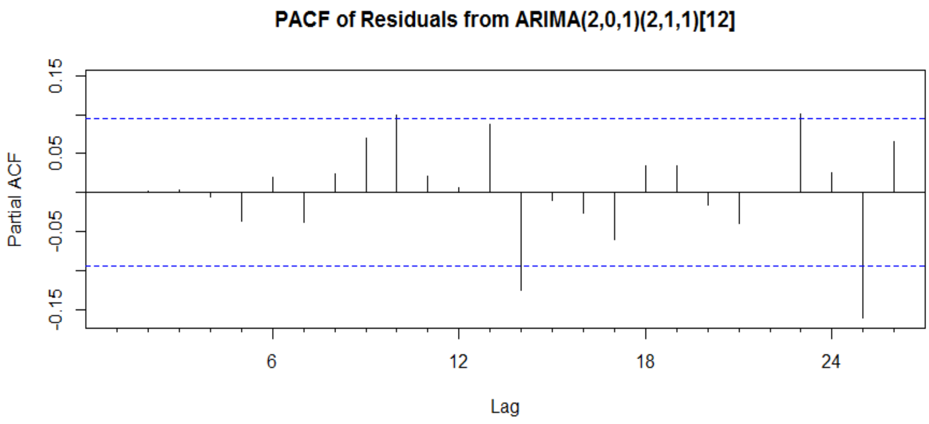

Fig. 9. PACF of residuals

Box-Pierce test

Table 6. Box-pierce test of residuals

Box-Pierce test		**data: residuals(fit)**
X-squared = 0.00012182,	df = 1,	p-value = 0.9912

The P-value indicates there is no evidence that the residuals are dependent. This further confirms that the SARIMA(2,0,1)(2,1,1)[12] is adequate. If the P-value was below about 0.05, there would be some cause for concern: it would imply that the terms in the ACF are too large to be a white noise.

4.5 Normality of residuals

Residuals have been assumed to be normally distributed if the model is truly adequate. Fig. 10 shows the Q-Q plot of residuals from SARIMA(2,0,1)(2,1,1)[12]. If the residuals do have a normal distribution, the points in the plot will lie close to the diagonal line. Which they are, hence the residuals are normally distributed. The histogram of residuals (Fig. 11) confirms this. It shows clearly that the residuals are normally distributed and there is only one obvious outlier. Thus, SARIMA(2,0,1)(2,1,1)[12] fits the rainfall data and is appropriate for forecasting future monthly rainfall in Nigeria.

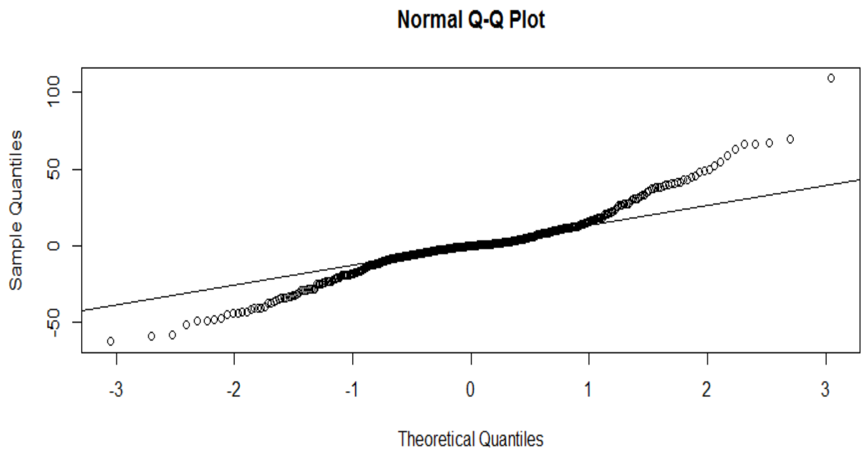

Fig. 10. Q-Q plot of residuals

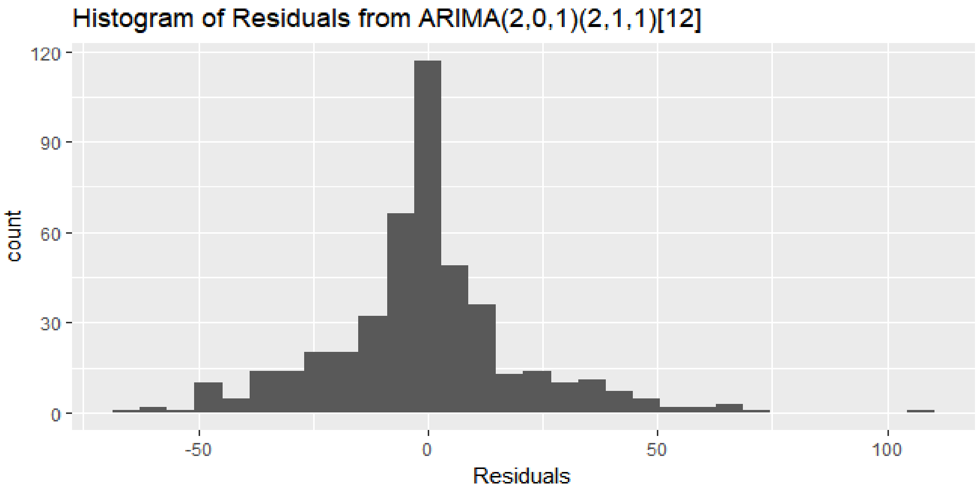

Fig. 11. Histogram of residuals

4.5 Forecasting

Appendix I provides the seventy-two (72) month forecast from SARIMA(2,0,1)(2,1,1)[12] with 95% confidence intervals. It shows that the month of April is the onset of rainfall in Nigeria while the month of November is the period of retreat. The month of August is a month at which Nigeria experiences its highest rainfall. Rainfall values are approximately equivalent throughout 2018-2021.

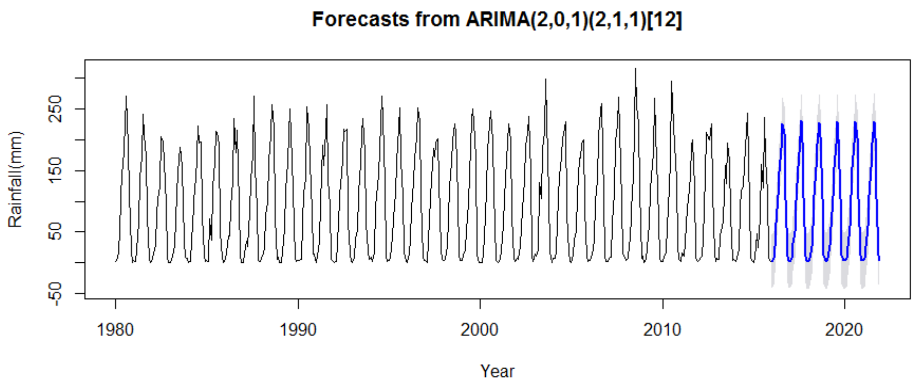

Fig. 12. Rainfall series with forecast from SARIMA(2,0,1)(2,1,1)[12]

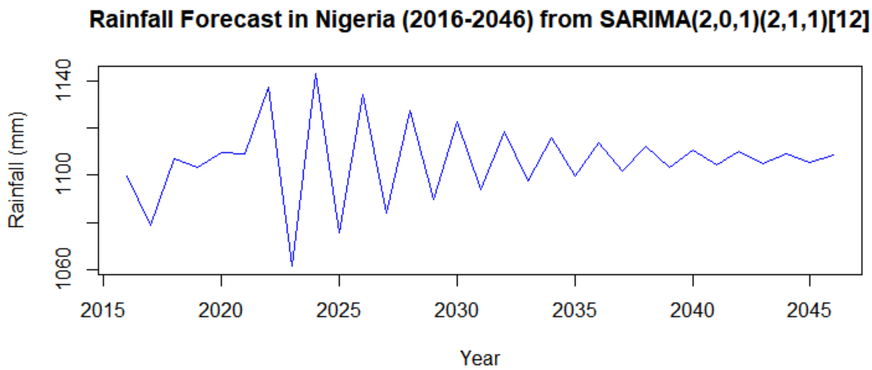

Fig. 13. Rainfall forecast in Nigeria (2016-2046) by SARIMA(2,0,1)(2,1,1)[12]

4.6 Discussion

Decomposition of the Nigerian rainfall series shows an early decline in rainfall amount between 1980-1984. This supports the findings of Olaniran & Summer [6,7], where they found that there was a progressive early decline of rainfall over the country. Following the pattern, they reported a noticeable and significant decline of rainfall frequency in September and October which coincide with the end of rainy season in almost every parts of the country especially in the Northern and Central parts of Nigeria. However, Odjugo [12] using rainfall data from 28 stations in the Northern and Southern Nigeria between 1970 and 2002 observed general decrease in the amount of rainfall in other stations apart from the coastal areas in the south with increasing rainfall. In this present study, there was no consistent trend (upward or downward) over the study period (1980-2015). Rainfall values have been approximately stable between 1990 to 2003 and raised at 2004, which recorded the highest rainfall year in the entire period. The amount of rainfall decreased till 2006. In this study, the month of April (4) was seen as the period of onset of rainfall while the month of November (11) was observed as the period of retreat. This agrees with the findings of Igwenagu [13] in Enugu state. Also, from this study, Nigeria will experience approximately equal amount of rainfall between 2018 to 2021 and experience a slight increase in rainfall by 2022 to about 1137.078 (mm). In 2023, Nigeria will experience a serious decline in rainfall to about 1061 (mm). Rainfall values will increase again to about 1142.756 in 2024, where it will continue to raise and fall yearly with decrease in variation over the years and achieve stationarity at around 2042 with approximately 1110.00 (mm) up to 2046.

5 Conclusion and Recommendations

5.1 Conclusion

In this study, Nigerian monthly rainfall data from 1980-2015 was analyzed to identify the best seasonal ARIMA (SARIMA) model to forecast future rainfall in Nigeria. From the results, there was no consistent trend (upward or downward) over the entire time span. SARIMA$(2,0,1)(2,1,1)_{[12]}$ was the best model that fit the data, with the maximum p-value from Box price test. The month of April was seen as the period of onset of rainfall with August the month of peak rainfall while the month of November was observed as the period of retreat. The delay in rainfall till April will force the nomads and peasant farmers to engage in indiscriminate burning of bushes thereby causing deforestation and environmental degradation over the country. The high rainfall amounts in August might have serious agricultural implications as some crops planted during this month will be unfavourably affected by heavy rainfall. Nigeria will experience approximately equal amount of rainfall between 2018 to 2021 and experience a slight increase in rainfall by 2022 to about 1137.078 (mm). In 2023, Nigeria will experience a serious decline in rainfall to about 1061 (mm). Rainfall values will raise again to about 1142.756 in 2024, where it will continue to rise and fall yearly with a decrease in variation over the years and achieve stationarity at around 2042 with approximately 1110.00 (mm) up to 2046.

5.2 Recommendations

Based on the findings of this research, the followings are recommended:

(i). The anticipation of the findings in this research by government, agro-business managers and farmers in Nigeria as guideline for policy making and investment decisions.
(ii). Government should provide more mechanized and dry farming methods to ease the outage of rainfall in future that may be caused due to natural (or unpredictable) variation.

Competing Interests

Authors have declared that no competing interests exist.

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APPENDIX I

Seventy-two (72) month ahead forecast for the monthly rainfall data

Month-Year	Forecast	Lo.95	Hi.95	Month-Year	Forecast	Lo.95	Hi.95
Jan-2016	2.583992	-40.2553	45.4233	*Jan-2019*	3.143881	-42.7735	49.06131
Feb-2016	7.392008	-35.9413	50.72535	*Feb-2019*	7.971985	-37.9495	53.8935
Mar-2016	26.2666	-17.4831	70.01633	*Mar-2019*	27.88017	-18.0448	73.80516
Apr-2016	64.66374	20.89077	108.4367	*Apr-2019*	57.4612	11.53602	103.3864
May-2016	110.2884	66.50619	154.0706	*May-2019*	107.6366	61.71138	153.5619
Jun-2016	148.2028	104.4198	191.9858	*Jun-2019*	155.3967	109.4714	201.322
Jul-2016	185.4803	141.6971	229.2635	*Jul-2019*	191.973	146.0478	237.8983
Aug-2016	225.4559	181.6726	269.2392	*Aug-2019*	228.7175	182.7922	274.6427
Sep-2016	210.4882	166.7049	254.2715	*Sep-2019*	200.9721	155.0468	246.8973
Oct-2016	102.16	58.37676	145.9433	*Oct-2019*	104.533	58.6077	150.4582
Nov-2016	11.72204	-32.0612	55.50526	*Nov-2019*	11.91201	-34.0132	57.8372
Dec-2016	3.647785	-40.1354	47.43094	*Dec-2019*	3.674312	-42.2508	49.59941
Jan-2017	2.687715	-41.2834	46.65882	*Jan-2020*	3.237849	-43.0208	49.49646
Feb-2017	8.089342	-35.8862	52.06486	*Feb-2020*	7.918459	-38.3479	54.18487
Mar-2017	31.28023	-12.699	75.2595	*Mar-2020*	26.94519	-19.3279	73.21824
Apr-2017	51.52661	7.547121	95.50609	*Apr-2020*	59.27097	12.99755	105.5444
May-2017	101.4896	57.51001	145.4691	*May-2020*	109.3163	63.0427	155.5898
Jun-2017	155.8914	111.9118	199.871	*Jun-2020*	154.9786	108.705	201.2521
Jul-2017	179.147	135.1675	223.1266	*Jul-2020*	194.9901	148.7165	241.2637
Aug-2017	230.0651	186.0855	274.0447	*Aug-2020*	228.2406	181.967	274.5142
Sep-2017	195.429	151.4495	239.4086	*Sep-2020*	202.7755	156.5019	249.0491
Oct-2017	105.9197	61.94014	149.8993	*Oct-2020*	104.0821	57.80853	150.3557
Nov-2017	11.47451	-32.505	55.45403	*Nov-2020*	12.0162	-34.2573	58.28969
Dec-2017	3.358884	-40.6206	47.33834	*Dec-2020*	3.753908	-42.5195	50.02731
Jan-2018	3.107591	-42.5634	48.77861	*Jan-2021*	3.248861	-43.1754	49.67314
Feb-2018	7.826212	-37.8834	53.53579	*Feb-2021*	7.948978	-38.4789	54.37684
Mar-2018	26.91095	-18.8314	72.65334	*Mar-2021*	27.12968	-19.3012	73.56061
Apr-2018	60.09258	14.34834	105.8368	*Apr-2021*	58.7469	12.31581	105.178
May-2018	109.3321	63.58709	155.077	*May-2021*	108.9949	62.56379	155.4261
Jun-2018	153.7648	108.0198	199.5099	*Jun-2021*	155.326	108.8948	201.7572
Jul-2018	192.9343	147.1892	238.6793	*Jul-2021*	194.8737	148.4425	241.3048
Aug-2018	227.7716	182.0265	273.5166	*Aug-2021*	228.4345	182.0033	274.8657
Sep-2018	204.0273	158.2822	249.7723	*Sep-2021*	202.1575	155.7263	248.5887
Oct-2018	103.7703	58.02525	149.5153	*Oct-2021*	104.2364	57.80519	150.6675
Nov-2018	11.95154	-33.7934	57.69651	*Nov-2021*	12.01077	-34.4203	58.44186
Dec-2018	3.726475	-42.0184	49.47135	*Dec-2021*	3.74491	-42.6861	50.1759

Source: forecast by SARIMA(2,0,1)(2,1,1)[12] from R-output

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