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Full Length Research Paper

Analysis of Forty Three Years Rainfall Distribution Pattern as a Guide for the Enhancement of Water Usage and Agricultural Production in North–Central Nigeria.

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Abstract
The year to year variation in agricultural yield in North Central part of Nigeria is majorly caused by rain, this is because larger percentage of the agricultural practices in that region is supported by rain i.e. rainfed agriculture. Rain schedule in this region is very unstable, especially with the present global climatic change. In this study, a monthly rainfall data from Ilorin Meteorological Station (Air Port) was analyzed to formulate appropriate model for prediction of monthly rainfall. ARIMA (1, 0, 1)(0, 1, 1)^{12} was found to be the appropriate model for the forecast. Although, the model could not accurately capture the peak monthly rainfall forecast as it reflects in fig. 9, however, it does give an ample information that can help decision makers establish strategies, priorities and proper use of water (rainfall) resources for North-Central Nigeria.

Key words: *Time series analysis, Autoregressive Integrated Moving Average (ARIMA), Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), Mean Annual Rainfall (MAR) and Rainfed agriculture.*

Introduction

North-Central Nigeria is predominantly savannah in nature, this is evidence with tall grasses and sparse trees regime that most times cluster only along the river banks. The rainfall pattern is humanly unpredictable as it's completely dynamic in nature, for instance the rainfall of August, 2008 that flooded Ilorin and it environ only repeated itself in September, 2010 but this time with heavy storm that destroyed places, which may likely occur soon or not in the next ample of years (Manta et al., 2010), this was further highlighted by Mackenzie et al. 2013, who described rainfall of a given intensity for a defined duration as an event which may have relative number of occurrences in a long period of events. The probability of a defined rainfall event can therefore be determined by the number of times rainfall events occur in the total number of occurrences.

Nigerian agricultural system mainly depend on rainfall; this is because more than 90% of its agriculture practices are rainfed, this implies, that the dynamic nature of the rainfall pattern will definitely have negative effect on the general agricultural system and by extension infringing negative effect on the economy of the nation, being the largest employer of labour of about 95% of the total labour force.

However, the climatic factors that are the only determinant for good yield in crop production are rainfall and soil moisture content. However, agriculturally developed countries that have long-time climatic data and experiences base their agricultural practices on those data with little or no problem (Manning, 1956); which is unlike with underdeveloped nations like Nigeria that mostly operate base on means of rainfall or total of means which does not agree with the convectional type of rainfall experienced in the country, this system of rainfall has high variability and can easily mislead farmers.
Though, Adugna (2005) have it that, the degree of yield variability over time is changed not only by the amount of rainfall, but also by the pattern and frequency of the rainfall cycle, thereby toning agriculturist believe towards the quantity of rainfall received by a place at given time which should determine the type of agricultural practices the rain can support successfully. This study attempts to show patterns of rainfall and provide insight into the preparation of an early warning system in the region, using time series analysis techniques model to see the pattern of rainfall and response of yield to rainfall as well as to previous yield shocks.

Materials and Methods

Study Area
This study was carried out in Kwara State, being one of the North-Central states of Nigeria. This part of the country occupies an approximate area of about 730,855km^2, lying between longitude 3^{0}E and 15^{0}E, and latitude 6^{0}N and 14^{0}N. The vegetation is completely savannah; a total grass land with sparse trees which only cluster along the river banks. Dual season of rainy and dry

period are experienced (Manta et al. 2010). The extend of dry period increases as you move northward, an average rainfall that ranges from 1200mm to 2500mm is experienced annually, with low humidity and a high temperature especially during dry season, except at the plateau areas (Met. Report, 2009). The major source of livelihood and occupation of the people in the area is farming. Farming is traditional in nature with emphasis on the cultivation of crops such as sorghum, cassava, yam, maize and melon (KWSMI, 2002, Mohammed, 2008).

Methodology

Time series analysis was taken for the study due to convectional type of rainfall experienced in this country, statistical analysis were run and various graph drawn. These together show the rainfall pattern for better utilization in terms of farming and other forms of rainfall applications.

Time Series Analysis of Monthly Rainfall

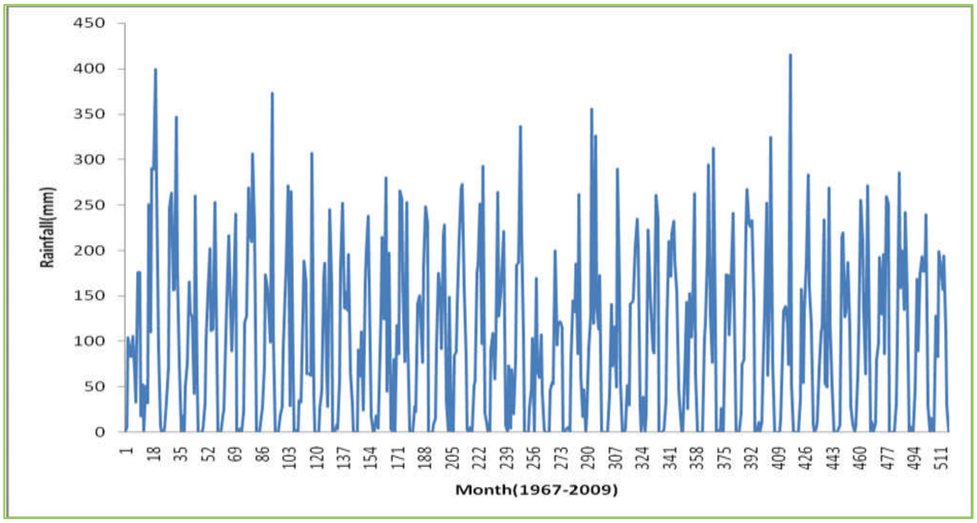

Fig 1: A time plot of mean monthly rainfall from January 1967 to December 2009

Figure 1 above has a characteristics movement of time series such as seasonality, a cyclical movement and or random components. What is not obvious is the long term trend. However, both suspected and unsuspected components shall be investigated during the decomposition of the series.

A typical time series data is assumed to contain at most four components, namely; long term trend (Tt), seasonal component (St), cycles (Ct) and irregular or random component or otherwise called white noise (It)

These components could be additive and in which case is defined as:

$$Y_t = T_t + S_t + C_t + I_t \qquad (1)$$

Or multiplicative, in which case is defined as

$$Y_t = T_t * S_t * C_t * I_t \qquad (2)$$

Where Y_t is rainfall (mm)

Sometimes the trend and the cycles are built together or inseparable or better still the model is believed to have no long term trend associated with the data. If this is the case, we then have what we called trend-cycle model and therefore equation 1 and 2 above can be re-written as

$$Y_t = M_t + S_t + I_t \qquad (3)$$

$$Y_t = M_t * S_t * I_t \qquad (4)$$

The justification as to which model above is appropriate to use and when is dependent on some criteria, investigations and or requirements to be met by the data in question. However an investigation using both autocorrelation and spectral density confirm the presence of seasons and revealed that the use of additive model is appropriate as far as descriptive time series is concern.

Seasonal Decompositions

The Seasonal Decomposition procedure decomposes a series into a seasonal component, a combined trend and cycle component, and an "error" component. The procedure is an implementation of the Census Method I, otherwise known as the ratio-to-moving-average method. This method will produce four outputs as follows;

SAF. Seasonal Adjustment Factors. These values indicate the effect of each period on the level of the series.

SAS. Seasonally Adjusted Series. These are the values obtained after removing the seasonal variation of a series.
STC. Smoothed trend-cycle components. These values show the trend and cyclical behaviour present in the series.
ERR(I). Residual or "error" Values. The values that remain after the seasonal, trend, and cycle components have been removed from the series.

Using SPSS syntax, the data is decomposed into its various components as seen in Table 1. The seasonal adjustment factor (SAF) is given below;

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SAF	-92.27	-88.59	-55.93	-0.01	59.15	84.05	52.54	43.08	132.91	43.01	-86.99	-90.95

If this SAF is subtracted from the original data, the result is called seasonally adjusted data or series (SAS), that is to say that seasonal trend has been removed. This is equivalent to subtracting S_t from both side of Equation 1 above.

We thus have $Y_t - S_t = T_t + C_t + I_t$ (5)

This was done to give room for emergence of other components present in the data and the result plotted to re-examine it as seen in figure 2.0

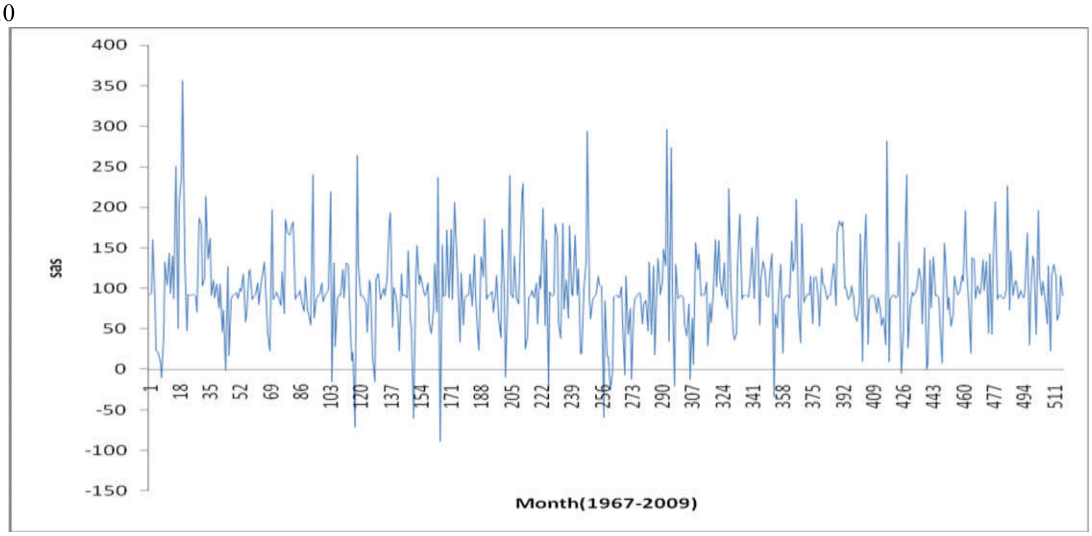

Fig 2: The plot of the seasonally adjusted data (SAS).

The figure above shows some presence of possible cycles and random components and probably long term trend pattern. Again we can adjust the data for cycle and random or irregular component pattern by removing the trend estimated by least square line ($Y_t = 98.737 - 0.001X_t$) from the seasonally adjusted equation 5 above.

i.e $Y_t - T_t - S_t - C_t + I_t$ (6)

The result is graphed and re-examined below.

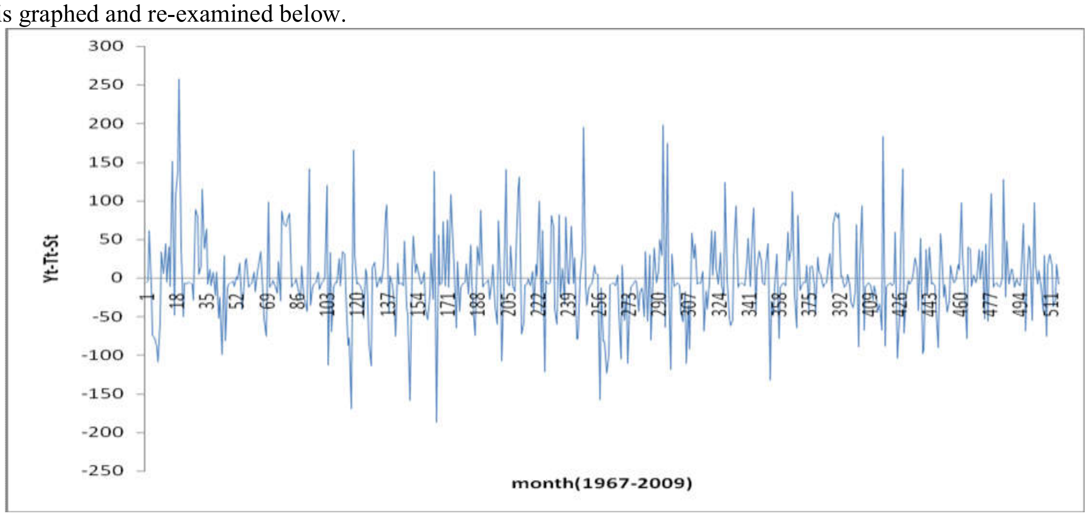

Fig 3: The plot of the de-trended de-seasonalized data

Figure 3 above is theoretically compost only of cyclic and irregular movements C_t and I_t. A moving average of order 7 was used to smooth out the random or the irregular components as shown in figure 4 below. A cycle was observed between 1970 and 1995, about 25 years apart.

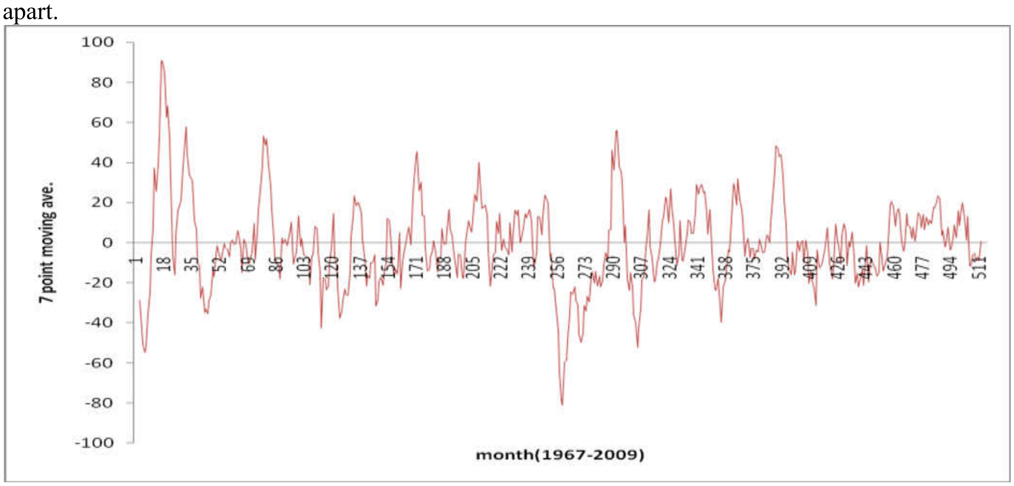

Fig. 4 The plot of the cycles

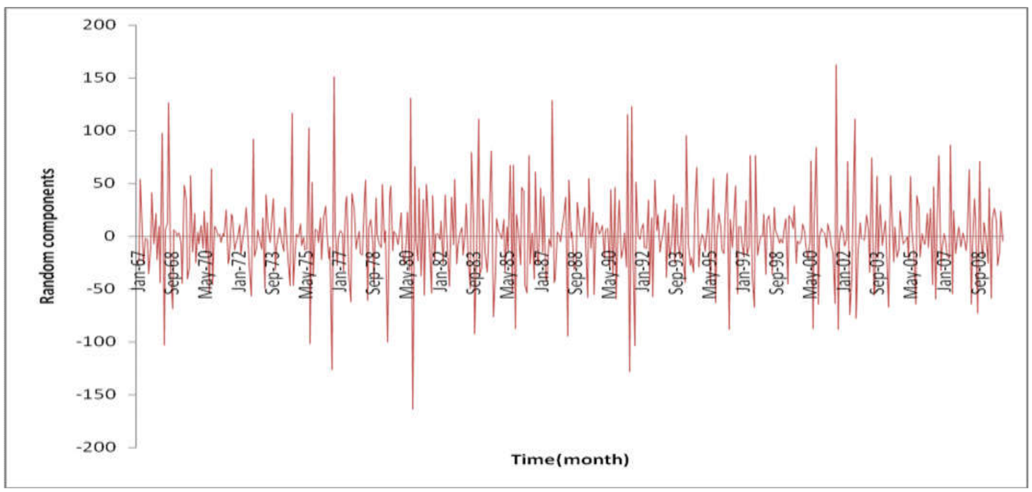

Fig 5: The random component (I_t) present in the series.

Lastly, figure 5 shows random or error component which is the only component remaining in the series. An astute observer will discover that the component is truly random because the peak and the trough cancel out.

ARIMA Model

Many methods and approaches for formulating forecasting models are available in literature. This study exclusively deals with time series forecasting model, in particular, the Autoregressive Integrated Moving Average (ARIMA). These models were described by Box and Jenkins (1976) and further discussed in some other resources such as Walter (1983).

The Box-Jenkins approach possesses many appealing features. It allows the manager who has only data on past years' quantities, rainfall as an example, to forecast future ones without having to search for other related time series data, for example temperature. Box-Jenkins approach also allows for the use of several time series, for examples rainfall, if these other time series data are correlated with a variable of interest and if there appears to be some cause for this correlation.

The general model introduced by Box and Jenkins includes autoregressive and moving average parameters as well as differencing in the formulation of the model. The three types of parameters in the model are: the autoregressive parameters (p), the number of differencing passes (d) and the moving average parameter (q). Box-Jenkins model are summarized as ARIMA (p, d, q). For example, a model described as ARIMA (1, 1, 1) means that this model contains 1 autoregressive (p) parameter and 1 moving average (q) parameter for the time series data after it was differenced once to attain stationary.

In addition to the non-season ARIMA (p, d, q) model introduced above, we could also identify seasonal ARIMA (P, D, Q) parameters for our data. These parameters are: Seasonal autoregressive (P), seasonal Differencing (D) and seasonal moving average (Q). For example, ARIMA $(1, 1, 1)(1, 1, 1)^{12}$ describe a model that includes 1 autoregressive parameter, 1 moving average parameter, 1 seasonal autoregressive parameter and 1 seasonal moving average parameter. These parameters were computed after the series was differenced once at lag 1 and differenced once at lag 12.

The general form of the above Box-Jenkins ARIMA model describing the current value Xt of time series by its own past is:

$$(1-\varphi_1 B)(1-\alpha_1 B^{12})(1-B)(1-B^{12})X_t = (1-\theta_1 B)(1-\gamma_1 B^{12})e_t \quad (7)$$

Where;

$1-\varphi_1 B$= Non seasonal autoregressive of order 1

$1-\alpha_1 B^{12}$= Seasonal autoregressive of order 1

B= The backward shift operator $BX_t = X_{t-1}$

$1-B$=1st order nonseasonal difference

$1-B^{12}$= Seasonal difference of order 1

$1-\theta_1 B$= Non seasonal moving average of order 1

$1-\gamma_1 B^{12}$= Seasonal moving average of order 1

e_t= The random or residuals or the expected white noise.

This model can be multiplied out and used for forecasting after the model parameter were estimated as shall be seen in subsequent sections.

Model Identification

The ARIMA model of a time series is defined by three terms (p, d, q). Identification of a time series is the process of finding integer, usually very small (e.g., 0, 1, or 2), values of p, d, and q that model the patterns in the data. When the value is 0, the element is not needed in the model. The middle element, d, is investigated before p and q. The goal is to determine if the process is stationary and, if not, to make it stationary before determining the values of p and q. Recall that a stationary process has a constant mean and variance over the time period of study.

The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) are the most important element of time series analysis and forecasting. The ACF measures the amount of linear dependence between observations in a time series that are separated by a lag k. The PACF plot helps to determine how many auto regressive terms are necessary to reveal one or more of the following characteristics: time lags where high correlations appear, seasonality of the series, trend either in the mean level or in the variance the series. If either an autocorrelation or a partial autocorrelation between observations k lags apart is statistically significant, the autocorrelation is included in the ARIMA model. The significance of an autocorrelation is evaluated from the 95% confidence intervals printed along it, or from the t distribution where the autocorrelation is divided by its standard error, or from the Box-Ljung statistic.

Diagnosing a Model

How well does the model fit the data? Are the values of the observations predicted from the model close to actual ones?
If the model is good, the residuals (differences between actual and predicted values) of the model are a series of random errors. These residuals form a set of observations that are examined the same way as any time series.
ACFs and PACFs for the residuals of the model are examined. As recommended by Pankrantz (1983), if the residuals represent only random error, the absolute value of t ($t = r_t/SE_r$) for autocorrelations at each of the first three lags should be less than 1.25 and for later lags less than 1.60. However, as McCain and McCleary (1979) point out, if there are many lags (say, 30 or more) one or two of the higher-order lags may exceed these criteria by chance even if the residuals are essentially random. If the residuals represent only random error, there should be no sizeable full and autocorrelations remaining in the data. All of the autocorrelations should fall within their 95% confidence intervals, and the criteria proposed by Pankrantz should be met. It is then we can say that the model is representative of our data.

Forecasting

Forecasting refers to the process of predicting future observations from a known time series and is often the major goal in non-experimental use of the analysis. Based on the known patterns in the data, what is the predicted value of observations in the near future? For example, based on previous patterns in the data, is the quantity of total monthly rainfall likely to increase or decrease in the preceding years. However, prediction beyond the data is to be approached with caution.

Results and Discussion

Since the data is a monthly rainfall, Fig. 1. shows that there is a seasonal cycle of the series and the series is not stationary. The ACF and PACF of the original data as shown in Fig. 6 also give credence to the fact that the series is not stationary. In order to fit an ARIMA model, stationary data in both variance and mean are needed. We could attain stationary in both the variance and the mean by having log transformation and differencing of the original data respectively. For our data, we need to have seasonal first difference, d=1, of the data in order to have stationary series. We would then test the ACF and PACF for the difference series to check for stationary.

As shown in Fig. 7, the ACF and PACF for the differenced and de-seasonalized rainfall data are almost stable which support the assumption that the series is stationary in both the mean and the variance after having 1st order seasonal difference. Therefore, an ARIMA (p, d, q)(P, 1, Q) could be identified for the differenced and de-seasonalized rainfall data. After ARIMA model was identified above, the p, q, P and Q parameters need to be identify for our model.

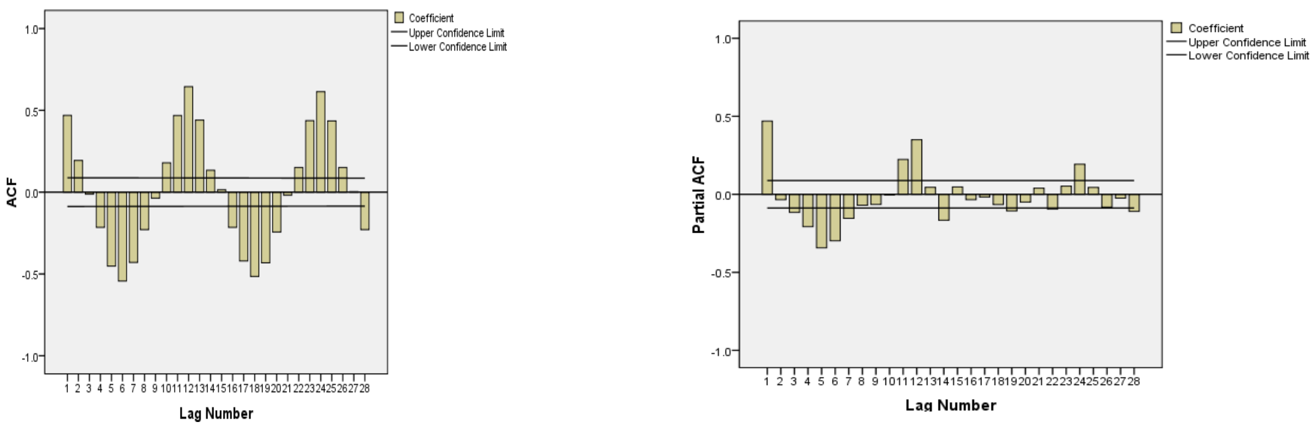

Fig. 6: ACF and PACF of the original data

In Fig. 7, we have one autoregressive (p) and one moving average (q) parameters and the ACF has exponential decay starting at lag 12. Similarly, the PACF has an exponential decay starting at lag 12. There was also a negative autocorrelation at the seasonal period (lag 12), so we consider adding SMA (seasonal moving average) to our model. These patterns suggest that we have ARIMA (1, 1) for non-seasonal and ARIMA (0, 1) for seasonal rainfall data. Since we identified the first order seasonal difference for the rainfall data, our tentative model will be ARIMA $(1, 0, 1)(0, 1, 1)^{12}$. In order to make surethat our model is representative for our data and could be used to forecast the upcoming rainfall data, we need to test the Autocorrelation function (ACF) and the Partial Autocorrelation function (PACF) for the residual errors resulted from fitting such model for our data. Fig. 8 shows the residual errors for the ARIMA fitted model. It is clear that no pattern was observed in the residual errors which show that the model could be used to represent our data.

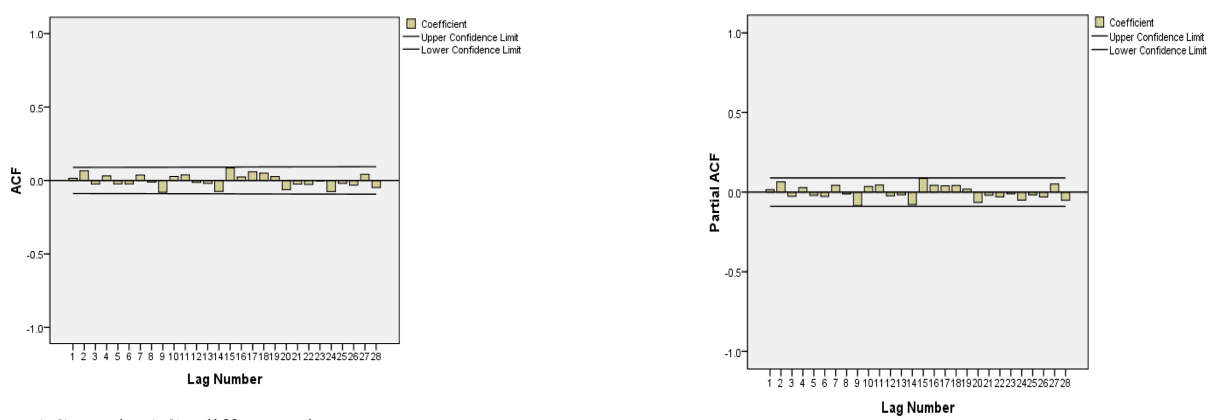

Fig. 7: ACF and PACF difference between

Also, as recommended by Pankrantz (1983), the absolute values of the t (t_r/SE_r) for the autocorrelations of the residuals created from our tentative ARIMA model were all less than 1.25. The Box-Ljung statistics were also not significant. This means that the ACFs are not significantly different from zero.

Next, we estimate the parameters values for our model as shown in Eq. 2. As a rule of thumb, in ARIMA modelling we need to minimize the sum of squared of residuals between the forecasted and existing values.

$$(1-\varphi_1 B)(1-B^{12})X_t = (1-\theta_1 B)(1-\gamma_1 B^{12})e_t \quad (8)$$

The sum of squared of residuals for the model was 1928000 while the adjusted residual sum of squared was 1670000 and the parameters values estimated are as shown in Table 2. All the parameters appear to be significant at 5% level since their approx.

sig. values are less than 0.05. Comparing their t- statistics value with the value of $t_{0.05}$ (513) =1.645 (516 is the length of the time series minus the number p, q, Q parameters), corroborates the earlier conclusion.

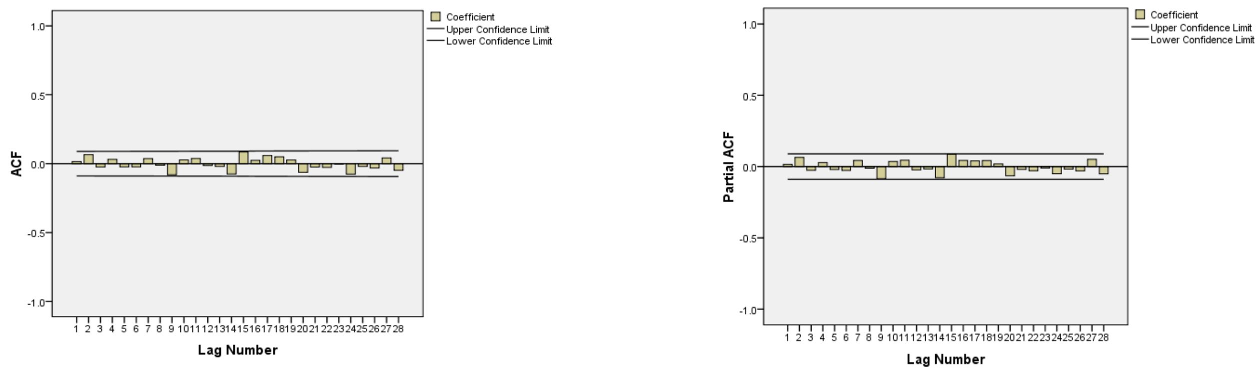

Fig. 8: Shows the residual errors for the ARIMA

Table 2: ARIMA (1, 0, 1)(0, 1, 1)12 model parameter characteristics

Parameter	Estimates	Std Error	t	Approx Sig
φ_1	.780	.312	2.498	.013
θ_1	.742	.332	2.236	.026
γ_1	.923	.035	26.392	.000

Finally, this conclude that ARIMA $(1, 0, 1)(0, 1, 1)^{12}$ model identified is adequate to represent our data and could be used to forecast the upcoming rainfall data.

After the model parameters were estimated, they would be used to forecast the upcoming rainfall data. Equation 8 above can be multiplied out and written in a form that is used in forecasting as in Eq. 9:

$$X_t = (1 + \varphi_1)X_{t-12} + \varphi_1 X_{t-1} + e_t - \gamma_1(1 + \theta_1)e_{t-12} - \theta_1 e_{t-1} \quad (9)$$

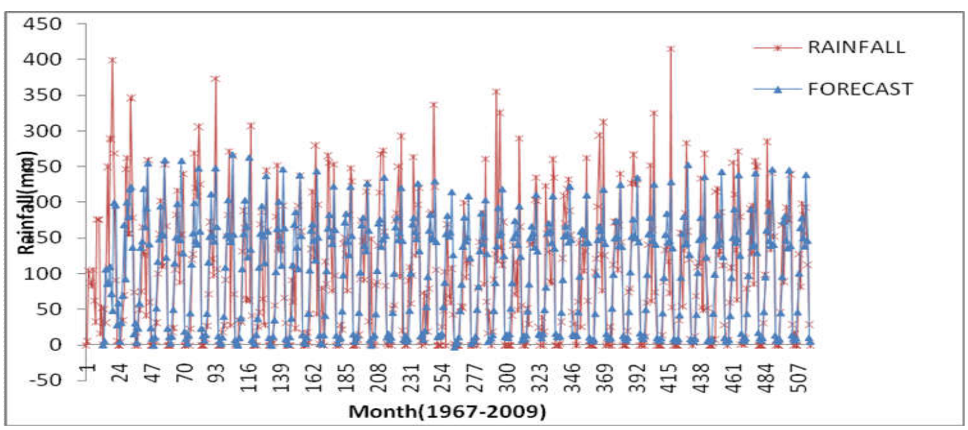

Fig. 9: Real and Simulated (forecasted) values of the overall time series using ARIMA (1, 0, 1)(0, 1, 1)

In Eq. 9, the value of $X_t$could be estimated by substituting the parameter values estimated above. Figure 9, shows a comparison between the real values and the ones resulted from the developed ARIMA model for the overall time series. Obviously the model could not represent the peak values. In addition, it is clear that rainfall pattern continues for the upcoming years. There is no indication that the amount of rainfall will decrease with time.

Conclusion

Time series analysis is an important tool in modeling and forecasting. A monthly rainfall data from Ilorin Meteorological Station (Air Port) was analyzed to formulate appropriate model for prediction of monthly rainfall. ARIMA $(1, 0, 1)(0, 1, 1)^{12}$ was found to be the appropriate model for the forecast. Although, our model could not accurately capture the peak monthly rainfall forecast as was seen in fig. 9 above, however, it does give a piece of information that can help decision makers establish strategies, priorities and proper use of water (rainfall) resources for North-Central Nigeria.

Table 3: ACF AND PACF Error for rainfall from ARIMA (1 0 1)(0 1 1)

Series: Error for rainfall from ARIMA(1 0 1)(0 1 1)

Lag	Partial Autocorrelation	Std. Error	Autocorrelation	Std. Error[a]	Box-Ljung Statistic		
					Value	df	Sig.[b]
1	.015	.045	.015	.045	.116	1	.733
2	.065	.045	.065	.045	2.265	2	.322
3	-.026	.045	-.024	.045	2.556	3	.465
4	.028	.045	.031	.045	3.045	4	.550
5	-.020	.045	-.023	.045	3.305	5	.653
6	-.027	.045	-.023	.045	3.576	6	.734
7	.043	.045	.037	.045	4.287	7	.746
8	-.011	.045	-.011	.045	4.350	8	.824
9	-.086	.045	-.080	.045	7.683	9	.566
10	.036	.045	.028	.045	8.077	10	.621
11	.044	.045	.038	.045	8.809	11	.639
12	-.023	.045	-.014	.045	8.905	12	.711
13	-.016	.045	-.020	.045	9.108	13	.765
14	-.078	.045	-.075	.045	12.005	14	.606
15	.087	.045	.084	.046	15.727	15	.400
16	.043	.045	.024	.046	16.022	16	.451
17	.040	.045	.059	.046	17.817	17	.400
18	.042	.045	.050	.046	19.115	18	.385
19	.018	.045	.027	.046	19.488	19	.426
20	-.065	.045	-.063	.046	21.568	20	.364
21	-.019	.045	-.024	.046	21.879	21	.407
22	-.030	.045	-.027	.046	22.263	22	.444
23	-.010	.045	-.002	.046	22.265	23	.504
24	-.050	.045	-.075	.046	25.288	24	.390
25	-.017	.045	-.020	.047	25.499	25	.435
26	-.030	.045	-.032	.047	26.032	26	.461
27	.051	.045	.042	.047	26.968	27	.466
28	-.051	.045	-.048	.047	28.210	28	.453

a. The underlying process assumed is MA with the order equal to the lag number minus one. The Bartlett approximation is used.
b. Based on the asymptotic chi-square approximation.

Recommendations:
It is recommended that better version software of Time Series or otherwise should be used for better result as the case may be in future research.

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Table 4. Mean monthly and total rainfall for Ilorin, Nigeria

Year/month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
1967	0.00	5.60	104.40	87.40	83.10	105.40	62.20	33.00	176.00	176.00	17.30	52.80	**903.20**
1968	1.30	51.10	31.80	250.20	110.00	290.10	289.10	399.50	269.00	91.20	6.10	0.00	**1789.40**
1969	0.00	4.30	34.80	70.60	246.40	262.90	156.20	156.70	346.70	179.30	74.70	0.00	**1532.60**
1970	18.00	0.00	50.30	75.70	165.40	131.10	126.20	42.40	260.30	60.70	0.00	0.00	**930.10**
1971	0.00	5.90	31.90	100.70	156.10	202.10	111.10	112.60	253.00	166.90	0.00	0.00	**1140.30**
1972	0.00	17.90	24.70	106.40	182.50	216.30	128.90	88.70	155.60	240.10	0.00	0.00	**1161.10**
1973	3.60	0.00	23.00	120.40	128.00	269.20	220.70	208.90	306.20	225.80	0.00	0.00	**1505.80**
1974	0.00	9.40	27.20	72.10	173.00	157.20	121.80	98.60	373.20	106.60	0.00	0.00	**1139.10**
1975	NA	17.90	28.00	91.80	152.90	182.50	271.50	28.70	264.80	71.70	0.50	2.50	**1112.80**
1976	0.00	35.30	33.00	132.20	188.80	164.40	63.50	64.70	62.10	307.40	41.80	0.00	**1093.20**
1977	0.00	0.00	26.00	46.20	169.70	186.40	65.40	28.20	244.70	162.10	0.00	0.00	**928.70**
1978	8.20	3.10	56.50	180.40	252.30	136.20	154.20	133.70	195.90	66.10	31.00	0.00	**1217.60**
1979	0.00	0.00	90.90	61.40	110.30	23.90	165.80	196.20	238.10	160.00	17.50	0.00	**1064.10**
1980	0.00	18.00	3.60	44.40	135.20	214.70	123.80	280.10	44.60	197.30	2.90	1.60	**1066.20**
1981	80.00	0.00	117.70	86.30	265.80	255.80	163.30	76.80	252.90	98.30	0.00	0.80	**1397.70**
1982	0.00	28.90	22.20	141.80	150.60	127.20	76.70	182.50	247.80	229.40	0.00	0.00	**1207.10**
1983	0.00	8.40	15.00	92.30	175.10	146.20	91.80	215.90	228.30	34.00	1.60	148.50	**1157.10**
1984	0.80	0.00	84.30	88.30	139.90	214.30	267.70	272.50	158.80	83.50	2.60	0.00	**1312.70**
1985	5.50	0.00	51.30	56.20	175.60	184.90	251.10	97.30	293.10	20.50	8.50	0.00	**1144.00**
1986	0.00	90.70	109.20	58.30	97.50	264.20	126.90	153.90	196.80	220.90	6.80	0.00	**1325.20**
1987	73.30	3.60	68.90	19.60	79.40	183.70	186.50	336.70	221.90	105.80	0.00	0.00	**1279.40**
1988	0.00	26.20	48.30	103.20	NA	169.30	69.20	59.60	107.70	43.10	2.60	0.30	**629.50**
1989	0.00	0.00	46.50	54.60	52.70	199.50	95.80	119.00	121.30	115.20	0.00	0.00	**804.60**
1990	3.10	5.40	0.00	80.10	144.80	132.40	185.00	86.00	261.40	61.40	16.90	46.60	**1023.10**
1991	0.00	19.70	92.10	128.00	355.70	119.00	325.90	138.80	112.70	172.90	0.50	0.00	**1465.30**
1992	0.00	0.00	0.00	41.50	140.40	72.50	116.30	49.20	289.70	166.40	55.60	0.00	**931.60**
1993	0.00	3.60	51.60	29.80	141.40	142.60	146.50	203.30	234.80	202.30	25.40	0.00	**1181.30**
1994	39.30	0.00	19.80	223.00	156.00	131.20	89.60	87.00	260.60	234.90	0.00	0.00	**1241.40**
1995	0.00	2.10	33.30	122.00	209.60	171.30	218.70	232.10	188.50	154.60	46.80	30.20	**1409.20**
1996	0.00	0.90	61.40	143.20	25.80	152.80	104.20	131.40	262.70	62.90	0.00	0.00	**945.30**
1997	0.00	0.00	102.40	121.20	194.80	294.40	128.30	76.60	312.80	126.00	0.00	2.50	**1359.00**
1998	0.00	26.30	0.00	112.90	173.10	172.40	106.30	168.80	240.70	144.50	0.00	0.00	**1145.00**
1999	0.00	20.10	74.90	79.70	227.10	267.00	229.50	225.60	232.90	144.30	0.00	0.00	**1501.10**
2000	11.00	0.00	11.50	59.90	140.50	251.80	62.30	162.20	324.90	74.30	0.00	0.00	**1098.40**
2001	0.00	0.00	14.20	89.10	133.70	138.30	117.50	73.70	415.20	53.60	0.00	0.00	**1035.30**
2002	0.00	0.00	35.60	157.60	54.30	133.50	184.80	283.30	159.80	119.70	8.80	0.00	**1137.40**
2003	3.60	12.20	69.40	109.90	115.80	234.20	53.10	49.40	268.50	119.70	51.90	0.00	**1087.70**
2004	0.00	0.00	2.30	8.20	215.00	219.70	126.10	132.50	186.80	112.50	28.20	7.80	**1039.10**
2005	0.00	8.00	60.10	108.80	255.70	211.50	133.80	63.80	271.50	179.80	1.00	11.90	**1305.90**
2006	0.70	10.00	79.40	97.50	192.40	129.70	195.40	86.00	259.00	250.70	0.00	0.00	**1300.80**
2007	0.00	0.00	31.60	98.90	285.50	158.20	199.30	134.10	241.70	152.90	0.30	6.60	**1309.10**
2008	0.00	0.00	46.20	168.60	89.40	173.94	193.00	176.89	176.40	239.50	29.10	0.00	**1293.03**
2009	16.10	0.00	0.00	128.02	82.40	198.90	182.10	157.00	193.70	113.00	29.10	0.00	**1100.32**
TOTAL	**264.50**	**434.60**	**1915.30**	**4248.42**	**6723.70**	**7792.84**	**6487.10**	**6103.89**	**9913.10**	**6047.80**	**507.50**	**312.10**	