Long Memory, Seasonality and Time Trends in the Average Monthly Rainfall in Major Cities of Nigeria

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Several features may be present in rainfall data, and sophisticated time series procedures are needed for the analysis. These features are that of seasonality, long range dependency of observations and time trend as observed in the climatological series. This paper therefore considered the analysis of these features in the monthly rainfall data of 37 meteorological stations across the six geo-political zones of Nigeria between 1981 and 2013. A fractional integration technique of time series analysis which permits the feature of rainfall time series to be examined in a single framework is employed. The procedure gives explicit formulas and directions that allow a moderately sophisticated analyst to perform trend analysis. The results show that the trend and persistence of long memory are fairly distributed across the six geo-political zones such that a zone cannot be singled out with intense or abnormal rainfall distribution. By removing the seasonal variation and focussing on the rainfall anomalies with respect to the average monthly means, we found significant time trend coefficients that are positive, thus indicating that monthly rainfall has increased during the sampled periods.

Keywords: Long range dependence, Rainfall, Seasonality, Trend coefficient

JEL Classification: C22, C32

1.0 Introduction

Discussions on climate change attract scientists in recent years as a result of global warming experiences. The change has significantly contributed to the increase of global disasters caused by weather, climate and water related hazards as both developed and developing countries of the world are bearing the burden of repeated floods, temperature extremes and storms in which Nigeria is not left out. Time series experts therefore find data that represent a particular factor of climate and try to examine the pattern over the months and years, and even spanning across decades and centuries. Evidences suggest that human activities are influencing the global climate system (IPCC, 1998).

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The highly variable nature of rainfall as compared with the relatively stable nature of the temperature appears to have imbued more relevance to the former as the major component in the study of climate in a particular region. Then, there is need to understand the dynamical processes that determine changes that occur in climate system, though this has been very difficult and challenging to climate scientists till today. IPCC (2001) stated that human activities such as the release of greenhouse gases into the atmosphere and change in land use which results in external forcing are only partly unpredictable. This is so since scientists lack the ability to predict the relevant characteristics of future human activities. It has been observed that an increase in the volume of greenhouse gases in the earth's atmosphere would affect negatively the long wave radiation if both the temperature of the atmosphere and land surface were held constant. Rainfall is in the form of condensed water vapour. Water vapour causes about 70 percent of the amount of greenhouse gases in the atmosphere and this is brought to the free troposphere by a variety of mixing and transport processes, and the feedback is determined by the effects of changes in the transport and in the rate at which water is removed by precipitation which occurs when air parcels are cooled down by rising motions (Harries, 1997).

Rainfall data are time structured and time series analyses are often employed in the analysis of the data. During the analysis, several features inherent in data are investigated. These features are that of seasonality, long range dependency of observations and time trend as observed in the climatological series. This paper therefore considered the analysis of these features in the monthly rainfall of 37 meteorological stations across the six geo-political zones of Nigeria between 1981 and 2013.

IPCC (1996) affirmed that rainfall indicates a small positive global trend in the central and southern regions of the Mediterranean basins. Rainfall trend analyses, on different spatial and temporal scales, have been of great concern to scientists in the past century (Longobardi and Villani, 2010). The authors also investigated the rainfall distribution in 211 stations in the Mediterranean area as a result of decrease in rainfall experienced in the Italian territory. It was observed that the trend in rainfall appears to be negative at both the annual and seasonal scales but this is positive during summer period. The authors further found both significant positive and negative trends for the whole sample data, with a negative trend in 97 % of the total rainfall stations.

The distribution of rainfall throughout the year is as important as the total annual amount of monthly or annual rainfall when evaluating its impact on biosphere, hydrosphere, lithosphere and atmosphere. For example, in South Africa, there is an adaptive response to changing rainfall by farmers. This has also led to the decline in fruit-bearing trees in Sahel (IPCC, 2014).

Nigeria experiences tropical wet and dry climate (Hastenrath and Greischar, 1997; Ogolo and Falodun, 2007 and Adeyemi and Ogolo, 2014). The weather across the year is roughly divided into two: the wet or rainy season between April and October for the Southern part, and May to September for the Northern parts. The dry season for the Southern parts is between November and March, and October to April for Northern parts of the country. Variations in climate of Northern part of Sudan-Sahel vegetational zone of West Africa. Changes in the anomalies, as a result of occurrence of droughts, dust storms and flooding have shortened the duration of the climate as against the normal cycles. Therefore, the inhabitants with the hostile climate wonder about the unpredictable weather. The persistence of drought in this part of the country is also due to the anti-cyclonic circulation of air mass of the atmosphere over the area (Kalu, 1987; Kamara, 1986). The authors further stated that most of the droughts that occur in the region are related to the late start of the rainy season and early cessation of rainfall. A number of studies conducted within the m Sahel region have shown significant trend towards false onset, late or delayed onset and early cessation of the summer rainfall over a 30-year period from 1969 to 1998 (Ekpoh, 1999, Floyd and Ekpoh, 2007). Ekpoh (2007) 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.

In South-Western Nigeria, rainfall begins in earnest in most cities (stations) between March ending and early April each year. Rainfall retreats truly towards the end of October and early November. Thus, the months of April and May are the first two months into the raining season, while the last two months to the end of rainy season in the Sub-regions are September and October. Adejuwon (2012) applied data from the South-South zone of the country to study seasonality in rainfall distribution. The author considered nine meteorological stations in the Niger Deltan belt and observed significant seasonal pattern from February/March to November and a short dry season from December to January/February. The results further showed a northward increase in rainfall in parts of the eastern side of the Niger Delta.

Generally, the analysis of rainfall data in Nigeria has been considered in Adejuwon (1988), Adejuwon *et al.* (1990), Odjugo (2005), Obot *et al.* (2010), Omogbai (2010), Nnaji (2011), Ekpoh and Nsa (2011), Aderogba (2012), Akinsola and Ogunjobi (2014) and Yaya and Fashae (2014). Adejuwon (1988), Adejuwon *et al.* (1990) and Omogbai (2010) considered rainfall in Nigeria and other West African countries by using non-time series approach. Odjugo (2005) studied rainfall pattern in 28 stations in the Northern and Southern Nigeria using data between 1970 and 2002 and observed general decrease in the amount of rainfall in other stations apart from the coastal area in the south with increasing rainfall. Obot *et al.* (2010) 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 Maiduguri in the North-east zone to show an increasing trend among other rainfall towns in other zones. As a follow up, Nnaji (2011) applied the Rescaled Statistic (R/S) and other long memory detecting approaches to obtain evidence of long range dependency in rainfall series in Nigeria.

Ekpoh and Nsa (2011) considered the rainfall in the North-Western Nigeria using monthly data between periods 1968 and 2008 using some descriptive measures and mean shift equation. The 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. Aderogba (2012) considered the future challenges of flooding in Lagos State of Nigeria and concluded that Ikeja, a city in the state is prone to intense rainfall which could lead to flooding. Akinsola and Ogunjobi (2014) 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.

Recent flooding experiences in some cities in the South-western part of Nigeria have shown the possibilities of such repeated occurrences in the future.

2.0 Long Memory, Time Trends and Seasonality

Looking at the monthly rainfall time series, we found that it is possible to obtain a time trend which tends to either positive or negative directions.

Positive direction implies possibility of excessive rainfall in the future while negative direction implies decrease in the amount of rainfall. The time trend may be insignificant at positive or negative direction implying that the amount of rainfall in the area over some years is normal. Generally, the trend indicates how much, and in what direction rainfall is changing in an area. Rainfall data are time dependent and this time dependency should be considered in order to estimate the parameters of the time trend. Rainfall data are expected to present some types of seasonal variations as well.

The standard approach to climatic change modelling tends to employ a linear regression function of time which is of the form,

$$X_t = \alpha + \beta\, t + Y_t, \quad t = 1, 2, \ldots \tag{1}$$

where X_t are the observations in the time series X at time *t*, and Y_t is the deviation from the time series. The parameters of the model are α and β, where α is the constant term and β gives the average change in X_t per time period. Then, the long-run excessive rainfall is experienced if β is significantly positive, which implies increasing rainfall distribution, while decrease in the amount of rainfall is experienced when β is significantly negative. It is therefore very necessary to adequately specify the deviation term, Y_t. For example, if Y_t is a random variable independently drawn from normal distribution with zero mean and constant variance, inference is then made based on classical t and F test statistics (See Gil-Alana, 2012). The least square estimation approach is based on the assumption that Y_t in (1) is well-behaved, in the sense that the possible dependencies between the errors will be of a weak form making the error term is integrated of order 0, (I(0)). Thus, this is represented by Autoregressive [AR(1)] process,

$$Y_t = \phi_1 Y_{t-1} + u_t, \quad t = 1, 2, \ldots \tag{2}$$

which has been widely applied in the climatological environment because of its relationship with the stochastic first-order differential equation. In the special case of seasonal data, equation (2) can be replaced by the seasonal AR(1) process,

$$Y_t = \phi_s Y_{t-s} + u_t, \quad t = 1, 2, \ldots \tag{3}$$

where *s* indicates the number of time periods per year, for example $s = 4$ with quarterly time series, and $s = 12$ with monthly time series.

We can similarly believe that the de-trended series is nonstationary, then taking ϕ_1 in (2) to be 1, and Y_t is then said to be integrated of order 1 that is *I*(1) series. in such a case, Y_t is nonstationary but its first differences, $Y_t - Y_{t-1}$ are stationary and statistical inference must rely on the difference process. In otherwords, Y_t is said to be I(1) if:

$$(1-B)Y_t = Y_t - Y_{t-1} = u_t, \qquad t = 1,2,... \tag{4}$$

where *B* is the lag operator $(BY_t = Y_{t-1})$ and u_t is *I*(0) series as defined above. Then, the models in (1) and (4) become:

$$\Delta X_t = \beta + u_t, \qquad t = 1,2,... \tag{5}$$

with $\Delta = (1-B)$ and a *t*-statistic for $\beta = 0$ against the one-sided alternative $\beta > 0$ is constructed.

The $I(0)$ and the $I(1)$ models described above are merely two particular cases of a much more general class of processes called fractionally integrated or $I(d)$ processes, where d, the number of differences required to get $I(0)$ may be a non-integer value. We then say that Y_t is integrated of order *d* that is $Y_t \approx I(d)$ if

$$(1-B)^d Y_t = u_t, \qquad t = 1,2,... \tag{6}$$

with $Y_t = 0,\ t \le 0$ and u_t is $I(0)$. The polynomial on the left hand side of (6) is expanded as,

$$(1-B)^d = \sum_{i=0}^{\infty} \binom{d}{j} (-1)^j B^j = 1 - dB + \frac{d(d-1)}{2} B^2 - \frac{d(d-1)(d-2)}{6} B^3 + ... \tag{7}$$

implying that,

$$\left(1-B\right)^{d} Y_t = Y_t - dY_{t-1} + \frac{d\left(d-1\right)}{2} Y_{t-2} - \frac{d\left(d-1\right)\left(d-2\right)}{6} Y_{t-3} + \dots \quad (8)$$

Thus, if d is an integer value, Y_t will be a function of a finite number of past time series observations, while if d is not an integer value, Y_t depends on the values of the time series that are far away in the past, and the higher the value of d is, the higher the level of dependency between the time series observations.

The $I\left(d\right)$ model with $d > 0$ defined in (6) is characterized because the spectral density function is unbounded at the origin. In situations where the singularity or pole in the spectrum occurs at other frequencies, seasonality is suspected. Then, we apply seasonally transformed fractional process. The seasonal fractional process is an extension of model (6), giving,

$$\left(1-B^{s}\right)^{d_s} Y_t = u_t, \qquad t = 1, 2, \dots \quad (9)$$

where d_s is any real value, as defined in the case of d in (6). The binomial expansion of (9) gives,

$$\left(1-B^{s}\right)^{d_s} = \sum_{i=0}^{\infty} \binom{d}{j} \left(-1\right)^{j} B^{js} = 1 - dB^{s} + \frac{d\left(d-1\right)}{2} B^{2s} - \frac{d\left(d-1\right)\left(d-2\right)}{6} B^{3s} + \dots \quad 10)$$

so that,

$$\left(1-B^{s}\right)^{d_s} Y_t = Y_t - d_s Y_{t-s} + \frac{d_s\left(d_s-1\right)}{2} Y_{t-2s} - \frac{d_s\left(d_s-1\right)\left(d_s-2\right)}{6} Y_{t-3s} + \dots \quad (11)$$

Thus, if d_s is non-integer, Y_t depends on past (multiple s) values (see Porter-Hudak, 1990); Gil-Alana, 2012 and Yaya and Fashae, 2014).

Since the data examined in this paper are monthly average rainfall, apart from the time trend, the authors have to take into account the long-term dependence of the series and the seasonal structure described above. Thus, the model considered is of the form in (1), i.e.,

$$X_t = \beta_0 + \beta_1 \, t + Y_t, \qquad t = 1, 2, ... \tag{12}$$

with

$$\left(1 - B\right)^d Y_t = u_t, \qquad u_t = \phi_s u_{t\text{-}12} + \varepsilon_t, \qquad t = 1, 2, ... \tag{13}$$

That is, a long term dependence process $I\left(d\right)$ for the long term evolution of the time series considered along with a seasonal $AR\left(1\right)$ structure to model the weak dependence structure.

3.0 Data

The data analysed in this paper are the monthly rainfall time series in major cities of Nigeria from 37 climatological stations, obtained from the Nigerian Meteorological Agency (NMA). The data span between 1981 and 2013 that is 33 years span covering 396 data points. The size of the time series satisfied World Meteorological Organization (WMO) which recommends at least 30 years data span to study climate variability or climate change assessment. Also, in studying fractional I(d) process, long time series is often needed. These stations are from the six geo-political zones of the country. These geo-political zones represent six regions in which the country is divided. The specific locations as well as their heights above sea level for each rainfall stations in the zones are displayed in Table 1. Nigeria is bounded at the south with latitude 4.0°N and in the north with latitude 14.0°N. The country is bounded in the west with longitude 3.0°E and in the east with longitude 15°E.

Figure 1 shows the plots of time series, with a plot for each region of the country: Sokoto (North-West), Jos (North-Central), Maiduguri (North-East), Ibadan (South-West), Portharcourt (South-South) and Enugu (South-East). The seasonal pattern can be observed on the plots. The amounts of rainfall in the South-south and South-east zones are found to be more than what was experienced in any of the Northern zones, this as a result of dominant maritime tropical airmass in the Southern Nigeria from the Atlantic Ocean. This is a warm moist sea to land seasonal wind with high humidity. This therefore has the tendency to ascend and produce copious rainfall, which as a result of the condensation of the water vapour in the rapidly rising air.

Table 1: Number of rainfall stations and locations

Geo-political zones/ Stations	Location		Heights above sea level (metre)
North-West			
Sokoto	13.03N	5.12E	265
Yelwa	10.84N	4.74E	274
Kaduna	10.28N	7.25E	575
Zaria	11.07N	7.77E	559
Katsina	12.51N	7.33E	492
Kano	12.02N	8.32E	456
Gusau	12.12N	6.40E	415
North-Central			
Jos	9.57N	8.49E	586
Minna	9.38N	6.31E	319
Abuja	9.05N	7.48E	484
Ilorin	8.32N	4.34E	274
Lokoja	7.47N	6.37E	216
Bida	10.58N	7.22E	575
Makurdi	7.45N	8.53E	308
North-East			
Maiduguri	11.50N	13.10E	377
Yola	9.15N	12.30E	429
Nguru	12.87N	10.45E	349
Potiskum	11.71N	11.07E	397
Ibi	8.18N	9.74E	112
Bauchi	10.20N	9.45E	559
South-West			
Ibadan	7.22N	3.58E	183
Iseyin	7.97N	3.60E	183
Saki	8.67N	3.39E	457
Ikeja	6.40N	3.45E	73
Abeokuta	7.15N	5.15E	233
Ijebu-Ode	6.81N	3.93E	73
Akure	7.25N	5.19E	233
Oshogbo	7.46N	4.56E	223
South-South			
Port-Harcourt	4.41N	6.59E	83
Calabar	4.58N	8.21E	99
Uyo	5.05N	7.55E	196
Ikom	5.96N	8.71E	122
Ogoja	6.66N	8.79E	128
Benin	6.25N	5.30E	138
Warri	5.52N	5.75E	159
South-East			
Enugu	6.27N	7.29E	183
Owerri	5.27N	6.59E	127

4.0 Empirical Results and Discussion

The estimation of the parameters in equation (12) jointly with equation (13) is then carried out here. The estimation of fractional differencing parameter is based on the Exact Maximum Likelihood (EML) approach (Doornik and Ooms, 2001). Maximum Likelihood estimation of fractional differencing parameter is well documented in Sowell (1992), and Doornik and Ooms (2001) developed the methodology in OxARFIMA package. The EML approach considers the log-likelihood given as,

$$\log L(d,\phi,\theta,\beta) = -\frac{T}{2}\log(2\pi) - \frac{T}{2} - \frac{1}{2}\log|R| - \frac{T}{2}\log\left[T^{-1}z'R^{-1}z\right] \qquad (14)$$

with $\hat{\sigma}_{\varepsilon}^{2} = T^{-1}z'R^{-1}z$.

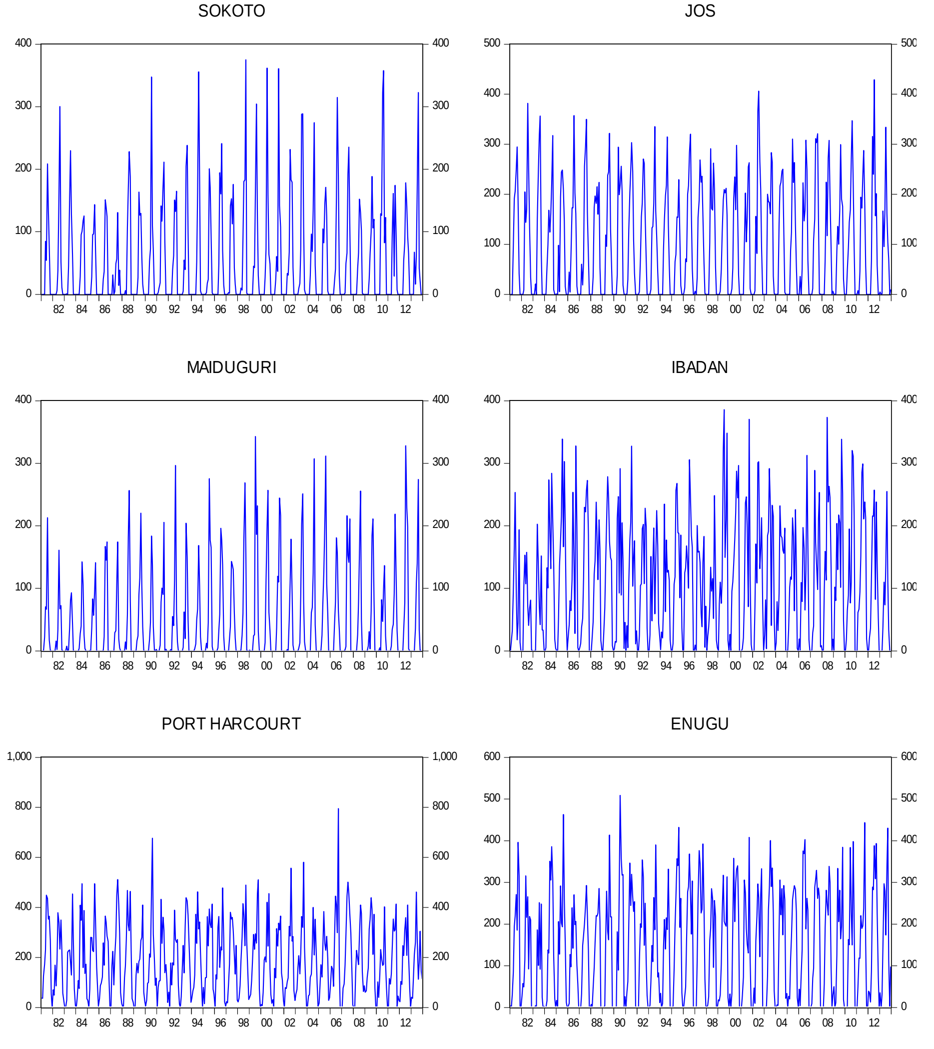

Figure 1: Time Series Plots of the Amount of Rainfall (millimetres)

The regression parameter, β is further concentrated out of the likelihood by using $\hat{z} = y - X\hat{\beta}$ and $\hat{\beta}' = \left(X'R^{-1}X \right)^{-1} X'R^{-1}y$ so that the likelihood becomes,

$$\log L\left(d, \phi, \theta\right) = -\frac{T}{2}\log\left(2\pi\right) - \frac{T}{2} - \frac{1}{2}\log\left|R\right| - \frac{T}{2}\log\left[T^{-1}\hat{z}'R^{-1}\hat{z}\right] \tag{15}$$

In the estimation, the function $-\frac{1}{2}\left(T^{-1}\log\left|R\right| + \log\sigma_{\varepsilon}^{2}\right)$ is used in the maximization procedure through Broyden-Fletcher-Goldfarb-Shanno (BFGS) numerical derivatives. Once d is estimated, the remaining parameters in the models (12) and (13) are jointly estimated using Ordinary Least Squares (OLS) or Weight Least Squares (WLS) approach.

Using equations (12) and (13), the estimates of the coefficient in the model were obtained in Table 2. The second column in the table gives the estimated values of *d* along with the standard error estimates; the third column presents the estimated time trend coefficients along with the corresponding *t* values; while the fourth column displays the seasonal AR coefficients. It is noticed that the estimates of fractional integration parameters are negative for series in five stations (Kaduna, Zaria, Bauchi, Ijebu-Ode and Ikom), implying that these are positive, in long memory ranges for the remaining 32 stations. Trend is also dominant in the amount of rainfall in these stations. There is positive trend for 27 stations, while there is negative trend in the remaining 10 stations. The trend and persistence of long memory are so fairly distributed across the six geo-political zones that we cannot single out a zone with intense or abnormal rainfall distribution. The estimates of seasonal AR(1) parameters are highly persistent in all cases, these ranging from 0.5436 to 0.8714, these indicating significant seasonality at monthly frequency.

4.1 Climate Change in the Anomalies

This section focuses on the analysis of climate change and the warming experiences in the anomalies. We subtract, the corresponding monthly mean observation for each observation, across the entire sample, which is a deterministic approach to removing the seasonal structure in the time series. The resulting series is the time series of the anomalies.

Table 2: Estimates of the Coefficients in Equation (12) and (13)

Geo-political zones/	*d* (s.e.)	Time trend	Seasonal
North-West			
Sokoto	0.0630	0.0423 (0.444)	**0.7366**
Yelwa	0.0988	0.0123 (0.085)	**0.7596**
Kaduna	-0.0674	0.0650 (0.672)	**0.8714**
Zaria	-0.0360	0.0422 (0.467)	**0.8048**
Katsina	0.0003	0.0460 (0.701)	**0.7585**
Kano	0.1947	0.0979 (0.352)	**0.7980**
Gusau	0.1857	0.0609 (0.318)	**0.7093**
North-Central			
Jos	0.0152	-0.0080 (-0.070)	**0.8187**
Minna	0.0971	0.0128 (0.083)	**0.8261**
Abuja	0.0806	-0.0192 (-0.114)	**0.8367**
Ilorin	0.1296	0.0083 (0.062)	**0.6569**
Lokoja	0.1494	0.0404 (0.258)	**0.6756**
Bida	0.0642	-0.0012 (-0.010)	**0.7065**
Makurdi	0.1184	0.0280 (0.194)	**0.6954**
North-East			
Maiduguri	0.0219	0.0476 (0.622)	**0.7808**
Yola	0.1031	-0.0552 (-0.454)	**0.7992**
Nguru	0.0705	0.0242 (0.0799)	**0.8358**
Potiskum	0.0417	0.0080 (0.084)	**0.7677**
Ibi	0.0391	-0.0133 (-0.142)	**0.6778**
Bauchi	-0.0463	0.1526 (1.280)	**0.8618**
South-West			
Ibadan	0.1009	0.0234 (0.197)	**0.6538**
Iseyin	0.0158	-0.0060 (-0.087)	**0.5695**
Saki	0.2514	-0.0268 (-0.146)	**0.5700**
Ikeja	0.0212	0.0701 (0.774)	**0.5436**
Abeokuta	0.1355	0.0073 (0.060)	**0.5720**
Ijebu-Ode	-0.0095	0.0663 (0.714)	**0.6512**
Akure	0.1430	0.0008 (0.007)	**0.6250**
Oshogbo	0.0977	-0.0145 (-0.123)	**0.5492**
South-South			
Port-Harcourt	0.1194	-0.0130 (-0.066)	**0.6691**
Calabar	0.0972	0.1815 (0.812)	**0.6587**
Uyo	0.0877	0.3342 (1.64)	**0.7040**
Ikom	-0.0308	0.0132 (0.099)	**0.7990**
Ogoja	0.1339	0.2041 (0.880)	**0.7141**
Benin	0.1504	0.1876 (0.893)	**0.6053**
Warri	0.1095	0.0441 (0.184)	**0.6442**
South-East			
Enugu	0.1048	0.0729 (0.394)	**0.7627**
Owerri	0.0622	-0.0221 (-0.119)	**0.7283**

[In parenthesis, in the second column, the standard errors for the values of *d*; in the third column, *t* values of the time trend coefficients. The values in bold implies significant AR and Trend coefficient estimates.]

Figure 2 displays the plots if the anomalies for the six time series presented earlier in Figure 1. It is observed that seasonal structure seems to be removed though we still notice quite some degree of dependency in the series.

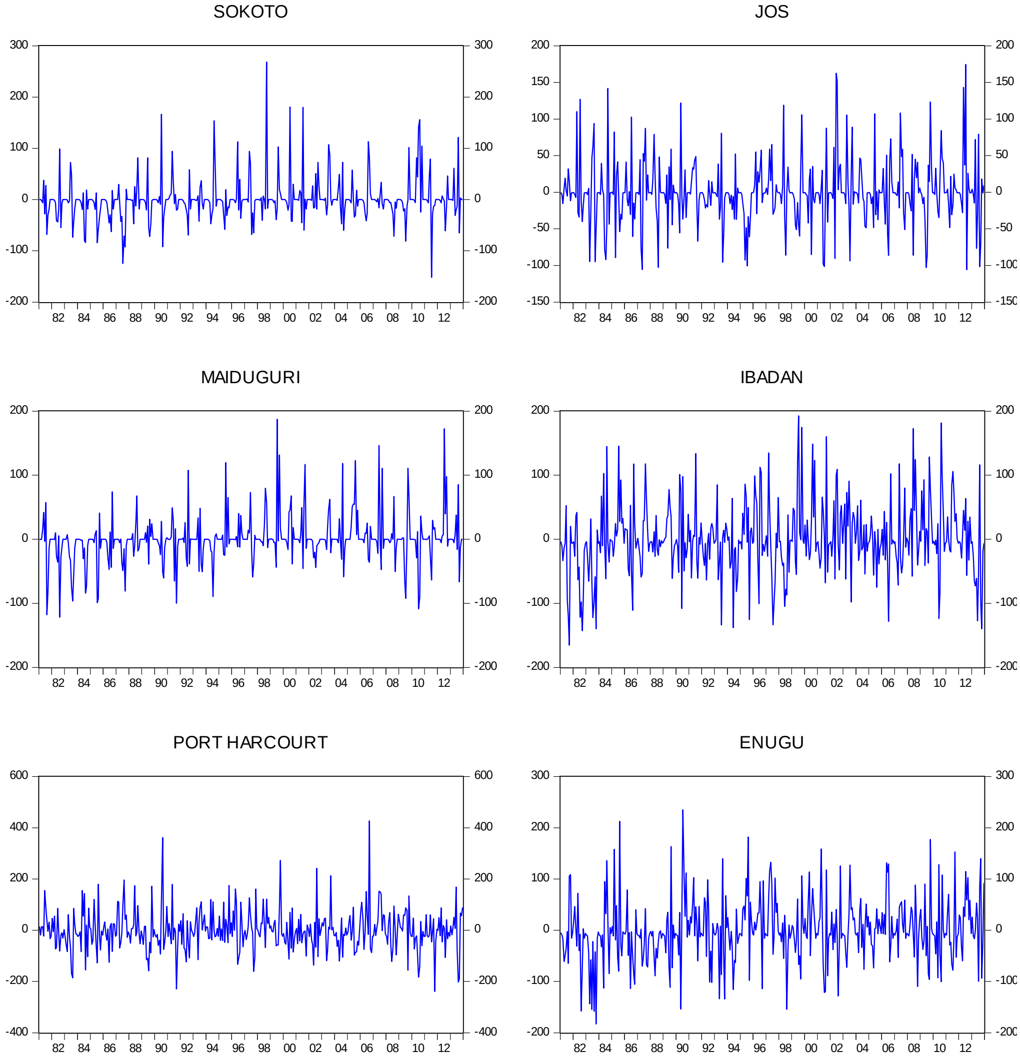

Figure 2: Time Series Plots of the Monthly Anomaly Rainfall (millimetres)

In the anomalies, we apply on models given by the equations (1) and (6) assuming that u_t in (6) is white noise (Table 3), and then considering the case of AR(1) disturbances u_t (Table 4). In other words, the specified model is now,

$$X_t = \beta_0 + \beta_1\, t + Y_t, \qquad (1-B)^d\, Y_t = u_t, \qquad t = 1, 2, \ldots \tag{16}$$

with white noise and AR(1) u_t.

Table 3: Estimates of the Coefficients in Equation (14) with White noise errors

Geo-political zones/	*d* (s.e.)	Time trend coefficient
North-West		
Sokoto	0.0093 (0.0437)	**0.0453 (2.420)**
Yelwa	0.0822 (0.0443)	0.0249 (0.812)
Kaduna	-0.0058 (0.0371)	0.0238 (1.140)
Zaria	-0.0732 (0.0437)	**0.0445 (3.080)**
Katsina	0.0852 (0.0412)	**0.0550 (2.400)**
Kano	0.2696 (0.0500)	0.1499 (1.720)
Gusau	0.1462 (0.0459)	0.0238 (0.565)
North-Central		
Jos	-0.0368 (0.0457)	0.0168 (1.020)
Minna	0.0308 (0.0445)	0.0401 (1.770)
Abuja	0.0431 (0.0433)	0.0179 (0.640)
Ilorin	0.0893 (0.0429)	0.0050 (0.145)
Lokoja	0.0358 (0.0410)	0.0380 (1.310)
Bida	0.0454 (0.0460)	0.0142 (0.505)
Makurdi	0.0314 (0.0394)	0.0308 (1.080)
North-East		
Maiduguri	0.0580 (0.0429)	**0.0601 (2.940)**
Yola	0.0487 (0.0426)	-0.0323 (-1.560)
Nguru	0.0163 (0.0416)	**0.0304 (2.520)**
Potiskum	0.0052 (0.0439)	0.0194 (1.130)
Ibi	0.0293 (0.0397)	0.0062 (0.243)
Bauchi	0.1271 (0.0452)	**0.1366 (3.020)**
South-West		
Ibadan	0.1366 (0.0431)	0.0520 (1.170)
Iseyin	-0.0146 (0.0422)	0.0060 (0.266)
Saki	0.1690 (0.0428)	0.0076 (0.161)
Ikeja	-0.0204 (0.0422)	**0.0695 (2.170)**
Abeokuta	0.0921 (0.0470)	0.0447 (1.170)
Ijebu-Ode	-0.0164 (0.0438)	**0.0956 (3.300)**
Akure	0.0188 (0.0470)	-0.0127 (-0.480)
Oshogbo	0.0510 (0.0437)	-0.0188 (-0.470)
South-South		
Port-Harcourt	0.0192 (0.0446)	-0.0043 (-0.116)
Calabar	0.0355 (0.0428)	**0.1699 (3.250)**
Uyo	0.1969 (0.0378)	**0.3174 (3.250)**
Ikom	-0.0221 (-0.0399)	0.0262 (0.924)
Ogoja	0.1640 (0.0413)	**0.2083 (2.960)**
Benin	0.0797 (0.0423)	**0.1681 (3.060)**
Warri	-0.0481 (0.0472)	-0.0113 (-0.299)
South-East		
Enugu	0.0596 (0.0418)	**0.0778 (2.250)**
Owerri	0.0461 (0.0426)	-0.0070 (-0.164)

In parenthesis, in the second column, the standard errors for the values of *d*; in the third column, *t* values of the time trend coefficients. In bold, significant Trend coefficient estimates.

First, with the case of white noise disturbances presented in Table 3, we observe that in 29 out of the 37 rainfall stations, *d* is significantly positive at 5% level, that is the null hypothesis of $d = 0$ cannot be rejected. Anti-persistence is then observed in the remaining 8 stations. These stations are Kaduna, Zaria (North-West), Jos (North-Central), Iseyin, Ikeja, Ijebu-Ode (South-West) and Ogoja, Warri (South-South). The trend coefficients were significantly positive in 12 stations, cutting across North-West, North-East, South-West, South-South and South-East zones. The trend was only negative in 6 stations, Yola (North-East), Akure, Osogbo (South-West), Portharcourt, Warri (South-South) and Owerri (South-East), and these are not significant at 5% level. This implying that there is positive trend in 31 rainfall stations.

Table 4: Estimates of the Coefficients in Equation (14) with AR(1) disturbances

Geo-political zones/ Stations	*d* (s.e.)	Time trend coefficient	AR(1)
North-West			
Sokoto	-0.0216 (0.0755)	**0.0458 (2.670)**	0.0443
Yelwa	0.0397 (0.0802)	0.0258 (0.949)	0.0591
Kaduna	0.1493 (0.0584)	0.0287 (0.892)	**-0.2541**
Zaria	-0.0281 (0.0830)	**0.0445 (2.700)**	-0.0601
Katsina	0.0556 (0.0637)	**0.0558 (2.630)**	0.0477
Kano	0.0340 (0.0922)	**0.1625 (3.720)**	**0.2963**
Gusau	0.0516 (0.0855)	0.0219 (0.684)	0.1277
North-Central			
Jos	-0.1333 (0.0827)	0.0184 (1.460)	0.1335
Minna	-0.0070 (0.0825)	**0.0406 (2.000)**	0.0518
Abuja	0.0150 (0.0733)	0.0185 (0.714)	0.0411
Ilorin	0.0763 (0.0726)	0.0053 (0.0336)	0.0192
Lokoja	0.1073 (0.0682)	0.0387 (1.090)	-0.1066
Bida	-0.0479 (0.0909)	0.0164 (0.760)	0.1240
Makurdi	0.1100 (0.0645)	0.0320 (0.902)	-0.1234
North-East			
Maiduguri	0.0679 (0.0773)	**0.0600 (2.850)**	-0.0140
Yola	0.0355 (0.0707)	-0.0321 (-1.610)	0.0196
Nguru	0.0488 (0.0701)	**0.0304 (2.300)**	-0.0484
Potiskum	-0.0070 (0.0797)	0.0193 (1.160)	0.0169
Ibi	0.1194 (0.0651)	0.0053 (0.162)	-0.1391
Bauchi	0.0376 (0.0804)	**0.1339 (3.820)**	0.1247
South-West			
Ibadan	0.1138 (0.0726)	0.0527 (1.270)	0.0337
Iseyin	0.0573 (0.0759)	0.0050 (0.180)	-0.1003
Saki	0.2654 (0.0762)	-0.0003 (-0.004)	-0.1305
Ikeja	-0.0183 (0.0697)	**0.0695 (2.160)**	-0.0031
Abeokuta	-0.0509 (0.0872)	0.0490 (1.910)	0.1934
Ijebu-Ode	-0.0889 (0.0688)	**0.0984 (0.0240)**	0.1116
Akure	-0.1176 (0.0920)	-0.0144 (-0.798)	0.1814
Oshogbo	0.0094 (0.0746)	-0.0196 (-0.551)	0.0604
South-South			
Port-Harcourt	-0.0495 (0.0772)	-0.0029 (-0.093)	0.0986
Calabar	0.0030 (0.0692)	**0.1688 (3.530)**	0.0497
Uyo	0.2843 (0.0590)	**0.3315 (2.650)**	-0.1472)
Ikom	0.0052 (0.0597)	0.0258 (0.849)	-0.0461
Ogoja	0.1417 (0.0628)	**0.2072 (3.120)**	0.0366
Benin	0.0503 (0.0673)	**0.1672 (3.290)**	0.0457
Warri	-0.1899 (0.0835)	-0.0148 (-0.574)	0.1936
South-East			
Enugu	0.0810 (0.0685)	**0.0780 (2.120)**	-0.0324
Owerri	0.0386 (0.0718)	-0.0070 (-0.166)	0.0112

In parenthesis, in the second column, the standard errors for the values of *d*; in the third column, *t* values of the time trend coefficients. In bold, significant AR and Trend coefficient estimates.

Looking at the case of AR(1) correlated disturbances in Table 4, we found the values of *d* for 25 locations to be positive while 12 are negative. Both the persistence and anti-persistence are found across 5 geopolitical zones (stations) except for stations in the South-East (Enugu, Owerri) which give long range dependence experiences in their amount of rainfall.

On the estimates of time trend coefficients, this time, Kano (North-West) and Minna (North-Central) stations are now significant at 5% level, leaving the stations with significant time trend at 15 out of 37 stations. 7 stations, Yola, Saki, Akure, Oshogbo, PortHarcourt, Warri and Owerri were found to present negative and insignificant time trend coefficients.

5.0 Concluding Remarks

We have examined in this paper the analysis of monthly average rainfall data in 37 meteorological stations in major towns of Nigeria. The rainfall stations cut across the six geopolitical zones in the country. The data span from 1981 to 2013, covering a total of 396 data points, large enough for the time series methodology employed. We apply procedure which allows one to analyze several features observed in the data such as linear time trends, long range dependencies and seasonality, in one framework.

By assuming first the seasonal unit root hypothesis, we found the estimates of the fractional integration parameters to be negative for series in five stations (Kaduna, Zaria, Bauchi, Ijebu-Ode and Ikom), implying that these are positive, in long range dependence ranges for the remaining 32 stations. These long range dependencies imply that future monthly average rainfall depends significantly on the past rainfall data. Seasonality is dominant in the series since the autoregressive coefficients are all less than unity implying the acceptance of the seasonal unit root hypothesis. Removing the seasonal effect by the deterministic approach, the results indicated anti-persistence in stations at Kaduna, Zaria, Jos, Iseyin, Ikeja, Ijebu-Ode, Ogoja and Warri. The 15 stations with significant trend coefficient imply the possibility of abundant rainfall in the future in the five geopolitical zones of the stations (North-West, North-East, South-West, South-South and South-East). Possible decrease in the amount of rainfall each year is not expected since the negative coefficients of trend is not significant in the six identified stations. Altogether, there is positive trend for 30 stations, while there is negative trend in the remaining stations. The long term effect of this is the heavy rainfall which could lead to flooding in those stations with positive trend. For example, flooding has been recorded in various parts of the country such as Lagos flood of July 2011, the cases of Ibadan flood of August 2011, Jigawa, Katsina, Kebbi and Sokoto floods of September 2010. Following IPCC (2014) report, increasing heavy rainfall is projected to increase erosion and inundation, and this has the consequence of damaging many low-lying ecosystems, infrastructure, and housing. Rainfall changes may also shift the base of agricultural production zones, and many plant species may face local or global extinction.

Towns with negative trend may also experience flooding due to soil texture and topography, structural, architectural and engineering problems. There is an indication that the high variability of extreme rainfall in major cities of the geo-political zones of Nigeria will continue to loom as global warming persists, in order words, more flooding experiences are bound to occur in additional cities.

References

Adejuwon, J.O. (2012). Rainfall seasonality in the Niger Delta Belt, Nigeria. *Journal of Geography and Regional Planning*, 5(2): 51-60.

Adejuwon, J.O., Balogun, E.E. and Adejuwon, S.A. (1990). On the annual and seasonal pattern of rainfall fluctuations in sub-Saharan West Africa. *International Journal of Climatology*, 10: 839–848.

Aderogba, K.A. (2012). Global warming and challenges of flood in Lagos Metropolis, Nigeria. *Academic Research International*, 2(1): 448-468.

Adeyemi, B. and Ogolo, E.O. (2014). Diurnal and Seasonal variations of surface water vapour density over some meteorological stations in Nigeria. *Ife Journal of Science*, 16, (2): 181-189.

Akinsola, A.A. and Ogunjobi, K.O. (2014). Analysis of Rainfall and Temperature variability over Nigeria. *Global Journal of Human Social*

Science: B Geography, Geo-Sciences, Environmental Disaster Management, 14(3). In Press.

Doornik, J. and Ooms, M. (2001). Computational Aspects of Maximum Likelihood Estimation of Autoregressive Fractionally Integrated Moving Average models. *Nuffield College, University of Oxford*, 8(2): 1-14.

Ekpoh, I.J. (1999). Rainfall and Peasant Agriculture in Northern Nigeria. *Global Journal of Pure and Applied Sciences,* 5(1), 123-128.

Ekpoh, I.J. (2007). Climate and Society in Northern Nigeria: Rainfall variability and farming. *The International Journal Series on Tropical Issues*, 8(3), 157-162.

Ekpoh, I.J. and Nsa, E. (2011). Extreme climatic variability in North-Western Nigeria: An analysis of rainfall trends and patterns. *Journal of Geographical Geology*, 3(1): 51-62.

Floyd, B.N. and Ekpoh, I.J. (2007). Transforming traditional agriculture. *Global Journal of Social Sciences*, 6(2), 97-102.

Gil-Alana, L.A. (2012). Long memory, seasonality and time trends in the average monthly temperatures in Alaska. *Theoretical and Applied Climatology*, 108: 385-396.

Harries, J.E. (1997). Atmospheric radiation and atmospheric humidity. Quarterly. *Journal of Meteorological Society*, 123: 2173-2186.

Hastenrath, S. and Greischar, L. (1997). Glacier Recession on Kilimanjaro, East Africa, 1912-1987. Setting the Scene. *Ecological Modelling*, 157: 89-100.

IPCC (1996). Climate Change 1995: The Science of Climate Change. *Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change* [Houghton, J.T., L.G. Meira Filho, B.A. Callander, N. Harris, A. Kattenberg, and K. Maskell (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, 572 pp.

IPCC (1998). The Regional Impact of climate Change: An Assessment of Vulnerability. *Special Report of IPCC Working Group II*. IPCC. Cambridge University Press, Cambridge, United Kingdom and New York, NY. USA 880pp.

IPCC (2001). Intergovernmental Panel on Climate change. *Third Assessment Report: Climate change 2001. WG1: The scientific basis, summary for policymakers*, Geneva, Switzerland.

IPCC (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Summaries, Frequently Asked Questions, and Cross-Chapter Boxes. A *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, ` M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken,P.R. Mastrandrea, and L.L. White (eds.)]. World Meteorological Organization, Geneva, Switzerland, 190 pp.

Kalu, A.E. (1987). The recurrence of severe droughts in northern Nigeria. *Proceedings of the 1985 Commonwealth Meteorologists Conference*. Meteorological Office College, Reading.

Kamara, S.I. (1986). The origin and types of rainfall in West Africa. *Weather*, 41: 48-56.

Longobardi, A. and Villani, P. (2010). Trend analysis of annual and seasonal rainfall time series in the Mediterranean area. *International Journal of Climatology*, 30(10): 1538-1546.

Nnaji, C.C. (2011). Time series analysis of monthly rainfall in Nigeria with emphasis on self-organized criticality. *Journal of Science Technology*, 31(1): 139–151.

Obot, N.I., Chendo, M.A.C., Udo, S.O., Ewona, I.O. (2010). Evaluation of rainfall trends in Nigeria for 30 years (1978–2007). *International Journal of Physical Science*, 5(14): 2217–2222.

Odjugo, P.A.O. (2005). An analysis of rainfall patterns in Nigeria. *Global Journal of Environmental Sciences*, 4(2): 139-145.

Ogolo, E.O. and Falodun, S.E. 2007. Variations and Trends in Long Term Annual Mean Air Temperatures over some selected cities in Nigeria. Journal of Physical Sciences. *International Research and Development Journal*. 3(2): 40-44.

Olutona, G.I., Ladipo, K.O., Ohamobi, S.I,. Gbobaniyi, E.O. and Akinlade, G.O. (2004). The Nigerian Micrometeorological Experimental (NIMEX) Overview. *Ife Journal of Science*. 6(2): 191-202.

Omogbai, B.E. (2010). Prediction of northern Nigeria Rainfall using sea surface temperature. *Journal of Human Ecology*, 32(2): 127–133.

Porter-Hudak, S. (1990). An application of the seasonal fractionally differenced model to the monetary aggregate. *Journal of the American Statistical Association*, 85: 338-344.

Sowell, F. (1992). Maximum Likelihood Estimation of Stationary univariate Fractionally Integrated time series Models. *Journal of Econometrics* 53: 165-188.

Yaya, O.S. and Fashae, O.A. (2014). "Seasonal Fractional Integrated Time Series Models for Rainfall Data in Nigeria". *Theoretical and Applied Climatology*, 116 (3-4): DOI 10.1007/s00704-014-1153-8.