

Time Series Analysis of Rainfall and Temperature in South West Nigeria.

Oluwafemi Samuel Oyamakin, Femi Joshua Ayoola, and Oluwatosin Tolulope Dare

Forestry Research Institute of Nigeria, PMB 5054, Jericho, Ibadan, Nigeria.

E-mail: fm_oyamakin@yahoo.com

ABSTRACT

In order to give an objective explanation to the effect of some natural phenomenon in the study of climate change, especially global warming, monthly recorded agro-meteorological data was collected from the Forestry Research Institute of Nigeria's (FRIN) agro-meteorological station. Least square method was used to estimate the trend in the series and the trend equation for rainfall and temperature. Time series method using additive model for the deterministic approach was employed in estimating the seasonal variation/index and also to make elementary forecast of the future values of temperature and rainfall. However, before the analysis was carried out, the time plots were plotted for the two variables.

The plots of the AC and PAC neither decay exponentially to zero or cut off which is a characteristic of autoregressive (AR) model. The reverse does not suggest moving average (MA) also. The two correlograms exhibit characteristics of autoregressive moving average (ARMA) based on the inability to display a characteristic pattern, which suggests it to be a mixed model of AR and MA. The minimum AIC value is 10.90464 which is less than the initial one (10.95916). There is no serial correlation in the residuals as indicated by the Durbin Watson statistic ($DW=2.034172$) and Breusch-Godfrey Serial correlation test and the model parameters are significant at 1% and 5% level.

(Keywords: agro-meteorological data, rainfall, temperature, least square method, climate change, moving average, correlogram)

INTRODUCTION

Climate change refers to a change in climate that is attributable directly or indirectly to human activities, that affects the atmospheric conditions of the Earth leading to global warming. It can also

be referred to as any long-term change in the statistics of weather over durations ranging from decades to millions of years. It can be manifest in changes to averages, extremes, or other statistical measures, and may occur in a specific region or for the Earth as a whole.

Climate change has the potential to affect all natural systems thereby becoming a threat to human development and survival socially, politically, and economically. According to a report published by the Federal Ministry of Environment, Nigeria with a population of about 140 million and with an area of 923,000 square kilometers, the various activities being carried out by this vast population coupled with variability in elements of climate such as rainfall and temperature, exposes the country to the impact of climate change.

Nigeria's vulnerability occurs in two ways according to the reports; the first results from the impacts of climate change and second relates to the impact of response measures. This is because Nigeria's economy is highly dependent on income generated from the production, export, and consumption of fossil fuels and associated energy-intensive products.

The negative impact of climate change such as temperature rise, erratic rainfall, sand storms, desertification, low agricultural yield, drying up of water bodies, and sea level rise are real in the desert prone eleven front line states of Nigeria. Environmental degradation and the attendant desertification are major threats to the livelihood of the inhabitants of the frontline states of Nigeria. These lead to increasing population pressures, intensive agricultural land use, overgrazing, bush burning, and extraction of fuel wood and other biotic resources.

Today, the entire global community has started suffering from the unfriendly climatic condition, the gradual disappearance of rain forest in the tropics, the loss of plant and animal species, changes in

rainfall patterns, and global warming resulting from climate change (Akinyemi, 2008). Babalola et al., 2008, opined that climate change will have significant effects on the energy sector in Nigeria. The most significant impact of climate change on energy will include (i) higher electricity demand for heating, cooling, water pumping, etc., (b) reduced availability of hydroelectricity and fuel wood, and (c) extensive damage to petrochemical industrial installations presented concentrated in the coastal belt. In particular, rising temperatures, changes in the amount of precipitation, and variation in humidity, wind patterns and the number of sunny days per year, could affect both consumption and production of energy.

Women and children are particularly the most vulnerable to the impact of climate change. The report advised governments at all levels to improve the financial status towards these issues. Inadequate funds hamper progress in achieving Nigeria's objectives on Climate Change. So far, very little has been dedicated to this issue of climate change in the National Budget, the report stated. It calls for increased public awareness, research, the building of strong climate change institutions, and the provision of appropriate institutional and legal frameworks with full government support. Minister of Environment, Mr. John Odey, at a press briefing during the World Environment Day (WED), declared that the Federal Government, while addressing the threat of climate change in Nigeria, both in terms of

mitigation and adaptation, is currently focusing on the implementation of the Clean Development Mechanism (CDM) projects and other climate friendly projects in the country. These projects are being executed on a public-private partnership basis with many investors, including some big banking institutions, indicating interest in some of the CDM projects ranging from afforestation and forest degradation programs to capturing of associated gas in the course of petroleum exploration.

RESULTS AND DISCUSSION

The monthly time plot for rainfall and temperature in Figure 1 revealed that the trends are varying and the series are stationary. Hence, the forecast generated for temperature and rainfall using probability forecast show that temperature increases slowly with time and rainfall decreases averagely with time. The time series analysis of Rainfall and temperature was carried out using E-views 5.0.

DISCUSSIONS AND CONCLUSION

Time plots for rainfall display series of cyclical behavior and this is due to seasonal changes from month to month across the year. Fairly seasonal behavior is also experienced in the temperature series.

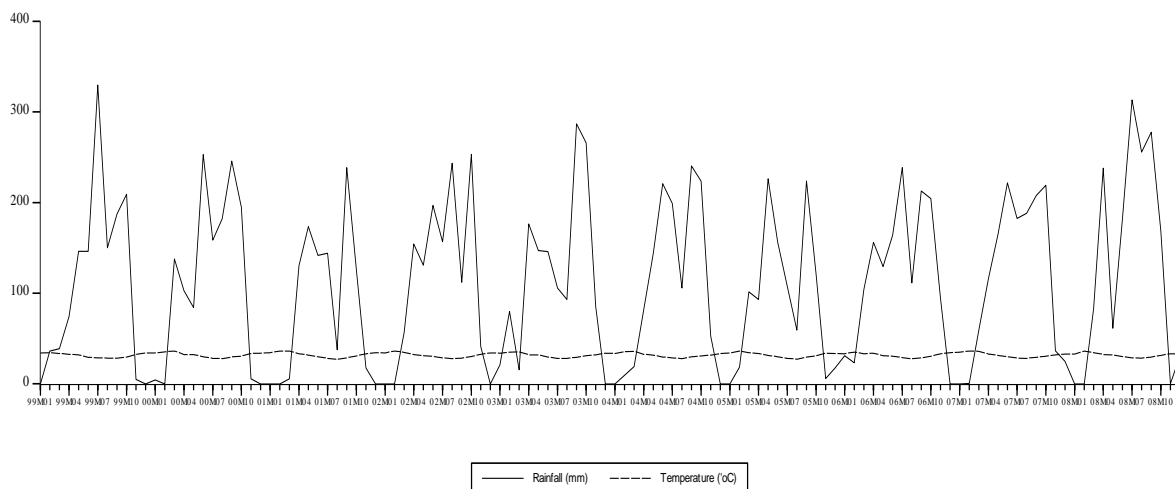


Figure 1: Time Plots of Rainfall (mm) and Temperature (°C).

The two series appear to be stationary and this is justified based on unit root (nonstationarity) tests presented in Table 1.

The results was computed up to lag 10 for Dickey and Fuller (1979) test otherwise known as Augmented Dickey Fuller (ADF) test and the Phillips-Perron (1988) test was computed based on automatic selection using the Eviews 5.0 software.

For the two tests (ADF and PP), Null hypothesis is Unit Root (nonstationary) and the results in the table indicate significance of the stationarity regression coefficients at 1%, 5%, and 10% level of significance which implies the rejection of the null hypotheses of Unit Roots for rainfall and temperature series. Hence, stationarity is confirmed in the rainfall and temperature data used in this research work.

The model is identified based on the shape of sample autocorrelation (AC) and partial autocorrelation (PA) plots. Following Figure 2 below, the autocorrelations are all significant indication that the series generating them are not noise process but sequence of random values, X_t .

The plots of the AC and PAC neither decay exponentially to zero or cut off which is a characteristic of autoregressive (AR) model. The reverse, does not suggest moving average (MA) also. The two corellograms exhibit characteristics of autoregressive moving average (ARMA) based on the inability to display a characteristic pattern, which suggests it to be a mixed model of AR and MA.

For the Temperature series, the computed values of the sample autocorrelations are high in compared to that of Rainfall given in Figure 1 above. This is confirmed based on the probability values ($p < 0.05, p < 0.01$).

Based on the pattern of the AC and PA, there is strong indication that the model is mixed that is ARMA model.

For the Temperature series, the autocorrelation plot is sinusoidal and the PAC shows some significant spikes. The model as well cannot be pure AR or MA but there is a suggestion for ARMA model.

RAINFALL SERIES

Model order is determined based on the minimum value of Akaike Information (AIC) criterion. For each of the series, a grid search over all possible values of (p, q) , (that is the order of autoregression and moving average) was set up and the corresponding model orders that give minimum Information values (AIC) are picked.

The grid search detects the full ARMA model to be of order $(p, q) = (9, 6)$ and this is too large as a model. The non-significant parameters will then be removed starting from the least significant in order to avoid this problem of over-parameterization.

The final model showing subset of significant parameters (after removing the insignificant ones) is presented above in Table 3.

Table 1: Series Unit Root (Nonstationarity) Tests

Test	Rainfall (mm) Series				Temperature (oC) Series			
	ADF		PP		ADF		PP	KPSS
<i>Statistic</i>	-6.216551		-5.577007		-6.255662		-4.795606	
1%	-3.486064	(0.0000)	-3.486064	(0.0000)	-3.486551	(0.0000)	-3.486064	(0.0001)
5%	-2.885063		-2.885863		-2.886074		-2.885863	
10%	-2.571818		-2.571818		-2.579931		-2.579818	

Figure 2: Sample Autocorrelation (AC) and Partial Autocorrelation (PAC) Plots (Corellograms) of the Rainfall (mm) Series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. ****	. ****	1	0.494	0.494	30.022	0.000
. **	. .	2	0.210	-0.045	35.478	0.000
. .	* .	3	-0.019	-0.138	35.521	0.000
** .	** .	4	-0.267	-0.263	44.533	0.000
**** .	** .	5	-0.468	-0.305	72.405	0.000
*** .	* .	6	-0.421	-0.085	95.161	0.000
*** .	** .	7	-0.380	-0.189	113.92	0.000
** .	. .	8	-0.200	-0.041	119.13	0.000
. .	* .	9	-0.049	-0.124	119.45	0.000
. *	. .	10	0.137	-0.021	121.94	0.000
. ***	. **	11	0.421	0.276	145.74	0.000
. ****	. *	12	0.513	0.165	181.35	0.000
. ***	. .	13	0.376	0.012	200.66	0.000
. *	** .	14	0.114	-0.207	202.46	0.000
. .	. .	15	-0.023	0.052	202.54	0.000
** .	. .	16	-0.207	0.063	208.56	0.000
*** .	. .	17	-0.326	0.014	223.64	0.000
** .	. .	18	-0.305	0.035	237.02	0.000
** .	* .	19	-0.260	-0.118	246.84	0.000
* .	. .	20	-0.176	-0.009	251.38	0.000
. .	. .	21	-0.027	0.028	251.49	0.000
. *	. .	22	0.110	-0.011	253.31	0.000
. **	. .	23	0.300	0.055	266.86	0.000
. ***	. *	24	0.425	0.096	294.36	0.000
. **	* .	25	0.242	-0.095	303.36	0.000
. *	. .	26	0.089	-0.040	304.60	0.000
* .	. .	27	-0.062	-0.046	305.21	0.000
* .	. *	28	-0.150	0.109	308.79	0.000
** .	. *	29	-0.204	0.087	315.52	0.000
** .	* .	30	-0.228	-0.083	323.95	0.000
* .	. .	31	-0.157	0.034	328.02	0.000
* .	* .	32	-0.134	-0.111	331.02	0.000
. .	. *	33	-0.027	0.113	331.14	0.000
. .	. .	34	0.063	-0.044	331.81	0.000
. *	* .	35	0.193	-0.058	338.21	0.000
. **	. .	36	0.265	0.038	350.45	0.000
. **	. .	37	0.223	0.024	359.18	0.000
. .	. *	38	0.065	0.073	359.94	0.000
. .	. .	39	0.024	0.018	360.05	0.000
* .	. .	40	-0.091	-0.048	361.55	0.000

Figure 3: Sample Autocorrelation (AC) and Partial Autocorrelation (PAC) Plots (Corellograms) of the Temperature (°C) Series.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.793	0.793	77.270	0.000
. ***	**** .	2	0.443	-0.498	101.61	0.000
. .	**** .	3	0.002	-0.463	101.61	0.000
*** .	**** .	4	-0.450	-0.488	127.13	0.000
***** .	** .	5	-0.757	-0.262	200.14	0.000
***** .	* .	6	-0.854	-0.151	293.81	0.000
***** .	* .	7	-0.728	-0.090	362.50	0.000
*** .	* .	8	-0.428	-0.148	386.48	0.000
. .	. .	9	-0.007	0.042	386.48	0.000
. ***	* .	10	0.384	-0.091	406.11	0.000
. *****	. .	11	0.660	-0.051	464.53	0.000
. *****	. *	12	0.781	0.105	547.12	0.000
. *****	** .	13	0.645	-0.237	604.03	0.000
. ***	* .	14	0.359	-0.069	621.82	0.000
. .	. .	15	-0.005	-0.046	621.83	0.000
*** .	. .	16	-0.360	-0.002	640.02	0.000
***** .	* .	17	-0.616	-0.115	693.99	0.000
***** .	. .	18	-0.680	0.022	760.42	0.000
*** .	* .	19	-0.574	-0.106	808.24	0.000
*** .	. .	20	-0.322	-0.013	823.43	0.000
. .	. .	21	0.019	-0.054	823.49	0.000
. **	* .	22	0.316	-0.175	838.38	0.000
. ****	* .	23	0.522	-0.098	879.43	0.000
. ****	** .	24	0.578	-0.196	930.32	0.000
. ****	. .	25	0.482	-0.025	966.18	0.000
. **	. .	26	0.268	-0.055	977.36	0.000
. .	* .	27	-0.004	-0.090	977.36	0.000
** .	* .	28	-0.266	-0.186	988.64	0.000
*** .	. .	29	-0.434	0.017	1019.0	0.000
*** .	. .	30	-0.464	-0.032	1054.1	0.000
*** .	* .	31	-0.395	-0.160	1079.8	0.000
** .	** .	32	-0.224	-0.207	1088.1	0.000
. .	* .	33	0.014	-0.071	1088.2	0.000
. **	* .	34	0.216	-0.132	1096.1	0.000
. ***	* .	35	0.351	-0.164	1117.3	0.000
. ***	* .	36	0.401	-0.084	1145.3	0.000
. **	*** .	37	0.317	-0.384	1163.0	0.000
. *	* .	38	0.180	-0.127	1168.8	0.000
. .	** .	39	0.008	-0.297	1168.8	0.000
* .	*** .	40	-0.164	-0.332	1173.7	0.000

Table 2: Grid Search for Minimum AIC for Rainfall Modeling.

p/q	$q=0$	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$	$q=6$
$p=0$	-						
$p=1$	11.57006	11.58207	-	-	-	-	-
$p=2$	11.58769	-	-	-	-	-	-
$p=3$	11.59324	-	-	-	-	-	-
$p=4$	11.51045	-	-	-	-	-	-
$p=5$	11.44118	-	-	-	-	-	-
$p=6$	11.42979	-	-	-	-	-	-
$p=7$	11.27094	-	-	-	-	-	-
$p=8$	11.26383	-	-	-	-	-	-
$p=9$	11.23565	11.24834	10.99661	11.00657	11.00686	11.00085	10.95916

Table 3: Model Estimation for Rainfall Series.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	111.9920	3.732385	30.00548	0.0000
AR(1)	0.419639	0.088286	4.753151	0.0000
AR(2)	-0.516563	0.084797	-6.091739	0.0000
AR(4)	-0.229900	0.047391	-4.851180	0.0000
AR(6)	-0.638237	0.052858	-12.07446	0.0000
AR(7)	-0.164504	0.086446	-1.902964	0.0600
AR(9)	-0.375157	0.072038	-5.207738	0.0000
MA(1)	-0.337022	0.041259	-8.168418	0.0000
MA(2)	0.307364	0.036109	8.512074	0.0000
MA(4)	0.190890	0.042570	4.484115	0.0000
MA(5)	-0.208449	0.053325	-3.909034	0.0002
MA(6)	0.883006	0.045663	19.33749	0.0000
R-squared	0.680575	Mean dependent var	110.7459	
Adjusted R-squared	0.645084	S.D. dependent var	90.05453	
S.E. of regression	53.64986	Akaike info criterion	10.90464	
Sum squared resid	284952.4	Schwarz criterion	11.19756	
Log likelihood	-593.2075	F-statistic	19.17565	
Durbin-Watson stat	2.034172	Prob(F-statistic)	0.000000	

The minimum AIC value is 10.90464 which is less than the initial one (10.95916).

There is no serial correlation in the residuals as indicated by the Durbin Watson statistic (DW=2.034172) and Breusch-Godfrey Serial correlation test in Table 4 and the model parameters are significant at 1% and 5% level.

The minimum AIC occurs at $(p, q)=(12, 6)$ with value 1.10087. This is also a large model with many parameters and the insignificant parameters cannot be removed due to sub-setting. This instead makes nearly all the parameters to be insignificant. So, the full ARMA (12, 6) is modeled for Temperature series. The model is presented in Table 7.

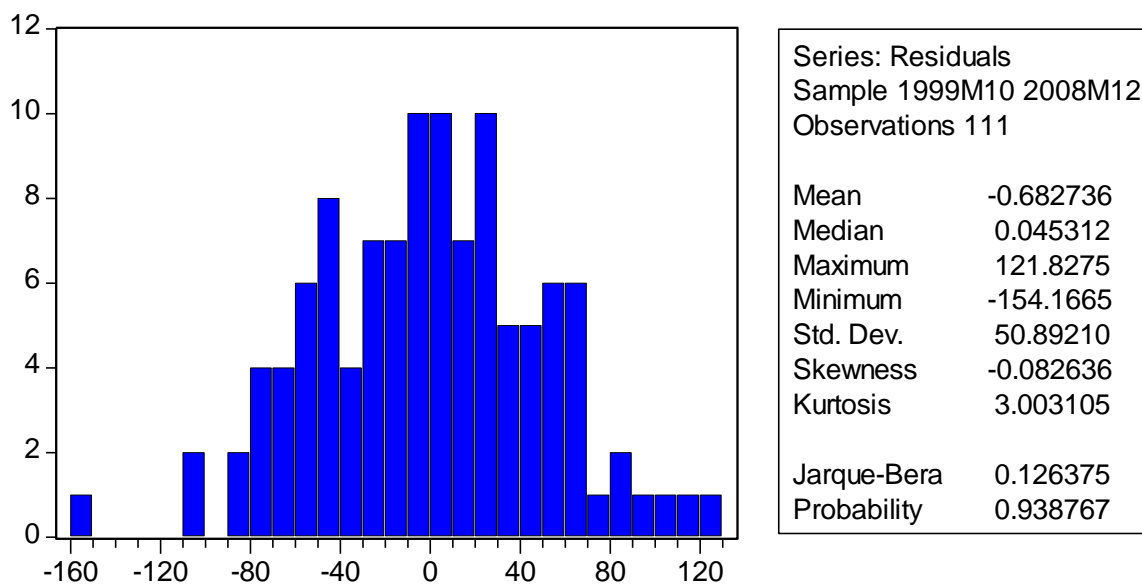
Table 4: Test for Serial Correlation.

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.215230	Probability	0.806740
Obs*R-squared	0.470342	Probability	0.790436

Figure 4: Correlograms of Residuals (Q- Statistics)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. .	. .	1	-0.028	-0.028	0.0897	
. .	. .	2	0.043	0.043	0.3057	
. *	. *	3	0.072	0.075	0.9141	
. .	. .	4	-0.016	-0.014	0.9441	
. .	. *	5	-0.050	-0.058	1.2361	
. *	. *	6	0.078	0.071	1.9561	
. .	. .	7	0.048	0.061	2.2355	
. .	. .	8	-0.032	-0.029	2.3572	
. *	. .	9	0.082	0.063	3.1861	
. .	. .	10	-0.019	-0.020	3.2317	
. .	. .	11	-0.057	-0.052	3.6333	
. *	. *	12	0.128	0.120	5.7205	0.017
. .	. .	13	-0.038	-0.034	5.9058	0.052
. *	. *	14	-0.168	-0.175	9.5445	0.023
. .	. .	15	-0.015	-0.047	9.5747	0.048
. *	. *	16	-0.135	-0.127	11.968	0.035
. *	. *	17	0.067	0.118	12.574	0.050
. *	. *	18	0.123	0.136	14.599	0.041
. .	. .	19	0.063	0.052	15.135	0.057
. .	. .	20	-0.029	-0.022	15.252	0.084
. *	. *	21	-0.062	-0.112	15.794	0.106
. *	. *	22	-0.092	-0.087	16.986	0.108
. *	. .	23	-0.093	-0.037	18.208	0.110
. *	. *	24	0.133	0.126	20.773	0.078
. .	. .	25	-0.021	0.005	20.840	0.106
. *	. *	26	-0.075	-0.082	21.668	0.117
. .	. *	27	-0.022	-0.089	21.741	0.152
. .	. *	28	0.051	0.084	22.138	0.179
. *	. *	29	0.073	0.135	22.964	0.192
. .	. .	30	0.029	-0.016	23.090	0.233
. .	. .	31	0.029	-0.012	23.226	0.278
. *	. *	32	-0.081	-0.089	24.262	0.281
. .	. .	33	-0.010	0.044	24.277	0.333
. *	. .	34	-0.089	-0.020	25.555	0.322
. *	. *	35	-0.073	-0.093	26.433	0.332
. *	. .	36	0.078	-0.035	27.455	0.334

Figure 5: Residual Normality Test



Skewness, Kurtosis and Jarque-Bera test indicate the normality of the residuals.

Table 5: Testing for Autoregressive Conditional Heteroscedasticity (ARCH)

ARCH Test:

F-statistic	0.060348	Probability	0.941469
Obs*R-squared	0.123971	Probability	0.939897

The ARCH effect is not significant.

The ARMA (9, 6) model presented in Table 3 is then the optimal and best model for the Rainfall series.

TEMPERATURE SERIES

Table 6: Grid Search for Minimum AIC for Temperature Modeling.

p/q	$q=0$	$q=1$	$q=2$	$q=3$	$q=4$	$q=5$	$q=6$	$q=7$
$p=0$	-	-	-	-	-	-	-	-
$p=1$	3.732291	-	-	-	-	-	-	-
$p=2$	3.414987	-	-	-	-	-	-	-
$p=3$	3.183246	-	-	-	-	-	-	-
$p=4$	2.875848	-	-	-	-	-	-	-
$p=5$	2.725953	-	-	-	-	-	-	-
$p=6$	2.586201	-	-	-	-	-	-	-
$p=7$	2.587355	-	-	-	-	-	-	-
$p=8$	2.572432	-	-	-	-	-	-	-
$p=9$	2.583390	-	-	-	-	-	-	-
$p=10$	2.548846	-	-	-	-	-	-	-
$p=11$	2.547900	-	-	-	-	-	-	-
$p=12$	2.346501	2.361736	2.308087	2.295500	2.190798	2.115490	1.910087	2.009491
$p=13$	2.360398	-	-	-	-	-	-	-
$p=14$	2.373942	-	-	-	-	-	-	-

Table 7: Model Estimation for Temperature Series.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	31.71648	0.059881	529.6608	0.0000
AR(1)	0.778313	0.106489	7.308827	0.0000
AR(2)	-1.041089	0.135304	-7.694434	0.0000
AR(3)	1.009745	0.175532	5.752475	0.0000
AR(4)	-1.064337	0.207735	-5.123532	0.0000
AR(5)	0.532631	0.236418	2.252920	0.0268
AR(6)	-0.837960	0.241492	-3.469928	0.0008
AR(7)	0.298453	0.241713	1.234742	0.2202
AR(8)	-0.328170	0.234753	-1.397940	0.1656
AR(9)	0.255779	0.205249	1.246191	0.2160
AR(10)	-0.481755	0.172091	-2.799413	0.0063
AR(11)	0.281946	0.130244	2.164750	0.0331
AR(12)	0.021502	0.103577	0.207592	0.8360
MA(1)	-0.682133	0.024226	-28.15720	0.0000
MA(2)	1.213672	0.027125	44.74318	0.0000
MA(3)	-1.344577	0.039220	-34.28291	0.0000
MA(4)	1.203769	0.037267	32.30094	0.0000
MA(5)	-0.680475	0.040516	-16.79533	0.0000
MA(6)	0.958375	0.024343	39.37014	0.0000
R-squared	0.958235	Mean dependent var	31.70748	
Adjusted R-squared	0.949692	S.D. dependent var	2.588498	
S.E. of regression	0.580585	Akaike info criterion	1.910087	
Sum squared resid	29.66294	Schwarz criterion	2.384701	
Log likelihood	-83.18965	Durbin-Watson stat	1.841262	

Durbin Watson fairly indicates serial correlation but this can be confirmed by Breusch –Pagan Serial Correlation test.

Table 8: Serial Correlation Test.

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.992202	Probability	0.142640
Obs*R-squared	4.736678	Probability	0.093636

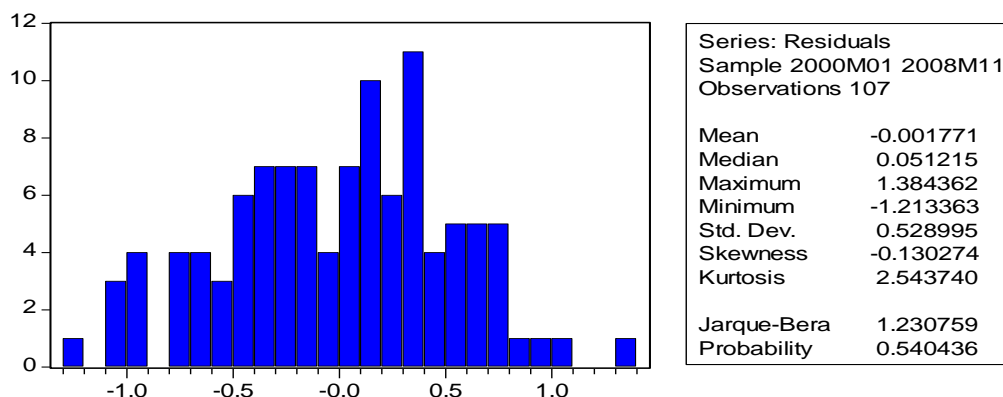
Serial correlation is not significant in the Temperature series.

Figure 6: Correlograms of Residuals (Q- Statistics).

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *	. *	1	0.067	0.067	0.4903	
. .	. .	2	-0.045	-0.050	0.7159	
. .	. .	3	0.019	0.025	0.7556	
. .	. .	4	0.064	0.059	1.2248	
. .	. .	5	0.039	0.033	1.4019	
. .	. .	6	0.002	0.003	1.4024	
. .	. .	7	0.024	0.025	1.4708	
. .	.* .	8	-0.055	-0.064	1.8252	
. .	. .	9	-0.053	-0.048	2.1550	
.* .	.* .	10	-0.074	-0.077	2.8121	
.* .	.* .	11	-0.138	-0.137	5.1196	
. .	. .	12	-0.039	-0.024	5.3034	
. .	. .	13	-0.023	-0.022	5.3707	
. .	. .	14	-0.015	0.001	5.4008	
.* .	. .	15	-0.071	-0.046	6.0388	
. .	. .	16	0.012	0.035	6.0575	
. .	. .	17	0.007	0.004	6.0637	
. .	. .	18	0.039	0.046	6.2665	
. .	. .	19	0.018	0.002	6.3099	0.012
.* .	.* .	20	-0.101	-0.122	7.6851	0.021
. .	. .	21	-0.002	-0.019	7.6857	0.053
. .	.* .	22	-0.014	-0.058	7.7109	0.103
. .	. .	23	-0.003	-0.026	7.7125	0.173
.* .	** .	24	-0.180	-0.196	12.248	0.057
. .	. *	25	0.063	0.085	12.813	0.077
. *	. .	26	0.070	0.039	13.510	0.095
. .	. .	27	-0.049	-0.020	13.864	0.127
.* .	. .	28	-0.060	-0.035	14.389	0.156
. .	. .	29	-0.054	-0.048	14.832	0.190
. *	. *	30	0.100	0.088	16.341	0.176
. .	. .	31	0.032	-0.007	16.498	0.223
. .	. .	32	-0.010	-0.037	16.514	0.283
.* .	.* .	33	-0.087	-0.128	17.695	0.279
. .	. .	34	-0.014	-0.030	17.726	0.340
. *	. .	35	0.086	0.018	18.920	0.333
. *	. *	36	0.073	0.084	19.790	0.345

The errors are white noise based on the results of Q-statistic above.

Figure 7: Residual Normality Test



The residuals are normally distributed as indicated by the normality V test in Figure. 7.

Table 9: Testing for Autoregressive Conditional Heteroscedasticity (ARCH).

ARCH Test:			
F-statistic	0.112624	Probability	0.893598
Obs*R-squared	0.231361	Probability	0.890760

No heteroscedastic effect in the Temperature series.

MODEL FORECAST

Forecast Values for Rainfall Series

Months/Year	Rainfall (mm)
2009M01	-3.8
2009M02	-33.0
2009M03	-23.3
2009M04	22.9
2009M05	92.5
2009M06	166.8
2009M07	227.2
2009M08	257.9
2009M09	249.7
2009M10	204.3
2009M11	134.5
2009M12	59.1
2010M01	-2.6
2010M02	-34.9
2010M03	-28.1
2010M04	16.3
2010M05	86.2
2010M06	162.6

2010M07	226.0
2010M08	259.7
2010M09	254.4
2010M10	210.8
2010M11	140.9
2010M12	63.5
2011M01	-1.2
2011M02	-36.6
2011M03	-32.7
2011M04	9.8
2011M05	79.7
2011M06	158.1
2011M07	224.4
2011M08	261.4
2011M09	259.0
2011M10	217.3
2011M11	147.5
2011M12	68.2

Forecast Values for Temperature Series

Months/Year	Temperature (°C)
2009M01	-
2009M02	-
2009M03	-
2009M04	-
2009M05	-
2009M06	-
2009M07	-
2009M08	-
2009M09	-
2009M10	-
2009M11	-
2009M12	-
2010M01	-
2010M02	-
2010M03	-
2010M04	-
2010M05	-
2010M06	-
2010M07	-
2010M08	-
2010M09	-
2010M10	-
2010M11	-
2010M12	-
2011M01	-
2011M02	-
2011M03	-
2011M04	-
2011M05	-
2011M06	-
2011M07	-
2011M08	-
2011M09	-
2011M10	-
2011M11	-
2011M12	-

EvIEWS 5.0 reports spurious forecasts of unexpected values for temperature forecast. This is then left for future research using another software.

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ABOUT THE AUTHORS

Oyamakin Samuel Oluwafemi is a part-time Lecturer and a Ph.D. student at the Department of Statistics, University of Ibadan, Nigeria. He is also the Head, Statistics Section, Department of Planning, Research, Statistics and Biometrics, Forestry Research Institute of Nigeria. He holds a Master of Science (M.Sc.) in Statistics from the University of Ibadan. His research interests are in Biometrics, Forestry and Econometrics.

Femi Joshua Ayoola, holds an M.Sc. in Statistics from the Department of Statistics, University of Ibadan, Nigeria. He is currently a Lecturer and is completing his doctoral studies in the same department.

Tolulope Dare is a graduate from the Statistics Department of the University of Ibadan and she is also presently a research assistant within that same department.

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