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Time Series Analysis of Nyala Rainfall Using ARIMA Method

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ABSTRACT - This paper presents linear stochastic models known as multiplicative seasonal autoregressive integrated moving average model (SARIMA).The model is used to simulate monthly rainfall in Nyala station, Sudan. For the analysis, monthly rainfall data for the years 1971–2010 were used. The seasonality observed in Auto Correlation Function(ACF) and Partial Auto Correlation Function(PACF) plots of monthly rainfall data was removed using first order seasonal differencing prior to the development of the SARIMA model. Interestingly, the SARIMA $(0,0,0)x(0,1,1)_{12}$ model developed was found to be most suitable for simulating monthly rainfall over Nyala station. This model is considered appropriate to forecast the monthly rainfall to assist decision makers to establish priorities for water demand, storage, distribution and disaster management.

Keywords: *Sudan, Nyala station, rainfall, Sarima model, ACF, PACF*

المستخلص – هذه الورقةِ تُقدّم النماذج الخطية التصادفية المعروفة بنماذج الانحدار الذاتي التكاملي المتوسط المتحرك الموسمية **(SARIMA)** . النموذج يُستَعملُ لمحاكاة المطرِ الشهريِ في محطةِ نيالا، السودان. للتحليلِ، إستعملتْ بيانات المطرِ الشهريةً للسَنَواتِ 1971–2010. الموسمية في بياناتِ المطرِ الشهريةِ الملاحظة فى مخططات دالة الترابط الذاتي **(ACF)** و دالة الترابط الذاتي الجزئي **(PACF)** أزيلت باستخدام التفريق من الدرجة الأولى الموسمى للبيانات قبل تطوير النموذج.بشكل مثير للأنتباه، وجد أن نموذج **SARIMA(0,0,0)X(0,1,1)** المطور أكثر ملائمة لمحاكاة المطرِ الشهريِ لمحطةِ. نيالا .هذا النموذجِ يعتبر ملائم لتَوَقُّع المطرِ الشهريِ لمُسَاعَدَة صانعيِ القرارفى تأسيس الأولوياتِ لمتطلباتِ الماءِ (تخزين – توزيع و إدارة كوارث).

INTRODUCTION

Sudan is one of the countries whose economy depends on rain fed agriculture associated with recurring cycles of natural drought. For many decades, recurrent drought, with intermittent severe droughts, became a normal phenomenon in Sudan. The most heavily affected areas in Sudan are Darfur and Kordofan, with 17 major droughts recorded in Darfur in the last century [1]. Drought threatens approximately twelve million hectares of rain fed land, particularly in the northern Kordofan and Darfur state[2].Severity of drought depends upon the variability of rainfall amount, as well as distribution and frequency. Rainfall is the most important climatic element that influences agriculture. Monthly rainfall forecasting plays an important role in the planning and management of agricultural scheme and water resources systems. The main objective of the present study is to develop a valid stochastic model to simulate monthly rainfall in Nyala region.

Rainfall is a seasonal phenomenon with twelve months period.Seasonal time series are often modeled by SARIMA techniques. Recently, a few researchers modeled monthly rainfall using SARIMA methods. Nimarla and Sundaram[3] fitted a SARIMA $(0,1,1)x(0,1,1)_{12}$ model to monthly rainfall in Tamilnadu, India. Etuk and Mohamed [4] fitted a SARIMA $(0,0,0)x(0,1,1)_{12}$ model to monthly rainfall in Gadaref, Sudan. In this study, linear stochastic models known as multiplicative seasonal autoregressive integrated moving average (SARIMA) models were used to model monthly rainfall in Nyala station, southern Darfur.

STUDY AREA

Darfur State has an area of about 490,000 km^2 and lies between latitudes 10° and 20° N and longitudes 22° and 27° E. The topography of the state is characterized by almost level or gently undulating plateau, with elevations ranging from 600 to 900 meters above sea level. The main water resources in Darfur State are the rainfall, groundwater, and seasonal khors. The rainfall decreases from South to North. The decrease in rainfall is associated with increased evaporation.

The temperatures also increase in variability, and reach substantially higher levels. Rainfall varies from year to year. This variation is crucial for rain fed farming. Water scarcity is one of the main causes of tension in the state. Darfur states are one of the biggest and environmentally most varied regions of the Sudan. The region is divided into four ecological zones based on the amount of rainfall and vegetation types[5]. These zones, from North to South, are desert, semi-desert, low woodland savanna and high woodland savanna. Nyala station, Figure 1, is characterized by annual rainfall (197- 626 mm) during the last four decades. The annual number of rainy days, (rainfall > 1 mm), is 95 days and the mean annual reference potential evapotranspiration (ET_o) using Penman / Monteith criterion for the station is about 2305mm[6].The climate in the Nyala is semi-arid with mean annual temperature near 26.9° C [7].

The urban economy of Nyala has been strongly associated with the rural economy of South Darfur, the most productive Darfur State [8]. As a trading centre it has also benefited from its strategic location, close to served by a railway and an international airport. Groundnuts, gum Arabic, millet, sorghum and sesame are South Darfur State main agricultural products. Along with livestock these have been its main exports, and also the base for much of Nyala's manufacturing industry.

DATA COLLECTION

For this study, Nyala rainfall gauge was considered and 480 monthly rainfall data was procured for the period from 1971 to 2010. The monthly rainfall records for Nyala station show most of the rain falls in the period from May to October, and reaches its peak in August.

MODELING BY SARIMA METHODS

For more than half a century, Box–Jenkins ARIMA linear models have dominated many areas of time series forecasting. Autoregressive (AR) models can be effectively coupled with moving average (MA) models to form a general and useful class of time series models called autoregressive moving average (ARMA) models. In ARMA model the current value of the time series is expressed as a linear aggregate of p previous values and a weighted sum of q previous deviations (original value minus fitted value of previous data) plus a random parameter [9]. However, an ARMA model can be used when the data are stationary. ARMA models can be extended to non-stationary series by allowing differencing of data series. These models are called autoregressive integrated moving average (ARIMA) models [10]. A time series is said to be stationary if it has constant mean and variance. The general non-seasonal ARIMA model is AR to order p and MA to order q and operates on dth difference of the time series; thus a model of the ARIMA family is classified by three parameters (p, d, q) that can have zero or positive integral values. The general non-seasonal ARIMA model may be written as

$$\phi(B)\nabla^d X_t = \theta(B)\varepsilon_t$$

where:$\phi(B)$and $\theta(B)$ = Polynomials of order p and q, respectively.

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots \phi_P B^p)$$

And

$$\theta(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q\right)$$

Figure 1: Map of Sudan showing Nyala

Often time series possess a seasonal component that repeats every s observations. For monthly observations s = 12 (12 in 1 year), for quarterly observations s = 4 (4 in 1 year). Box et al. [11] have generalized the ARIMA model to deal with seasonality, and define a general multiplicative seasonal ARIMA model, which are commonly known as SARIMA models. In short notation the

SARIMA model described as ARIMA (*p, d, q)* x *(P, D, Q)* *s*, which is mentioned below:

$$\phi_p(B)\Phi_p(B^s)\nabla^d\nabla_s^D(Z_t) = \theta_q(B)\Theta_Q(\mathrm{B}^s)\varepsilon_\mathrm{t}$$

Where p is the order of non-seasonal autoregression, d the number of regular differencing, q the order of nonseasonal MA, P the order of seasonal autoregression, D the number of seasonal differencing, Q the order of seasonal MA, s is the length of season, Φ_p and Θ_Q are the seasonal polynomials of order P and Q, respectively. In this work the statistical and econometric software Eviews-6 was used for all analytical work. It is based on the least squares optimization criterion.

RESULTS AND DISCUSSIONS

Time series plot was conducted using the monthly rainfall data for Nyala station to assess the stability of the data, and Figure 2 was obtained. Since the data is a monthly rainfall, Figure 2, shows thatthere is aseasonal cycle of the series and the series is not stationary. The seasonal fluctuations occur every 12 month, resulting in period of time series S =12. The time-plot shows no noticeable trend.

Non-stationary is confirmed by the Augmented Dickey- Fuller Unit Root Test (ADF) on the monthly rainfall data. The ADF Test was done on the entire rainfall data. Table I displays results of the test: statistic value -1.2517 greater than critical vales -2.5697, -1.9414, -1.6162 all at 1%, 5%, and 10% respectively. The ACF illustrated in Table II, also, shows clearly that the series is not stationary.

If there is seasonality and no trend takes a difference of lag *S*=12, this occurs because it is a monthly data with seasonality. The monthly rainfall data was differenced by one seasonal degree of differencing to achieve stationary, as shown in Table III. Augmented Dickey-Fuller Unit Root Test was done again on the seasonally differenced rainfall data (deseasonalized data). The results of the test: statistic value-7.7919less than critical vales -2.5700, -1.9415, -1.6162 all at 1%, 5%, and 10% respectively. This indicates that the series are stationary and confirms that the rainfall data needed to be differenced to be stationary.

In this step, the model that seems to represent the behaviour of the series is searched, by the means of autocorrelation function (ACF) and partial auto correlation function (PACF), for further investigation and parameter estimation. The behaviour of ACF and PACF is to see whether the series is stationary or not.For modelling by ACF and PACF methods, examination of values relative to auto regression and moving average were made. An appropriate model for estimation of monthly rainfall for Nyala station was finally found. Many models for Nyala station, according to the ACF and PACF of the data, were examined to determine the best model. The model that gives the minimum Akaike Information Criterion (AIC) is selected as best fit model, as shown in Table IV. Obviously, model SARIMA $(0,0,0)x(0,1,1)_{12}$ has the smallest values of AIC and then one would temporarily have a model SARIMA (0,0,0) x $(0,1,1)_{12}$.

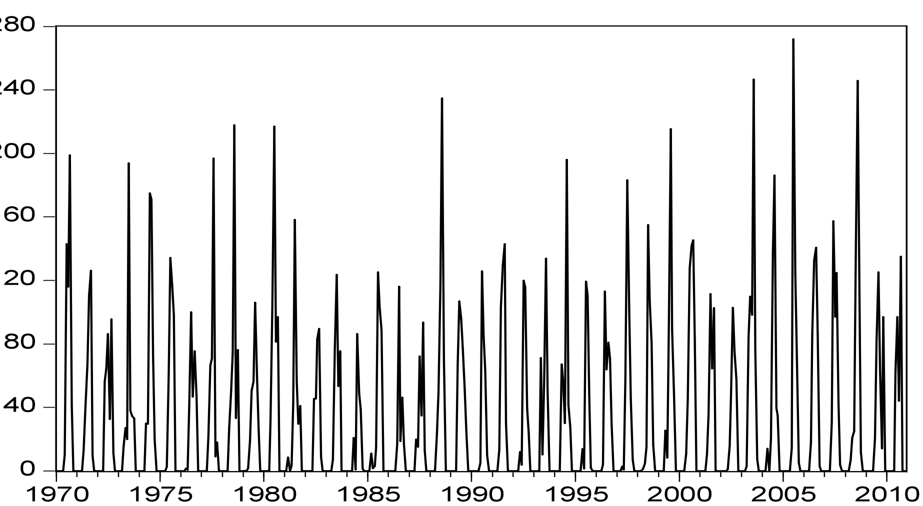

Figure 2: Monthly Rainfall Data for Nyala Station (1971-2010)

Table I: ACF and PACF Plots For Nyala Station Monthly Rainfall Series

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|**** |</td><td>.|**** |</td><td>1</td><td>0.516</td><td>0.516</td><td>131.67</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>*|. |</td><td>2</td><td>0.176</td><td>-0.123</td><td>147.02</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>**|. |</td><td>3</td><td>-0.142</td><td>-0.250</td><td>157.02</td><td>0.000</td></tr>
<tr><td>**|. |</td><td>*|. |</td><td>4</td><td>-0.325</td><td>-0.181</td><td>209.79</td><td>0.000</td></tr>
<tr><td>***|. |</td><td>*|. |</td><td>5</td><td>-0.385</td><td>-0.149</td><td>283.64</td><td>0.000</td></tr>
<tr><td>***|. |</td><td>**|. |</td><td>6</td><td>-0.394</td><td>-0.211</td><td>361.33</td><td>0.000</td></tr>
<tr><td>***|. |</td><td>**|. |</td><td>7</td><td>-0.372</td><td>-0.261</td><td>430.81</td><td>0.000</td></tr>
<tr><td>**|. |</td><td>**|. |</td><td>8</td><td>-0.309</td><td>-0.282</td><td>478.72</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>9</td><td>-0.137</td><td>-0.194</td><td>488.23</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>10</td><td>0.178</td><td>0.046</td><td>504.17</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|* |</td><td>11</td><td>0.492</td><td>0.213</td><td>626.39</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|*** |</td><td>12</td><td>0.701</td><td>0.383</td><td>875.37</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>13</td><td>0.501</td><td>0.071</td><td>1003.0</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>14</td><td>0.177</td><td>-0.025</td><td>1018.9</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>.|. |</td><td>15</td><td>-0.135</td><td>-0.054</td><td>1028.1</td><td>0.000</td></tr>
<tr><td>**|. |</td><td>.|. |</td><td>16</td><td>-0.308</td><td>-0.009</td><td>1076.6</td><td>0.000</td></tr>
<tr><td>***|. |</td><td>.|. |</td><td>17</td><td>-0.366</td><td>0.003</td><td>1145.3</td><td>0.000</td></tr>
<tr><td>***|. |</td><td>.|. |</td><td>18</td><td>-0.377</td><td>-0.021</td><td>1218.3</td><td>0.000</td></tr>
<tr><td>***|. |</td><td>.|. |</td><td>19</td><td>-0.366</td><td>-0.055</td><td>1287.2</td><td>0.000</td></tr>
<tr><td>**|. |</td><td>.|. |</td><td>20</td><td>-0.297</td><td>-0.057</td><td>1332.6</td><td>0.000</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>21</td><td>-0.148</td><td>-0.106</td><td>1343.9</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>22</td><td>0.164</td><td>-0.007</td><td>1357.8</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|* |</td><td>23</td><td>0.517</td><td>0.170</td><td>1496.1</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>24</td><td>0.616</td><td>0.022</td><td>1692.8</td><td>0.000</td></tr>
</table>

Table II: ADF- Unit Root Test for Nyala Monthly Rainfall

Station	Variable	ADF test	Level of Confidence	Critical Value	Probability	Result
Nyala	Monthly Rainfall	-1.2517	1%	-2.5697	0.1939	Non-stationary
			5%	-1.9414		
			10%	-1.6162		

Table III: Comparison of AIC for the Selected Model

Variable	Station	Model	AIC
Monthly Rainfall	Nyala	SARIMA(0.0.0)(0.1.1)	9.572
		SARIMA(0.0.1)(0.1.1)	9.747
		SARIMA(0.0.1)(2.1.1)	9.669
		SARIMA(0.0.0)(1.1.1)	9.577

After the identification of the model using the AIC criteria, estimation of parameters was conducted. The values of the parameters are shown in Table IV. The result indicated that the parameters are significant since their p-values are smaller than 0.05 and should be retained in the model. SARIMA. All validation tests were carried out on the residual series. The ACF and PACF of residuals of the model SARIMA (0, 0, 0) x(0, 1, 1)$_{12}$ are shown in Table V.

As shown in Table V, most of the values of the RACF and RPACF lies within confidence limits except very few individual correlations appear larger compared with the confidence limits. The figures indicate no significant correlation between residuals.

The model verification is concerned with checking the residuals of the model to see if they contain any systematic pattern which still can be removed to improve the chosen the Ljung-Box Q-statistic is employed for checking independence of residual. From Table VI, one can observe that the p-value is greater than 0.05 for all lags, which implies that the white noise hypothesis is not rejected. The Breusch-Godfrey Serial Correlation LM test accepts the hypothesis of no serial correlation in the residuals, as shown in Table VII. The *Q*-statistic and the LM test both indicated that the residuals are none correlated and the model can be used. Since the coefficients of the residual plots of ACF and PACF are lying within the confidence limits, the fit is good and the error obtained through this model, (1971-2010), is tabulated in the Table VIII. Finally, this concludes that SARIMA (0,0,0) x$(0,1,1)_{12}$ model identified previously is adequate to represent the monthly rainfall data and could be used to forecast the upcoming rainfall data.

Table IV: ACF and PACF Plots for Nyala Station afterone seasonal difference

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.023	0.023	0.2573	0.612
.|. |	.|. |	2	-0.024	-0.025	0.5398	0.763
.|. |	.|. |	3	0.010	0.011	0.5864	0.900
.|. |	.|. |	4	-0.025	-0.026	0.8956	0.925
.|. |	.|. |	5	-0.018	-0.016	1.0571	0.958
.|. |	.|. |	6	-0.003	-0.003	1.0612	0.983
.|. |	.|. |	7	0.013	0.013	1.1434	0.992
.|. |	.|. |	8	-0.005	-0.006	1.1541	0.997
.|. |	.|. |	9	0.010	0.010	1.1999	0.999
.|. |	.|. |	10	0.017	0.015	1.3380	0.999
*|. |	*|. |	11	-0.094	-0.094	5.6710	0.894
***|. |	***|. |	12	-0.347	-0.346	65.307	0.000
.|. |	.|. |	13	-0.052	-0.058	66.669	0.000
.|. |	.|. |	14	0.003	-0.012	66.675	0.000
.|. |	.|. |	15	0.038	0.045	67.389	0.000
.|. |	.|. |	16	0.018	0.001	67.554	0.000
.|. |	.|. |	17	-0.005	-0.019	67.566	0.000
.|. |	.|. |	18	0.001	-0.005	67.567	0.000
.|. |	.|. |	19	-0.012	-0.009	67.644	0.000
.|. |	.|. |	20	0.020	0.020	67.836	0.000
.|. |	.|. |	21	-0.049	-0.047	69.050	0.000
*|. |	*|. |	22	-0.089	-0.103	73.081	0.000
.|. |	.|. |	23	0.065	-0.004	75.250	0.000
**|. |	***|. |	24	-0.218	-0.408	99.388	0.000

Table V: Summary of Parameter Estimates and Selection Criteria (AIC) for Nyala Monthly Rainfall

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(12)	-0.949281	0.014215	-66.77889	0.0000
R-squared	0.426765	Mean dependent var		-0.355208
Adjusted R-squared	0.426765	S.D. dependent var		38.25668
S.E. of regression	28.96502	Akaike info criterion		9.572136
Sum squared resid	401867.7	Schwarz criterion		9.580831
Log likelihood	-2296.313	Hannan-Quinn criter.		9.575554
Durbin-Watson stat	2.062543			
Inverted MA Roots	1.00	.86-.50i	.86+.50i	.50+.86i
	.50-.86i	.00+1.00i	-.00-1.00i	-.50+.86i
	-.50-.86i	-.86+.50i	-.86-.50i	-1.00

Table VI: ACF and PACF Plots of SARIMA (0, 0, 0)x(0, 1, 1) Residuals

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>-0.032</td><td>-0.032</td><td>0.4948</td><td></td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.007</td><td>0.006</td><td>0.5167</td><td>0.472</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>0.029</td><td>0.030</td><td>0.9300</td><td>0.628</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>-0.028</td><td>-0.026</td><td>1.3174</td><td>0.725</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.015</td><td>-0.017</td><td>1.4297</td><td>0.839</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>-0.010</td><td>-0.012</td><td>1.4792</td><td>0.915</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.004</td><td>0.006</td><td>1.4888</td><td>0.960</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.007</td><td>-0.006</td><td>1.5108</td><td>0.982</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>-0.006</td><td>-0.007</td><td>1.5282</td><td>0.992</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>0.024</td><td>0.023</td><td>1.8207</td><td>0.994</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>11</td><td>-0.080</td><td>-0.078</td><td>4.9642</td><td>0.894</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>12</td><td>0.080</td><td>0.075</td><td>8.0961</td><td>0.705</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.011</td><td>-0.008</td><td>8.1586</td><td>0.773</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>0.052</td><td>0.057</td><td>9.4887</td><td>0.735</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>0.038</td><td>0.033</td><td>10.193</td><td>0.748</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>-0.006</td><td>-0.002</td><td>10.211</td><td>0.806</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>-0.003</td><td>-0.006</td><td>10.215</td><td>0.855</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>18</td><td>-0.000</td><td>0.002</td><td>10.215</td><td>0.894</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.005</td><td>-0.003</td><td>10.229</td><td>0.924</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>0.011</td><td>0.012</td><td>10.287</td><td>0.946</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>-0.041</td><td>-0.037</td><td>11.143</td><td>0.942</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>-0.013</td><td>-0.025</td><td>11.232</td><td>0.958</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>23</td><td>0.060</td><td>0.073</td><td>13.038</td><td>0.932</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>24</td><td>-0.157</td><td>-0.164</td><td>25.480</td><td>0.326</td></tr>
</table>

Table VII: The Breusch-Godfrey Serial Correlation LM test

F-statistic	0.244495	Prob. F(2,477)	0.7832
Obs*R-squared	0.151221	Prob. Chi-Square(2)	0.9272
F-statistic	0.662316	Prob. F(12,467)	0.7879
Obs*R-squared	7.697345	Prob. Chi-Square(12)	0.8083

Table VIII: Errors Measures Obtained for the Selected Model

Error Measure	Value
RMSE	29.20
MAE	15.16

CONCLUSION

It may be concluded that the monthly rainfall in Nyala, Sudan follows a SARIMA (0,0, 0)x$(0,0,1)_{12}$ model. This model is considered appropriate to predict the monthly rainfall for the upcoming years to assist decision makers establish priorities for water demand, storage and distribution

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