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A Comparison of the Forecasting Models of Rainfall Data of Umudike, Abia State Nigeria

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Abstract

The forecasting ability of some Time series Models in forecasting the rainfall data of Umudike was investigated. Monthly rainfall data of Umudike in Abia State were collected from Meteorological Department of National Root Crops Research Institute (NRCRI) Umudike from 2008-2017. Triple Exponential Smoothing (Holt-Winters Method), Multiple Linear Regression approach and SARIMA Model were employed to model the data. Mean Error (ME), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) and Friedman Statistic test were used to ascertain the forecasting ability or performance of the models. The Friedman test for the significant difference among the models showed that there was no significant difference among the three models. Further, based on the accuracy measures, it was shown that the Multiple Linear Regression approach has lower accuracy error measures than other models considered, and as such it is regarded as the most appropriate model for forecasting rainfall pattern of Umudike, when judging from the view of Accuracy Measures. It was also deduced from the analysis that Friedman test Statistics is the most appropriate method for testing the performance of competing models, since it makes use of statistical tools for inference.

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INTRODUCTION

Rainfall is a meteorological phenomenon that has the greatest impact on human activities and the most important environmental factor limiting the development of the Nigeria regions (Ngatuame *et al.*, 2014). Understanding rainfall variability is essential to optimally manage the scarce water resources that are under continuous stress due to the increasing water demands, increase in population, and the economic development. There are many aspect of water resources management including the optimal water allocation, quality assessment and preservation , and prediction of future water demands to strategize water utilization, planning, and decision making. Rainfall is a stochastic process, whose upcoming events depends on some precursors from other parameters such as the sea surface temperature for monthly to seasonal time scales, the surface pressure for weekly to daily time scales, the surface pressure for weekly to daily to hourly time scales (Afolayan *et al.* (2016). A lot of attention has been directed towards modeling and forecasting the amount of rainfall in various parts of Nigeria. The results from time series analysis derived from the study of rainfall in the past have proved inadequate, due to evidence in the occurrence of sudden natural disasters like very heavy rainstorms, floods and erosion. These have taken a lot of people by surprise and claimed lots of lives and properties. Many researchers, such as Awolalu (2006) and Akpanta *et al.* (2015) have employed ARIMA and SARIMA respectively to model and forecast rainfall of Umudike, but they did not compare their models with other suitable models for forecasting rainfall data of Umudike, so as to select an appropriate model from the set of models. However, Offorha *et al.* (2018) have attempted to compare the forecasting abilities of Holt Winters Exponential Smoothing and SARIMA Models using four forecast error measures- Mean Error (ME),Mean Absolute Error(MAE), Mean Square Error (MSE) and Root Mean -Square Error (RMSE). In all their works, they were considering only two models and using descriptive forecast errors for comparison. This paper therefore seeks to compare three different models- Triple Exponential Smoothing, SARIMA and Multiple Linear Regression Models to forecast the rainfall data of Umudike, and to apply Friedman iest statistic and the various descriptive measures to select an appropriate model from the competing models. Also, there works did not compare their models with other suitable models for forecasting rainfall data of Umudike.

There have been numerous time series analysis studies on rainfall, most especially on the amount of rainfall. In recent times, researchers are trying something new on rainfall. Dimgba (2000), in her work constructed a mathematical model for the rainfall data of Onne , which could be used to predict reliable and dependable future rainfall values. Specifically, it was intended to estimate and isolate the components of time series data namely, Trend, Seasonal variation, Cyclical variation and Irregular component present in the data using the descriptive time series approach. The study covered the period of 1989-1997, while 1998 data was removed so that it can be compared with the predicted values. The data was collected from IITA Onne in River State. The results of the analysis showed amongst others that all the components of time series were present in the data. On the average, the rainfall of Onne within the period under consideration is 203.14mm with a standard deviation of 154.87mm.Based on the results of the analysis, it was suggested that a probability model be filled to the data in order to obtain a more sound result. Also, observations of more than 20 years should be analyzed so that the effect OC cycle will be greatly felt. Ezurike (1999), did a time series analysis on the rainfall data of Umudike for the period of 10year. She found that the periodic heavy rain occurred between May and October with maximum in August and September and a slight decline in July. She came up with the conclusion that rainfall data of Umudike from 1989-1998 had constant trend and exhibit seasonal pattern throughout the period of study. Delson (2004) , in his study, employed Multiple Regression model to explain and predict mean annual rainfall in Zimbabwe. The historical annual mean rainfall data in Zimbabwe for the period 1974-2009 was collected from Zimbabwe Department of Meteorological services. The mean annual rainfall values were calculated by averaging the monthly rainfall totals. In this work, dependent rainfall variable is expressed in terms of independent explanatory variable. The aim of the study is to develop a simple but reliable tool to predict annual rainfall for one year in advance using Darwin Sea level Pressure (Darwin SLP). Also, a weighted multiple regression approach is used to control for heteroscedasticity in the error terms. The model developed has a reasonable fit at the 5% statistical level can easily be used to predict mean annual rainfall at least a year in advance.Folorunsho and Adesesan (2012), on their work, opined that weather forecasting is a vital application in Meteorology and has been one of the most common scientifically and technologically challenging problems around the world in the last century. They investigated the use of Data Mining techniques in forecasting maximum temperature, rainfall, evaporation and wind speed. And they carried this out using Artificial Neural Network and Decision Tree Algorithms and Meteorological data collected between 2000 and 2009 from the city of Ibadan, Nigeria. A data model for the meteorological data was developed and this was used to train classifier algorithms. The performances of these algorithms were compared using standard performance metrics, and the algorithm which gave the best results used to generate classification rules for the mean weather variables. A predictive Neural Network model was also developed for the weather prediction. Program and the results compared with actual weather data for the predicted periods. The results show that given enough case data, Data Mining techniques can be used for weather forecasting and climate change studies. Akpanta *et al.* (2015) on their research considered the frequency of monthly rainfall from 1996-2011 obtained from NRCRI Umudike in Nigeria. The analysis was based on probability time series modeling approach. Emphasis would only be placed on the seasonal ARIMA (SARIMA) models. From the plots: Time series plot (Top Panel), ACF plot (Centre panel) and PACF plot (Bottom panel). It could be seen that the time series plot displays a wave like pattern, an evidence of seasonality and no trend is observed which implies that the time series is stationary. The sinusoidal or periodic pattern in the ACF plot is again suggesting that the series has a strong seasonal effect. The graph further displays evidence of seasonality and it was removed by seasonal differencing. The plots of the ACF and PACF show spikes at seasonal lags respectively. It could be concluded that the frequency, not the amount of rainfall from 1996-2011 obtained from National Root Crop Research Institute (NRCRI) Umudike in Nigeria, is analyzed using probability time series modeling approach. Though the diagnostic check on the model favored the fitted model, the Auto regressive parameter was found to be statistically insignificant and this led to a reduced SARIMA (0, 0, 0) $(0,1,1)_{12}$ model that best fit the data and was used to make forecast. Comparison of the actual/observed frequency from July to December 2011 was done with their corresponding forecast values and a T- test of significance showed no significant difference. Offorha *et al.* (2018) on their work carried out a comparison of forecasting methods for frequency of Rainfall in Umuahia, Abia state, Nigeria. Two different forecasting techniques,

Box Jenkins SARIMA and Holt-Winters Exponential Smoothing were adopted for the analysis. The data used for the study were collected from the National Roots Crop Research Institute, Umudike (2007-2016) with a view to determining a better forecasting method. This was achieved using four forecast errors statistics- Mean Error (ME), Mean Square Error (MSE), Mean Absolute Error (MAE) and Root Square Mean Error (RSME). SARIMA method has the minimum error values, a paired-sample t-test shows that there is no significant difference between the forecast values obtained from the two forecasting methods. This therefore pre-supposes that the Holt-Winters was equally a good forecasting method for the frequency of Rainfall in Nigeria.
Murat *et al*.(2018) made use of ARIMA and Regression models to model the Meteorological time series of four European regions. They used the methods of the Box-Jenkins and Holt-Winters seasonal auto regressive integrated moving-average, the autoregressive integrated moving-average with external regres-sors in the form of Fourier terms and the time series regression, including trend and seasonality components methodology with R software. It was demonstrated that obtained models are able to capture the dynamics of the time series data and to produce sen-sible forecasts. However, they did not compare the models in order to isolate the most appropriate one for the series. Related works are also carried out by Etuk *et al.* (2016), Iwok (2016), Attah and Bankole (2011), Uba and Bakari (2015), and many others.

Methods of Analysis

The data for this study was collected from the Meteorological Department of the National Root Crop Research Institute (NRCRI), Umudike. This data is a monthly data between the year (2008-2017), making it 10 years of monthly rainfall data.

Triple Exponential Smoothing

Triple exponential smoothing extends the double exponential smoothing to model time series with seasonality. The method is also known as the Holt-Winters in recognition of the name of the inventors. Winters improved the Holt's method by adding a third parameter to deal with seasonality. Thus, the method allows for smoothing time series when the level, trend and seasonality can vary. There are two main variations of the triple exponential model and they depend on the type of seasonality. If the seasonality is multiplicative (i.e. non-linear), then the three smoothing equations pertaining to level, trend and seasonality of *p*-period cycles are given by :

$$L_t = \alpha(X_t/I_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (1)$$
$$T_t = \gamma\,(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \quad (2)$$
$$I_t = \delta(X_t/L_t) + (1-\delta)I_{t-p}$$

The forecast equation *h*-steps ahead at time *t* from the Holt-Winters with multiplicative seasonality is given by

$$\hat{F}_{t+h} = (L_t + hT_t)I_{t-p+h}, \quad h = 1, 2, 3, \ldots \quad (3)$$

and its associated forecast error at time *t* is

$$e_{t+h} = X_{t+h} - F_{t+h} = X_{t+h} - (L_t + hT_t)I_{t-p+h}. \quad (4)$$

If the seasonality is additive (i.e. linear), the smoothing equations are given by

$$L_t = \alpha(X_t - I_{t-12}) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (5)$$

$$T_t = \gamma\,(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \quad (6)$$
$$I_t = \delta\,(X_t - L_t) + (1-\delta)I_{t-p} \quad (7)$$

The forecast equation at time *t* from the Holt-Winters method with additive seasonality is given by

$$\hat{F}_{t+h} = (L_t + hH_t)I_{t-p+h}, \quad h = 1, 2, 3, \ldots \quad (8)$$

and its associated forecast error at time *t* is

$$e_{t+h} = X_{t+h} - F_{x+h} = X_{t+h} - L_t - hT_t - I_{t-p+h}. \quad (9)$$

where,
I_t= smoothed seasonal index at the end of the period.
p=is the number of period in seasonal cycle,
α = the smoothing constant used for L_t (level)
γ= the smoothing constant used to calculate the trend (T_t)
δ = its smoothing constant such that used for calculating the seasonal index
h= horizon length of the forecasts of F_{t+h} or number of forecast steps into the future
T_t= Smoothed value of trend through period t
L_t=smoothed value at the end of t after adjusting for seasonality.

X_t= Actual value for the period t.
T_{t-1}= past trend at time t
T_{t+1}= Forecast of the Time series for period $t+1$
hT_t= number of forecast into the future of Trend
I_{t-p+h}= smoothed seasonal index for period $t+1$.
e_{t+h}= error in period $t+1$.

2.2 Multiple Linear Regression Model

It is an extension of simple linear regression. It is used to explain the relationship between one continuous dependent variable and two or more independent variable.

The Multiple Regression model as applied to time series data according to (De-lurgious, 1998) is given by

$$Y_t = a_0 + b_0 t + \alpha_1 X_{1t} + \alpha_2 X_{2t} + \cdots + \alpha_{11} X_{11t} + e_t \quad (10)$$

Where,
Y_t= The dependent variable,
t = the time in months, X_{it} are the dummy variables representing the months where the values occur (i.e 1 if the value is in that month and 0 otherwise);
$\alpha_i$are the dummy variable coefficients representing ith months (season)
e_t= random error term,
a_0, b_0= trend coefficients
Notice here that the month of January is excluded to avoid a 'dummy variable trap'.

Seasonal ARIMA (SARIMA) Models

Ekpenyong and Udoudo (2016) started that a time series is said to be seasonal of order d if there exists a tendency for the series to exhibit periodic behavior at regular or almost regular time interval d. The time series $\{X_t\_\_\}$ is said to have a multiplicative (p, d, q)x(P, D, Q)s seasonal ARIMA model if:

$$A(B)\Phi(B^s)\Delta^d\nabla^D{}_s X_t = B(B)\Theta(B^s)\varepsilon_t \quad (11)$$

Where Φ *and* Θ *are polynomials of order P and Q respectively. That is*

$$\Phi(B^s) = 1 + \phi_1 B^s + \cdots + \phi_p B^{sp} \quad (12)$$
$$\Theta(B^s) = 1 + \theta_1 B^s + \cdots + \theta_p B^{sp} \quad (13)$$

Where ϕ_j *and* θ_j are constants such that the zeros of equation (12) and (13) are all outside the unit circle for stationarity and invertibility conditions respectively. Equation (12) and (13) represents the Autoregressive (AR) and Moving Average (MA) operators respectively. Existence of a seasonal nature in a series is often evidentfrom the time plot. Moreover, for a seasonal series, the Autocorrelation Function (ACF) exhibits a spike at the seasonal lag. Seasonal differencing is necessary to remove the seasonal trend. If there exists a secular trend, then non-seasonal differencing is necessary. Etuk (2012) stated that to avoid undue model complexity, orders of differencing d and D should add up to at most 2 (i.e d+D< 3). If the ACF of the differenced series has a positive spike at the seasonal lag, then a seasonal AR component is suggestive; but if it has a negative spike, then a seasonal MA term is suggestive. As it is already known, an AR (p) model has a Partial Autocorrelation function (PACF) that truncates at lag p and an MA (q) has an ACF that truncates at lag q. In practice,$\pm 2/\sqrt{n}$, where nis the sample size, are the confidence limits for both functions.

The Friedman Test

The Friedman test is a non-parametric statistical test developed by Milton Friedman. Similar to the parametric repeated measures ANOVA, it is used to detect differences in treatments across multiple test attempts. The procedure involves ranking each row (or block) together, then considering the values of ranks by columns
.

$$F_r = \frac{12}{bk(k+1)}\sum_{i=1}^{k} R^2{}_i - 3b(k+1) \quad (14)$$

where, k is the number of models, b is the data size.

The hypothesis here is that the models are not significantly different from one another against the alternative hypothesis that the models are significantly different from one another for at least one of the models.

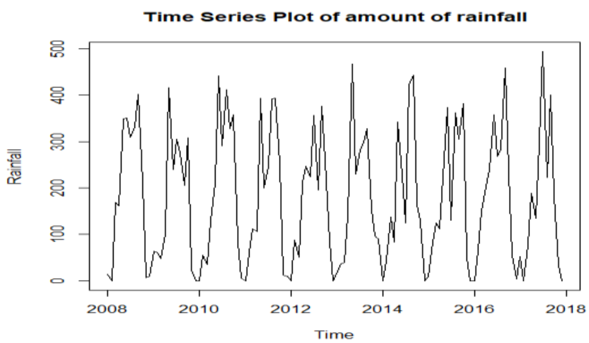
The decision rule is that H_0 is rejected if $F_r > \chi_\alpha{}^2, k-1$, otherwise it is accepted.

Results and Discussion

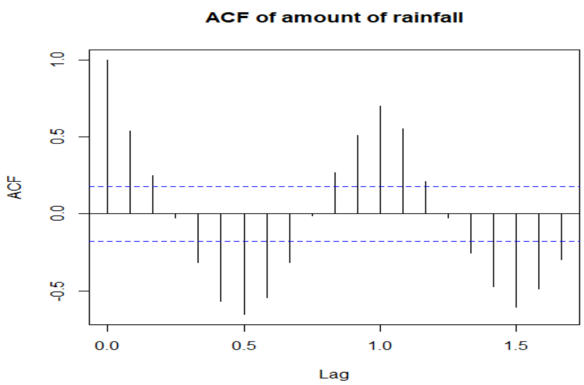
R version 3.5.1 was explicitly used for all analyses in this study. All statistical tests conducted were done at 5% level of significance.

Exploratory Data Analysis

(A)



(B)



(C)

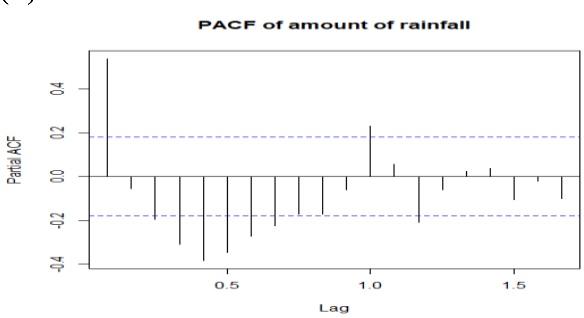


Figure 1: Plot of the original Series (A), ACF (B) and PACF (C) of the frequency of monthly rainfall of Umudike, Umuahia from January 2008 to December 2017.

From the plot in figure 1 it could be seen that the time series Plot clearly indicates the presence of seasonality in the time series, and it also shows that there is no trend in the time series, since the time series does not seem to change (increase or decrease) over a reasonable period of time. We could equally observe from the same plot that the mean is constant hence no need for any mean correction and the series does not vary with time indicating that there is no need for data transformation. The periodic pattern in figure 2 and 3 is again suggesting that the series has a strong seasonal effect. The Augmented Dickey-Fuller (ADF) was performed in order to verify the stationarity claim of the visual display with Hypothesis the rainfall data is not stationary against the alternative hypothesis that the rainfall data is stationary.

Table 1

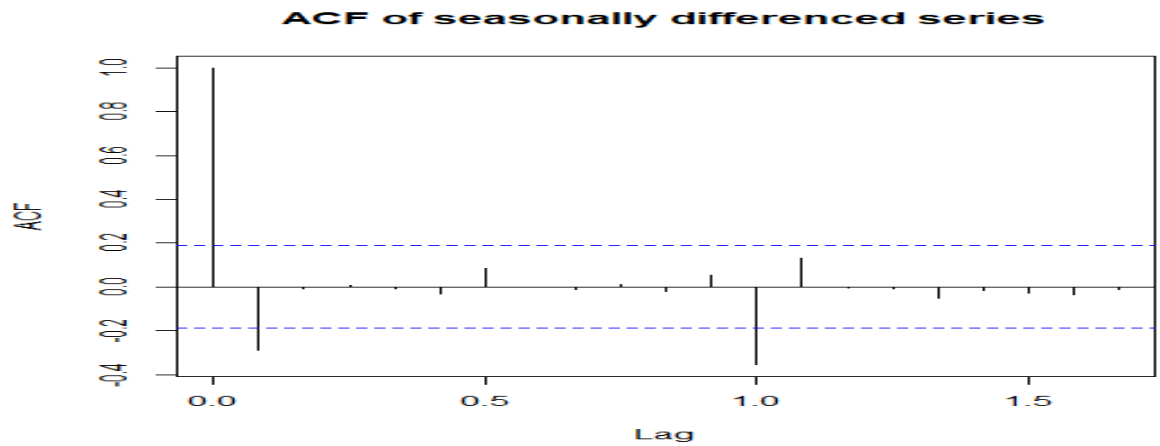
Test	Test Statistic	P-value
Dickey-Fuller	-4.9922	0.01

From Table 1, it can be deduced that P-value is less than 0.05 which is in favour of the alternative hypothesis. Thus, there is a strong evidence against the null hypothesis at 5% level of significance.
In order to eliminate the seasonal effect from the time series, we subject the data to seasonal differencing and the data is re-examined visually.

SARIMA MODEL

SARIMA models are multiplicative combination of the trend and seasonal parts of the time series which is denoted as SARIMA, $(p,d,q)(P,D,Q)_s$ respectively. From the initial investigations in figure 1, we found that the series shows a constant trend hence d=0. Also, we found that the series shows a cyclic pattern indicating seasonality; hence we subject the series to first seasonal differencing with lag 12, so D = 1. Once the effect of seasons has been removed the next step is to determine the remaining parameters of the seasonal part, which are P and Q.

This was achieved using the ACF and PACF plots presented in Figure 2(A) and (B).



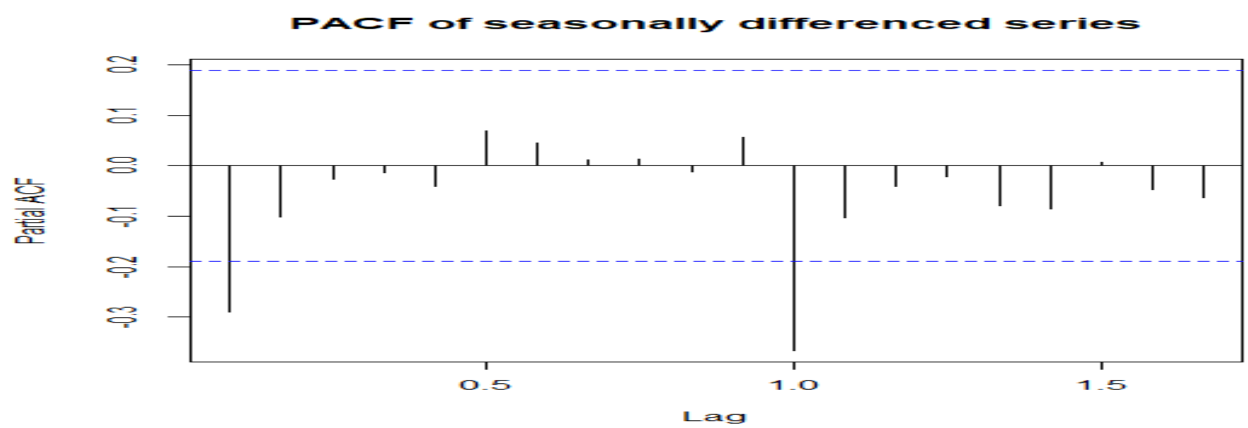


Figure 2: ACF (A) and PACF (B) plots of the first seasonal differencing of the frequency of rainfall in Umudike, Umuahia, Abia State (Jan. 2008- Dec. 2017).

The optimal SARIMA Model obtained by using "auto.arima" in R-Software, with minimum AIC in SARIMA (2,0,0) $(2,1,0)_{12}$

Table 2: Parameter Estimates of the Model

Coefficients	SAR1	SAR2
Estimates	-0.5652	-0.3375
Standard Error	0.1011	0.1057

Table 3: Accuracy Measures

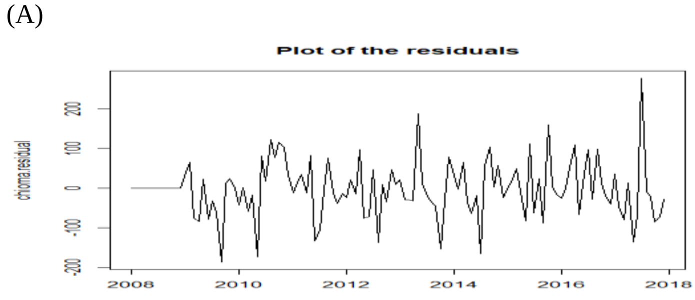
ME	RMSE	MAE	MSE
-2.638199	70.94317	50.54664	0.7445393

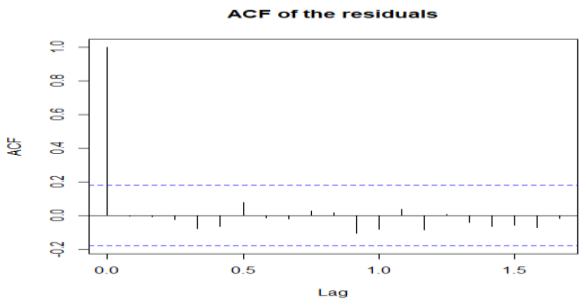
Model Validation

It is ideal that after a model has been fitted on a time series data for diagnostics checks to be conducted to ascertain if the model fits the data adequately. These checks are carried out on the residuals.

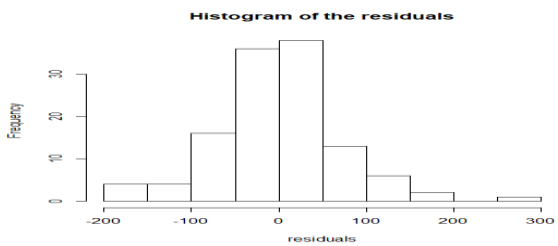
Diagnostic Checks On The Residuals

(A)





(B)



(C)
(D)

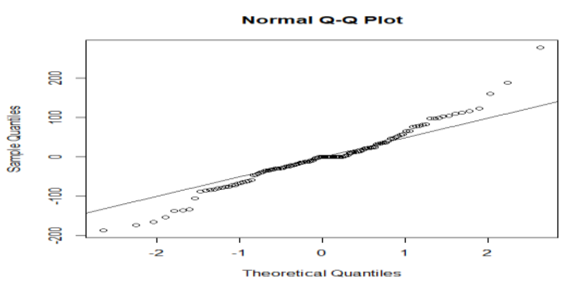


Figure 3: Adequacy checks of the fitted SARIMA (2, 0, 0) $(2,1,0)_{12}$ model using its residuals.

From Figures 3 (C) and (D) used on checking the normality of the residuals, they clearly indicate that the residuals could be said to be from a normal distribution. but, Figure 3(B) of the residuals clearly shows that none except one of the spikes is significant as all are contained inside the confidence band. Hence, we conclude that the adjacent observations are not autocorrelated. Also, the residual plot (Figure 3 A) shows that the residuals fluctuate around zero, indicating that the residuals has a zero mean with a constant variance.

3.2 Holt-Winters Triple Exponential Smoothing

This Section shows the forecast results obtained from the Holt-Winters' model. R- Statistical Software package is used in obtaining the parameters of the model and making forecasts based on the fitted model. The parameters' estimates are shown in Table 3.

Table 4: Table Estimated Parameter for Holt-winters Triple Exponential Smoothing

Smoothing Parameters	Estimated value
Alpha (α)	0.018315638
Gamma (γ)	0.018315638
Sigma (δ)	68.6751

From Table 4, α is very low and this shows that the level estimates are based on very recent observations in the series. The γ value shows that the trend is slightly updated but in a very minimal way. The δ value depicts that the estimate of seasonal indices are based on observations from the distant past.

Table 5: Accuracy Measures for Holt-Winter's Triple Exponential

ME	RMSE	MAE	MSE
-0.299845	64.54482	48.94898	0.7210063

Multiple Linear Regression

This Section shows the estimation results obtained from the Multiple Linear Regression.

Table 6: Parameter Estimate For Multiple Linear Regression

Coefficients	Estimate	Std.Error	t value	Pr(>/t/)
(intercept)	16.76465	23.14530	0.724	0.4704
Trend	-0.04363	0.17968	-0.243	0.8086
Season 2	34.04885	29.71265	1.180	0.2408
Season 3	78.98518	29.70905	2.598	0.0084 ***
Season 4	129.11612	29.70653	4.346	3.16e-05 ***
Season 5	292.01975	29.70510	9.831	< 2e-16 ***
Season 6	279.89339	29.70475	9.423	1.04e-15 ***
Season 7	266.40702	29.70549	8.968	1.10e-14 ***
Season 8	304.93066	29.70732	10.264	<2e-16 ***
Season 9	349.88429	29.71023	11.777	<2e-16 ***
Season 10	236.55792	29.7142	7.961	1.93e-12 ***
Season 11	43.27156	29.71932	1.456	0.1483
Season 12	-1.46621	30.55814	-0.048	0.9618

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

Table 7: Accuracy Measures

ME	RMSE	MAE	MSE
-2.810252e-16	64.19477	48.45201	0.388838

Models' Comparison: Use of Accuracy Measures

To compare the performance of the fitting models from the three frameworks: SARIMA Model, Holt-Winters and Multiple Linear Regression .we use four measures of error statistics, the Mean Error(ME), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for this comparison. Table 8 is used to make comparison based on their accuracy measures.

Table 8: Summary of the Accuracy Measures of the Models

Accuracy Measures	Forecasting Models		
	SARIMA	Holt-Winters	Multiple Regression
ME	-2.638199	-0.299845	-9.765048e-16
MSE	0.7445393	0.7210063	0.3890477
RMSE	70.94317	64.54482	64.19683
MAE	50.54664	48.94898	48.47814

From Table 8, it could be observed that the Multiple Linear Regression approach has lower error statistics when compared to Holt Winters and SARIMA Models. Therefore, the Multiple Linear Regression Model is the most appropriate model for forecasting rainfall pattern of umudike among the three models. This is seconded by Holt-Winters Model.

Use of Friedman Test Statistic to compare the ranks of the residual of the three models

Table 9: Sum of Ranks of the absolute errors of individual models

Model	Sum of Ranks
SARIMA	222
HOLT-WINTERS	243.6
MULTIPLE LINEAR REGRESSION	254.4

From Table 9, the Friedman test Statistic is given as

$$F_r = \frac{12}{bk(k+1)}\sum_{i=1}^{k} R^2{}_i - 3b(k+1)$$

where b=120, k=3

$$F_r = \frac{12}{(120)(3)(3+1)}(222^2 + 243.6^2 + 254.4^2) - 3(120)(3+1) = 4.536$$

.

The hypothesis here is that the models are not significantly different from one another against the alternative hypothesis that the models are significantly different from one another for at least one of the models.

The decision rule is that H_0 is rejected if $F_r > \chi_\alpha{}^2, k-1$, otherwise it is accepted.

Hence, $\chi_{0.05}{}^2, 2 = 5.99$

Since $F_r = 4.536 < \chi_\alpha{}^2, k-1 = 5.99$. Therefore, we do not reject H_0 and hence we conclude that the models are not significantly different from one another at $\alpha = 0.05$.

CONCLUSION

In comparing the three models: SARIMA Model, Triple Exponential Smoothing and Multiple Linear Regression Approach, it was observed that the Multiple Linear Regression has much lower accuracy error measures and as such was considered the most appropriate model for forecasting rainfall pattern of Umudike. Further, in using the Friedman test statistic to test for the difference In performances of the models, we observed that the models were not significantly different from one another in terms of performance, unlike the use of accuracy measures. For future investigation the use of Friedman test is recommended, because it involves the use of statistical tool for inference, whereas the use of only Accuracy Measures of MSE, MAE, etc. does not require any statistical test. In addition, models for Forecasting Rainfall or other Climatic factors should be compared for adequacy before use.

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