Analysis of Rainfall Pattern in the Western Region of Ghana

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ABSTRACT

The primary aim for this paper is to examine the pattern of rainfall in the western region of Ghana. Data was obtained from the Ghana Meteorological Agency. The sample include January to September pattern of the amount of rainfall, for the years 2006 to 2016. That is nominal daily rainfall recorded (1485) aggregated into monthly rainfall value (99 data point). The analysis includes fitting an auto regression moving average model (ARMA) model for the data. The series was found to be non-stationary which resulted from the presence of a unit root in it. The series became stationary after eliminating the unit root by finding the first difference in the amount of rainfall. The time series component found in the model were a trend and random variation. ARMA (1, 1) which has all parameters significant was fitted for the data and found to be the most suitable model for the conditional mean. A Ljung Box test statistic of 47.207 with a normalised BIC of 6.420 and a Root Mean Square error of 24.16 supported by a probability value of 0.001 show that the fitted model is appropriate for the data. An R^2 = 0.532 indicates that about 53% of the variations seen in the pattern of rainfall recorded for the period is being explained by the fitted model. The 18-month forecast for the mean actual rainfall and mean returns could show that the fitted model is appropriate for the data and an increasing trend of rainfall for the forecasted period.

Keywords: Auto regression moving average; Unit root; ACF; PACF; forecast; stationarity, parameter estimates; ADF test statistic.

1. INTRODUCTION

Rainfall variability has severe implications for livelihood and food production in developing regions such as West Africa. In this region, irrigation is restricted and inter-annual and multi-decadal variability leads to declining rainfall total. The situation is exacerbated by the fact that more than half of the adult population in the sub-region is directly engaged in essentially rain-fed agriculture. Ghana, like the other parts of the sub-continent, has undergone a period of declining annual rainfall total since the early 1970s and she is only recently showing signs of recovery since 2000 [1]. Increases in annual rainfall totals in many parts of Ghana after the year 2000 are evident in the spilling of the Akosombo dam on the Volta River in November 2010. This was the first time in 20 years that the dam had to be spilled due to increases in rainfall [2]. About 42 % of Ghana's $238{,}540\ km^2$ is suitable for crop cultivation but only about 27 % of this is under cultivation as estimated by the

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Food and Agricultural Organization (FAO) in 2005. In a pilot study in Wenchi, located on the northern fringe of mid-Ghana, [2] identified, in addition to an overall drying, greater reductions in the mean rainfall totals and the mean number of rainy days during the minor rainy season and a slight increase of rains in the short dry spell. This reduction in rainfall and potential diminution of the minor rainy season, if present throughout humid mid-Ghana, is likely to prevent the cultivation of crops and crop varieties that have longer growing seasons, as well as the adoption of a single crop per year, instead of the current two crops, under rain-fed agriculture. Such an occurrence will negatively impact on food security. Government agencies and international organisations are currently encouraging the application of seasonal forecast information and weather index insurance as some of the adaptation measures [3, 4].

However, to develop a model for predicting changing rainfall patterns or to utilise available forecasted information, it is important to understand both the spatio-temporal nature of the declining and shifting rainfall pattern in the agriculturally important regions in mid-Ghana. According to FAO in 2008, rainfall variability is an inherent part of the African climate and it is deeply entrenched in West Africa. Thus, there is inadequate rain for irrigation in many African countries and as such countries whose economies rely highly on agriculture are greatly vulnerable to economic instability. According to the International Scientific Research (ISR) Journal [2], “in the event of large deviations from the normal rainfall, people are highly affected as floods and droughts are most often the by-products. Government’s scarce resources are directed to humanitarian missions to help people affected by floods and other disasters that come with these extreme weather conditions”.

During the last 10 to 15 years, there have been worldwide perceptions that droughts and floods have intensified [5]. In Ghana, it has been observed that the annual rainfall total has generally declined while the total number of extreme events such as droughts has been on the increase [2, 6]. Similar studies conducted by [7] for West Africa, [8] for east Africa, [9] for South Africa, [10, 11] for various parts of Africa show that some regions on the continent, especially west Africa have suffered drastic changes such as prolonged drought and prolonged flood.

In Ghana, the situation is no different, the Ministry of Finance, in 2007 indicated that the problem of rainfall variability is paramount and continues to have serious consequence on the Ghanaian agriculture, accounting for about 35% of the country’s Gross Domestic Product (GDP). Farmers depend on shared knowledge and experience with the weather as well as observations of natural phenomena to forecast forthcoming cropping season and weather condition [12]. However, in recent times, the frequency of change in climate has increased considerably, and local experience and knowledge are no longer sufficient to guide agricultural planning and decision making [13]. Hence the initiation of models as a guide to understanding these drastic changes and future circumstances could, therefore, be predicted based on the knowledge acquired from these models.

Climate change in Ghana has become a threat to livelihoods. Drought and over flooding in some parts of Ghana have developed into yearly worry to people and government. In the south particularly, the coastal areas, aquatic life is of great importance because of the fishing activity that goes on there, and farmers in these parts also dwell mainly on the rains for farming since there are no major irrigational facility. As such, changes in rainfall affect the level of water bodies as well as crop farming. This problem influences the economic activities in these areas and the country at large. As a result, the Government of Ghana contracts researchers and engineers to come out with ways to solve these problems every now and then [4]. One of the ways used is time series analysis, thus, studying the past and current pattern of rainfall in a systematic approach would help to fit a suitable model for future predictions.

The major purpose of this study is to identify rainfall pattern in the Western Region of Ghana, West Africa by considering the years 2006 to 2016 and fitting an appropriate time series model for forecasting future rainfall pattern (values) in the Western Region. Findings of this paper will be significant since it will enable farmers to plan their farming activities ahead of time and provide empirical evidence to stakeholders on rainfall trends to help them formulate policies that can benefit the region concerned and the nation at large.

2. DATA AND METHODS

This article considered a model based on information and real data obtained from the

Ghana Meteorological Station, Sekondi. The sample includes January to September pattern of the amount of rainfall, for the years 2006 to 2016, that is nominal daily rainfall recorded (1485) aggregated into monthly rainfall value (99 data point).

2.1 Time Series Analysis

In time series analysis, the past and present behaviour of variables are observed and examining them often suggest the method of analysis as well as statistics that will be of use in summarising any information in the data, so that values predicted from the data may fit the present situation as well as the future. Time series data are often obtained through monitoring industrial processes or tracking corporate business metrics. Data used in time series can be continuous or discrete in nature, it is said to be continuous when the observations are made over time interval and it is described as discrete when observations are made at specific time periods. Usually these observations in time series are taken at regular intervals such as days, months, quarters and years. There are two mutually exclusive approaches usually applied in time series analysis, these are the time domain approach and the frequency domain approach. Conversely, the time domain approach which is adapted in this study is generally motivated by the assumption that correlation between times is explained best in terms of a dependence of the current value on the past values. This approach focuses on modeling some future value of a time series as a parametric function of the current and past values. A more current method in the time domain approach well-known to statisticians is the use of the additive model or the multiplicative models [14, 15].

Time series data exhibit at least one of the following features; Secular (Trend), Seasonal variations, Cyclical variations, and Irregular (Random) variations. Secular (Trend) are continuous long-term movement in a variable over an extended period that is, a general increase or decrease in a time series data over several consecutive periods. Trend can be linear or nonlinear. A linear trend tends to increase or decrease at a constant rate, however, a nonlinear trend is likely to move steadily upwards, as others decline. Seasonal Variation is a wavelike pattern that is repeated throughout a time series with a recurrent period at most one year but, usually on weekly, monthly, quarterly, or annual basis. These are the short-term regular variations in data, generally caused by factors such as weather, holidays, festivals etc.

Seasonal component is a pattern in time series which indicate a change of monthly data that repeats itself within a year. A Cyclical Variation exhibits repetitious pattern with a recurrent period longer than one year. This occurs mostly in businesses which indicate variations in the general level of national economic measures such as unemployment, gross national product, stock market index etc. over a relatively long period of time, thus these points toward a cycle. Irregular (Random) Variation is often referred to as the “noise” in the data that are unpredictable in the times series data and cannot be associated with trend, seasonal, or cyclical component of time series. Events such as industrial strike actions, earth quakes, floods, outbreak of epidemics, wars etc., may lead to odd movements in a time series data [14, 15]. The types of patterns of fluctuations in a time series may be represented as;

T = trend value of the series
S = value of the seasonal variation
C = value of the cyclical variation
I = value of the irregular variation

Thus let;

Y_t = observed values of the time series at time t (1)

Hence the additive and multiplicative models may be represented as

$$Y_t = T + S + C + I \text{ and} \tag{2}$$

$$Y_t = T \times S \times C \times I \text{ respectively.} \tag{3}$$

If the data however, do not contain one of the type of variation (e.g., cycle) the value for that missing component is zero. For instance, there is no cycle for a yearly series since cyclical variation cannot be observed over a one-year period, hence the additive model becomes;

$$Y_t = T + S + I. \tag{4}$$

Likewise, in the multiplicative model if the trend, seasonal variation, or cycle is missing, then the value is assumed to be 1. So, for series with a period of one year, where there is no cycle then;

$$Y_t = T \times S \times I. \tag{5}$$

2.2 Trend Analysis and Forecasting Techniques

Time series analysis is aimed at projecting trend by fitting a trend line to a series of historical data points through which a model is fit for prediction of future values over a period. Several trend Equations can be developed based on exponential or quadratic models, however, the simplest is a linear trend model (least square method- LSM) that is developed using Regression analysis. Equation for Linear Trend is given by

$$T_t = b_0 + b_1 t \quad (6)$$

Where;

T_t = trend value in period t (predicted value)
b_0 = intercept of the trend line
b_1 = slope of the trend line
t = time

It should be noted that t is the independent (or predictor) variable and T_t is the dependent (response) variable. Computing the Slope (b_1) and Intercept (b_0) using the Least Square Method (LSM). The slope (b_1) is given by;

$$b_1 = \frac{n\sum tY_t - \sum t \sum Y_t}{n\sum t^2 - (\sum t)^2} \quad (7)$$

and the intercept (b_0) is also given by;

$$b_0 = \frac{\sum Y_t}{n} - b_1 \frac{\sum t}{n} = \overline{Y}_t - b_1 \overline{t} \quad (8)$$

Where;

Y_t = actual value in period t
n = number of periods in time series

Quadratic trend model is a non-linear trend model also known as a second-degree polynomial model. It is the simplest curvilinear model with a general equation given by;

$$T_t = b_0 + b_1 t + b_2 t^2 \quad (9)$$

Where;

b_0 estimates the value of T_t when t=0
b_1 is the linear effect coefficient
b_2 is the curvilinear effect coefficient

Time series data is deseasonalized when the seasonal effects in a time series data is to be removed before trend is fitted and usually seasonal index are computed for such purpose. Seasonal pattern is the short-term cycle occurs within or at most a year. The seasonal variation can be expressed in terms of deviations from the original data in the case of additive model or as percentage of the trend in the case of multiplicative model. Thus, the deseasonalized value for an additive model is given by;

$$\text{Deseasonalized value} = \text{time series observation} - \text{seasonal index} = Y_t - I_S$$

and that of multiplicative model is also given by;

$$\text{Deseasonalized value} = \frac{\text{time series observation}}{\text{corresponding seasonal index}} = \frac{Y_t}{I_S} \quad (10)$$

Thus, applying the LSM, $T_t = b_0 + b_1 t$ in this case, Y_{st} the deseasonalized time series value at time t is used in-place of the actual value of the time series (Y_t). The resulting line equation is therefore used to make trend projections. Projection of trend into the future is usually known as forecasting, the time series data are plotted so that their trends over time are observed. If there is a long term upward or downward trend in the data the least square forecasting method can be considered especially when dealing with annual data. However, if there is no trend then either the moving average or the exponential smoothing forecasting techniques may be employed. Exponential smoothing is a forecasting tool also used predicts future time series data. In this type of forecast technique, the forecast is based on a weighted average of a historic time series data. The weighted average usually represented by alpha (α) [14, 15, 16]. Thus, the forecast value for a current time series is computed as;

$$F_{t+1} = \alpha Y_t + (1 - \alpha) F_t \quad (11)$$

Where;

F_{t+1} is the new forecast for time t + 1
Y_t is the previous period actual demand
F_t is the previous forecast for the time t
α is the smoothing constants ($0 \le \alpha \le 1$)

2.3 Measures of Forecast Error (Forecast Error = (Y_t - F_t))

The forecast error is the deviation of the forecast values (F_t) from the actual values (Y_t). There are four main errors measured in forecast data. These errors include Bias, Mean Absolute Deviation (MAD), Mean percentage deviation error (MAPE) and the mean square error (MSE)

[14, 15, 16]. In time series analysis Bias, MAD, and MAPE are the usual errors employed to assess the amount of errors related to a forecast. Bias is similar to the arithmetic mean, that is, the sum of the forecast errors divide by the number of period, *T* and it is given by

$$\mathrm{Bias} = \frac{\sum_{t=1}^{T}(\text{Forecast error})}{T} = \frac{\sum_{t=1}^{T}(Y_t - F_t)}{T} \qquad (12)$$

Mean Absolute Deviation (MAD) is the sum of the absolute forecast error divide by the number of period, *T*. Mathematically,

$$\mathrm{MAD} = \frac{\sum_{t-1}^{T}|\text{Forecast error}|}{T} \qquad (13)$$

$$= \frac{\sum_{t=1}^{T}|Y_t - F_t|}{T}$$

Mean square deviation is more sensitive measure of usually large forecast error than Mean Absolute Deviation [14, 15, 16]. Mean Absolute Percentage Error (MAPE) [17] is the division of each percentages of the absolute forecast error by their actual values, then all summed and divide by the number of period, *T*. Hence.

$$\mathrm{MAPE} = 100\frac{\sum_{t=1}^{T}\frac{|Y_t - F_t|}{Y_t}}{T} \qquad (14)$$

Mean Square Error (MSE) is similar to simple sample variance [14, 15, 17]. Standard Error is the standard deviation of the sampling distribution (the square root of the MSE) given as

$$\mathrm{MSE} = \frac{\sum_{t}^{T}(\text{Forecast error})^2}{T} \qquad (15)$$

$$= \frac{\sum_{t=1}^{T}(Y_t - F_t)^2}{T}$$

3. RESULTS AND DISCUSSION

The analysis that follows is focused on the pattern of rainfall in the western region of Ghana. The analysis includes fitting an ARMA model for the observed rainfall data. This article considered a model based on information and real data obtained from the Ghana Meteorological Station, Sekondi. The sample include January to September pattern of the amount of rainfall, for the years 2006 to 2016, that is nominal daily rainfall recorded (1485) aggregated into monthly rainfall value (99 data point). Time Series Analysis and the statistical computing package R were used for the modelling.

3.1 Rainfall Distribution

The time plot of a given series gives a fair idea of the stationarity of the series which is considered as a form of statistical stability. A series with trend or seasonal pattern are considered as non-stationary. That is the mean of the given series change with time. The time plot of the series in Fig. 1 shows that the series exhibit a random fluctuation showing a periodic or seasonal variation with maximum value of 408.30 in June. 2011 and a minimum value of 1.20 in January. 2009. We also observe that the mean of the amount of rainfall changes over time, which suggest the series is non-stationary. The histogram with a normal curve and normal Q-Q plot indicates that the empirical distribution of the series is not normally distributed and skewed to the right. By performing the unit root test on the series, we found that the Augmented Dickey-Fuller (ADF) root test statistic (-1.9453) is higher than the critical value (-2.86431), at a 5% significance level indicating that we fail to reject the null hypothesis that there is a unit root in the series which is supported by a p-value of 0.234.

For us to eliminate the unit root, we found the first difference in the rainfall pattern and conducted the test again. The results of the test show an ADF test statistic for the first difference (-8.2038), with a p-value of 0.01and critical value (-2.86431) which make us reject the null hypothesis of a unit root in the series. Hence, we conclude that the rate return series is stationary.

Fig. 2 shows the first difference of amount of rainfall and its distribution. The series appears to be stationary around the mean (top), the histogram looks symmetric with heavy tail to the right and the normal Q-Q plot indicates a normal series with few outliers.

3.2 Determining Order of Dependency of 1st Differenced Series

The autocorrelation and partial autocorrelation functions (ACF/PACF) for the first differenced in the amount of rainfall are illustrated in Fig. 3.

From Fig. 3, we could observe that both the Autocorrelation and Partial autocorrelation functions showed dependency in the differenced rainfall series. As a result, a correlation structure in conditional mean is required.

It can also be observed that the ACF show a significant number of lags of an MA at lag1 and PACF also show a significant number of lags of an AR at lag 1. This indicates that the model for the conditional mean is ARMA (1, 1). This is confirmed by the selection of model using the Alkaike Information Criterion shown in Table 1

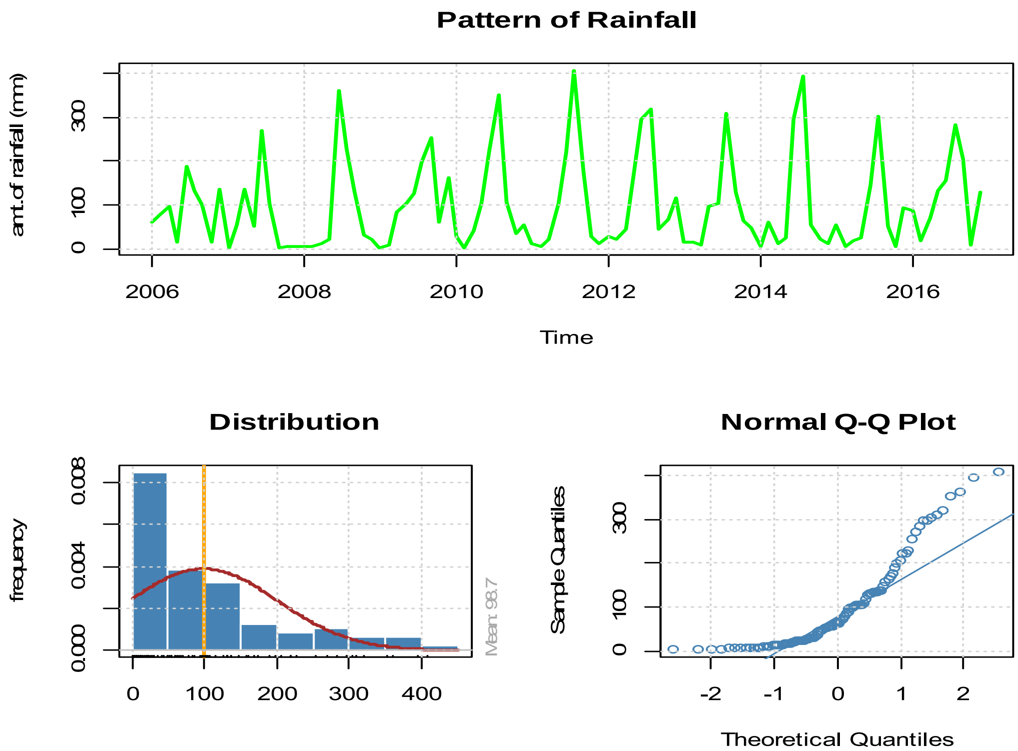

Fig. 1. Time plot, Distribution and Normal Q-Q plot for Monthly Rainfall Series

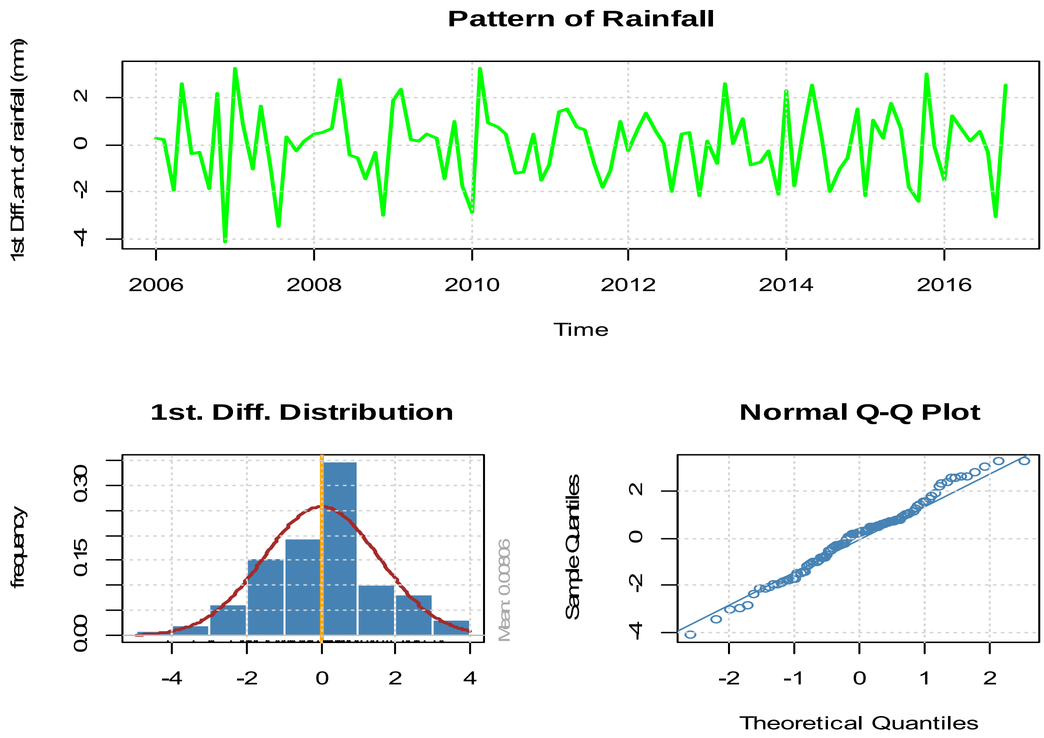

Fig. 2. First Differenced of Monthly Rainfall Series

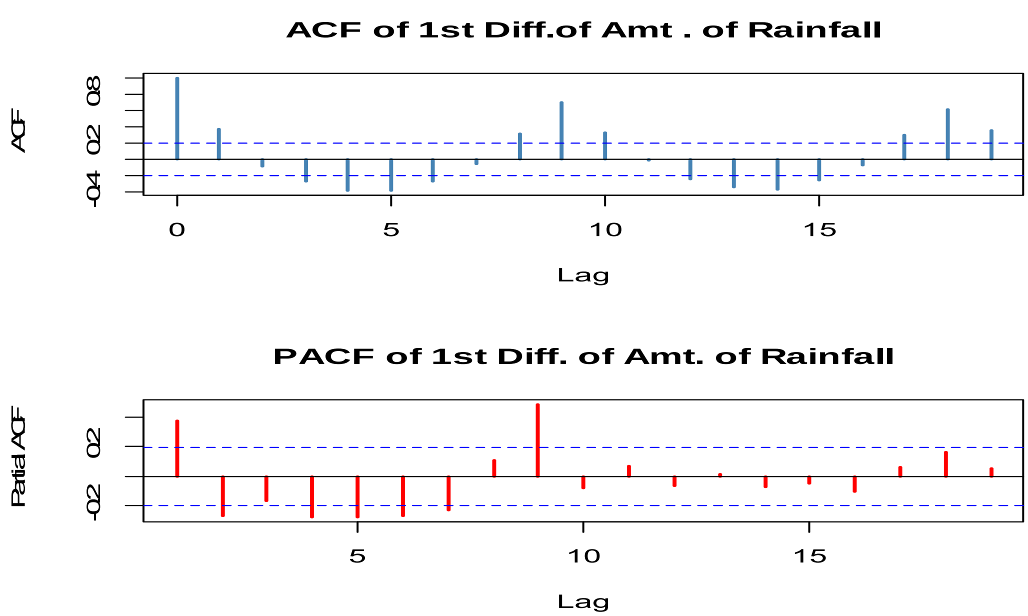

Fig. 3. ACF and PACF of 1st differenced monthly rainfall pattern

Table 1. Model Selection by Alkaike Information Criterion

ARMA (p, q)	AIC
ARMA (1, 0)	364.91
ARMA (0, 1)	362.21
ARMA (1, 1)	**339.33**
ARMA (1, 2)	343.17
ARMA (2, 1)	342.97
ARMA (0, 2)	342.51
ARMA (2, 0)	365.42
ARMA (2, 2)	382.16

Using the Alkaike Information Criterion, we choose the model with the smallest value of AIC. From Table 1, the suitable model for the conditional mean is ARMA (1, 1) with an AIC value of 339.33. The parameter estimates are shown in Table 2.

3.3 Conditional Mean Model the Differenced Rainfall Series

The ARMA (p, q) model states that the current value of some series r_t depends linearly on its own previous values and a combination of current and previous values of a white noise error term ε_t. In the general form, the model can be written in the form:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} + \varepsilon_t$$

$$E(\varepsilon_t) = 0,\ E(\varepsilon_t^2) = \sigma^2,\quad E(\varepsilon_t \varepsilon_s) = 0, \qquad t \neq s$$

Our model for the conditional mean of the differenced rainfall series is ARMA (1, 1) given by

$$y_t = -0.004271 + 0.415772 y_{t-1} - 0.996001 \varepsilon_{t-1} + \varepsilon_t$$

(see Fig. 4).

The time plot of the standardised residuals shows no obvious patterns (does not follow any specific component). The ACF of the standardised residuals and squared standardised residuals show no apparent departure from the model assumptions as shown in Fig. 5

From Fig. 6 below the histogram appears to be symmetric and generalised normal q-q plot of the standardised residuals show no departure from model assumptions (i.e. the assumed conditional mean distribution captured the high kurtosis and the heavy tails of the residuals).

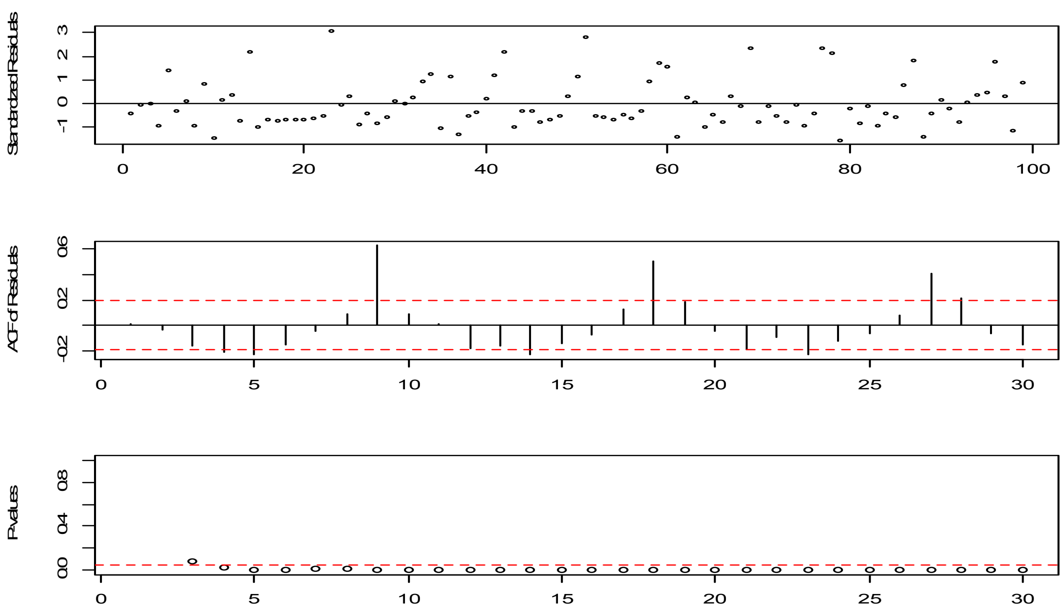

Fig. 4. Model Diagnosis of ARMA (1, 1)

Table 2. ARMA (1, 1) Model's Parameter Estimates and Standard Errors

Variable	Coefficient	Standard Error	T-Statistics	Probability
Constant	-0.004271	0.006400	-0.667	0.505
AR (1)	0.415772	0.096789	4.296	1.74e-05
MA (1)	-0.996001	0.032122	-0.667	2e-16

σ^2 = 1.757, conditional sum of squares = 170.2, AIC = 339.33

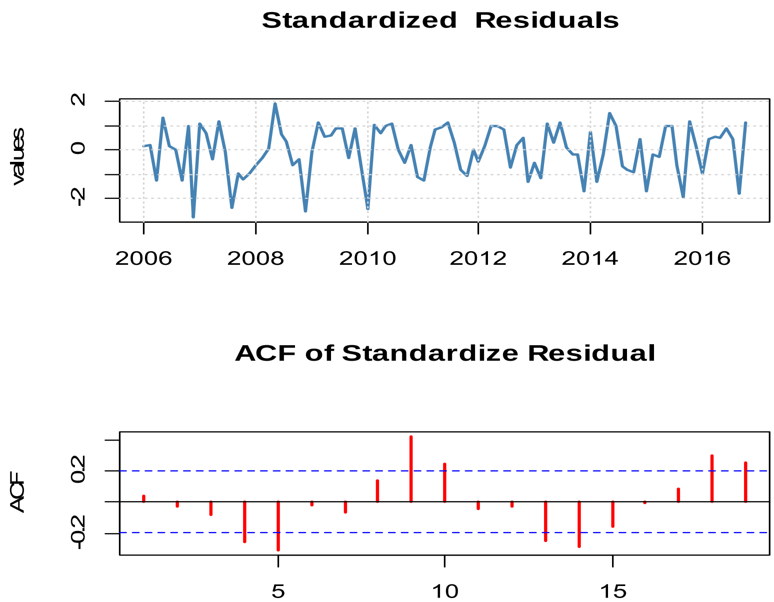

Fig. 5. Time plot and ACF of Standardised Residuals

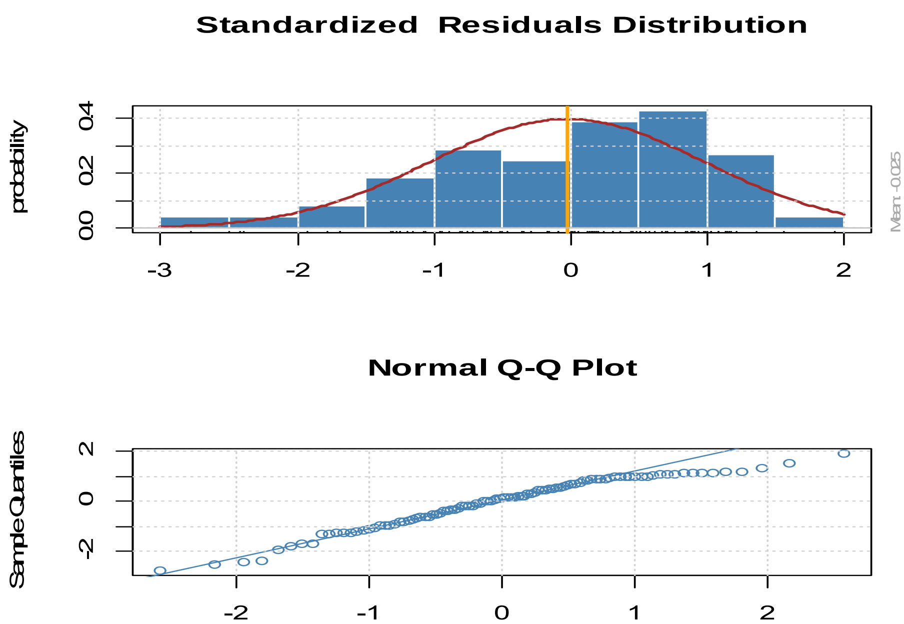

Fig. 6. Histogram and Normal Q-Q Plot of Standardised Residuals

Table 3. Summary Statistics of Standardised Residuals

Statistic	Value	Statistics	Value
Mean	0.001041	SE mean	0.101015
Median	-0.303789	Variance	1.010203
Minimum	-1.530580	Std. dev.	1.005089
Maximum	3.093621	Kurtosis	0.586320
LC L mean	-0.199420	Skew	1.089648
UVL mean	0.201502	Sum	0.103062
Nobs	99.000000	NAS	0.000000

This suggests the residuals are independent generalised error distribution hence the model seem to be adequate for the data. Consequently, the ARMA (1, 1) is adequate for describing the conditional mean of the differenced rainfall series at 5% significance level.

The descriptive statistics of standardised residuals in Table 3 shows a standard deviation (1.005) with a general mean (0.001). The empirical distribution of residuals indicates normal kurtosis (0.586) and skewness (1.090). This indicates non-normality of standardised residuals and positively skewed with a lighter tail to the right.

3.4 Model Validation

A model validation test conducted produces a Ljung Box test statistic of 47.207 with a normalised BIC of 6.420 and a Root Mean Square Error of 24.16 supported by a probability value of 0.001. Hence, we fail to reject the null hypothesis that the model is appropriate and suitable for predicting future rainfall figures. An R^2 = 0.532 indicates that about 53% of the variations seen in the pattern of rainfall recorded for the period is being explained by the fitted model i.e. ARMA (1, 1).

The fitted model was again used to predict mean actual rainfall for the next two years. That is data up to 2015 was used to predict the mean actual rainfall for 2016 and from 2016 for 2017 mean rainfall respectively. It can be observed from the table 4 that the mean rainfall forecasted are very close to the mean rainfall for the forecasted period suggesting that the fitted model is appropriated for the data.

3.5 Prediction of Next 18 Observations of Mean Rainfall Returns

The fitted model was again employed to predict the mean 1st differenced rainfall for the next two years. That is data from January, 2006 to December, 2016 was used to forecast 2017/2018 mean rainfall values. The time plot for the forecasted mean returns is shown in figure 7.

The up and down movement in black is the actual mean rainfall from January 2006 to December 2016 and the green and blue curve shown is the lower and upper bound of the 95% confidence interval constructed for the forecasted period. Within the confidence bound is the horizontal broken line which show the predicted mean rainfall values for the forecasted period. We can observe that the predicted mean rainfall values for the forecasted period lies within the confidence interval, indicating that the model fitted is adequate suitable for the observed rainfall series (see Fig. 5).

Table 4. Mean Forecast of Actual Rainfall for 2016/2017

Year (2016)	Actual Rainfall	Forecasted Rainfall	Year (2017)	Actual Rainfall	Forecasted Rainfall
Jan.	86.2	1.89	Jan.	-	92.21
Feb.	19.9	18.9	Feb.	-	33.90
Mar.	69.8	70.1	Mar.	-	76.09
Apr.	131.4	129.4	Apr.	-	67.23
May.	156.7	158.3	May.	-	401.20
Jun.	283.6	290.6	Jun.	-	312.76
Jul.	205.4	200.4	Jul.	-	138.43
Aug.	10.0	9.8	Aug.	-	98.98
Sep.	130.7	128.9	Sep.	-	101.90

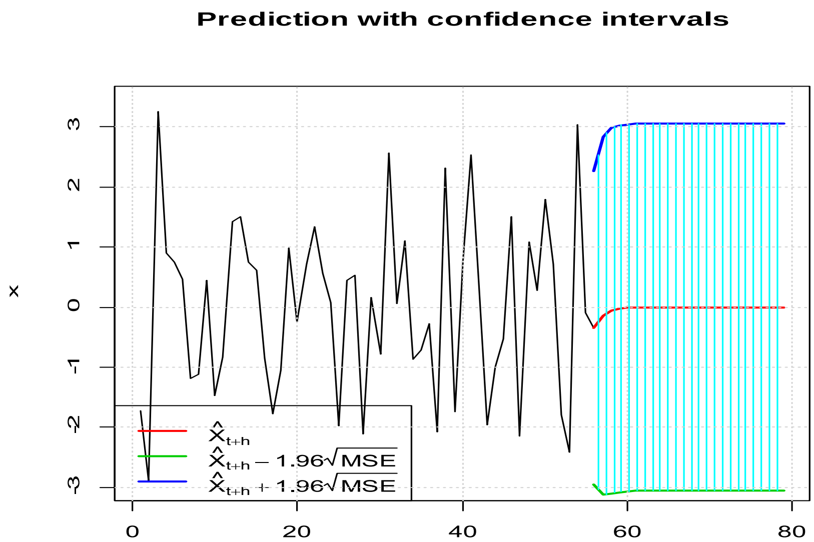

Fig. 7. Time Plot of 1st Difference Forecasted Rainfall

Table 5. Forecast of 1st Difference in Rainfall for 2017/2018 with Confidence Interval

Mean Forecast	Mean Error	Standard Deviation	Lower Interval	Upper Interval
7.804897600	101.0965	101.0965	-190.3406	205.9504
5.447387320	122.6698	101.0976	- 234.9809	245.8757
3.801975392	131.9076	101.0985	-254.7321	262.3360
2.653568772	136.1814	101.0994	-264.2571	269.5642
1.852044399	138.2161	101.1003	-269.0465	272.7506
1.292624669	139.1970	101.1011	-271.5285	274.1138
0.902180604	139.6729	101.1018	-272.8517	274.6561
0.629672218	139.9046	101.1026	-273.5784	274.8377
0.439476420	140.0179	101.1032	-273.9905	274.8695
0.306730261	140.0734	101.1039	-274.2321	274.8456
0.214080776	140.1009	101.1044	-274.3787	274.8068
0.149416554	140.1147	101.1050	-274.4703	274.7691
0.104284500	140.1218	101.1055	-274.5293	274.7379
0.072784819	140.1256	101.1060	-274.5683	274.7138
0.050799783	140.1277	101.1065	-274.5945	274.6961
0.035455442	140.1291	101.1069	-274.6125	274.6834
0.024745939	140.1300	101.1077	-274.6251	274.6746
0.017271299	140.1308	101.1077	-274.6340	274.6686

Table 5 shows the mean forecasted values of 1st differenced rainfall values for 2017 to 2018. The values obtained indicates that higher rainfall is expected for the period forecasted.

4. CONCLUSION

The series was found to be non-stationary which resulted from the presence of a unit root in it. The series became stationary after eliminating the unit root by finding the first difference in the amount of rainfall, hence the probability law that governs the behaviour of the process does not change over time. The distribution of the 1st differenced series look symmetric with non-constant variance skewed to the right.

Both the ACF and PACF showed dependency in the 1st differenced series at lag 1, ARMA (1, 1), which has all the parameters to be significant. Thus, the fitted data was found to be the most suitable model for the conditional mean. The model explains the stochastic mechanism of the observed series in ARMA (1, 1). The time series component found in the model were trend and random variation.

A Ljung Box test statistic of 47.207 with a normalised BIC of 6.420 and a Root Mean Square Error of 24.16 supported by a probability value of 0.001 show that the fitted model is appropriate for the data. An R^2 = 0.532 indicates that about 53% of the variations seen in the pattern of rainfall recorded for the period is being explained by the fitted model. An 18-month forecast for the mean actual rainfall and mean 1st difference rainfall values made showed that the fitted model is appropriate for the data and an increasing trend of rainfall for forecasted period.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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