

Modeling and Forecasting Rainfall Pattern in Ghana as a Seasonal Arima Process: *The Case of Ashanti Region*

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Abstract

Understanding the rainfall process is critical for the solution of several regional environmental problems of integrated water resources management at regional scales, with implications for agriculture, climate change, and natural hazards such as floods and droughts. Statistical modeling and data analysis are key instruments for studying these processes. The main objective of this article is to examine rainfall pattern over time, from 1974 to 2010, in Ashanti region of Ghana. Data for the study was obtained from the Ashanti regional division of Ghana meteorological service. It was subsequently analyzed using Seasonal Autoregressive Integrated Moving Average (SARIMA). The results showed that rainfall pattern in Ashanti region significantly changes over time. There are periods of low variability and others of extreme variability separated by periods of transition. Also, it was found that there is a slight decrease in rainfall figures from August to December when the post sample forecast is compared to the actual rainfall figures. However, February to March experienced a slight increase in rainfall figures in terms forecast figures. Generally, therefore, the forecast figures for the months show an increase in the rainfall figures for the subsequent year(s), all things being equal.

Keywords: Rainfall, Time Series, SARIMA Model and Pattern.

1. Introduction

Understanding the rainfall process is critical for the solution of several regional environmental problems of integrated water resources management at regional scales, with implications for agriculture, climate change, and natural hazards such as floods and droughts. Statistical modeling and data analysis are key instruments for studying these processes.

The majority of climatic change studies try to identify significant variations of central tendency values of time series, especially for temperature and less frequently for rainfall series. These studies begin to achieve clear results in relation to temperature: increasing minimum temperature values, particularly for urban environments. On the contrary, rainfall research does not achieve such precise results, and in some cases discrepancies can even be found in different studies referring to the same spatial area; that is the case of the Mediterranean (Tabony, 1981; Djellouly et al., 1989; Maheras, 1988; Maheras et al., 1990; Benito, Orellana y Zurita, 1994). However, variability pattern has rarely been under consideration in this type of studies. More often, this topic has been indirectly dealt with by use of the analysis of extreme events (Kutiel et al., 1996) and the IPCC document even uses this methodology when examining variability trends (Houghton et al., 1996). The same considerations can be made in relation to the North Atlantic Oscillation. Most research has been focused on trend analysis (Kalnicky, 1987; Makrogiannis et al., 1991; Hurrell, 1995; Karl, 1995 and Ruizdelvira and Ortizbeviá, 1997) but very little has been done to analyse its variability. So, various reasons would seem to suggest the need for this type of study in our region.

The main objective of this paper is to examine rainfall pattern over time, from 1974 to 2010, in Ashanti region of Ghana. Also, the study seeks to forecast rainfall figures. The World Bank climate change experts' opinion is that the poorest of the poor in South Asia are the most affected by climate change.

The impact of higher temperatures, more extreme weather events such as floods, cyclone, severe drought, and sea level rise are already being felt in South Asia, and will continue to intensify (Huq et al., 1998; Karim et al., 1998; Ali, 1999). Long-term planning is impossible without any idea of the change of climate to be happened in future. Climate models are the main tools available for developing projections of climate change in the future (Houghton et al., 2001; Houghton et al., 1995).

In recent years, Atmosphere-Ocean General Circulation Models (AOGCMs) have been used to predict the climatic consequences of increasing atmospheric concentrations of greenhouse gases (McCarthy et al., 2001; McGuffie and Henderson-Sellers, 1997).

Climate is a driver for almost every natural resource management issue being tackled by regional bodies, and climate change will have far reaching impacts on many ecological, hydrological and resource- degrading processes. The highest horizontal resolution of any AOGCM published is around 300 km (Murphy and Mitchell, 1995). Yet in order to assess potential impacts of climate change, regional information at a scale of 100 km or finer (typically around 50 km) is needed (Dickinson et al., 1989; Hack et al., 1993; Grell et al., 1994; Robinson and Finkelstein, 1991). Regional Climate Model (RCM), therefore, is the best tool for dynamical downscaling of climate features in case of obtaining detailed information for a particular region (Jones et al., 2004; Georgi and Hewitson, 2001). Downscaling from RCM outputs are important in understanding the local phenomena.

2. Materials and Methods

2.1 Study Area

In order to study rainfall variability in Ashanti region, records from twenty seven meteorological district stations were selected. All of them were well distributed over the region and span a period of 35 years, as can be seen in Figure 1.

2.2 The Box-Jenkins Method

In economic time series analysis, the Box–Jenkins modeling method, named after the statisticians Box and Jenkins (1970), describes stationary time series and applies autoregressive moving average ARMA or autoregressive integrated moving average ARIMA models to find the best fit of a time series to past values of this time series in order to make forecasts. The methodology involves three steps and these are;

a. The first step is model identification- Identification of model consists of specifying the appropriate structure (AR, MA or ARMA) and order of model. Models can also be identified by looking at plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF). Thus making sure that the variables are stationary, identifying seasonality in the dependent series and using plots of the ACF and PACF of the dependent time series to decide which (if any) autoregressive or moving average component should be used in the model (Box and Jenkins 1970).

b. The second step is to estimate the parameters of the model- Coefficients of the models can be estimated by maximum likelihood estimation or non-linear least-squares estimation methods. Estimation of parameters of MA and ARMA models usually requires a more complicated iteration procedure (Box and Jenkins, 1970; Chatfield, 2004).

c. The third step is model checking and Forecasting- Two important elements of checking are to ensure that the residuals of the model are random, and to ensure that the estimated parameters are statistically significant. Usually the fitting process is guided by the principal of parsimony, by which the best model is the simplest possible model. Plotting the mean and variance of residuals over time and performing a Ljung-Box test or plotting autocorrelation and partial autocorrelation of the residuals are also helpful to identify misspecification (Anderson, 1976).

2.3 Types of models

2.3.1 Autoregressive (AR) and Moving Average (MA) Models

An autoregressive model is a model in which one uses the statistical properties of the past behavior of a variable to predict its behavior in the future.

The general representation of an autoregressive model of order p , AR(p) is

$$Y_t = \mu + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \dots + \Phi_p Y_{t-p} + \varepsilon_t$$

where the term ε_t is the source of randomness and is called white noise. $\Phi_1, \Phi_2, \Phi_3 \dots \Phi_p$ are unknown parameters relating Y_t to $Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$ and must be estimated from sample data.

The notation MA(q) also refers to the moving average model of order q given by

$$Y_t = \mu + \Phi_1 \varepsilon_{t-1} + \Phi_2 \varepsilon_{t-2} + \dots + \Phi_q \varepsilon_{t-q} + \varepsilon_t$$

where the Φ_1, \dots, Φ_q are the parameters of the model, μ is the expectation of Y_t (often assumed to equal 0), and the $\varepsilon_t, \varepsilon_{t-1}, \dots$ are again, white noise error terms (Gershenfeld, 1999; Shumway, 1988)

2.3.2. Autoregressive-Moving-Average Modeling (ARMA)

We have seen from above that the AR model includes lagged terms on the time series itself, and that the MA model includes lagged terms on the noise or residuals. By including both types of lagged terms, we arrive at ARMA model. Therefore ARMA (p, q), where p is the autoregressive order and q the moving-average order can generally be represented as $Y_t + \Phi_1 Y_{t-1} + \dots + \Phi_p Y_{t-p} = \varepsilon_t + \Phi_1 \varepsilon_{t-1} + \dots + \Phi_q \varepsilon_{t-q}$

2.3.3 Seasonal ARIMA Model

Seasonality usually causes the series to be non-stationary because the average values at some particular times within the seasonal span (months, for example) may be different than the average values at other times.

The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is

$$\text{ARIMA}(p, d, q) \times (P, D, Q)S,$$

with p = non-seasonal AR order, d = non-seasonal differencing, q = non-seasonal MA order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern.

Without differencing operations, the model could be written more formally as

$$(1) \quad \Phi(B^S)\varphi(B)(x_t - \mu) = \Theta(B^S)\theta(B)w_t$$

The non-seasonal components are:

$$\text{AR: } \varphi(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p$$

$$\text{MA: } \theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q$$

The seasonal components are:

$$\text{Seasonal AR: } \Phi(B^S) = 1 - \Phi_1 B^S - \dots - \Phi_P B^{PS}$$

$$\text{Seasonal MA: } \Theta(B^S) = 1 + \Theta_1 B^S + \dots + \Theta_Q B^{QS}$$

Seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of S . With $S = 12$, which may occur with monthly data, a seasonal difference is

$$(1-B^{12})x_t = x_t - x_{t-12}.$$

The differences (from the previous year) may be about the same for each month of the year giving us a stationary series. With $S = 4$, which may occur with quarterly data, a seasonal difference is $(1-B^4)x_t = x_t - x_{t-4}$.

Seasonal differencing removes seasonal trend and can also get rid of a seasonal random walk type of non-stationarity.

Non-seasonal differencing: If trend is present in the data, we may also need non-seasonal differencing. Often a first non-seasonal difference will “detrend” the data using $(1-B)x_t = x_t - x_{t-1}$ in the presence of trend (Penstate, 2012).

3. Results and Discussion

The general objective of this study is to investigate the phenomenon of flood in recent times most especially in some parts of Kumasi in Ashanti Region Ghana in the context of the mathematical modeling using time series analysis.

SPSS was used to model and estimate the model parameters of the second order seasonal ARIMA(0,0,0)x(2,1,0) model of rainfall in Ghana.

The paper is also intended to characterize and forecast rain pattern using time series analysis in order for stakeholders in Ghana to take decisions when rains set in prevent flood killing people as it did in previous years. Preliminary time series analysis of the data was performed using the Box-Jenkins ARIMA modeling methodology.

3.1 Preliminary Data Analysis

Preliminary time series analysis was performed on monthly rain data recoded from 1974 to 2010 using the Box-Jenkins ARIMA modeling methodology. Time series plot was done using the raw data to assess the stability of the data and the following Fig. 1 was obtained.

The plot shows that the time series is non-stationary. A non-stationary series is the one whose values do not vary over time around a constant mean and variance.

The ACF and PACF plots indicate that there are seasonality trend which need to be removed in order for the data to be stationary. Seasonality usually causes the series to be nonstationary because the average values at some particular times within the seasonal span are different than the average values at other times.

3.2 Data Stationarity Check

Non-stationarity is also confirmed by the ADF test on the raw rain data in the table 1 below. Augmented Dickey-Fuller Unit Root Test was done on the entire rain data. The table displays results of the test: statistic value -0.872752 greater than critical vales -2.570444, -1.941582, -1.616245 all at 1%, 5%, and 10% respectively. This indicates that the series are non- stationary and also confirm that raw rain data needs differencing in order to be stationary.

3.3 Data Differencing (Seasonality)

If there is seasonality and no trend take a difference of lag $S=12$ because it is a monthly data with seasonality. Thus we may need to apply a seasonal difference and examine the ACF and PACF of

$$(1-B^{12})x_t = (x_t - x_{t-12})$$

3.4 Stationarity confirmation using ADF test

Augmented Dickey-Fuller Unit Root Test was done on the entire rain data. The table 2 below displays the results of the test: statistic value -5.194807 less than critical vales -2.570509, -1.941591, -1.616239 all at 1%, 5%, and 10% respectively. This indicates that the series are stationary and confirms that the rain data needed to be differenced to be stationary.

3.5 Model Identification

After series of model test the following tentative models were obtained with the best model having the least BIC value of 8.592.

3.5.1 Tentative Seasonal ARIMA Models

ARIMA (0, 0, 0) x (2, 1, 0)	BIC = 8.592
ARIMA (0, 0, 0) x (2, 0, 0)	BIC = 8.602
ARIMA (0, 0, 0) x (1, 0, 0)	BIC = 8.690
ARIMA (0, 0, 0) x (1, 1, 0)	BIC = 8.698

3.6 Parameter Estimation

The Seasonal ARIMA(0,0,0)x(2,1,0)₁₂ is expressed as follows:

$$x_t = (1 + \phi_1)x_{t-12} + (\phi_1 - \phi_2)x_{t-24} + \phi_2 x_{t-36}$$

After fitting in the model parameters from (table 4) the following mathematical expression obtained;

$$x_t = (0.307)x_{t-12} - 0.323x_{t-24} - 0.370x_{t-36}$$

From table 3, the test statistic values of the AR lag1 and lag2 are all significant at 5% level of significance because the p-values are 0.000. Bayesian Information Criterion (BIC) value is confirmed in table 4.

3.7 Model Adequacy or Diagnostic Test

Besides testing that the estimated parameters are statistically significant, we also ensure that plotting of autocorrelation and partial autocorrelation of the residuals of the model obtained are helpful to identify misspecification. The Fig. 3 confirms that the model is very good as there are no spikes that cut the level.

3.8 Post-sample forecast test

After post-sample test the model $x_t = (0.307)x_{t-12} - 0.323x_{t-24} - 0.370x_{t-36}$ gives the following forecast values in Table 5.

It is realized that the difference between the actual values and the model forecasted values are not great and is an indication of reliability of the model.

4. Conclusion

Rainfall pattern in Ashanti region significantly changes over time. There are periods of low variability and others of extreme variability separated by periods of transition. The results from the post sample forecast versus the actual rainfall figures indicates that there is a slight decrease in rainfall figures from August to December, which certify the validity of the rainfall model. However, February to March experienced a slight increase in rainfall figures in terms forecast figures. Generally, therefore, the forecast figures for the months show an increase in the rainfall figures for the subsequent year(s), all things being equal.

The following intervention could be necessary; stakeholders, particularly the National Disaster Management Organization (NADMO), should begin to create awareness to enable the populace clear their choked gutters to allow free drainage when rains set in, since this will avoid flooding in some communities. Again, metropolitan assemblies should step up efforts to curb the putting up of buildings/structures on water ways.

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Appendix

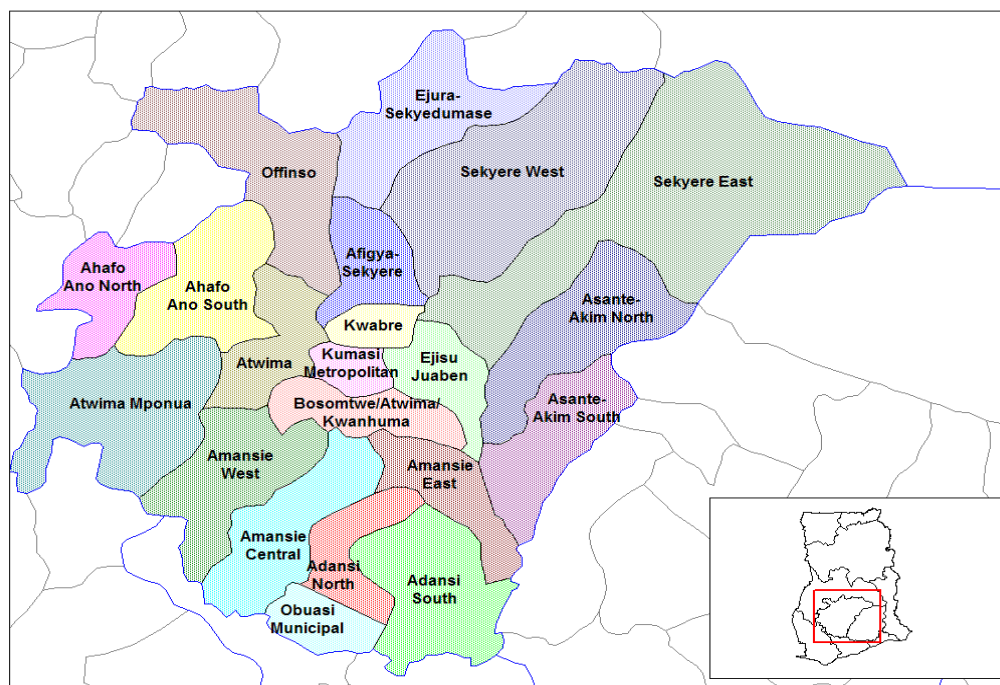


Figure 1: Map of the districts of the Ashanti region of Ghana. Created by Rarelibra for public domain use. Created using MapInfo Professional v7.5 and various mapping (en.wikipedia.org/wiki/File:Ashanti_districts.png)

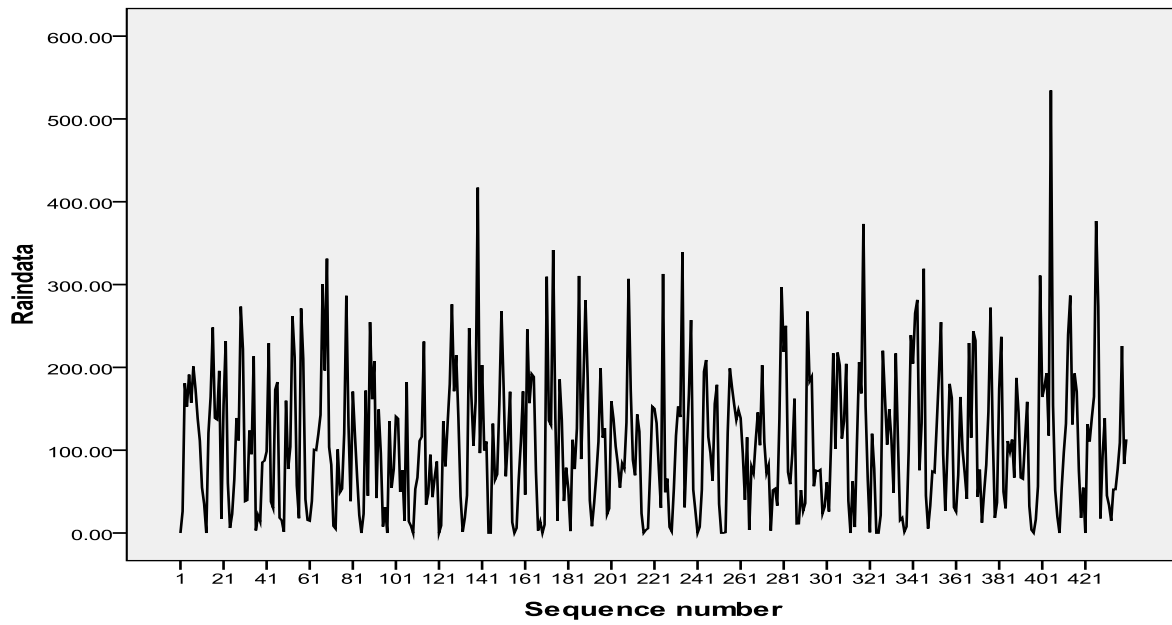


Figure 2: Time Series Plot

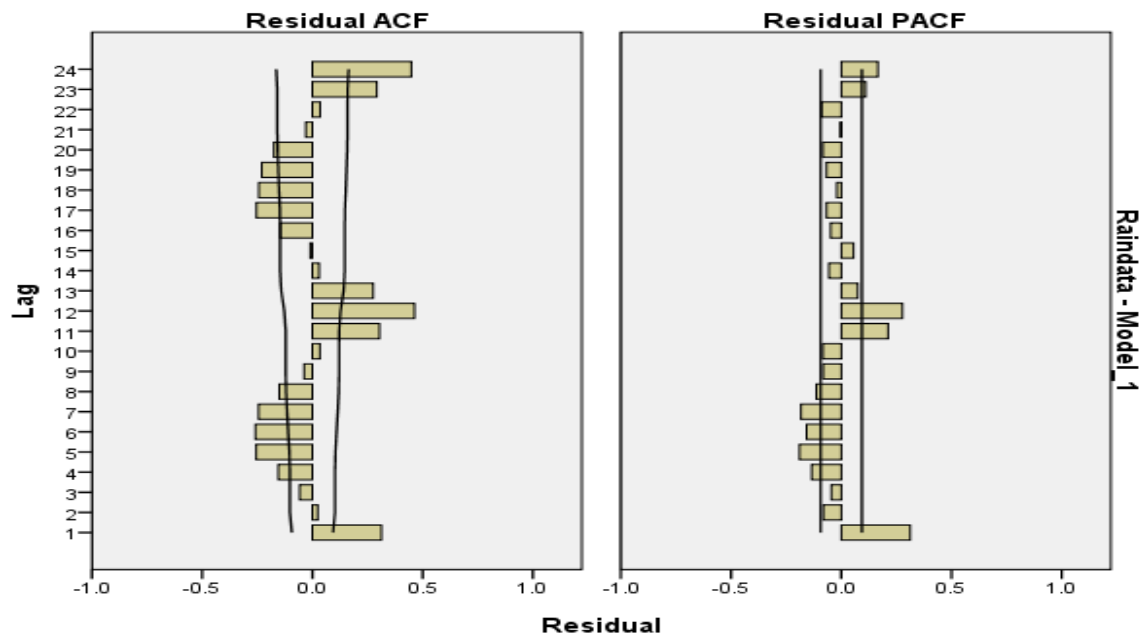


Figure 3: ACF and PACF plot of the raw data with constant term

Table 1: Augmented Dickey –Fuller Unit root test on raw rain data

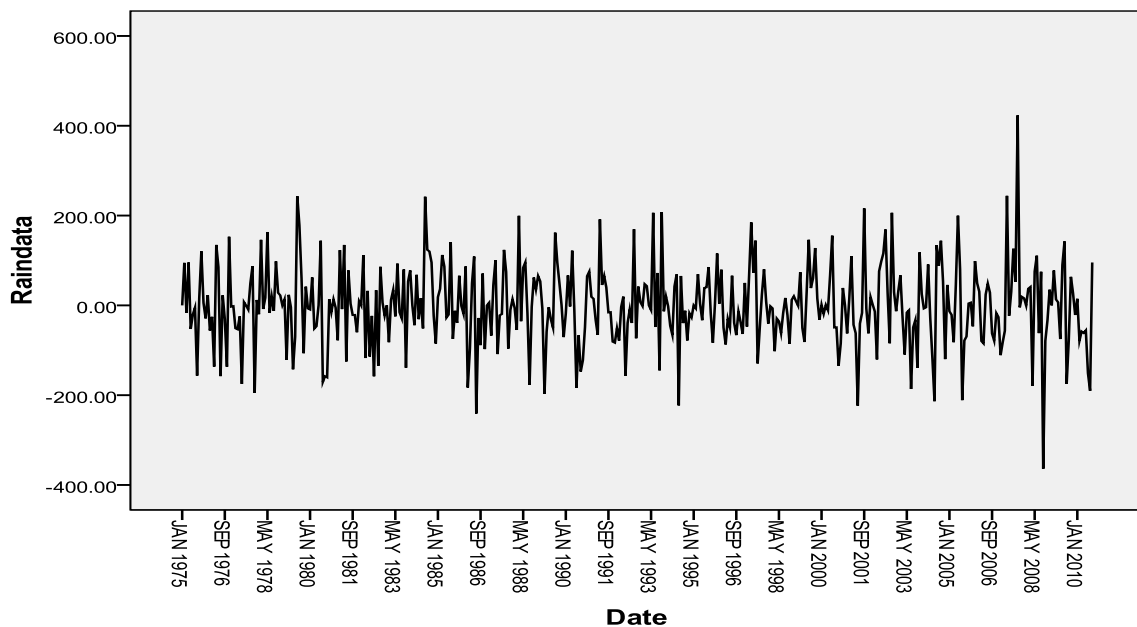
Null Hypothesis: tseries has a unit root
 Exogenous: None
 Lag Length: 12 (Automatic Based on AIC, MAXLAG=16)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-0.872752	0.337511
Test critical values:		
1% level	-2.570444	
5% level	-1.941582	
10% level	-1.616245	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
 Dependent Variable: D(tseries)
 Method: Least Squares
 Included observations: 427 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob
tseries(-1)	-0.028240	0.032357	-0.872752	0.383304
D(tseries(-1))	-0.781036	0.057105	-13.677219	0.000000
D(tseries(-2))	-0.826536	0.064287	-12.857002	0.000000
D(tseries(-3))	-0.782290	0.066894	-11.694399	0.000000
D(tseries(-4))	-0.762321	0.068378	-11.148599	0.000000
D(tseries(-5))	-0.793903	0.067565	-11.750143	0.000000
D(tseries(-6))	-0.770210	0.067078	-11.482359	0.000000
D(tseries(-7))	-0.787933	0.066437	-11.859875	0.000000
D(tseries(-8))	-0.763674	0.065632	-11.635713	0.000000
D(tseries(-9))	-0.701285	0.065074	-10.776731	0.000000
D(tseries(-10))	-0.713691	0.062209	-11.472562	0.000000
D(tseries(-11))	-0.476951	0.058070	-8.213390	0.000000
D(tseries(-12))	-0.142212	0.048658	-2.922694	0.003660
R-squared	0.485502		Mean dependent var	0.264871
Adjusted R-squared	0.010581		S.D. dependent var	101.902514
S.E. of regression	74.145170		Akaike info criterion	11.479899
Sum squared resid	2275967.600430		Schwarz criterion	11.603407
Log likelihood	-2437.958398		F-statistic	30.051367
Durbin-Watson stat	1.996599		Prob(F-statistic)	0.000000



Transforms: seasonal difference(1, period 12)

Figure 4: Time series plot of seasonal differenced rain data

Table 2: Augmented Dickey –Fuller Unit root test on order one differenced rain data

Null Hypothesis: D(tseries) has a unit root				
Exogenous: None				
Lag Length: 16 (Automatic Based on AIC, MAXLAG=16)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-5.194807	0.000000
Test critical values:	1% level		-2.570509	
	5% level		-1.941591	
	10% level		-1.616239	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(tseries,2)				
Method: Least Squares				
Included observations: 422 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob
D(tseries(-1))	-2.482040	0.477792	-5.194807	0.000000
D(tseries(-1),2)	1.001673	0.460342	2.175933	0.030138
D(tseries(-2),2)	0.705494	0.438098	1.610356	0.108099
D(tseries(-3),2)	0.508650	0.412816	1.232147	0.218609
D(tseries(-4),2)	0.400082	0.385292	1.038387	0.299710
D(tseries(-5),2)	0.315010	0.356959	0.882482	0.378039
D(tseries(-6),2)	0.243703	0.327508	0.744112	0.457240
D(tseries(-7),2)	0.195171	0.297245	0.656600	0.511811
D(tseries(-8),2)	0.229200	0.268095	0.854922	0.393100
D(tseries(-9),2)	-0.164539	0.243721	-0.675112	0.499990
D(tseries(-10),2)	-0.339345	0.214416	-1.582648	0.114282
D(tseries(-11),2)	-0.418929	0.185786	-2.254906	0.024673
D(tseries(-12),2)	-0.456021	0.157048	-2.903712	0.003889
D(tseries(-13),2)	-0.492854	0.128047	-3.849011	0.000138
D(tseries(-14),2)	-0.484603	0.098475	-4.921098	0.000001
D(tseries(-15),2)	-0.453495	0.067660	-6.702557	0.000000
D(tseries(-16),2)	-0.399617	0.035714	-11.189301	0.000000
R-squared	0.835838		Mean dependent var	0.000000
Adjusted R-squared	0.681333		S.D. dependent var	1.449127
S.E. of regression	0.598627		Akaike info criterion	1.851094
Sum squared resid	145.133380		Schwarz criterion	2.014044
Log likelihood	-373.580761		F-statistic	121.298580
Durbin-Watson stat	1.918800		Prob(F-statistic)	0.000000

Table 3: ARIMA Model Parameters

			Estimate	SE	t	Sig.
raindata-Model_1	raindata	No Transformation				
		AR, Seasonal Lag 1	-.693	.047	-14.886	.000
		Lag 2	-.370	.048	-7.756	.000
		Seasonal Difference	1			

Table 4: Model Statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	Normalized BIC	Statistics	DF	Sig.	
raindata-Model_1	0	.343	8.592	9.682	16	.883	0

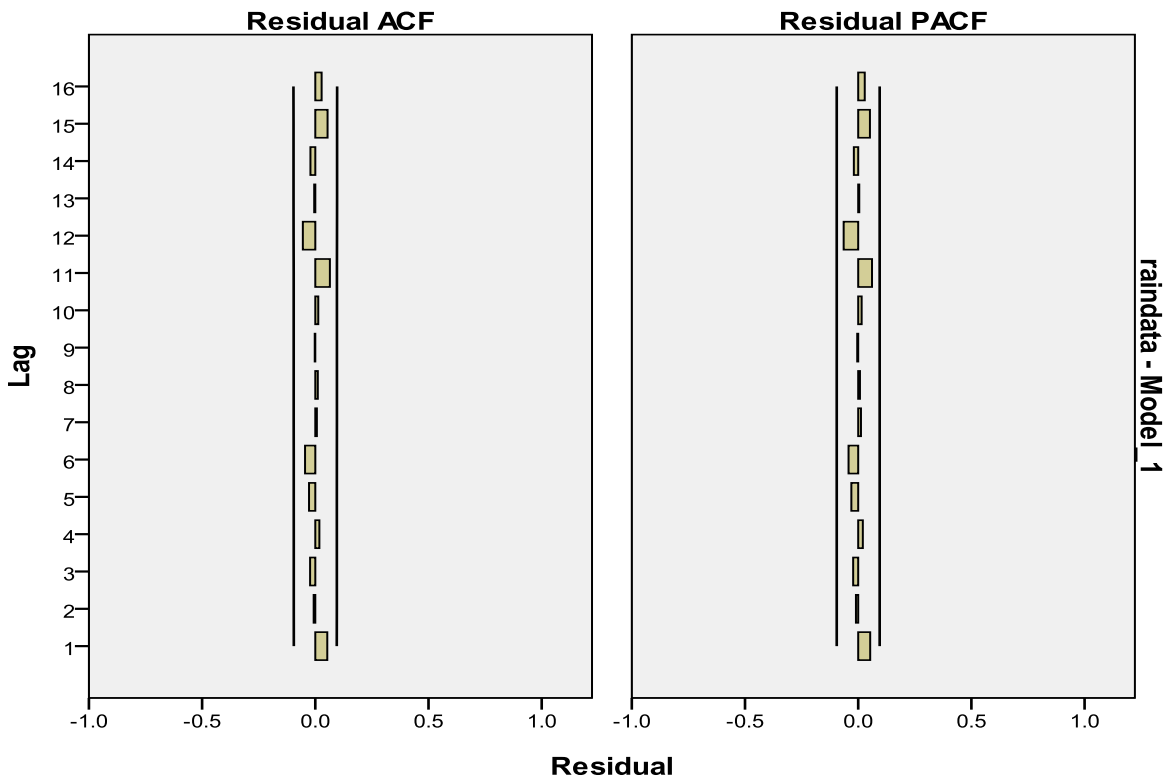


Figure 5: ACF and PACF of ARIMA (0,0,0)x(2,1,0)₁₂ Residual

Table 5: Forecast

Model		Aug 2010	Sep 2010	Oct 2010	Nov 2010	Dec 2010	Jan 2011	Feb 2011	Mar 2011
raindata-Model_1	Forecast	111	281	124	39	35	5	79	88
	UCL	252	423	265	180	176	146	220	229
	LCL	-30	140	-17	-102	-106	-137	-63	-53

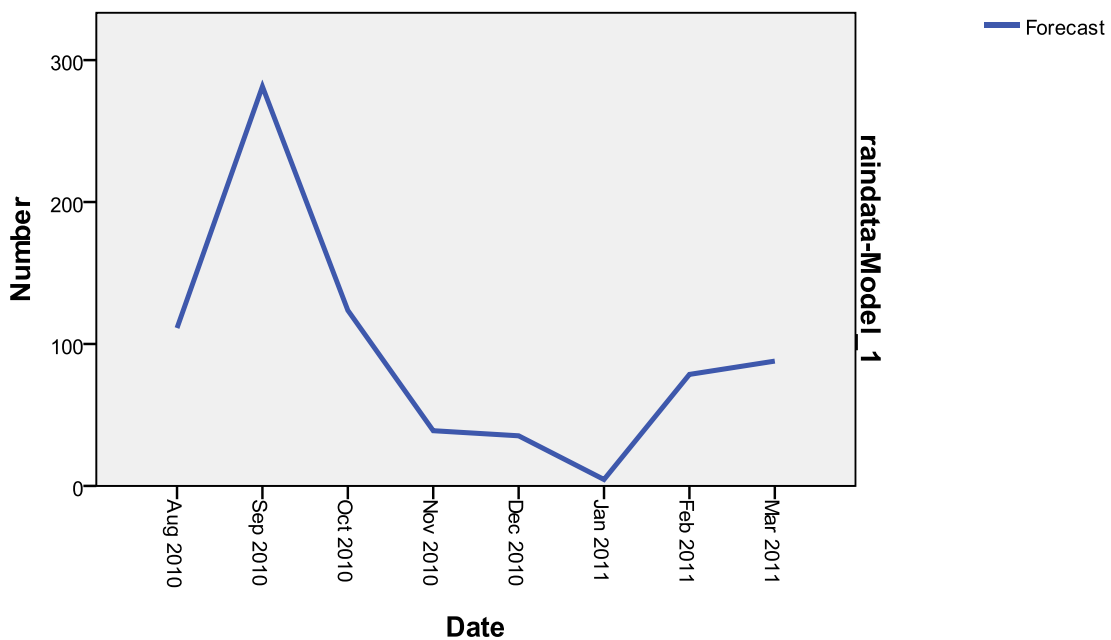


Figure 6: Forecast graph