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TIME SERIES ANALYSIS, MODELING AND FORECASTING OF CLIMATE VARIABLE RAINFALL: A CASE STUDY OF RAJSHAHI DISTRICT IN BANGLADESH

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ABSTRACT

The purpose of the present study was to investigate the time series components, and to build an appropriate model to forecasttherainfall of Rajshahi district in Bangladesh using the monthly rainfall data over January, 1975 to June, 2012 collected from Bangladesh meteorological department.The statistical software R with the packages ‘forecast’ and ‘zyp’ was used for whole analysis. The descriptive statistics of rainfall showed high fluctuation from their mean, positively skewed and platykurtic curve. The time series rainfall data was decomposedinto stochastic trend, seasonal variations and random movements. The yearly rainfall data showed decreasing trend by 11.25 mm/year. The moving average smoothing of monthly rainfall intended to be decreased over May, 2007 to June, 2012. But, after first seasonal difference, the rainfall data became stationary and that wasconformed using appropriate tests. The SARIMA(0, 0, 0)(4, 1, 0)$_{12}$ model was found as best model on the basis ofdiagnostic test, stability and reliability. The forecasted values from July, 2012 to December, 2025 divulged adecreasing pattern that may be a threat to the cultivators as well as to the nature as a whole.

Keywords: Box–Jenkins modeling strategy, moving average smoothing, Sen’s slope, trend, unit root.

INTRODUCTION

Rainfall is the most natural resourcedominant element of the climate of Bangladesh because it is located in the tropical monsoon region and the amount of rainfall is very high. The most of the people of Bangladeshhave occupation on agriculture and hence,is calledan agriculture based country. Rainfall is very important for agriculture, because plants needwater to survive. Usually, theregular rain is vital for healthy plants, too much or too little rainfall can be made flood or soil parch that is harmful, respectively.The rainfall is not onlyeffect on the production of agricultural yieldsand calamity for floodbut also affects health of human being.

One of the causes of contributes to seasonal variations in a mental disorder namely bi-polar disorder is rainfall. The rainfall and minimum temperature are two most important weather variables significantly contributed towards the rate of increment of black rot disease (Dutta et al. 2010).Rajshahi is a city in western part of Bangladesh and the district headquarters as well as administrative division as well. Using the classification of Köppen climate, Rajshahi has a tropical wet and dry climate, and the climate of Rajshahi is generally marked with monsoons, high temperature, considerable humidity and moderate rainfall (Banglapedia, 2004). The hot season commences early in March and continues till the middle of July.The maximum mean temperature observed is about 32 to 36°C during the months of April, May, June and July and the minimum temperature recorded in January is about 7 to 16°C. Annual average maximum temperature of Rajshahi district is 37.8°C and that minimum is 11.2°C. The highest rainfall is observed during the months of monsoon and the annual rainfall in the district is about 1,448 mm(BBS).Proper modeling to forecast on rainfall is very important that may be useful for all precautions and making policy formation. However, modeling and long term forecastonrainfall is difficult comparedto other climatic parameters but time series analysis seems to besuitable tool for such analysis.The Box–Jenkins modeling strategy is the most important modeling framework for time series analysis and forecast. Several authors have done this analysis with different models. Pudprommarat and Apichatibutarpong (2006) found SARIMA(0, 1, 1)(0, 1, $1)_{12}$model for forecasting monthly rainfall of Thailand. Sharifan and Ghahraman(2007) analyzed the monthly rainfall data of four stations and showed that SARIMA models with different order are more accurate. Yusof and Kane (2012) used rainfall data and showed thatETS state space, and SARIMA(1, 1, 2)(1, 1, $1)_{12}$ and SARIMA(4, 0, 2)(1, 0, $1)_{12}$ models for two stations are adequate. Mahsin et al. (2012)analyzedthe monthly rainfall data of Dhaka district and showed that it is followed SARIMA(0, 0, 1)(0, 1, $1)_{12}$ model. Zakaria et al. (2013) used the weekly rainfall in the semi-arid Sinjar District at Iraq and found SARIMA(3,0,2)(2,1,$1)_{30}$, SARIMA(1,0,1)(1,1,$3)_{30}$, SARIMA(1,1,2)(3,0,$1)_{30}$and SARIMA(1,1,1)(0,0,$1)_{30}$models for four stations were developed with highest precision. Mondal et al. (2012) used Mann–Kendall and Sen's slope estimator to observe the trend of rainfall of North–Eastern Part of Cuttack District, Orissa. Osarumwense (2013) used quarterly rainfall data and showed that the SARIMA(0, 0, 0)(2, 1, $0)_4$ model isappropriate.The gap of the study is thatthe rainfall patterns are extremely local but effect on global, and that's why it is necessary to investigate the rainfall pattern with different regions. Therefore,the purpose of the present study is toanalysis, modeling and forecasting of monthly rainfall data of Rajshahidistrict in Bangladesh.

MATERIALS AND METHODS

1.1 Study Area, Dataand Software

Rajshahidistrict is bounded by Naogaondistrict, India, Kushtia district–Ganges, Natoredistrict, and Nawabgangdistrict on the north, west Bengal, south, east and west, respectively. The total area of Rajshahidistrict is 2407.01 sq. km. with population 2262483 (male 51.20% and female 48.80%) and the main occupations areagriculture (38.73%), agricultural labourer(23.64%), commerce (12.44%), service (8.81%)etc. The daily rainfall data of Rajshahi district was collected from Bangladesh meteorological department, Dhaka, Bangladesh. The daily rainfall data was converted as monthly and yearly total by taking summation of daily rainfall within month and year, respectively. Therefore, the data are reduced as monthly from January, 1975 to June, 2012 (37 years and 6 months) with 450 realizations and yearly from same time with 38 realizations. The rainfall measured by standard rain gauge with measurement unit is millimeter. The Microsoft Excel and word 2010 are used to arrange rainfall data as time series and written an article, respectively. The popular statistical software R with the packages 'forecast' and 'zyp' are used the whole analysisaccording to objective.

1.2 Decomposition of Time series

There are two methods such as (i) Decomposition by additive hypothesis, and (ii) Decomposition by multiplicative hypothesis are commonly used for decomposition of a time series into its components. Thedecomposition by additive hypothesis method is used and it has been expressed a time series as eq. (1)as follows:

$y_t = T_t + S_t + C_t + R_t$ (1)

where, y_t, T_t, S_t, C_t and R_t are represent the time series, trend, seasonal, cyclic and random fluctuations at time *t*, respectively.

1.3 Moving Average Smoother

A smoother is a tool for describing the trend in dependent variable as a function of one or more regressors. Smoothers are useful because the amount of horizontal scatter in data will often make it difficult to see the trend in a data set when there is a trend. The most common technique is moving average smoothing which replaces each element of the series by either the simple or weighted average of *n* surrounding elements, where *n* is the width of the smoothing "window" (Box and Jenkins, 1976;Velleman and Hoaglin, 1981). Moving average smoother is a method in which only the dependent variable is used to describing trend. This smoother is widely used in univariate time series analysis.

1.4 Sen's Slope Estimator for Trend Test

The magnitude of trend is predicted by the Sen's estimator (Sen, 1968). According to Sen, the slope (T_i) of all data pairs is computed as

$T_i = \dfrac{x_j - x_k}{j - k}$ for*i*=1,2,. . ., *N*(2)

where, x_j and x_k are considered as data values at time *j* and *k* (*j* >*k*) correspondingly. The median of these *N* values of T_i is represented as Sen's estimator of slope which given as:

$$Q_i = \begin{cases} T_{\frac{N+1}{2}} & N \text{ is odd} \\ \frac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right) & N \text{ is even} \end{cases} \qquad (3)$$

Positive value of Q_i indicates an upward or increasing trend and a negative value of Q_i gives a downward or decreasing trend in the time series.

1.5 BoxJJenkins Modeling Strategy

The Box–Jenkins modeling strategy is a popular approach and it is widely used in time series modeling and forecasting (Box and Jenkins, 1970).The Box–Jenkins approach consists of a four step iterative procedure: (i) tentative identification, (ii) parameters estimation, (iii) diagnostic checking, and (iv) forecasting. The first step in developing a Box–Jenkins model is to determine if the time series is stationary and if there is any significant seasonality that needs to be modeled.The line graph,autocorrelation function, partial autocorrelation function and formal tests are used to check the stationarity of the variable. Non-stationarity of a time series can be found if the line graph has a trend, seasonality and autocorrelation plot with very slow decay and it is called random walk in the language of econometrics but some time non-stationary is found without showing any trend. The formal test of stationarity based on very popular methods, Augmented Dickey–Fuller (Dickey and Fuller, 1979), Phillips–Perron (Phillips and Perron, 1988) and Kwiatkowski–Phillips–Schmidt–Shin (Kwiatkowski et al., 1992) are used. The identification step is permit autocorrelation and partial autocorrelation function to select the order of models. The estimation step is complited using the maximum likelihood method. The model selection criteria such as residual variance,Akaike information criteria (Akaike, 1974), corrected Akaike information criteria (Sugiura, 1978; Hurvich and Tsai, 1989) and Bayesian information criteria (Schwarz, 1978) are used for selecting best model. The diagnostic checking is done by standardzied residual plot for outliers, ACF plot and Ljung–Box (Ljung and Box, 1978) test statistic of residuals for checking white noise. And, the root mean squarein–sample forecast error and root mean squareout–sample forecast error are used for checking stability of selected model (structural change). Finally, the selected best modelmight be used for forecasting and policy purpose.

1.6 Autoregressive integrated moving average (ARIMA) model

An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. The ARIMA model is applied in some cases where data show evidence of non-stationarity. The model is generally referred to as an ARIMA(*p*, *d*, *q*) model, where *p*, *d*, and *q*are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model, respectively. The ARIMA(*p*, *d*, *q*) model can be written in a compact way aseq. (4) as follows:

$¤(B)\nabla^d y_t = c + ¯(B)£_t$ with $\{£_t\} \sim WN(0, ±^2)$(4)

where, *WN* stands for white noise.

$\nabla^d = (1-B)^d$ (The *d* order differencing operator)

$¤(B) = 1 - ¤_1 B - ¤_2 B^2 - \cdots - ¤_p B^p$ (The *p* order of AR operator)

$¯(B) = 1 + ¯_1 B + ¯_2 B^2 + \cdots + ¯_q B^q$ (The *q* order of MA operator)

$£_t$ is random shocks, *c* is constant and y_t is any time series.

1.7 Multiplicative Seasonal ARIMA (SARIMA) Models

The general ARIMA model is called seasonal ARIMA (SARIMA) model when the time series shows any seasonal effect. The general multiplicative SARIMA model is denoted by SARIMA(*p*, *d*, *q*)(*P*, *D*, *Q*)$_s$and can be written as eq. (5) as follows:

$\Phi(B^S)¤(B)\nabla_S^D \nabla^d y_t = c + \Theta(B^S)¯(B)£_t$ (5)

where,

$\Phi(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_P B^{PS}$ (The *P* order ofseasonal AR operator)

$\Theta(B^S) = 1 + \Theta_1 B^S + \Theta_2 B^{2S} + \cdots + \Theta_Q B^{QS}$ (The *Q* order ofseasonal MAoperator)

$¤(B)$ and $¯(B)$ are same as equation (4); $\nabla^d = (1-B)^d$ and $\nabla_S^D = (1-B)^D$ refers non–seasonal and seasonal difference operator;*c* is constant, y_t is time series and $£_t$ is the usual Gaussian white noise process.We denote the number season by *s* and the identification tools for SARIMA(*p*, *d*, *q*)(*P*, *D*, *Q*)$_s$is presented in Table 1.

Table 1: Behavior of the ACF and PACF for seasonal AR, MA and ARMA models

	AR(P)$_s$	MA(Q)$_s$	ARMA(P, Q)$_s$
ACF	Tails off at lag k's, k=1, 2, …	Cuts off after lag Q's	Tails off at lag k's
PACF	Cuts off after lag P's	Tails off at lag k's, k=1, 2, …	Tails off at lag k's

2. Results and Discussion

The popular statistical software R with the packages'forecast' and 'zyp' are used fortime series analysis, modeling and forecasting of rainfall data. These data for the period January, 1975 to June, 2012 are used.The descriptive statistics e.g., mean, minimum, maximum, range, standard deviation, skewness and kurtosis of rainfall data are computed. The mean, minimum, maximum and range of monthly rainfall are 120.20, 0.00, 763.00 and 763.00, respectively. The standard deviation (SD) of rainfall(SD = 138.88)shows high fluctuation from their mean. The distribution curve of rainfall is positively skewed (skewness = 1.31) and platykurtic (kurtosis =

1.42) that is, if we draw the curve for the given rainfall distributions it will have longer tail towards the right and more flat than the normal curve.

The decomposition of rainfall data is presented in Figure 1.The time series plot (top of Figure 1) of rainfall has stochastic nature. This figure clearly shows that the rainfall datacontains a stochastic trend, seasonal variations and random movements (2^{nd}, 3^{rd} and bottom graphs of Figure 1). To see the actual seasonal nature within each year, monthly rainfall data are plotted against each year and it's shown in Figure 2.The distribution of rainfall within a year (Figure 2) is different for the different years. From Figure 2, it is clear that the maximum rainfall occurs in June, July, August and September; minimum occurs in April, May and October; and extreme minimum in January, February, November and December.The similar results were obtained by analysis of drought in eastern part of Bangladesh, monthly drought analysis showed that generally the month of January, February, March, November and December are drought-affected; April faces drought almost every year; May and October face drought occasionally; and June, July, August and September experience heavy rainfall (Keka et al., 2012). The moving average smoothing of monthly rainfall intends to be decreased over May, 2007 to June, 2012 (Figure 3). The result of moving average smoothing is strongly supported by trend components of rainfall(just below the top in Figure 1). To observe the actual trend per year, the Sen's slope of yearlyrainfall totalis considered and found that the estimated value of intercept and slope are 23891.62 and 11.25, respectively. Since, the estimated slope (-11.25) is negative, hence the rainfall has decreasing trend by 11.25 millimeter per year. Therefore,the climate change for rainfalltakes place because the long-term change in the statistical distribution of rainfall patterns over long periods of time. So, the different agricultural yields, trees and so on that depend on rainfall of Rajshahi district areaffected.Similar results werealso observed by other researchers. Ferdous and Baten(2011) reported that the annual rainfall was decreasing trend over Rajshahi region.Farhana and Rahman(2011) stated that the yearly rainfall data of Comillaregion was significantly decreasing trend.Alam et al. (2011) stated that the western part of Bangladesh was the most vulnerable for the agricultural drought.

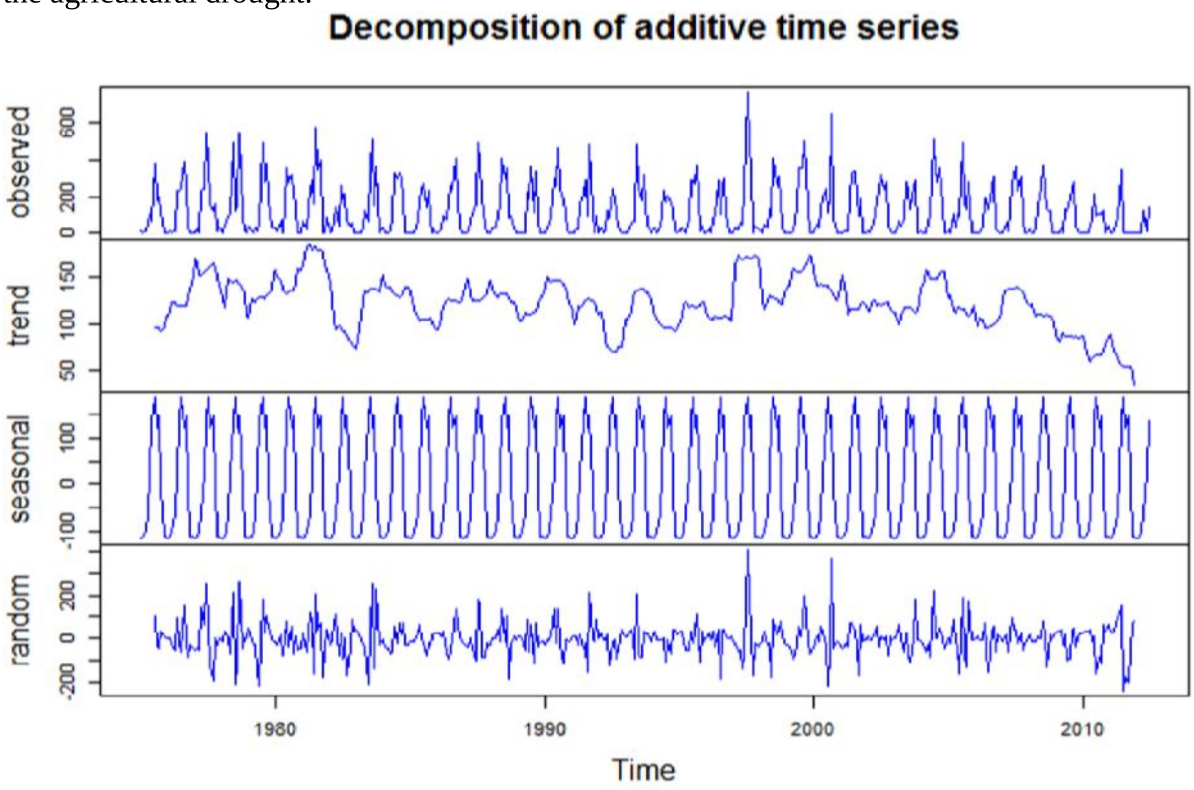

Figure 1. Decomposition of monthly original rainfall data

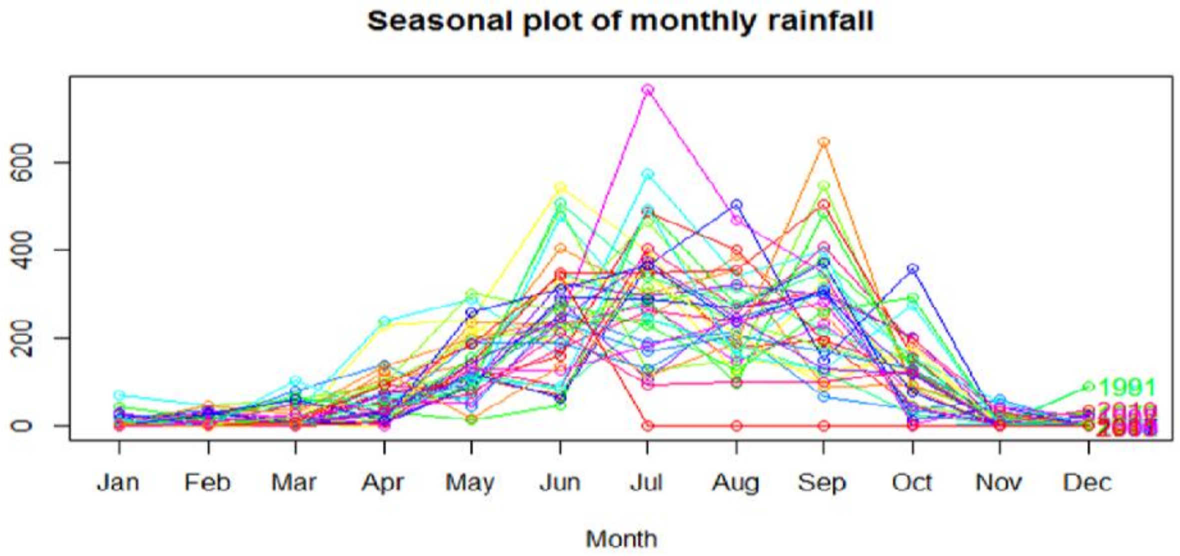

Figure 2. Seasonal plot of monthly rainfall data

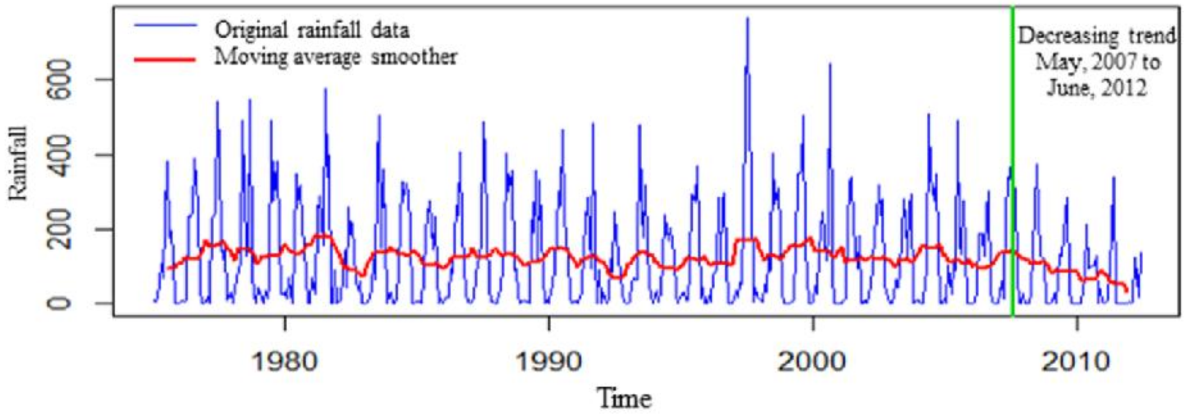

Figure 3. Plot of original rainfall data after using moving average smoother

The autocorrelationand partial autocorrelation functions (Figure 4) for original rainfall dataclearly showthat there is a strong seasonality, and same result has obtained from Figure 1 and Figure 2.Therefore, the rainfall data is non-stationary because it has contained theseasonal effects.

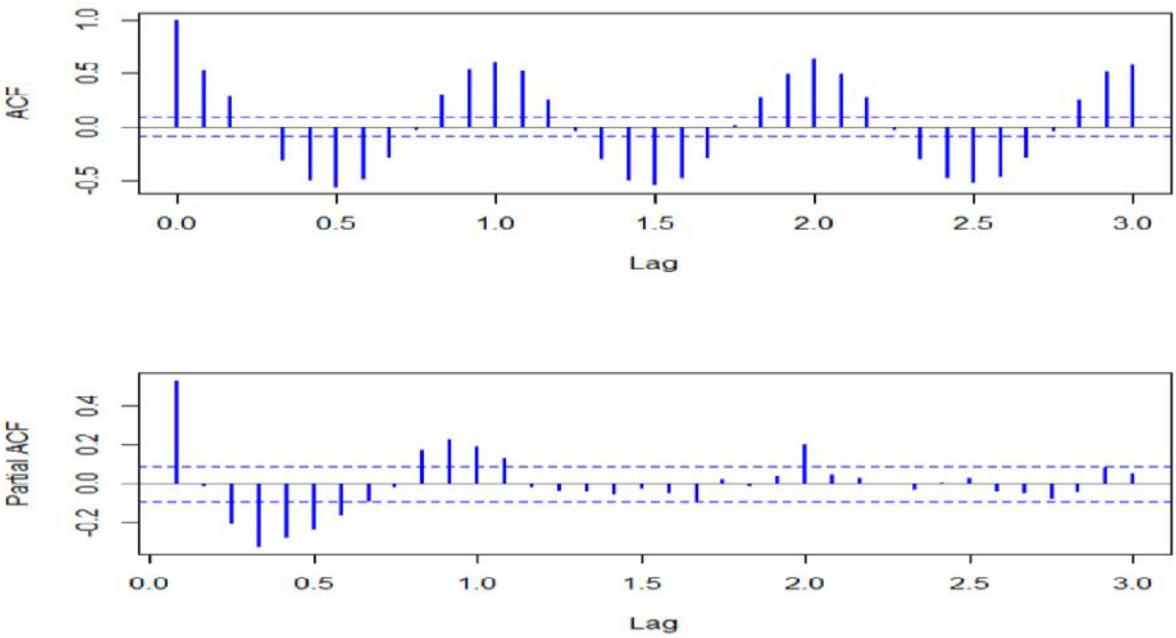

Figure 4. Plot of ACF and PACF of monthly rainfall data

The first seasonal difference of the original rainfall data has been taken for making stationary and checking whether it needs more non-seasonal differences or not. The ACF and PACF of the first seasonal differencerainfall data (Figure 5) doesnot showany seasonal pattern, and most of thespikes lie within two confidence limits. So, thefirst seasonal difference rainfall data may be stationary.To conform stationarity of the de-seasonalized rainfall data, formal tests such as Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Philips–Schmidt–Shin(KPSS) are used. The calculate values of ADF, PP and KPSS with associated *p*–value (Table 2) have suggested that the de-seasonalized rainfall time series data is stationary.

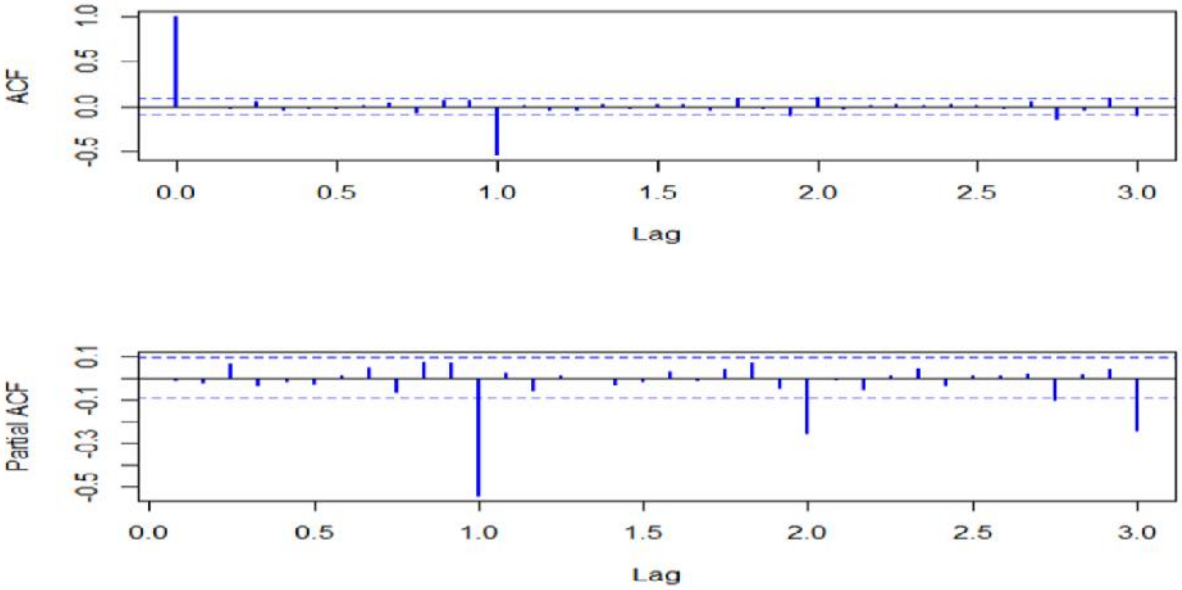

Figure 5. ACF (top) and PACF (bottom) plot of monthly de-seasonalized rainfall data

Table 2. Table for ADF, PP and KPSS test statistics

Name of test statistic	Calculate value	Lag order	Truncation lag parameter	*p*–value	Comment
ADF	-7.1252	7	---	<0.01	Stationary
PP	-441.2599	---	5	<0.01	Stationary
KPSS	0.1035	---	4	<0.10	Stationary

Now, Box–Jenkins modeling strategy can be applied to build SARIMA(p, d, q)(P, D, Q)$_{12}$ model. The rainfall data is stationary at thefirst seasonal difference. So, the value of d and D is equal to 0 and 1, respectively.Therefore,the SARIMA(p, d, q)(P, D, Q)$_{12}$ models become SARIMA(p, 0, q)(P, 1, Q)$_{12}$ models. The significant spikes (Figure 5) at lag 12 and 33 for ACF, and 12, 24, 33 and 36 for PACF havebeen observed. The models whose model parameters are significant and less than one in absolute value have been considered among the several models. The considered models with its values of residual variance ($\pm^{2}$), Akaike information criteria (AIC), corrected Akaike information criteria (AICc) and Bayesian information criteria (BIC) are presented in Table 3. The smallest values of $\pm^{2}$, AIC, AICc and BIC (Table 3) among the chosen modelsis presented by the modelSARIMA(0,0,0)(4,1,0)$_{12}$. Therefore,the final selected best model is SARIMA(0,0,0)(4,1,0)$_{12}$. Themaximum likelihood estimated parameters, standard error and t-values of selected SARIMA(0,0,0)(4,1,0)$_{12}$ modelis presented in Table 4.

Table 3. Summary of model selection criteria of different models

Model	$\pm^{2}$	AIC	AICc	BIC
SARIMA(0, 0, 0)(1, 1, 0)$_{12}$	10346	5300.22	5300.25	5308.38
SARIMA(0, 0, 0)(2, 1, 0)$_{12}$	9512	5267.51	5267.56	5279.75
SARIMA(0, 0, 0)(3, 1, 0)$_{12}$	8553	5227.07	5227.16	5243.40

SARIMA(0, 0, 0)(4, 1, 0)$_{12}$	8362	5220.41	5220.55	5240.82

Table 4. Model summary of selected SARIMA(0, 0, 0)(4, 1, 0)$_{12}$ model

Coefficient	Estimate	Standard error	Calculate t-value	Comment
Φ_1	-0.8521	0.0489	-17.4254	Significant
Φ_2	-0.6058	0.0629	-9.63116	Significant
Φ_3	-0.4517	0.0639	-7.06886	Significant
Φ_4	-0.1529	0.0515	-2.96893	Significant

The diagnostic checking of selected SARIMA(0,0,0)(4,1,0)$_{12}$ model is done by using standardized residuals plot for checking outlier; autocorrelation function of residuals plot for checking individual autocorrelations is equal to zero;Ljung–Box test for checking white noise property of residuals; and root mean squared forecast errors of in–sample and out–sample for checking stability(structural change) of selected model. The standardized residuals plot (top of Figure 6), ACF of residuals plot (middle of Figure 6) and probability values (p-values) of Ljung–Box statistic plot (bottom of Figure 6) are shown in Figure 6.

The standardized residuals plot (top graph in Figure 6) shows six points outlying [-3, 3] and these points are considered as outliers. The six outliers areoccurred at June, 1977; September, 1978; September, 1982; July, 1997; September, 2000; and September, 2001 with associated standardized residual values 3.97, 3.61, -3.13, 6.01, 3.29 and -3.53, respectively. The maximum number of outlier occurs (4 out of 6) in the month September, which means that the extreme maximum rainfall occurs in the month September within sample range.

The ACF of residual plot (middle graph in Figure 6) shows that individual autocorrelation for different lags are lying within 95% confidence limit. This implies that the residuals are stationary and white noise.

The p value of Ljung–Box plot (bottom graph in Figure 6) shows that the null hypothesis (H_o: all the autocorrelation functions up to 36 lags are simultaneously equal to zero) is accepted.

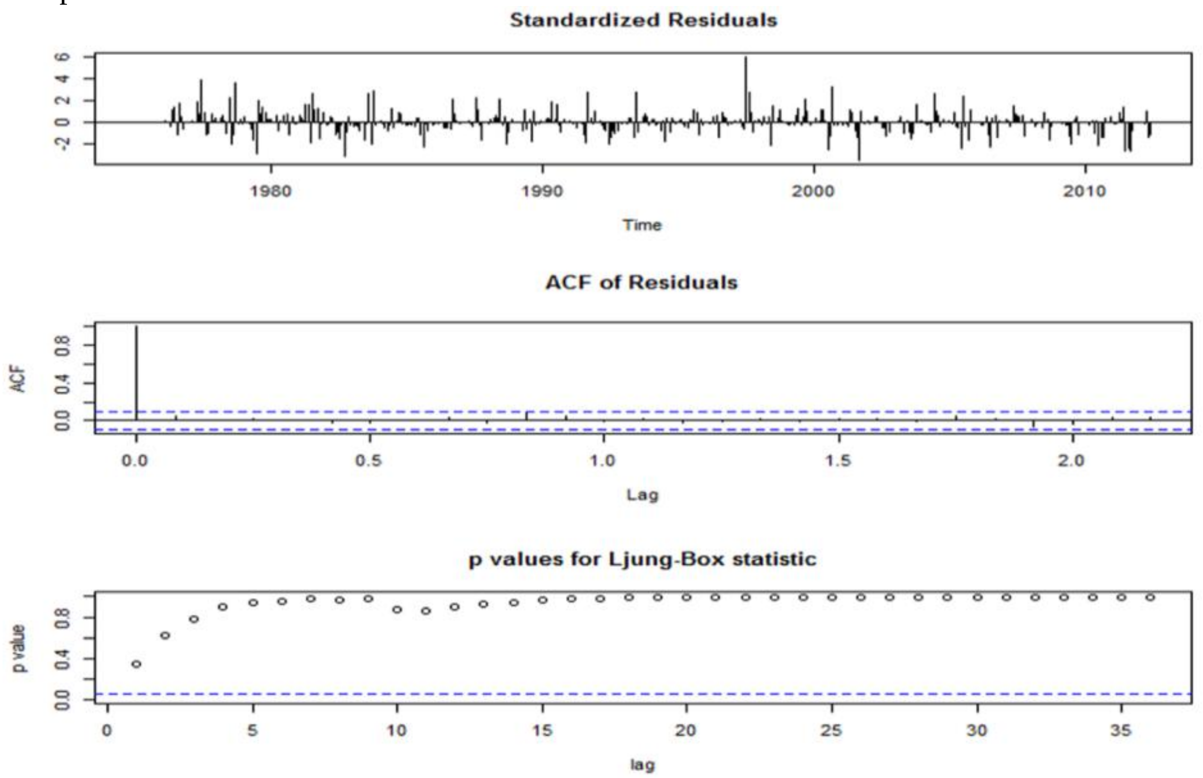

Figure 6. Standardized, ACF and p values for Ljung–Box statistics of residual plots

To investigate the structural change (test for stability) of the selected model, the root mean squared forecasterrors (RMSFEs) of in–sample and out–sample are considered. The

RMSFEsof in−sample (January, 1975 to December, 1999)and out−sample (January, 2000 to June, 2012) are 90.68and 90.21, respectively, implying that the selected model isadequate because the RMSFE for in−sample is greater than out−sample. Thus, the residuals of selected SARIMA(0, 0, 0)(4, 1, $0)_{12}$ model is found to be approximately stationary and white noise. And, the selected model is stable with no structural change. Hence,the appropriate SARIMA(0, 0, 0)(4, 1, $0)_{12}$ model can be used for forecasting purpose.

The forecasted values with 95% confidence limit from July, 2012 to December, 2025 usingSARIMA(0,0,0)(4,1,$0)_{12}$model is shown in Figure 7.The blue color line of Figure 7 indicated the forecasted values. The upper and lower lines of blue color line indicate the 95% upper and lower confidence limits, respectively. The most of the values of lower confidence limit(Figure 7) are negative, which is impossible because the lower limit of rainfall is 0, when no rainfall occurs.So, the negative lower confidence limit indicates the value zero that means no rainfall. The forecasted values of rainfall are shown to have decreasing trend.

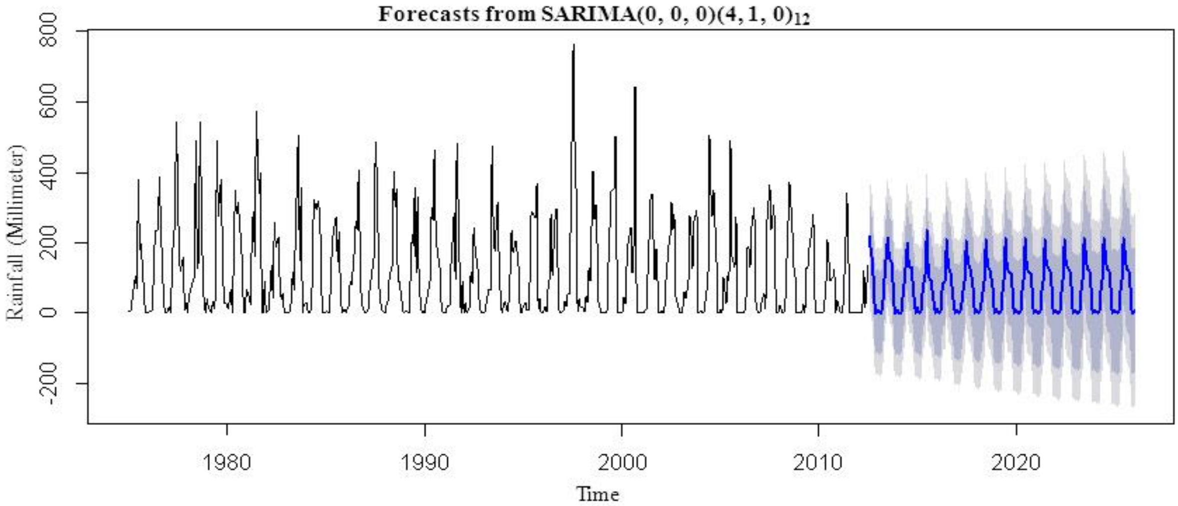

Figure 7. The forecasted value of monthly rainfall from the fitted SARIMA(0, 0, 0)(4, 1, $0)_{12}$ model from July, 2012 to December, 2025

CONCLUSION

Rainfall is one of the most important elements of climatic parameters. So the study of variability ofrainfall data is essential. Time series analysis offers such analysis. This study has showed that the monthly rainfall datacontains three time series componentssuch as stochastic trend, seasonal variations and random movements. The descriptive statistics of rainfall data has showed that the high fluctuations from their central value (mean), positively skewed and platykurtic curve. The decomposition and moving average smoothing of monthly rainfall data intends to be decreased over May, 2007 to June, 2012. The Sen's slope of long periodyearly rainfall data has decreasing trend by 11.25 mm/year. Hence, the climate change for rainfall occurs in Rajshahi district of Bangladesh.The monthly rainfall data followed by SARIMA(0,0,0)(4,1,$0)_{12}$ model which gives lowest values of residuals variance, Akaike information criteria, corrected Akaike information criteria and Bayesian information criteria. And this model is considered asthe best model. The diagnostic checking of selected model has showed stationary, white noise and very few outliers of residuals.The fitted model is found stable with no structural change. Finally, the SARIMA(0, 0, 0)(4, 1, $0)_{12}$ model can be used for forecasting from July, 2012 to December, 2025. These results verifypreviews research work for rainfall data but the order of SARIMA models is different because of geographical conditions of regional impact. This research hasdivulged a decreasing pattern that may be a threat to the cultivators as well as to the nature as a whole. Therefore, this studymight be useful for policy implicationof Rajshahi district in Bangladesh also for the rest of earth.

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