British Journal of Applied Science & Technology
4(11): 1644-1656, 2014

SCIENCEDOMAIN *international*
www.sciencedomain.org

Analysis and Prediction of Time Series Variations of Rainfall in North-Eastern Bangladesh

Ahmad Hasan Nury[1*], Manfred Koch[2] and Md. Jahir Bin Alam[1]

[1]Department of Civil and Environmental Engineering, Shahjalal University of Science and Technology, Sylhet, Bangladesh.
[2]Department of Geohydraulics and Engineering Hydrology, University of Kassel, Germany.

Authors' contributions

This work was carried out in collaboration between all authors. Author AHN designed the study, performed the statistical analysis and wrote the first draft. Author MK managed the analyses of the study and literature searches of the manuscript. Author JBA wrote the protocol and coped literature searches. All authors read and approved the final manuscript.

Original Research Article

Received 6th November 2013
Accepted 3rd February 2014
Published 15th February 2014

ABSTRACT

Time series analysis and forecasting has become a major tool in different applications in meteorological phenomena, such as rainfall, humidity, temperature, draught and environmental management fields. It has two goals, perception or modeling random mechanism and prediction of future series quantities according to the past. In this research, ARIMA (Auto Regressive Integrated Moving Average) model has been used to carry out short term predictions of monthly rainfall in Sylhet and Moulvibazar district (north-eastern region) for years 2012 to 2014. Based on the inspection of the ACF, PACF autocorrelation plots, the most appropriate orders of the ARIMA models are determined and evaluated using the AIC-criterion. For the monthly rainfall in Sylhet district at Tajpur and Kanairghat station ARIMA (1,1,1) $(0,1,1)^{12}$ is obtained, whereas the respective models in Moulvibazar district at Chandbagh, Sreemangal and Manu railway bridge are ARIMA (0,1,1) $(1,1,1)^{12}$, ARIMA (1,1,1) $(1,1,1)^{12}$ and ARIMA (1,1,0) $(0,1,1)^{12}$. Among five rainfall stations PBIAS is the least (-1.07%), NSE (88%) and Index of agreement (87%) are the highest at Kanairghat station. Negative Mann-Kendall test statistics of monthly rainfall series (for the period between 1980 and 2011) indicates that monthly rainfall is

**Corresponding author: E-mail: hasancee@yahoo.com;*

decreasing with time except Kanairghat station (0.075). Mean rainfall with their standard deviation indicates rainfall is fluctuating with time. The outcomes from this study will assist water engineers and hydrologists to establish strategies, priorities and proper use of water resources in Sylhet and Moulvibazar districts.

Keywords: ARIMA models; mann-kendall's statistics; rainfall; standard deviation.

1. INTRODUCTION

Climate change in world is always one of the most important topics in water resources management. Weather parameter such as precipitation could be practically useful in making decisions, risk management and optimum usage of water resources [1,2,3,4]. This parameter has undeniable effects on hydrological cycle, production of crops products cycle, water usage specifically agricultural usage, people activities and the environments [5,6,7,8,9]. Rainfall is considered as the major parameter in storm water studies and designs to prevent flooding events [10,11,12,13]. Hence an understanding of the variations of rainfall is indispensable for the design of hydraulic structures, drainage systems, storm water management plans etc [14,15,16,17]. Information on rainfall is also important in various types of hydrological studies concerned with the determination of peak runoff and its volume [18,19]. Small hydraulic structures such as culverts, storm sewers, drainage structures in air field etc. are usually designed on the basis of rainfall data. So it is very important to know the behavior of rainfall data from its historical records. Prediction of rainfall can be applied on huge and long-term schematization specifically for resistance to nature disasters [20,21,22]. In order to modeling and forecasting, stochastic methods are useful [23,24,25,26]. Time series analysis and forecasting has become a major tool in numerous hydro-meteorological applications, to study trends and variations of variables like rainfall, humidity, temperature, streamflow and many other environmental parameters [27,28].

Soltani et al. [29] developed an ARIMA (Autoregressive Integrated Moving Average) model to fit the monthly rainfall data from 1970 to 2000 for 28 rainfall stations of Iran. Correlation coefficients R^2>0.78 and Nash and Sutcliffe efficiency NSE >85% were obtained for the fitted ARIMA models for all stations.

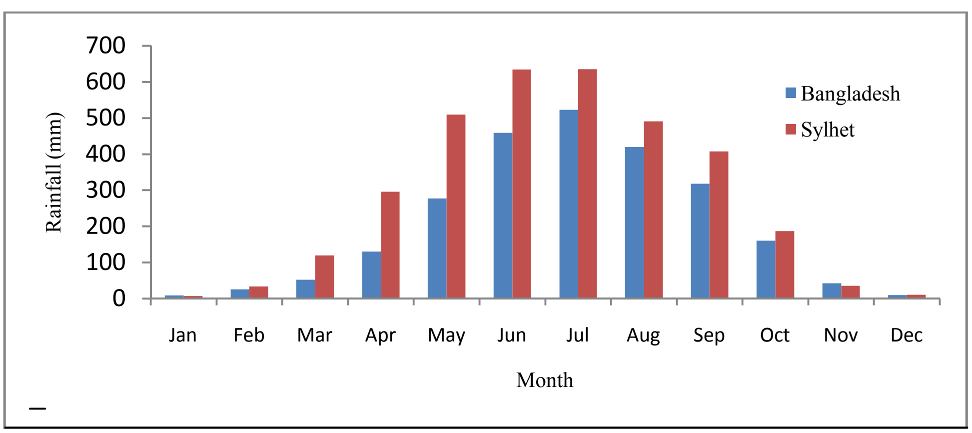

Fig. 1. Average Monthly Precipitation of Bangladesh and Sylhet from 1980 to 2010

Modarres and Sarhadi [30] did a rainfall trends analysis in Iran for the last half of the 20th century. In this study, the observed annual and 24-hr maximum precipitation for 145 stations in Iran was analyzed by means of Mann-Kendall trend tests. The results indicate that the annual rainfall is decreasing for 67% of the stations, while the 24-hr maximum rainfall is increasing at 50% of the stations. Negative trends of annual rainfall are mostly observed in the northern and northwestern regions, whereas positive trends of 24-hr maximum rainfall are mostly located in the arid and semiarid regions of Iran.

Sylhet, the northeastern administrative division of Bangladesh, is located at 24º53' latitude and 91º52' longitude. The climate of the Sylhet division is tropical monsoon with a predominantly hot and humid summer and a relatively cool winter. The annual average precipitation is about 3366.4 mm. The comparison curve of average rainfall between Bangladesh and Sylhet for the study period 1980 to 2009 is showed in Fig. 1.

A number of classical time series studies have been conducted in recent years to assess the nature of the climate change, as it has occurred over the world as well as in Bangladesh in the recent past and as it will more likely do so in the future. As for Bangladesh, Mahsin et al. [31] analyzed monthly rainfall time series for the 1981-2010 periods in the Dhaka division using a seasonal ARIMA model. An ARIMA (0, 0, 1) $(0, 1, 1)^{12}$ model was found adequate and this model is used to forecast the monthly rainfall for the upcoming two years to help decision makers to establish priorities in terms of water demand management.
Objectives of the study are:

- Quantitative statistical analysis of the time series of rainfall to see trends in the Sylhet and Moulvibazar districts (north-eastern Bangladesh).
- Predictions of the time series changes by means of auto regressive integrated moving average (ARIMA) models.

2. METHODOLOGY AND THEORITICAL BASES

2.1 Meteorological data

For this study monthly rainfall time series for five stations of Northeastern (Sylhet and Moulvibazar districts) Bangladesh were selected. Monthly Rainfall data of 32 years from 1980 to 2011 has been collected from Bangladesh Meteorological Department. Spatial location of these rainfall stations is presented in the Fig. 2. Latitude and longitude of rainfall stations are showed in Table 1.

Table 1. Selected rainfall station

Districts	Area (km^2)	Station Name	Latitude	Longitude
Sylhet	3490.40	Tajpur	24º47'16"	91º44'56"
		Kanairghat	24º48'56"	91º46'18"
Maulvibazar	2799.39	Chandbagh	24º36'45"	91º53'37"
		Sreemangal	24º18'22"	91º44'9"
		Manu Railway bridge	24º25'32"	91º56'11"

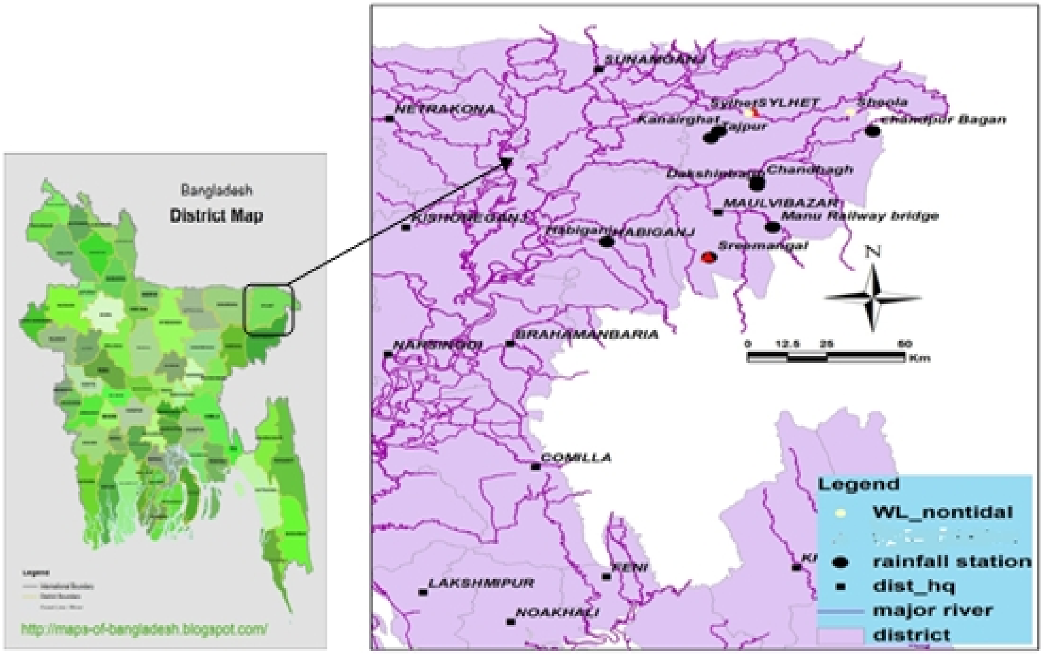

Fig. 2. Location of rainfall station

2.2 Mann-Kendall's trend Test

Mann-Kendall test [32,33] is was applied to assess the statistical significance of trends of monthly rainfall series. This test evaluates whether outcome values tend to increase or decrease over time. The hypothesis of Mann and Kendall's trend test is

H0: Time series values are independent and identically distributed i.e. there is no trend.

HA: There is a monotonic (not necessarily linear) trend

So, it is two-tailed test.

The Mann-Kendall trend test analyzes the sign of the difference between later-measured data and earlier-measured data. Each later-measured value is compared to all values measured earlier, resulting in a total of n(n-1)/2 possible pairs of data, where n is the total number of observations.

The test statistic, S (score) is then computed as

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(y_j - y_i) \quad (1)$$

Where, $sign(y_j - y_i)$ is equal to +1, 0 or -1

A positive value of S indicates an ‘upward trend’ and a negative value of S indicates ‘downward trend’. More specifically, when S is a large positive number, later-measured values tend to be larger than earlier values and an upward trend is indicated. When S is a large negative number, later values tend to be smaller than earlier values and a downward trend is indicated. When the absolute value of S is small, no trend is indicated.

The test statistic τ (Kendall’s tau) is used to measure the association between two measured quantities and computed as:

For large samples (if n>8) S is normally distributed with mean zero and variance is

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \tag{2}$$

Therefore, the test statistic Z is calculated as

$$Z = \begin{cases} \frac{(S-1)}{\sqrt{var(S)}} if S > 0 \\ 0, if S = 0 \\ \frac{(S+1)}{\sqrt{var(S)}} if S < 0 \end{cases} \tag{3}$$

Z follows standard normal distribution with mean zero and variance unity. A positive value of test statistic indicates a positive association, a negative value of test statistic indicates negative association and test statistic equal zero means no association. The null hypothesis of no trend is rejected when S and Z are significantly different from zero.

2.3 ARIMA Model

In time series analysis, the Box–Jenkins methodology, named after the statisticians George Box and Gwilym Jenkins [34], applies autoregressive 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. We could identify seasonal ARIMA (*P, D, Q*) parameters for our data. These parameters are: Seasonal autoregressive (*P*), seasonal Differencing (*D*) and seasonal moving average (*Q*). The general form of the Seasonal ARIMA (p, d, q) (P, D, Q)$_S$ model using backshift notation is given by,

$$\varphi_{AR}(B)\varphi_{SAR}(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_{MA}(B)\theta_{SMA}(B^s)e_t \tag{4}$$

Where,

s = number of periods per season, φ_{AR}= non-seasonal autoregressive parameter, θ_{MA}= non-seasonal moving average parameter, φ_{SAR} = seasonal autoregressive parameter, θ_{SMA} = seasonal moving average parameter and B= backward shift operator.

The step in developing a ARIMA model is i) model identification ii) estimation of model parameters iii) Diagnostic checking for the identified model appropriateness for modeling and iv) Application of the model (forecasting).

2.4 AIC (Akaike Information Criterion)

The Akaike information criterion [35] is a measure of the relative goodness of fit of a statistical model. In the general case, the AIC is

$$AIC = 2k - 2\ln(L) \tag{5}$$

Where k is the number of parameters in the statistical model and L is the maximized value of the likelihood function for the estimated model.

2.5 Predictive Capability of ARIMA Model

To evaluate the predictive capability of ARIMA model outputs, PBIAS (percent of BIAS) and NSE (Nash-Sutcliffe efficiency) parameter has been used.

2.5.1 Percent of bias (PBIAS)

Percent of bias (PBIAS) [36] measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias. The percent of bias (PBIAS) defined as

$$PBIAS(\%) = \frac{\sum_{i=1}^{n}(O_i - S_i) * 100}{\sum_{i=1}^{n}(O_i)} \tag{6}$$

Where PBIAS is the deviation of data being evaluated, expressed as a percentage.

2.5.2 Nash-sutcliffe efficiency (NSE)

The Nash-Sutcliffe efficiency (NSE) [37] is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance. NSE indicates how well the plot of observed versus simulated data fits. NSE ranges between $-\infty$ and 1.0 (1 inclusive), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unaccepted level of performance. The Nash-Sutcliffe model efficiency (NSE) coefficient defined as

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right] \tag{7}$$

2.5.3 Modified Index of agreement (d)

The modified index of agreement [38] varies from 0.0 to 1.0, with higher values indicating better agreement between the model and observations. Here 0.0 and 1.0 represent no correlation and perfect fit respectively. d is described as

$$d = 1.0 - \frac{\sum_{i=1}^{N}|O_i - S_i|}{\sum_{i=1}^{N}(|S_i - \bar{O}| + |O_i - \bar{O}|)} \tag{8}$$

Where n is the number of compared values, O_i is observed data, $\bar{O}$ is observed mean, S_i is simulated data, $\bar{S}$ is simulated mean.

3. RESULTS AND DISCUSSION

Mean rainfall with their standard deviation of each month for last 32 years (from 1980 to 2011) are given in the Fig. 3. The observation shows that variation of mean rainfall in year to year is high.

Mann-Kendall Statistics and their corresponding p-Value at 5 % significance level for monthly rainfall between 1980 and 2011 are shown in Table 2. Table 2 indicates p-Value is lower than significance level (0.05). So the null hypothesis rejected. Negative value of test statistic indicates a decreasing trend of rainfall except Sylhet station CL228 (increasing trend).

The ACF (Autocorrelation function) and PACF (Partial Autocorrelation function) graph of original time series of rainfall of Sylhet and Moulvibazar station are mentioned in the Fig. 4a and 4b respectively. It shows that the non stationarity and seasonality exist in the time series of rainfall at Tajpur station.

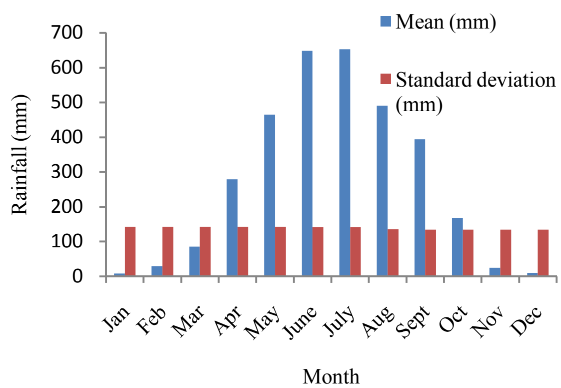

Fig. 3. Mean and standard deviation of monthly rainfall of Tajpur station

Table 2. MK Statistics and their corresponding p-Value at 5% significance level for Rainfall

Station	Test statistic	p-Value
Tajpur	-0.112	0.003
Kanairghat	0.075	0.022
Chandbagh	-0.102	0.009
Sreemangal	-0.109	0.007
Manu Railway bridge	-0.061	0.034

The original time series has been differenced at lag 1. ACF and PACF after differencing have been given in the Fig. 5a and 5b respectively. The ACF measures the amount of linear dependence between observations in a time series that are separated by a lag k. It is used to determine the order of moving average. The PACF plot helps to determine how many auto regressive terms are necessary to reveal one or more of the following characteristics:

Time lags where high correlations appear, seasonality of the series, trend either in the mean level or in the variance of the series.

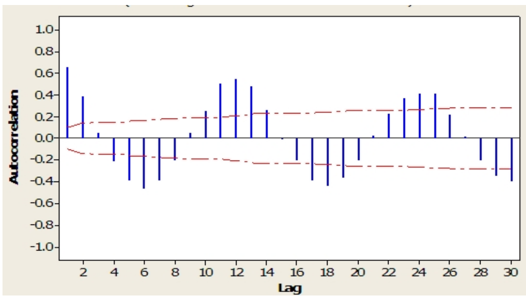

Fig. 4a. ACF (Autocorrelation function) of monthly rainfall at Tajpur station.

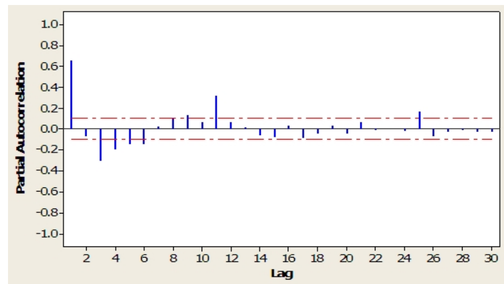

Fig. 4b. PACF (Partial Autocorrelation function) of monthly rainfall at Tajpur station.

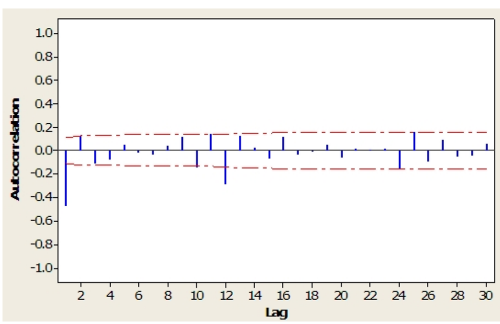

Fig. 5a. ACF of monthly rainfall at Tajpur station after differencing.

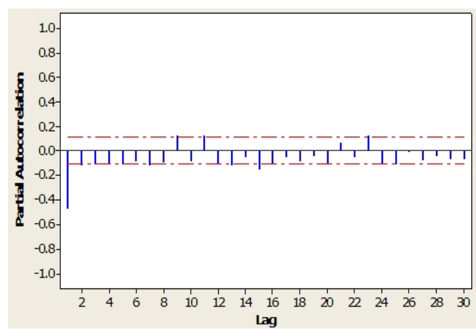

Fig. 5b. PACF of monthly rainfall at Tajpur station after differencing.

The selected ARIMA models are shown in Table 4.

Table 4. ARIMA model for Rainfall

Station	ARIMA Model	AIC
Tajpur	$(1, 1, 1)\ (0, 1, 1)^{12}$	994.278
Kanairghat	$(1, 1, 1)\ (0, 1, 1)^{12}$	1617.383
Chandbagh	$(0, 1, 1)\ (1, 1, 1)^{12}$	1017.383
Sreemangal	$(1, 1, 1)\ (1, 1, 1)^{12}$	887.383
Manu Railway bridge	$(1, 1, 0)\ (0, 1, 1)^{12}$	1224.617

Fig. 6a and 6b represent diagnostics for ARIMA $(1, 1, 1)\ (0, 1, 1)^{12}$ of Tajpur station. Visual inspection of the Fig. 6a shows histogram of residuals fitted well. There is no trend in residual scatter plot Fig. 6b.

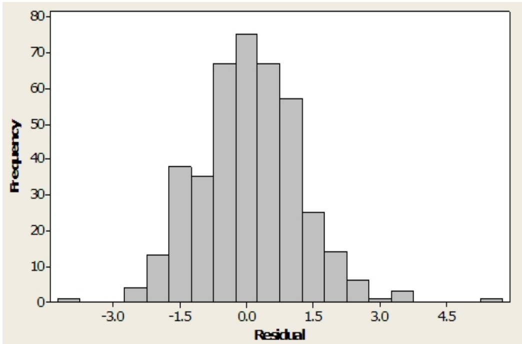

Fig. 6a. Histogram of residuals

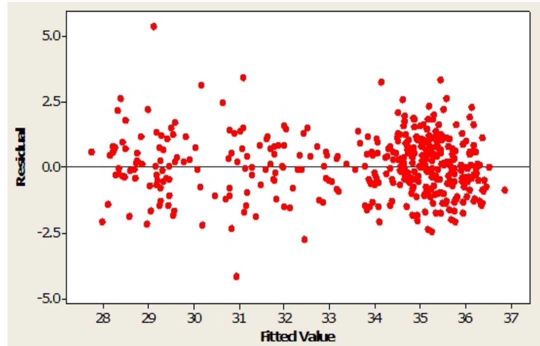

Fig. 6b. Residuals versus fits

Figs. 7a and 7b indicate ACF and PACF of residuals at Tajpur station. The spike at different lags in ACF and PACF are within assumption lines. So the ARIMA (1, 1, 1) $(0, 1, 1)^{12}$ is adequate to represent the data of monthly rainfall at Tajpur station.

The verification graph of ARIMA model for the last two years (2010 to 2011) of the monthly rainfall are given in Fig. 8. The observation shows predicted series is almost close to the observed series.

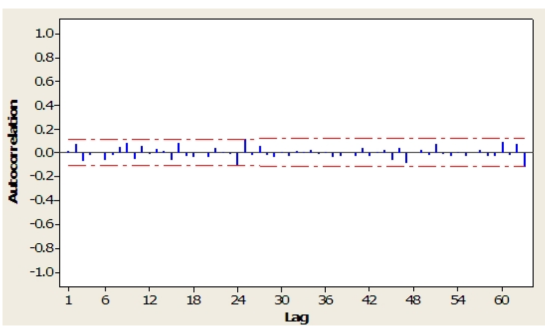

Fig. 7a. ACF of residuals

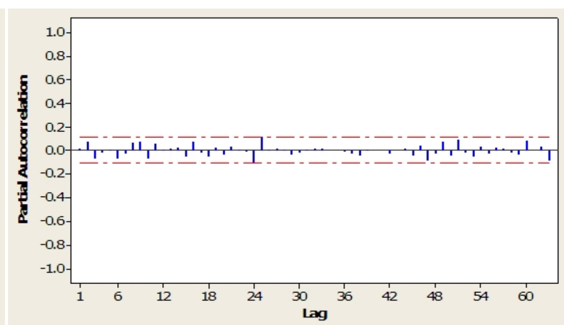

Fig. 7b. PACF of residuals

Percent of bias (PBIAS), Nash and Sutcliffe Efficiency (NSE) and index of agreement (d) of various ARIMA model are illustrated in Table 5. It postulates that the monthly rainfall predicted by the models fits correctly the observed values with PBIAS < ±6%, NSE > 82% and index of agreement (d) >78% to the observed rainfall and the fitted ARIMA models are satisfactory in all stations.

Table 5. PBIAS, NSE and d of predicted monthly rainfall

Station	PBIAS (%)	NSE (%)	d
Tajpur	4.50	84	81
Kanairghat	-1.07	88	87
Chandbagh	-3.62	85	82
Sreemangal	-5.56	83	79
Manu Railway bridge	-1.89	87	84

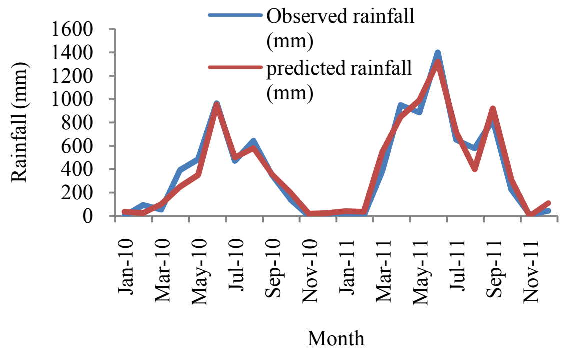

Fig. 8. Validation graph of observed vs. predicted values of rainfall data at Tajpur station.

Fig. 9a, 9b, 9c, 9d and 9e describe forecasted time series for three years (between 2012 and 2014) of various rainfall stations. The slope of forecasted time series are -0.012, -0.009, -0.006 and -0.005, indicating decreasing trend of monthly rainfall except rainfall station CL228 (positive slope, 0.015).

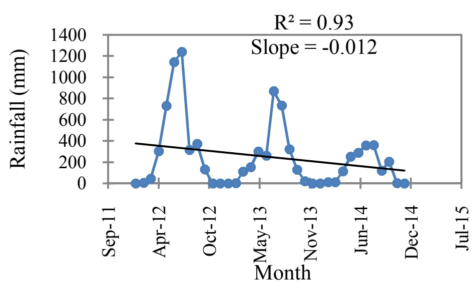

Fig. 9a. Forecasted time series of monthly rainfall of Tajpur station.

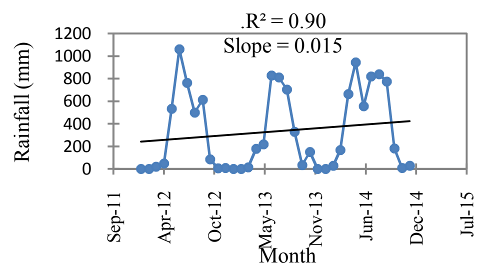

Fig. 9b. Forecasted time series of monthly rainfall of Kanairghat station.

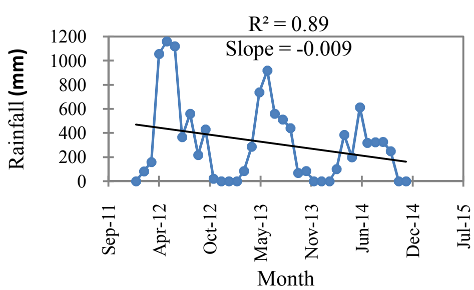

Fig. 9c. Forecasted time series of monthly rainfall of Chandbagh station.

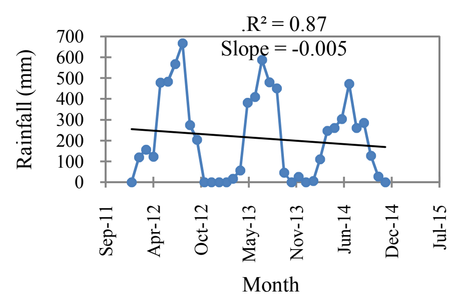

Fig. 9d. Forecasted time series of monthly rainfall of Sreemangal station.

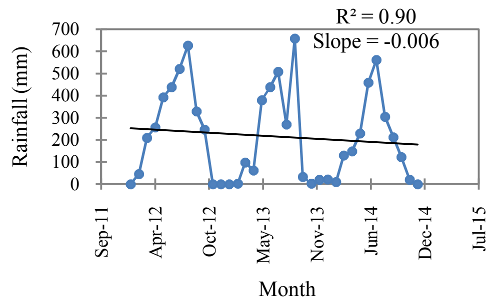

Fig. 9e. Forecasted time series of monthly rainfall of Manu Railway bridge.

4. CONCLUSION

Mean rainfall with their standard deviation indicates the variation of rainfall in year to year is high. This might be the result of climate change in this region. Mann-Kendall test statistics of time series of rainfall (for the period between 1980 and 2011) are -0.112, -0.102, -0.109 and -0.061, indicating that monthly rainfall is decreasing with time except Kanairghat station (positive test statistics, 0.075). The value of PBIAS of Kanairghat is -1.07%, comparatively small. NSE and modified index of agreement of Kanairghat station are 88% and 87% respectively. So the ARIMA model fitted well to the monthly rainfall of Kanairghat station. The forecasted time series for 2012 to 2014 shows decreasing trend of monthly rainfall with fluctuations except Kanairghat rainfall station (increasing trend).The rainfall time series fitted to ARIMA model for the selected stations might be used for estimating missing data and forecasting.

COMPETING INTERESTS

Authors declare that there are no competing interests.

REFERENCES

1. Baigorria GA. Jones JW. GiST: A Stochastic Model for Generating Spatially and Temporally Correlated Daily Rainfall Data. J Climate. 2010;23(22):5990–6008. doi:10.1175/2010JCLI3537.1.
2. Barbulescu A, Pelican E. ARIMA models for the analysis of the precipitation evolution. Proceedings of the WSEAES 13th international conference on Computers. World Scientific and Engineering Academy and Society (WSEAS). Stevens Point, USA. 2009;221-226.
3. Chattopadhyay S, Chattopadhyay G. Univariate modelling of summer-monsoon rainfall time series: Comparison between ARIMA and ARNN. Comptes Rendus Geosciences. 2010;342(2):100–107. doi:10.1016/j.crte.2009.10.016.
4. Gleckler PJ, Taylor KE, Doutriaux C. Performance metrics for climate models. Journal Geophysical Reaserch. 2008;18:113-120.
5. Zhang, Z, Switzer P. Stochastic space-time regional rainfall modeling adapted to historical rain gauge data. Water Resour. Res. 2007;43:3. doi:10.1029/2005WR004654.
6. Singhrattna N, Babel MS. Changes in summer monsoon rainfall in the Upper Chao Phraya River Basin Thailand. Clim Res. 2011;49(2):155–168. doi:10.3354/cr01015.

7. Unal YS, Deniz A, Toros H, Incecik S. Temporal and spatial patterns of precipitation variability for annual, wet, and dry seasons in Turkey. Int J Climatol. 2012;32(3):392–405. doi:10.1002/joc.2274.
8. Krishnamurti TN, Stefanova L, Chakraborty A, Kumar T, Cocke S, Bachiochi D, Mackey B. Seasonal forecasts of precipitation anomalies for North American and Asian monsoons. J Meteorol Soc Jpn. 2002;80(6):1415–1426.
9. Hurile, Yu-xin SHI, Gong-hua WU. Study on model of multiple seasonal ARIMA for precipitation in Hailar region. Journal of Inner Mongolia Agricultural University. 2008;24(3):137-150.
10. Fowler H, Kilsby C, Connell PO, Burton A. A weather-type conditioned multi-site stochastic rainfall model for the generation of scenarios of climatic variability and change. J Hydrol. 2005;308(4):50–66. doi:10.1016/j.jhydrol.2004.10.021.
11. Garcia M, Peters-Lidard CD, Goodrich DC. Spatial interpolation of precipitation in a dense gauge network for monsoon storm events in the south western United States. Water Resour Res. 2008;44(5):135-145. doi:10.1029/2006WR005788.
12. Kim BS, Hossein SZ, Choi G. Evaluation of temporal-spatial precipitation variability and prediction using seasonal ARIMA model in Mongolia. KSCE J Civ Eng. 2011;15(5):917–925. doi:10.1007/s12205-011-1097-9.
13. Adamowski K, Dalezios NR, Mohamed FB. Space-time ARIMA modeling for regional precipitation forecasting, J COMPUT MATH. 1987;5(3):249–263.
14. Agosta, EA, Compagnucci RH. Central-West Argentina Summer Precipitation Variability and Atmospheric Teleconnections. J. Climate. 2012;25(5):1657–1677. doi: 10.1175/JCLI-D-11-00206.1.
15. Brissette FP, Khalili M, Leconte R. Efficient stochastic generation of multi-site synthetic precipitation data. J Hydrol. 2007;345:121–133. doi: 10.1016/j.jhydrol.2007.06.035.
16. Das T, Dettinger MD, Cayan DR, Hidalgo HG. Potential increase in floods in California's Sierra Nevada under future climate projections. Climatic Change. 2011;109(1):71–94. doi: 10.1007/s10584-011-0298-z.
17. Deepesh, M, Madan K J. Time Series Analysis of Hydrologic Data For Water Resources Planning and Management: A Review. J Hydrol Hydromech. 2006;54(3):237–257.
18. Burn DH, Elnur MAH. Detection of Hydrologic Trends and Variability. Journal of Hydrology. 2002;255:107-122.
19. Chung ES, Park K, Lee KS. The relative impacts of climate change and urbanization on the hydrological response of a Korean urban watershed. Hydrological Processes. 2011;25:544-560.
20. Delsole T, Shukla J. Linear Prediction of Indian Monsoon Rainfall. J Climate. 2002;15(24):36453658. doi: 10.1175/15200442(2002)015<3645:LPOIMR>2.0.CO;2.
21. Kallache M, Rust HW, Kropp J. Trend assessment: applications for hydrology and climate research. Nonlinear Processes in Geophysics. 2005;12:201–210.
22. Singhrattna N, Rajagopalan B, Clark M, Krishna K. Seasonal forecasting of Thailand summer monsoon rainfall. Int J Climatol. 2005;25(5):649–664. doi: 10.1002/joc.1144.
23. Unkasevic D, Vujovic D, Tosic I. Trends in extreme summer temperatures at Belgrade. Theoretical and Applied Climatology. 2005;82:199–205.
24. Sigrist F, Künsch HR, Stahel WA. An autoregressive spatio-temporal precipitation model. Procedia Environmental Sciences. 2011;3:2–7. doi: 10.1016/j.proenv.2011.02.002.
25. Goddard L, Mason S, Zebiak S, Ropelewski CF, Basher R, Cane M. Current approaches to seasonal to interannual climate predictions. Int J Climatol. 2001;21(9):1111–1152. doi: 10.1002/joc.636.

26. Khalili M, Leconte R, Brissette F. Stochastic multisite generation of daily Precipitation data using spatial autocorrelation. J Hydrometeor. 2007;8(3):396–412. doi: 10.1175/JHM588.1.
27. Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Klein Tank AMG, Haylock M, Collins D, Trewin B, Rahimzadeh F. Global observed changes in daily climate extremes of temperature and precipitation, J Geophys Res. 2006;111(5):130-145. doi: 10.1029/2005JD006290.
28. Kwon H, Lall U, Khalil AF, Stochastic simulation model for nonstationary time series using an autoregressive wavelet decomposition: Applications to rainfall and temperature. Water Resour Res. 2007;43(5):112-124. doi: 10.1029/2006WR005258.
29. Soltani S, Modarres R, Eslamian SS. The use of time series modeling for the determination of rainfall climates of Iran. International Journal of Climatology. 2007;27:819–829. doi: 10.1002/joc.1427.
30. Modarres R, Sarhadi A. Rainfall trends analysis of Iran in the last half of the twentieth century. Journal of Geophysical Research. 2009;114:1-9. D03101, doi: 10.1029/2008JD010707.
31. Mahsin M, Akhter Y, Begum M. Modeling Rainfall in Dhaka Division of Bangladesh Using Time Series Analysis. Journal of Mathematical Modeling and Application. 2012;1(5):67-73.
32. MANN HB. Non-parametric tests against trend. Econometrica. 1945;13:245–259.
33. KENDALL M.G. Rank Correlation Methods Charles Griffin, London, U.K; 1975.
34. Box GEP, Jenkins GM. Time Series Analysis: Forecasting and Control. Revised Edn., Hoden-Day. San Francisco; 1976.
35. Akaike H, A new look at the statistical model identification. IEEE Trans. Automat. Contr. 1974;19(6):716–723. doi: 10.1109/TAC.1974.1100705.
36. Gupta H, Sorooshian S, Yapo PO. Status of automatic calibration for hydrological models. J Hydrologic Eng. 1999;4(2):135-143.
37. Nash JE, Sutcliffe JV. River flow forecasting through conceptual models. J Hydrology. 1970;10(3):282-290.
38. Legates DR, Mccabe GJ. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. Water resources research. 1999;35(1):233-241

Peer-review history:
The peer review history for this paper can be accessed here:
http://www.sciencedomain.org/review-history.php?iid=434&id=5&aid=3717