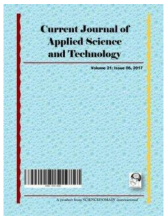

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Prediction of Runoff in Dachigam Catchment and Generation of Time Series Autoregressive Model

Sheikh Umar[1*], Junaid N. Khan[1], Mohd Ayoub Malik[1], Saika Manzoor[1] and Jasir Mushtaq[2]

[1]Division of Agricultural Engineering, Sher-e-Kashmir University of Agricultural Sciences and Technology (SKUAST), Kashmir-190025, India.
[2]Department of Civil Engineering, National Institute of Technology, Srinagar, Jammu & Kashmir- 190006, India.

Authors' contributions

This work was carried out in collaboration between all authors. Author SU designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors SU, JNK and MAM managed the analyses of the study. Authors SM and JM managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

The study was conducted with the prime objective to generate a stochastic time series model, capable of predicting runoff in Dachigam catchment area of Dal lake. It covers an area of 141 sq. km. The runoff data of the catchment from the year 1993-2013 was collected and used for the generation of model. Autoregressive (AR) model of order, 1 were used for annual runoff series and different parameters were estimated by the general recursive formula. The goodness of fit and adequacy of models were tested by Box-pierce portmanteau test, Akaike Information Criterion and by comparison of historical and simulated graphs. The AIC value of runoff for AR (1) was model (326.35) which is satisfying the selection criteria. The mean forecast error is also very less in case of runoff AR (1) model. On the basis of the statistical test, Akaike Information Criterion the AR (1) models with estimate model parameters can be used efficiently for the future predictions in

**Corresponding author: E-mail: s.umar2050@gmail.com, umarnabi997@gmail.com;*

Dachigam Catchment. The graphical representation between historical and generated correlogram has also proved that there is a very close agreement between simulated and observed runoff. The coefficient of determination R^2 for runoff AR (1) model is 0.98.The comparison between the measured and simulated run off by AR (1) model clearly shows that the generated model can be used efficiently for the prediction of runoff in Dachigam Catchment, which can benefit the farmers and research workers for water harvesting, ground water recharge, flood control and development of their water management strategies.

Keywords: Stochastic time series model; Autoregressive (AR) models; Akaike information criterion; box-pierce portmanteau test.

1. INTRODUCTION

Water demand already exceeds supply in many parts of the world and as the world population continues to rise, so too does the water demand, water is most precious gift of nature, essential for human and animal life [1] and plays an important role for plant growth [2,3]. "Development of autoregressive time series model for prediction of runoff for Manshara watershed of lower Gomati catchment [4]. The principal aim of time series analysis to describe the history of moments in time of some variable at a particular site. A comprehensive review on time series analysis technique used in climatology and hydrology. it was suggested to use more important powerful test for stationary and trend detection in time series [5]. Most hydrologic system have both deterministic as well as stochastic component , but stochastic time series model such as Autoregressive (AR) [6,7,8] moving average (MA) and Autoregressive moving average (ARMA) [9] are widely used to predict annual runoff identification generally depends on the characteristics of overall water resources system, the characteristics of time series and the models input [10]. Demonstrated these of physical consideration of the type of model. To explore the influence of the inflow on the outflow in a river system and to exploit the internal interaction of the outflows, bivariate time series models were needed [11].

The main sources of water are precipitation and snow melt. Using watershed as the basic unit because all hydrological and geomorphic processes occur within the watershed [12]. An appropriate knowledge and understanding of the process of runoff is essential for the development of effective water storage structures, the operation and proper maintenance of various water bodies and flood and drought mitigation. The planning and designing of water resource projects need information on different hydrological events that are not governed by the known physical and chemical laws, but are governed probability.

The efficient management of water and other natural resources will likely be an increasingly significant issue in future years. Growing social pressure on the available resources requires the development of method for all phase of resources management; data collection, planning, development and management. Any decision regarding the planning or operation of water resources development and flood control projects requires the prediction of the characteristics and quantity of water available.

According to available estimates, the total withdrawal / utilization for all uses in the year 1990 was 552 km^3 or 655 m^3 / person/year [13] out of total water utilized in the country irrigation accounted for nearly 83%; followed by drinking and municipal use (4.5%), energy development (3.5%) and industries (3%). Other uses of water were approximately 6% of the total use.

The historical hydrologic data would indicate the characteristics of the river flow. The river flow is treated as a random process. The appropriate word for this is "stochastic". It justifies that river flow is a function of precipitation and other process, which at the present level of knowledge seem to evolve randomly in time and space. Even if the underlying phenomena and their interactions were thoroughly understood, it would not be able to describe mathematically the rate of discharge in a natural watercourse without involving unsystematic unknown effects. Non-availability of long-term sequence needs a mean by which sufficient data can be generated to overcome the problem caused by short term and which requires an adequate mathematical model. Since the river flow and other hydrological sequences are characterized by variability and oscillatory behavior this highlights the importance of studying time series, the properties of which are of great significance in planning, designing and operation of water resources systems.

1.1 Study Area

The study area is located in Dachigham catchment of Dal Lake situated 22 kilometres from Srinagar, Jammu and Kashmir with Latitude 34°7' - 34°3'N, Longitude 74°4' - 74°5'E, with an altitude of 1690 – 4300m. From above mean sea level as depicted in Fig.1.

2. METHODOLOGY

2.1 Autoregressive (AR) Model

In the Autoregressive model, the current value of a variable is equated to the weighted sum of a pre assigned number of part values and a variate that is completely random of previous value of process and shock. The p^{th} order autoregressive model AR (p), representing the variable Y_t is generally written as.

$$Y_t = \bar{Y} + \Phi_1 (Y_{t-1} - \bar{Y}) + \Phi_2 (Y_{t-2} - \bar{Y}) + ... + \Phi_p (Y_{t-p} - \bar{Y}) + \varepsilon_t \quad (1)$$

$$Y_t = \bar{Y} + \sum_{j=1}^{p} \Phi_j (Y_{t-j} - \bar{Y}) + \varepsilon_t \quad (2)$$

Where,

Y_t = The time dependent series (variable)
ε_t = The time independent series which is independent of Y_t and is normally distributed with mean zero and variance σ^2
$\bar{Y}$ = Mean of annual runoff data
$\Phi_1, \Phi_2, ... \Phi_p$ = Autoregressive parameter
P = Order of model

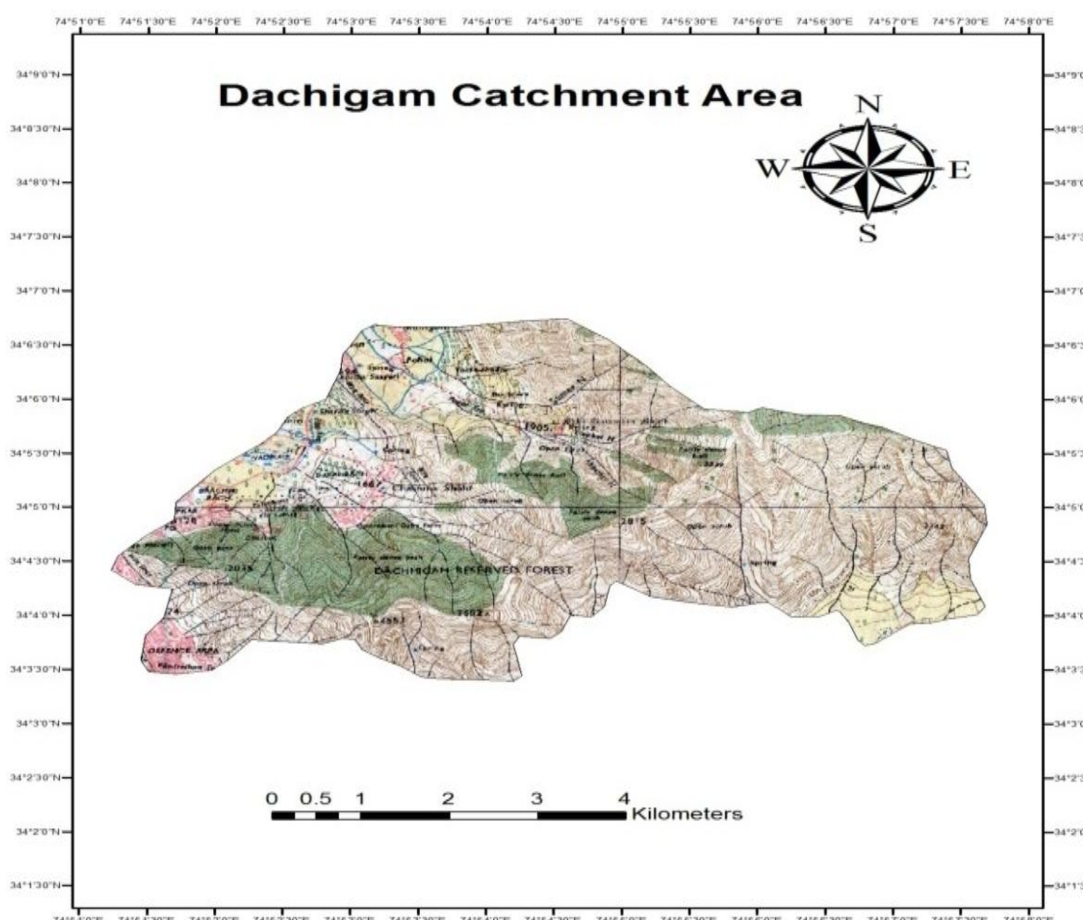

Fig. 1. Location map of study area

2.2 Estimation of Autoregressive Parameter (Φ) Maximum Likelihood Estimate

For estimation of the model parameter method of maximum likelihood will be used [14].

Consider the sum of cross-products, and difference operator

$$D_{ij} = \frac{N}{(N+2-i-j)} \quad (3)$$

where,

D = difference operator
N = sample size
i,j = maximum possible order

The maximum likelihood estimates of the parameters $\Phi_1,\ldots, \Phi_p$ are found by solving the system of equations

$$D_{ij} = \Phi_1 D_{j2} + \Phi_2 D_{j3} + \ldots + \Phi_p D_{j,p+1},\ j=2,\ldots, p+1 \quad (4)$$

for $\Phi_1,\ldots, \Phi_p$ in particular,

$$AR\ (1): \Phi_1 = \frac{D_{1,2}}{D_{2,2}} \quad (5)$$

$$AR\ (2): \Phi_1 = \frac{D_{1,2}D_{3,3} - D_{1,3}D_{2,3}}{D_{2,2}D_{3,3} - D_{2,3^2}} \quad (6)$$

$$\Phi_2 = \frac{D_{1,3}D_{2,2} - D_{1,2}D_{2,3}}{D_{2,2}D_{3,3} - D_{2,3^2}}$$

2.3 Autocorrelation Function

The autocorrelation function r_k of the variable Y_t of equation (7) is obtained by multiplying both sides of the equation (7) by Y_{t+k} and taking expectation term by term. The relationship proposed by [15] for the computation of autocorrelation function of lag K was used which is expressed as:

$$r_k = \frac{\sum_{t=1}^{N-K}(Y_t - \overline{Y})(Y_{t+k} - \overline{Y})}{\sum_{t=1}^{N}(Y_t - \overline{Y})^2} \quad (7)$$

where,

r_k = Autocorrelation function of time series Y_t at lag k
Y_t = Stream flow series (historical data)
$\overline{Y}$ = Mean of time series Y_t
k = Lag of K time unit
Y_{t+k} = Stream flow series at lag t+k
N = Total number of discrete values of time series Y_t

The following equation was used to determine the 95 per cent probability levels. [16].

$$r_k\,(95\%) = \frac{-1-1.96\sqrt{N-K-1}}{N-K} \quad (8)$$

Where, N = Sample size and K=lag

2.4 Partial Autocorrelation Function

The following equation was used to calculate the partial autocorrelation function of lag K. [17].

$$PC_{k,k} = \frac{r_k - \sum_{j=1}^{k-1} PC_{k-1,j}\, r_{k-j}}{1 - \sum_{j=1}^{k-1} PC_{k-1,j}\, r_j} \quad (9)$$

Where,

PC_k= Partial autocorrelation function at lag K
r_k= Autocorrelation function at lag K

$$PC_{k,j} = PC_{k-1,j} - PC_{k,k}PC_{k-1,k-j} \quad (10)$$

j = 1, 2, ……. K-1

The 95 percent probability limit for partial autocorrelation function was calculated using the following equation. [16].

$$PC_k(95\%) = \pm \frac{1.96}{\sqrt{N}} \quad (11)$$

2.5 Parameter Estimation of AR (p) Models

The average of sequence Y_t was computed by following equation:

$$\overline{Y} = \frac{1}{N}\sum_{t=1}^{N} Y_t \quad (12)$$

The σ^2_ε of Y_t was computed by the following equation:

$$\sigma^2{}_\varepsilon = \frac{1}{(N-1)}\sum_{t=1}^{N}(Y_t - \overline{Y})^2 \quad (13)$$

After computation of $\overline{Y}$ and $\sigma^2{}_\varepsilon$, the remaining parameters Φ_1, Φ_2,….Φ_p of the AR models were estimated by using the sequence:

$$Z_t = Y_t - \overline{Y}, \quad (14)$$

t = 1,2,…. N

The parameters Φ_1, Φ_2,…. $\Phi_p$were estimated by solving the p system of following linear equations [18].

$$r_k = \Phi_1 r_{k-1} + \Phi_2 r_{k-2} + \ldots\ldots + \Phi_p r_{k-p} \qquad K>0 \quad (15)$$

or

$$r_k = \sum_{j=1}^{p} \Phi_j r_{k-j} \qquad K>0$$

Where, r_1, $r_2$were computed from equation (7).

2.6 Statistical Characteristics

Mean forecast error

Mean forecast error was calculated to evaluate the performance of auto regressive models fitted to time series of run off. The mean forecast error (MFE) was computed for the annual stream flow series by the following equation [19].

$$MFE = \frac{\sum_{i=1}^{n}\chi_c(t) - \sum_{i=1}^{n}\chi_0(t)}{\eta} \quad (16)$$

where,

$\chi_c(t)$ = Computed stream flow value
$\chi_0(t)$ = Observed stream flow value
η = Number of observations
n = Total number of events

Mean absolute error

The performance of the model, were evaluated by mean absolute error was computed by following equation [19].

$$MAE = \frac{\sum_{i=1}^{n}\left|\chi_c(t) - \chi_0(t)\right|}{\eta} \quad (17)$$

Mean relative error

The mean relative error was computed by following equation [19].

$$MRE = \frac{\dfrac{\sum_{i=1}^{n}\left|\chi_c(t) - \chi_0(t)\right|}{\chi_0(t)}}{\eta} \quad (18)$$

Mean percent error

The mean percent error was computed by following equation [19].

$$MSE = \frac{\text{Error}}{\text{Actual Value}} \times 100 \quad (19)$$

To test the Validity of Autoregressive (AR) models

Box-Pierce Portmanteau lack of fit test

$$Q = N\sum_{k=1}^{L} r_k{}^2 \quad (20)$$

where,

Q = Box-pierce portmanteau statistics
N = Number of observations
r_k = Serial correlation or autocorrelation of series Y_t

Akaike information criterion

The Akaike Information Criterion [20] was used for checking whether the order of the fitted model is adequate compared with the order of dependence model. Akaike Information Criterion for AR (P) models, was computed using the following equation.

$$\text{AIC (P)} = \text{N 1n} \left(\hat{\sigma}_{\varepsilon}^{2} \right) + 2(P) \tag{21}$$

Where,

N= Number of observations
$\hat{\sigma}_{\varepsilon}^{2}$ = Residual variance

A comparison was made between the AIC (p) and the AIC (p-1) and AIC (p+1). If the AIC (p) is less than both AIC (p-1) and AIC (p+1), then the AR (p) model is best otherwise, the model which gives minimum AIC value was the one to be selected model.

Generation of synthetic series using AR (P) models

The Shapiro-Wilk Test is used to check the normality of the data, if p-value is greater than (0.05), we retain the null hypothesis that the data are normally distributed, or if p-value is less then (0.05) we reject the null hypothesis and conclude with 95% confidence that the data are not normally distributed test is done by using Mini-tab software. The p-value determines the chances that the sample comes from normal distribution. The lower this value smaller is chance that data is from normal distribution. Statisticians use a value of 0.05 as a cutoff, so when the p-value is lower than 0.05, we conclude that the sample deviates from normality. The fitted autoregressive AR (P) model is used for generation of synthetic series in R-software.

3. RESULTS AND DISCUSSIONS

In this study, autoregressive time series model were generated for annual runoff. The underlying stochastic process of annual runoff is characterized by autoregressive model.

3.1 Model Identification

The annual run off series Y_t was modelled through the autoregressive model. The various steps involved in are identification, estimation of parameters and verification of the model type, order and parameters. The general shape of the autocorrelogram and partial autocorrelogram are used as a basis for identification. The autocorrelagram is a plot of autocorrelation function against lag K and partial autocorrelation is a plot of partial autocorrelation function against lag K.

3.2 Autocorrelation Function

It is illustrated from the Table 1 that the autocorrelation function varies in its values from -0.151 (lowest) at lag five to 0.454 (highest) at lag first, this shows data in lag first is time dependent as it crosses the (95%) tolerance limit and therefore run off autoregressive model of order one is selected.

3.3 Partial Autocorrelation Function

It is illustrated from the Table 2 that the partial autocorrelation function varies in its values from 0.046 (lowest) at lag second to 0.534 (highest) at lag first, this shows data in lag first is time dependent as it crosses the (95%) tolerance limit and therefore runoff autoregressive model of order one is selected.

Partial autocorrelation of annual rainfall and runoff along with 95 per cent probability limits are represented in Fig. 2. It is illustrated from Fig. 2. that at lag first partial autocorrelation function crosses the tolerance limit. Therefore result revealed that the runoff autoregressive model of first order, AR (1) runoff model was selected [4].

Table 1. Autocorrelation of measured annual stream flows for runoff volume for Dachigam catchment

Lag	95%lower limit	Autocorrelation function	95% upper limit
1	-0.477	0.454	0.377
2	- 0.490	- 0.332	0.385
3	- 0.504	0.167	0.393
4	- 0.520	-0.422	0.402
5	- 0.536	-0.151	0.411

Table 2. Partial autocorrelation of measured annual stream flows for runoff discharge for Dachigam catchment

Lag	95% lower limit	Partial autocorrelation function	95% upper limit
1	-0.427	0.534	0.427
2	-0.427	0.046	0.427
3	-0.427	-0.252	0.427
4	-0.427	-0.347	0.427
5	-0.427	0.294	0.427

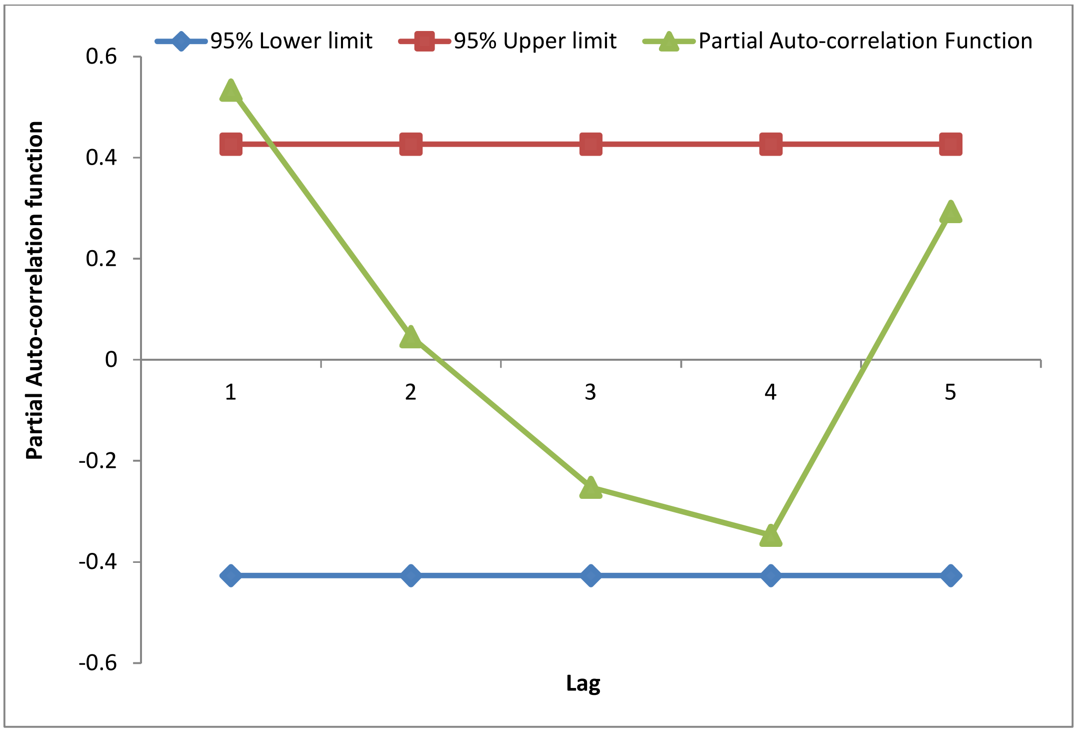

Fig. 2. Partial Autocorrelation of measured annual stream flows for runoff volume

3.4 To Test the Validity of Models of AR Family

The autoregressive models of order 1 were used in this study [16]. The parameters of AR models of order 1 were determined through equation 8 to equation 11 and models are given as under:

Runoff
AR (1) : Y_t= 1613.95+0.6270(Y_t-1)+0.77

3.5 Box Pierce Portmanteau Test for AR Model

The test statistic tabulated in Table 3. The table data reveals that the value of test statistic for run off AR(1) model is (Q=0.3963) , therefore AR(1) model for runoff are giving good fit and are acceptable [4]. Box Pierce Portmonteau test shows that data generated by AR (1) model contains less error and is good fit. The results are in agreement with the findings of [4,21].

3.6 Akaike Information Criterion Test for AR Models

The computed values of AIC runoff are given in Table 3 respectively. It is clear from the Table 3 that AIC value of rainfall AR (1) model is (AIC= 326.35), therefore it was considered suitable model for further prediction of run off

3.7 Statistical Characteristics of Data

The mean, standard deviation and skewness of historical and generated data was calculated to evaluate the fitting of the model in moment preservation. The results are tabulated in Table

4.The results clearly shows in Table 4 that the skewness of generated data by runoff AR (1) model and historical data is 0.270 to 0.392 that is lying between -1 to +1 and therefore rainfall AR(1) model preserved the mean and skewness better. Skewness is a measure of the probability of real valued random variables about its mean. The skewness value can be positive or negative. The results are in agreement with the findings of [4,21].

Table 3. Statistical parameters of autoregressive (AR) model for runoff

Model	AR (1)
Autoregressive parameter	Φ_1=0.6270
Akaike Information Criteria (AIC)	326.35
Value of portmanteau statistics (Q)	0.3963

3.8 Comparison of the Historical and Selected Model Graphs

Graphical comparisons of historical graph with the selected model are shown in Fig. 3. The graphical representation of the data shows a closer agreement between historical graphs of runoff and selected model. The models slightly overestimate and underestimate runoff in different time periods; however difference was within reasonable limits .It also reveals that the generated models for runoff can be utilized for the prediction of runoff with minimum chance of error in Dachigam catchment.

3.9 Measured and Simulated Runoff of Dachigam Catchment

It is observed from Fig. 3 that the simulated values are in close agreement with measured values. The model slightly overestimate and underestimate runoff in different time periods, however difference was within reasonable limits.

3.10 Performance Evaluation of AR (1) Model for Runoff

To evaluate the performance of the model beside the comparison of historical and generated values some other statistical characteristics such as MFE, MRE, MPE and ISE were also used to prove the adequacy of the model for future prediction with higher degree of correlation to previous measured observations. The different errors for runoff and generated by runoff AR(1) model are calculated and presented in Table 5.The value of mean forecast error is -11.37 it

Table 4. Statistical characteristic of measured and simulated runoff AR (1)

Sr.No.	Statistical characteristic	Measured runoff (mm)	Simulated runoff (mm)
1	Mean	1613.95	1625.24
2	Standard deviation	361.42	342.27
3	Skewness	0.270	0.392

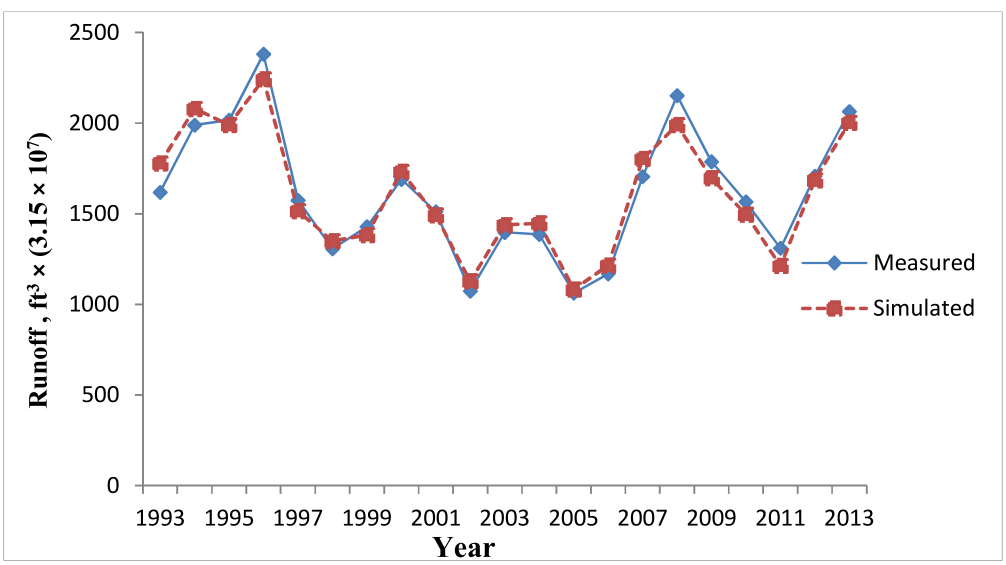

Fig. 3. Plot between measured and simulated by runoff AR (1) model

Table 5. Evaluation of regeneration performance with statistical errors of runoff AR (1) model

Sr. No.	Statistical error	Autoregressive (AR 1) model Runoff discharge (cusec)
1	Mean Forecast Error	-11.37
2	Mean Relative Error	0.46
3	Mean Percent Error	0.70
4	Integral Square Error	0.012

indicates that model has under estimated the predicted value than measured. The tabular data clearly represents that for stream flow prediction AR (1) model is giving the best results. Since all other errors are comparatively very less, than size of measurement. It indicates that AR (1) model can used for runoff prediction in Dachigam catchment.

The co-relation between the measured and simulated values of runoff are presented in Fig. 4 The graphical representation of data shows the strong co-relation between measured and predicted values for both runoff (R^2 =0.981). These values also prove the accuracy of the developed model for prediction of runoff in Dachigam catchment.

The scatter plot between measured and simulated runoff shows R^2 value 0.981.The R^2 value shows good agreement with field measured and model simulated runoff value. The results obtained in present study are in agreement with findings of [4,21].

From the Fig. 5 it is evident that most of the data points are close to the line, which means that data is from normal distribution. The p-value determines the chances that the sample comes from normal distribution. The lower this value smaller is chance that data is from normal distribution. Statisticians use a value of 0.05 as a cutoff, so when the p-value is lower than 0.05, we conclude that the sample deviates from normality.

Since p-value is greater than 0.05 we retain null hypothesis that the data are normally distributed.The results obtained in present study are in agreement with findings of [4,21].

3.11 Future Trend Generated by Model

It is illustrated from the fig.6 that the Runoff varies in its values from 1207.97, cusec (lowest) during year 2020 to 2171.51, cusec (heights) during 2014, this shows that random trend has been observed in runoff.

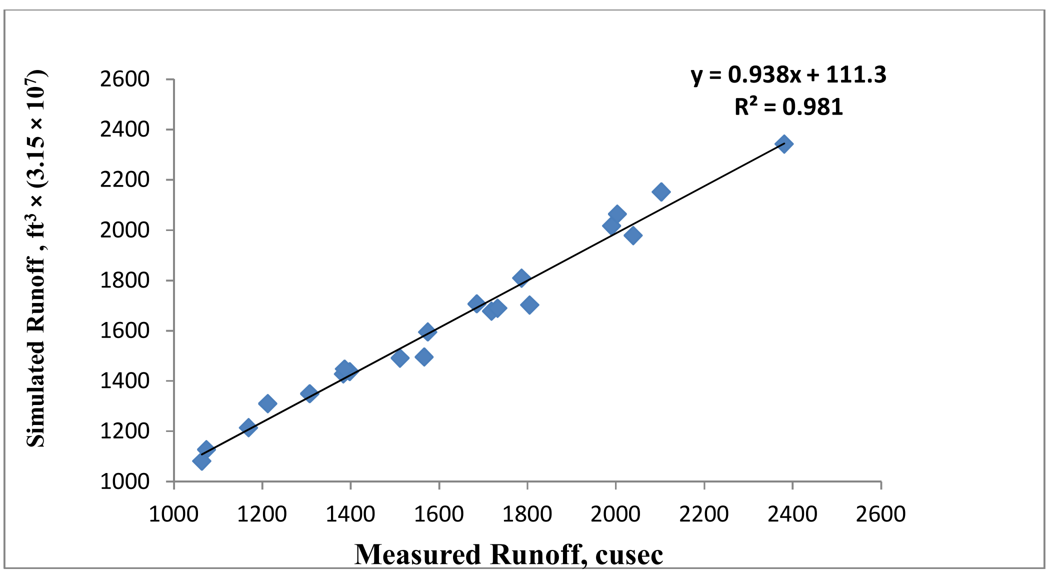

Fig. 4. Plot between measured and simulated runoff of AR (1) model

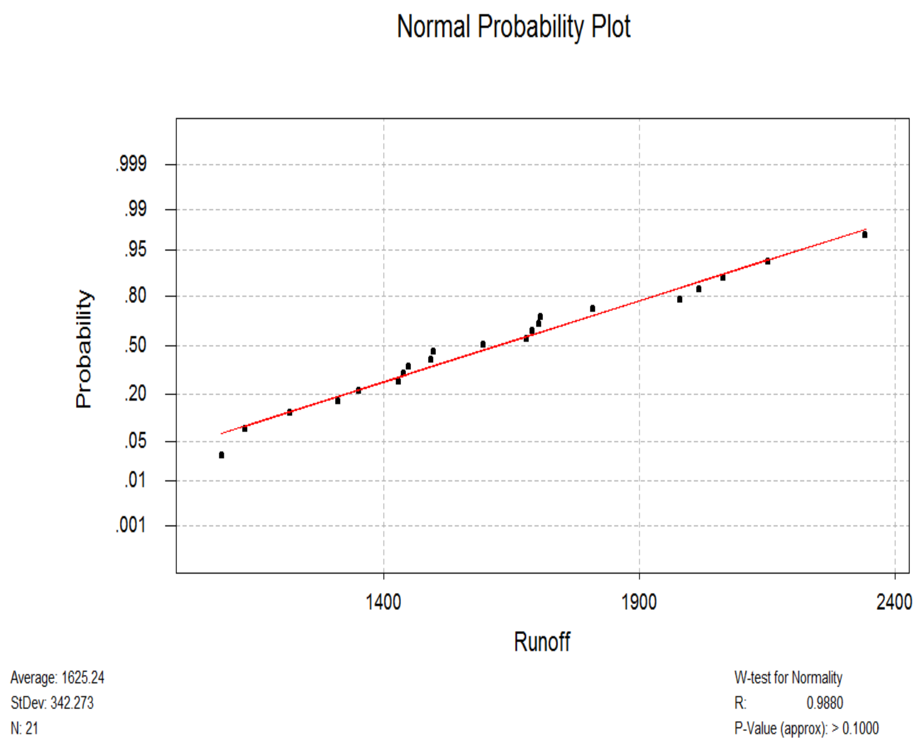

Fig. 5. Normal probability plot of runoff

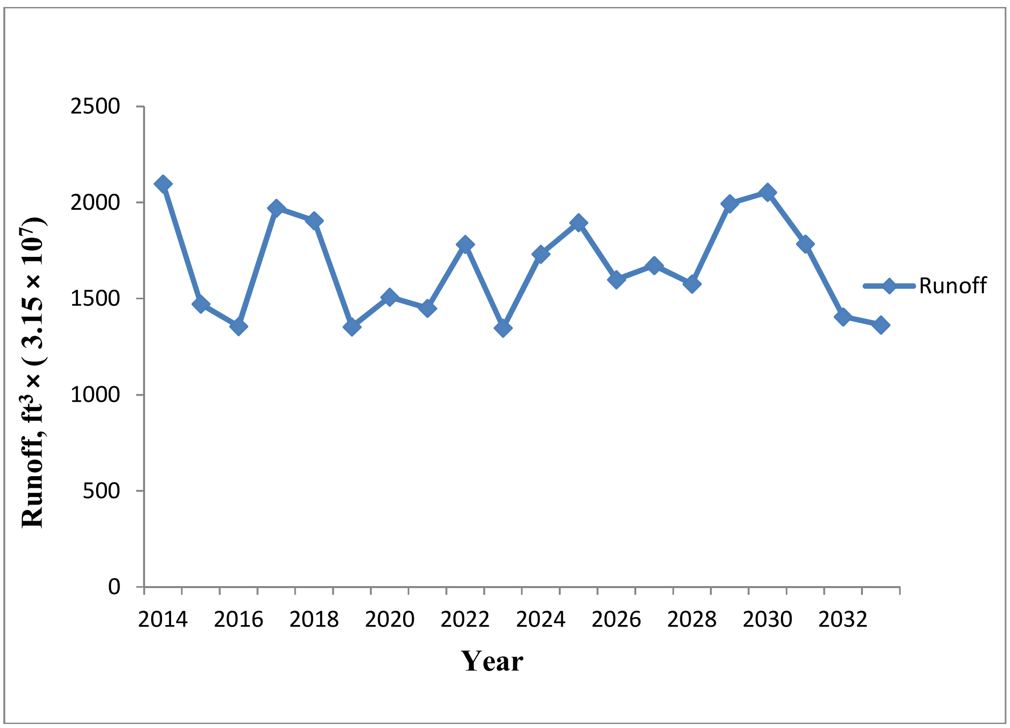

Fig. 6. Future trend graph of runoff by AR (1) model

4. CONCLUSION

In case of runoff generation there is an effective agreement between historical and generated data with mean forecast error, mean relative error, mean percent error, and integral square error. The lower values of error indicate the adoptability of the model for prediction of runoff. On the basis of the statistical characteristics and graphical representations, autoregressive AR (1) model is proposed for generation of runoff in Dachigam catchment. The scatter plot between measured and predicted AR(1) model of runoff shows R^2 value 0.98.The R^2 value shows good agreement with field measured and model predicted runoff value. For runoff the AIC value for AR (1) model is (326.35) which is less than AIC value for AR(2) model (356.31) and satisfy the selection criteria. The results clearly shows that the skewness of generated data by runoff AR (1) model and historical data is lying between -1 to +1 and therefore AR (1) model preserved the mean and skewness better. It is concluded that generated autoregressive AR (1) model can be used for prediction the annual runoff in Dachigam catchment.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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