MONTHLY RAINFALL MODELLING USING ARTIFICIAL NEURAL NETWORK FOR ALMORA

Thesis

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(Devendra Singh Rawat)
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CERTIFICATE

This is to certify that the thesis entitled **"Monthly rainfall modelling using artificial neural network for Almora"** submitted in partial fulfilment of the requirements for the degree of **MASTER OF TECHNOLOGY** in **Agricultural Engineering** with major in **Soil and Water Conservation Engineering** of the College of Post Graduate Studies, G. B. Pant University of Agriculture & Technology, Pantnagar, is a record of *bona fide* research carried out by **Mr. Devendra Singh Rawat,** Id. No. **43371**, under my supervision and no part of the thesis has been submitted for any other degree or diploma.

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We, the undersigned, members the Advisory Committee of **Mr. Devendra Singh Rawat, Id. No. 43371,** a candidate for the degree of **Master of Technology** in **Agricultural Engineering** with major in **Soil and Water Conservation Engineering** agree that the thesis entitled **"Monthly rainfall modelling using artificial neural network for Almora"** may be submitted in partial fulfilment of the requirements for the degree.

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LIST OF SYMBOLS AND ABBRIVATIONS

ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial Neural Network
ARMA	Auto Regressive Moving Average
ASCE	American society of civil engineering
Avg.	Average
BP	Back propagation
BPNN	Back propagation neural network
CC	Correlation coefficient
CE	Coefficient of efficiency
E	East
Engg	Engineering
et al.	And others
FFBNN	Feed-forward Back-propagation neural network
FFNN	Feed Forward Neural Network
FG	Fuzzy logic
Fig	Figure
GT	Gamma test
IDNN	Input delay neural network
ISE	Integral Square Error
i.e.	That is
LM	Levenberg Marquardt
LP	Learning process
MLP-ANN	Multi-Layer Perceptron Neural Network
mm	Milli meter
MRA	Multiresolution analysis
MSL	Mean sea level

MSE	Mean square error
N	North
No.	Number
P	Rainfall
PBIAS	Percentage bias
r	Correlation coefficient
RBFNN	Radial basis function neural network
RMSE	Root mean square error
Sci.	Science
SNN	Single neural network
T	Temperature
Tanh	Hyperbolic Tangent or tangent hyperbolic
Viz.	Namely
W-ANN	Wavelet Artificial Neural Network
Σ	Summation
%	Percentage

Introduction

Chapter 1 INTRODUCTION

Rainfall is the outcome of complex physical processes. Rainfall is a crucial dimension of the ecosystem and is an important driver of the hydrological cycle on the planet. The rainfall shows discrepancy around time and space, i.e. rainfall differs accordingly in relation to variation in location and time period. Rainfall is considered as a vital parameter, which is the most reliable scale of the climate change. The discrepancies in the distribution of rainfall influences the spatio-temporal dimension of the distribution of soil moisture, runoff, ground water recharge etc.

In India, out of 143 million hectares of the land under cultivation around 85 million hectare land is rainfed, which account for 60 per cent of the cultivated land. Dry lands contributes around 40 per cent to food grain production. By the year 2030, India will need to have 308.5 million tonnes of the food grains to feed the population Around 70 per cent of the rural households resides in the areas where dry farming is practiced and they rely upon success and failure of the crops in order to sustain their livelihood, in present context, 3 hectares of the dry lands can yield cereal grains which is equivalent to the yield of 1 hectare irrigated crop, hence management of dry lands have a key role to play, therefore rainfall is the chief component supporting dry land areas and prediction of rainfall can guide as preliminary step in the management of dry land agriculture and sustaining the productivity of nation.

Rainfall is considered as an eminent component of nature, from the view point of crop production, as agriculture in Indian scenario is a kind of gamble with monsoon. Agriculture in India heavily hinges upon the amount of rainfall, therefore the farmers and meteorologists are always in a keen hunt for finding the quantum of rainfall, which the land is going to receive in the rainy season. In India, monsoon season is constituted of four months (the months of June to September receives around 80 per cent of rainfall) when there is emergence of the south-west monsoon and occurrence of thunderstorms. This period (June to September) is regarded as the most productive wet season. Though the distribution of rainfall differs from heavy to scarce around different zones of the country but on average, India encounters an average rainfall of 125 cm. The distribution of rainfall in nation is lopsided in nature; some regions face the hardships of heavy floods while in some regions there is preponderance of droughts.

Both the situations are complementary of each other and are liable for risking and hampering the agricultural production of the regions, therefore water management practices have an important role to play, one of the main lacuna in the management of water resources is the prediction of rainfall. Prediction of rainfall is not only complex but also crucial for planning and implementing of various strategies in relation to agriculture of nation. Rainfall prediction is an important decision making process in the countries having agrarian economy.

As India is having diverse land forms (mountains, hills, valleys, plains etc.) so the pattern of rainfall differs accordingly with different land forms. Generally hills receives low amount of rainfall, particularly Uttarakhand which is situated at the lap or foothills of Himalayas. Uttarakhand is considered as a hilly state due to predominance of the hilly tracts, it is the northernmost hilly state, enveloping almost all geo climatic zones, which sustains commercial opportunities for floricultural and horticultural enterprises. During the South West monsoon 2018, Uttarakhand has received rainfall which was 3 per cent below the normal rainfall. Though this figure falls under the normal category, however a different picture was painted by the data related to the district level. The lopsided distribution of rainfall was observed in Uttarakhand i.e. out of 13 districts of state, four districts viz. Almora, Pauri Garhwal, Tehri Garhwal and Udham Singh Nagar have received deficit rains. Whereas, the three districts viz. Bageshwar, Chamoli and Haridwar have received rainfall in abundance. Out of the remaining six districts four districts are on marginally positive side and two districts are on marginally negative side.

By focusing on the rainfall deficit area of Uttarakhand particularly Almora district which is a rainfed area and majority of the population is clutched to agriculture so the rainfall is having utmost significance in the area. In Almora the rainy season strikes in the months of June, July, August and September. The average amount of precipitation in the district is 1130.00 mm, and the dry period occurs in the months of March, April, November and December. On an average the month of August is observed as the wettest months whereas, month of November is observed as the driest month. As the area is rainfed and is dependent on rainfall for meeting its demands related to agriculture and other activities, so forecasting the rainfall can assist the farm households to plan their agricultural strategies accordingly so that losses can be minimised and output can be maximised.

Rainfall is a complex phenomenon occurring globally and it is non-linear and extremely sensitive in its nature, therefore the physical description which is purely deterministic in approach can never be able to forecast the rainfall. But rainfall can be forecasted by the implementation of system theoretic modelling technique through the incorporation of artificial neural networks (ANNs) which has been built for the rainfall modelling. In the present context artificial neural networks (ANNs) are having more utility because ANNs are accustomed with desirable attributes of the universal approximation. Besides that ANNs are also capable of learning from the illustrations, without understanding the physics behind the natural phenomena.

Artificial neural networks (ANNs) basically are the tools to predict semi parametric regression and ANNs can approximate any enumerated function up to an arbitrary magnitude of accuracy. The best point about ANNs is that they do not require having a systematically defined physical input-output conversion relationship. It only needs to have a collection of input-output pairs which are representative of the desired mapping. ANNs then yields desired outcomes when presented with the training data. The main job of ANNs is mapping set of inputs to the outputs set by incorporation of massive parallel distributed information, which resembles with the neural networks of human brain. The technique of ANN has been proved to be more efficient and promising in the field of hydrological simulation and water resources. Previous studies related to ANNs suggested the application of ANNs on non-hydrological processes i.e. stream flow, simulation of water quality, management of groundwater, rainfall-runoff and rainfall forecasting. The technique of ANNs, yields satiable outcomes without going into deep information related to characteristics of the catchment.

ANN is basically a non-parametric model, while majority of the statistical models are parametric model. ANNs have a property of generalising i.e. After learning from relationships of the initial input, it can generalise and can make predictions regarding the unseen data. In comparison with other models ANN does not restrict the input variables. With the incorporation of neural networks, we can derive solutions of such problems or queries for which algorithmic method is very costly or it does not have any existence. ANNs network have the accuracy and they are faster than the conventional models.

The multilayered artificial neural networks or the multilayer perceptron is the most commonly used approach in the case of handling investigations related to hydrology. In this approach, more than one neuron is present in the hidden layer. The count of neurons in the hidden layer, greatly influences the performance of the model. Keeping in mind, the points highlighted above in relation to artificial neural networks (ANNs), the study aims to predict the rainfall at Almora district, the study is accomplished with following objectives:

1. To study distribution pattern of rainfall of Almora.
2. To develop and validate ANN models for monthly rainfall of Almora and
3. To evaluate the performance adequacy of developed model.

Review of Literature

Chapter 2 REVIEW OF LITERATURE

This chapter has featured the past studies associated with hydrological modeling and their applications. The chapter presents application of data driven techniques particularly the application of artificial neural networks in water resources, management of groundwater, stream flow, watershed hydrology, rainfall-runoff modeling, simulation of groundwater and predictions regarding rainfall or rainfall forecasting.

ASCE (2000a) explained a brief introduction of ANNs technique in hydrology. Apart from, multiple descriptions of manifold aspects of ANN, some vital guidelines on their applications were described. To enumerate advantages and backdrops of ANNs model, when it was employed to process any complex nature hydrological problem, overall analysis was performed. The outcomes yielded from the overall analysis were than compared with the other alternative approaches viz., models based on physics.

ASCE (2000b) highlighted that part of ANNs, which was considered to have plenty of utility for diverse fields of hydrology. The paper has thrown a light on the identification of advantages and limitations associated with ANNs. The deep knowledge and understandingof the hydrological process by incorporation of laws related to physics, can be applied for the selection of input vectors and configuration of an efficient neural network. The type of data, effects the performance of ANN, ANN can be applied to process any kind of data, therefore for the implementation of ANN in any problem related to hydrology, there is no utility for having any kind of fixed design.

Luck *et al.* (2000) compared forecasting regarding short term rainfall by configuring ANNs model having different order lag and spatial inputs ofvarious numbers.Through the different configuration of ANN model and training them to optimality, a good generalized data has been achieved. The study implied that predictions generated by the ANN models were been most accurate and précised with optimality in counts of spatial inputs incorporatedinto the networks which have been modeled. The lower lag models performed better.

Silverman *et al.* (2000) explored the long range rainfall predicting possibility of ANNs modelsincorporatingclimate influencing parameters on climatic zones ofCalifornia. The outcomes of ANNs models, which were having time lag of 1 year were founded close to the observed rainfall. It was concluded that ANN models can be applied for the identification of vital climate influencing parameters or climatological parameters.

Toth *et al.* (2000) applied techniques of auto regressive moving average, artificial neural networks and nearest neighbors method(non-parametric), in order to forecast the rainfall of Apennines Mountain, Italy. A lumped conceptual runoff model of rainfall was employed individually to predictthe output generated from the techniques enlisted above. These models forecasted rainfall for a time duration of 1 to 6hr. The study compared the relative benefits and backdrops of the above enlisted time series methods. The outcomes of the study revealed that in comparison with simple approaches of rainfall prediction, the better flood forecasting was observed in the case of ANNs technique.

Tokar and Markaus (2000) forecasted runoff using data related to rainfall, temperature and snow. The conceptual water balance model along with ANNswere employed to predict the monthly streams. The Sacramento Soil Moisture Accounting method along with ANNs was employed to predict the daily rainfall runoff. The daily rainfall runoffwas also configured withsimple conceptual rainfall runoff model together with ANNs. In all the above designed models, the technique of ANNs reflected better accuracy. As various inputs were employed in all the models, whichresulted in the biased comparisons.

Zhang and Govindraju (2000) configured complex runoff of rainfall of three watersheds data whose stream flow was categorized as high, medium and low, with ANNs which were possessing architecture that was modular in nature. Three architectures of modular method with mean monthly rainfall of both, the current month and the previous one and mean monthly temperature were taken as input of the ANN models. The findings of the study implied that modular network was good for the rainfall prediction.

Abrahat and White (2001) proposed the immense potential advantages related to modelling sediment transfer. Some initial beginner experiments were carried out to analyse the competence of the back propagation network to yield a combined model of the sediment transfer, which was sketched during implementation phase of methods of land management and when diverse kind of agricultural practices were amalgamated. The findings of the research proceedings revealed that the limitations associated with the traditional technique of multiple regression, can be overcome by the solution of a neural network.

Dawson and Wilby (2001) studied exhaustive reviewed application of artificial neural networks for modelling of rainfall runoff and forecasting of flood. Basic principles related to ANNs and algorithms employed for training were observed. Themes regarding division and the preprocessing of data associated with training and testing of ANNs models. Standardization techniques of data methodology and evaluation of the model performance were explored. It was extracted from the study that, afterproceedings of the survey, no current guideline is there for modelling practices which were incorporated currently for the ANN models and the differences preponderating between ANNs and conventional statistical methods. The study developed a crucial template to assist in development of ANN models for theirutility to be applied in modelling of rainfall runoff. The study necessitates a need of researches targeting ANN, to rule hydrology.

Jain (2001) established a relationship between, sediment and discharge at Mississippi river for two gauging stations by employing ANN models. The outcomes which were yielded by the ANN method were then compared with the existing techniques. ANN technique yielded most accurate results, as observed outcomes were closer to the measured values.

Luk *et al.* (2001) incorporated the multilayer feed forwarded neural networks, partial recurrent neural network and time delay neural networks, for prediction of the one time step advance distribution of rainfall over an urban catchment. The networks which were having lower lag performed better than the networks which were having higher lag. The study implied thatseries of rainfall have dependence structures which are short term in nature.

Birikundavyi *et al.* (2002) performed the project evaluation of artificial neural network in prediction of the daily stream flow of Mistassibi River. The comparison was made between ANNs and conceptualmodel, autoregressive models. The findings of the study in relation to mean square error and coefficient of efficiency, illustrated that ANN models performed betterthan conceptual models and auto-regression model along with kalman filters.

Brath et *al.* (2002) employed linear stochastic models, nearest neighborhood methods and artificial neural networks for predicting the short run rainfall of the future and upgrading the forecast related to discharge. The prediction which was generated using ANN was superior and best in comparison with other two models. The findings of prediction for upgrading discharge, was consistent with the findings of short run rainfall prediction.

Nagy *et al.* (2002) incorporated ANNs in the estimation of suspended sediment concentration of the rivers and developed a suitable model to record it. The input parameters which were added to the model were; Stream width ratio, Froude number, mobility number, Reynolds number and the output was processed assediment concentration. ANNs along with different formulas related to discharge of sediments were applied to 80 data observations. The obtained outcomes then compared with one another and the findings of the study concluded that the ANN model made the best predictions regarding sediment discharge as compared to any other model employed in the study.

Perera *et al.* (2002) forecasted the daily rainfall occurrence in Sri Lanka. By incorporating two models associated with 1st and 2nd order of Markov process, data was collected from 9 meteorological stations, situated at Sri Lanka. The models were capable of forecasting a given day's status at an average of 73%. The results of the dry zones were found to be better than the results of wet zones. The models have shown insensitivity towards the data incorporated in the study.

Rajurkar *et al.* (2002) configured daily flows of the monsoon season at large catchment located at Narmada river by making subdivisions in the catchment and working out average rainfall of each and every sub catchment as an input to ANN models. The linear multiple input single output (MISO) model was employed to depict the relationship of rainfall runoff. The outcomes of the study yielded that the joint effect of ANNs and MISO models, enhanced performance and accuracy of the existing model.

Cigizoghu (2003) predicted and estimated daily data on flow of rivers in Turkey, by employing the technique of multi layer perception artificial neural network. The capability of extrapolating beyond the range of calibration was explored in the study. For testing the estimationability of the model, River flow data was collected from the nearby stations. The graphs were plotted, in order to make comparisons between ANNs and the existing models, it was indicated from the plots that ANNs model are the best fit models in comparison with the existing models.

Huang *et al.* (2003) configured model of Regional Neural Network for water level (RNN-WL) by incorporating feed forward back propagation structures for the forecasting of water levels in the long run. Hour data for a month was employed to train the model and the same procedure was validated for the data of the succeeding month. The findings of the study reflected that, on the long run basis,forecasting of both, tidal and non tidal level of water was rated as very good. The model performed satisfactorily when applied to locations which were situated at a longer distance at remote stations of National Oceanographic and Atmospheric Administration (NOAA).

Tayfur *et al*. (2003) applied ANNs in barren soils in order to estimate sediment load from the surfaces. A fuzzy logic algorithm was employed in which, slope and rainfall intensity were entered as input variables and they in turn assigned the triangular membership function. The outcomes yielded by the fuzzy algorithm were consistent with the sediment measured or the observed data. Comparisons were made between fuzzy algorithms under ANN, ANN models along with the physical based models reflected good performance of the fuzzy models when the value of rainfall intensities was observed to be high over values of different slopes incorporated with different value of the intensities of rainfall, which were coded as input variables.

Zhang and Govindaraju (2003) discovered the geomorphology based artificial neural network (GANN) for estimating runoff hydrographs of two watersheds,along with the incorporation of some storm events, which were situated at Indiana. The geomorphologic unit hydrograph (GUH), yielded some outcomes which were then compared with the outcomes of GANN models along with the observed hydrographs. The findings of the study revealed that, for the estimation ofdirect runoff the outcomes of GANNs were considered as more desirable in comparison with the outcomes obtained through GIUH.

Nayak *et al.* (2004) developed a model for the modeling of hydrological time series and it was elaborated by an application which has applied ANFISand modeled the river flow of Baitarani River, situated at Odhisa. The findings of the study which were derived using adapted neuro-fuzzy interference system (ANFIS) were compared with the outcomes ofthe ANNs and also with the results of the conventionalmodel to check the performance and accuracy of the model. For evaluating the performance of these models the parameters adopted were; efficieny, computational speed, forecast error and estimation of peak flow.

Olsson *et al.* (2004) carried out study in Chicago river basin and discovered the trending of areas, each area was influencing the rainfall, the influence was worked out with the help of correlation analysis. Prediction was made by incorporating data of wind speed and mean rainfall of 12 hr by using technique of ANN.The input fed to the NN model was, the weighted average of the values predicted. It was revealed in the study thatvariation in rainfall and atmospheric data can be predicted accurately by the use of NN models. Whereas, binary NN were the better estimator of wet and dry periods.

Pan and Wang (2004) predicted rainfall runoff in the short run having lead time of 3 hrby employing state space neural network (SSRN) in watershed of Wu-Tu, Taiwan. In order to establish the link between concepts related to physics and weights of the networks, unit hydrographs were produced which were based on the weights assigned to the networks. A latest method of SSRN training was developed in order to make SSRN a time variant model. The outcomes yielded by the SSRN model were validated in accordance with four criteria. During the training phase of SSRN model, encouraging results were shown by the method of new learning. The performance evaluation of the model necessitated the utility of model in order to make short term forecasting.

Riad *et al.* (2004) incorporated the technique of multiple layer perception neural networks for configuring the relationship between rainfall and runoffin Morroco for a semiarid watershed. The findings of the study reflected that the test was more powerful in comparison with regression model employed for the prediction of river flow and its suitable application in the vast multidimensional field of hydrology.

Kisi (2005) forecasted 2 to 7 years based benchmarks which were based on stream flow data of three year time period, using three simple architectures of neural network. The ANNs architecture which was considered best was in terms of hidden layers and selected nodes. Both, autoregressive (AR) models were compared numerically as well as graphically. The correlation coefficient and sum of squares errors were used to evaluate the performance of the models. The NN models predicted better outcomes as compared to AR models.

Cigizoglu *et al.* (2006) employed ANN for the estimation of suspended sediments through inclusion of available data in the model which was developed for the purpose of study. Optimum numbers of nodes were selected in the form of input which was dependent on the analysis of statistical parameter of stream flow and the sediment data. When calibration data statistics of the model was consistent with validation data of the model which is represented by k-fold data partition set in the model training, then limited availability of data can yield better results for the estimation of sediments. One of the main feature of the range dependent neural network (RDNN), which was considered as significant due to its potential of self training via single network by incorporation of whole data set that is used in caliberation. Much closer values were estimated by RDNN, which represents good command of RDNN in prediction of the results by establishingcorrelation of outcomes with high and low observed values in the data series.

Kumarsiri *et al.* (2006) incorporated Artificial Neural Networks based on feed forward back propagation architecture, for the forecasting of both, short and long term date of a meteorological station situated at Colombo. For one day ahead depth of monthly and yearly rainfall, three neural networks nodes were there. The predictive accuracy of neural networks technique, depth of monthly and yearly rainfall was observed to be 74.24 per cent, 58.32 per cent and 76.56 per cent respectively at 5 per cent level of uncertainty. As number of time steps increased, the accuracy of the model decreased. The study also reported the rainfall trends observed during monsoon season.

Raghuvanshi *et al.* (2006) employed five ANNs (artificial neural network) models out of which, daily runoff was estimated by three models and weekly runoff along with sediment yield values were estimated by the rest two. All of the models were incorporated with hidden layers which were one and two in numbers. A total of five year data relating to the months from June to October was used to train the model. For the network training, Levenberg-Marquadt back propagation method was employed. The performance evaluation of the models was done by making comparison between runoff together with yields of sediments simulated by and the values observed and also by the parameters selected. The training data was also employed for runoff development by the model and sediment regression models. In comparison with all the models which were employed, the performance of ANNs model was reported better. The double hidden layer models were more efficient and accurate in comparison with single layer models. Those models performed better in which both, rainfall and temperature were used as input as compared with those in which only rainfall was taken as input variable. The models made satiable predictions in relation to daily and weekly runoff.

Somvanshi *et al.* (2006) predicted rainfall by using 104 years data related to mean annual rainfall ofHyderabad, India by employing techniques of artificial neural networks (ANN) and autoregressive integrated moving average (ARIMA). The ANN and ARIMA techniques were used to obtain weights and regression coefficients. The training of the model was done by incorporating data of 94 years whereas, 10 years of data was incorporated for the testing of model. The outcomes of ANN and ARIMA models were compared and it was concluded that ANNs models were better in performance.

Terzi *et al.* (2006) incorporated ANFIS model by using variables like solar radiations, daily evaporation, air and water temperatures and relative humidity to explore the influence of each explanatory variable on estimation of evaporation, which was a limitation of Penman method. When the outcomes were compared, it was observed that the R^2 (coefficient of determination) of ANFIS model was reported to be high (0.98) and average performance error was reported to be low (4.6 per cent), which was less than acceptable limit (10 per cent) in meteorological station.

Dogan *et al.* (2007) employed the ANN technique for estimation of load of daily suspended sediment. The study was carried out at Harisits stream, Lyi stream, Olter stream, Coarath River in the region of Black Sea which is situated in Turkey. For the predictions in relation to MLR and SRC, ANFIS model was incorporated in the study. The statistical parameters obtained through ANFIS, i.e. $R^2$and RMSE, showed much accuracy, in comparison with the predicted values of MLR and SRC.

Pan *et al.* (2007) developed deterministic linearized recurrent neural network (DLRRN) to describe the rainfall runoff transition process. For the given transition, the weights of DLRRNwere associated with unit hydrographs. The technique was employed in Wu-Tu watershed which was situated at Taiwan. The DLRRN model were then compared with feed forward neural networks and it was concluded thatthe rainfall runoff simulationwassuperiorly performed by the DLRRN model.

Shamseldin *et al.* (2007) analyzed data of 8 watersheds and compared the performances of multi layer perception neural network (MLPPN), simple neural network (SNN) and radial basis function neural network (RBFFN). In each watershed, ANN technique employed simulated river flow of two black box and conceptual models. The joint performance of all these models was found better than the individual runoff performance used in study. The results yielded by MLPPN were better than the results yielded by the combination of rest two models. The SNN model performed slightly better as compare to RBFFN technique, although there was not any difference in coefficient of efficiency obtained from the two methods. The study revealed that MLPPN can be employed for simulation of river flows.

Ayetak *et al.* (2008) collected CIMIS database of 4 years from 3 stations and proposed CANFIS model for the daily reference evapotranspiration, by incorporating variables like solar radiations, relative humidity and wind speed. The comparison of the model was made with the CIMIS Penman equation, the Penman Monteith equation, Turc equation and Hargreaves equation. The performance of the CANFIS was evaluated by root mean square error, coefficient of efficiencyand coefficient of determination and differential statistics like mean and standard deviation. The study revealed that the CANFIS model performed better in comparison with alternative ET_0 models.

Guhathakurta (2008) forecasted rainfall of monsoon, at meteorological subdivisions situated in India, by employing technique of feed forward neural network with back propagation. For the predictions related to monsoon rainfall in Indian subdivision and at all India level, the deterministic neural networks have been developed, which reflected good performance.

Kisi *et al.* (2008) used adaptive neuro fuzzy technique and developed a model in order to estimate monthly suspended sediments from two stations which were located in Turkey. By incorporating ANN along with the sediments rating curve, two different models were developed. The comparison was made between the results of neuro fuzzy technique to that of SRC and ANN. The goodness of fit criterion incorporated correlation coefficients, mean absolute errors and root mean square errors, for evaluation of the model performance. Among all other models the neuro fuzzy model was observed as better performing model. The comparison of the outcomes yielded by the models enlighted that for the prediction of monthly suspended sediments in the watershed, the neuro fuzzy models can be employed.

Mutlu *et al.* (2008) examined the radial basis neural network (RBFNN) along with the multilayer perception, in order to predict daily flows in watershed located at Eucha, Oklahoma. Various combinations of stream flow and rainfall data sets at different lags were employed and compared in relation to their effectiveness in flow predictions at four gauging stations. The cross, auto and partial autocorrelation were selected as input data. Although both the models were good in terms of performance but MLP model performed slightly better. Due to clustering methods incorporated, resulted in high difference in training time for RBFNN method.

Picouet *et al.* (2009) employed statistical approaches and modeled sediment concentration during the rising and receding phase of flood. The lumped conceptual model was the second model, developed by incorporating the contributions of two sediments reservoirs.The hill slope erosion was represented by the first reservoir and the sediment deposit in channel in association with the bank erosion was represented by the second reservoir. The outcomes yielded from both of the models were reliable but in comparison with simple regression models, the outcomes were poor in nature.

Solaimani Karim (2009) employed the technique of artificial neural network and feed forward back propagation method for modelling of the rainfall runoff relationship in a semi-arid watershed situated at Iran. The monthly stream flow data for the period of 1969-2000, was used for the caliberation of the models. The comparison was made in between conjugate gradient, gradient descent (GDX) and Levenberg-Marquardt (L-M) training algorithms. The potential and performance of ANN was compared with hydrological approaches which were used to predict the stream flows. It was concluded from the comparisons madethat artificial neural networks were more efficient and better relative to regression models.

Besaw *et al.* (2010) incorporated a generalized regression based on artificial neural networks by employing counter propagation in order to predict stream flows in ungauged watersheds. The comparison was made between the generalized artificial neural networks and autoregressive moving average method along with multiple linear regression approach of flow forecasting. The meteorological and stream flow data obtained from watersheds were employed fortraining and comparing the models. The watershed data which was used to predict the stream flow of the nearby watershed was employed to train the ANNs models. The data for stream flow was generated with balanced accuracy as reported the data employed for trainings. The study also presented the comparison of the ANN models for forecasting daily and hourly data.

Talei *et al.* (2010) made comparison between 15 ANFIS models to find out the effect of inputs which were segregated by the rainfall choice and discharge on the event based runoff forecasting. By employing the criteria of the goodness of fit, shift time and peak discharge the performance of the model was evaluated. The models which incorporated only rainfall antecedent performed better for longer time discharge whereas the models which incorporatedinput as one day lag discharge were observed to predictstorms and times in a better way. The models, in which a non-sequential time series and antecedent discharge were incorporated performed better for predicting two time steps ahead it was found better in the case of models which were using the non-sequential rainfall time series.

Nayak and Jain (2011) applied Sugero inference system of first order, to predict the stage, discharge and the sediment relationship. The study was carried out on two rivers, one was located in USA and the other one was located at India. The main objective of the study was to work out the discharge; simulation of the concentration of sediment was also set up priority zone for study. With the assistance of clustering algorithm, fuzzy rules had been generated, the main component of which was the least square estimation, and therefore fuzzy rules were believed to have a crucial significance. The fuzzy rules were trained by the help of back propagation algorithms. The statistical parameters namely,root mean square and sum of the square error illustrated superiority of the neuro-fuzzy model over the multi linear models and other conventional models during prediction of some relationship.

Raju ***et al.*** **(2011)** forecasted the weekly spring discharge near Ranichauri by making the use of artificial neural networks (ANNs) employing temperature, rainfall and evaporation with a different lag time. The quick propagation along with back propagation and the Levenberg-Marquardt algorithm were incorporated to train the models. For the development of the best performing model multiple number of neurons and different network architecture were tried. For the best simulation model, the statistical parameters incorporated were, coefficient of determination, coefficient of efficiency and correlation coefficient. The study concluded that the results obtained from employing ANN technique were better in comparison to results of the multiple linear regression.

Kumar ***et al.*** **(2012)** used ANN models to estimate potential evaporation in relation to relative humidity, solar radiations, temperature, evaporation and wind speed of Pantnagar, by estimating data of 236 months. Incorporatingdata on the above parameters, ANN models were trained and tested. The value of correlation coefficient was reported to be high i.e. 0.926 and the value of root mean square error was reported to be low, i.e. 0.9863, the outcomes necessitates the potential of the model for potential evaporation estimation.

Muhammadi ***et al.*** **(2012)** carried out study at Karaj dam, in which input incorporated the data on two parameters i.e, water temperature at entry site of dam and discharge of water database. The input was fed in the ANN, ANFIS and SRC models, which were employed to resolve the problems associated with the sediment concentration. The study outcomes were processed in the form of statistical terms like correlation coefficient and root mean square error, which ultimately reflected that ANFIS performed better than SRC and ANN models.

Pucheta ***et al.*** **(2012)** predicted cumulative rainfall time series in association with feed forward and the neural networks which were related to non-linear autoregressive filter (NAR) technique. The Mackey-Glass (MG) delay differential equations' five time series, two series of the Cordoba which is situated at Argentina were employed to examine this approach. Simulation of 18 time series values was done for the performance evaluation of this technique. The outcomes of the forecasting reflected good results.

Dornelles ***et al.*** **(2013)** examined conditions of initial training, assessment of performance and strong seasonal component in short run samples and ranked the results by using weighted scores of the ANNs model. Sequential partitioning was observed as satiable for the data series having strong seasonal component. The measure of the performance was reflected by non-exceeded error together with its frequency. Several indices were used for the estimation of weight score, also considered best method to evaluate or access the performance of the model. For training the ANN a random stating condition was developed. The configure model was then applied to the Quarai River basin in order to test the goodness of fit of the model. The ANN in comparison with all other models yielded the accurate results and performed better.

Kumar ***et al.*** **(2013)** employed feed forward neural network in association with Levenverg-Marquardt back propagation method to predict rainfall of Mirzapur in relation to evaporation, monthly temperature and relative humidity, frequency and cloud cover were incorporated as inputs in the model. The statistical measures like Standard deviation, error mean, standard deviation ratio, mean, error mean and error standard deviation were worked out for predicted and observed rainfall. The best fit of the model was indicated by high correlation coefficient i.e. 0.9845.

Subbaiah ***et al.*** **(2013)** desegregateddata related to seasonal inflow to data of monthly series of the River Mahi by employing feed forward neural network in association with back propagation algorithm. The transfer function incorporated was the identity and hyperbolic tangent function. Around 70 per cent data was incorporated for training purpose and rest 70 per cent was incorporated for the purpose of validation, based on the values of MSE obtained through ANNwas found to be optimum for which the SIC , AICand r values were lower. The study revealed that this model can be implied for disaggregating seasonal runoff into the monthly runoff.

Goyal ***et al.*** **(2014)** employed the artificial neural network along with Least Square Support Vector Regression, Adaptive neuro-fuzzy interference system and Fuzzy logic techniques forestimating of daily pan evaporation by employing 3801, daily records of rainfall, sunshine hours, maximum and minimum temperature and minimum and maximum humidity of the targeted watershed. The most vital parameters were cognized with the help of the Gamma Test (GT). The ANN models incorporated the feed forwarded backpropagation technique along with Levenberg-Marquardt (L-M) algorithm. The outcomes of ANN, LSSVR, ANFIS and fuzzy logicwere compared with the outcomes of Stephans-Stewart method (SS) and Hargreaves and Samani method (HGS). The Root Mean Square Error (RMSE) and correlation coefficient were used to evaluate the performance of the models. It was observed that the outcomes yielded by Fuzzy logic and LSSVR were comparatively better than ANN and ANFIS. In addition to this the machine model performed better than the HGS and SS techniques.

Tezel and Buyukyildiz (2015) incorporated ANNs model (multilayer perceptron along with radial function network) and ∈- support vector regression for the estimation of the monthly pan evaporation by employing data ofrainfall, temperature, wind speed and relative humidity as input variables from the period of1975 to 2005 obtained from Beysehir meteorology. The outcomes of the study were then compared with the Romanenko and Meyer methods along with the observed class. Four different training algorithms were used for the training purpose. Theperformance of the models was evaluatedby making comparisons through coefficient of determination, absolute error and root mean square error. It was observed that the ANNs and∈-SVR models performed better when compared with Romanenko and Meyer methods.

Hosseini and Mahjouri (2016) conducted study in Iran by combining SVR model with a geomorphologic based ANN model for simulating the daily runoff. The outcomes yielded by SVR-GANN were then compared with the outcomes of ANN-BP along with traditional SVR, ANFIS and ANN-GA in relation to similarity in runoff hydrograph and other parameters of the model. It was observed that the SVR-GANN model was having better prediction accuracy in comparison with the other models.

Sukanya and Prabha (2017) discussed technique of data mining which was suitable from the view point of rainfall prediction. The study was conducted by employing various classification algorithms viz. Artificial Neural Network and Decision tree. In order to boost up the data mining capability, ANN was incorporated which is basically a non-linear tool used for data modelling, it provides flexibility, high degree of accuracy, parallel processing, distributed storage and good robustness. The study analysed historical and current facts in order to make future predictions. Various data mining techniques along with ANNs are discussed and compared for prediction of the rainfall.

Mishra *et al.* (2018) incorporated technique of artificial neural network in order to develop rainfall prediction models for Northern India which were one month and two month ahead forecasting models usingmonthly rainfall data. The method of Feed Forward Neural Network (FFFN) along with Back Propagation algorithm and Levenberg-Marquardt training function has been employed in the study. The technique of Regression analysis, Magnitude of relative error (MRE) and Mean Square Error (MSE), was used to evaluate and assess the performanceof the models incorporated. The findings of the study revealed that the one month ahead forecasting model was having better performance in comparison with two months ahead forecasting model.

Materials and Methods

Chapter 3

MATERIALS AND METHODS

The objective of the present study is to construct a monthly predictive rainfall model at Almora raingauge station by employing Artificial Neural Networks (ANNs). This chapter features the general description of the study area, collection of data, artificial neural networks (ANNs), the development of Ann's models and performance evaluation indices of predictive models.

3.1 Description of the Study Area

Almora (the cultural hub of Kumaon region) lies in the Western Himalayan agro-ecological region; it is located at a height of 1,638 m above the mean sea level. The district falls between 29°37' N and 79°40'E. The district envelops an area of 3,144 sq. km and adjoins its boundaries with Bageshwar from North, Nainital from south, Pithoragarh from East and on its west lies Pauri Garhwal. Figure 3.1 is presenting the map of Almora district.

The maximum temperature recorded in Almora district is around 29.3℃, on the contrary the minimum temperature of the district recorded is around -2℃. The district receives an annual average rainfall of 1054mm. The month of June is realized as the warmest month of the year whereas, the coldest month observed in the district is December, January and February. In Almora, summers are companied by rainfalls on the contrary very low amount of rainfall is recorded during the winter.

3.2 Data Collection

The monthly rainfall data of 54 years (1964-2018) was collected from the Vivekananda Parvatiya Krishi Anusandhan Sansathan, Almora for the development of monthly rainfall prediction model by incorporating artificial neural networks.

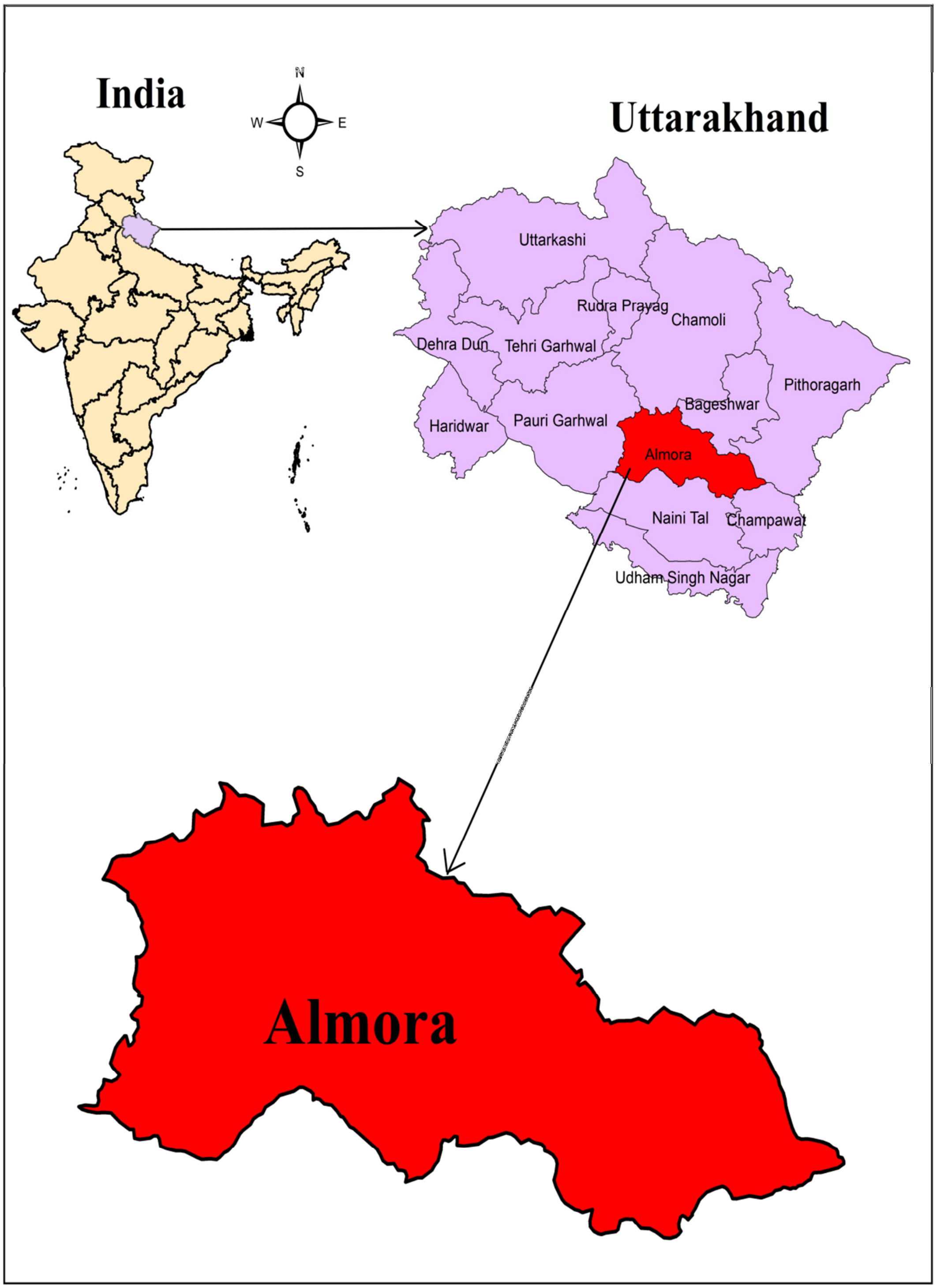

Fig. 3.1 Location of Almora district

3.3 Cumulative Sum Technique

The cumulative sum (CUSUM) technique (Mc Gilchrist and Woodyer, 1996), a valuable tool in detecting intermediate term changes in mean value of sequence of regularly spaced observations, is used to examine the temporal sequence of rainfall. The cumulative sum is defined as

$$s_i = \sum_{i=1}^{i}(x_i - \bar{x}) \qquad \text{...(3.1)}$$

Where x_i is the regularly spaced observations.

The CUSUM distribution is a normalized distribution and it reveals the runs of observations greater than the long term mean with a positive slope and those less than the long term mean with a negative slope. Such positive or negative slopes are used to detect intermediate term changes in the mean value. The actual ordinates values are not relevant it is the slope that is important.

3.4 Artificial Neural Network Model

ANNs, is a kind of soft computing system which is composed of numerous simple highly interconnected processing components, which processes the data by stimuli of their dynamic state and then forwards as external input. ANN is perceived to be an effective and promising technique for modelling distinct processes in hydrology along with meteorology. Generally, in the modelling of hydrological processes, ANNs customized with one hidden layer are commonly employed. This is mainly due to the fact that one hidden layer along with function of non-linear activation is considered to be satiable in the case of non-linearity of multiple hydrological process.

Figure 3.2 shows a schematic diagrammatic presentation of ANN network model. Its computing systems are comprised of numerous artificial neurons and number of joints or interconnections present between them. The network is composed of several layers of neurons. The network also comprised of one or more than one intermediate layer(s) which are synonymous to hidden layer(s) in surplus to input layers. Each layer is in connection with the previous layer with the help of interconnection weights. No computation is performed by the input nodes but these nodes serve in distributing the inputs into the network. The processing of these input signals occurs in the hidden layer(s) and the outcomes of the processed inputs are synthesized in the output layer. The network due to this peculiar composition are also regarded as feed forward network, as transfer of information takes place via input layer to the hidden layer for processing which is then decoded as output through the output layer hence this flow is a unidirectional flow.

3.4.1 ANN model based on Multiple layer perceptron

The ANN model underlying the category of multiple layer perceptron models is the widely employed neural network framework being incorporated in the modern era. In general. The multiple layer perceptron neural network models are composed of simple neurons which are technically termed as perceptrons. The main feature of perceptron is to enumerate a single outcome from multiple real figured inputs by generating a linear combination in relation to its input weights and then the output is transferred via non-linear activation function. Generally, the composition of multilayer perceptron is an amalgamation of interconnected layers comprising artificial neurons, input layer, hidden layer and the output layers. When data is coded via input layer, the propagation of data is supported by the neurons present in input layer and then the hidden layers weight the data and random selection is done. Then determination of net sum occurs in the hidden node, the node in turn generates an outcome as response by incorporating a transfer function.

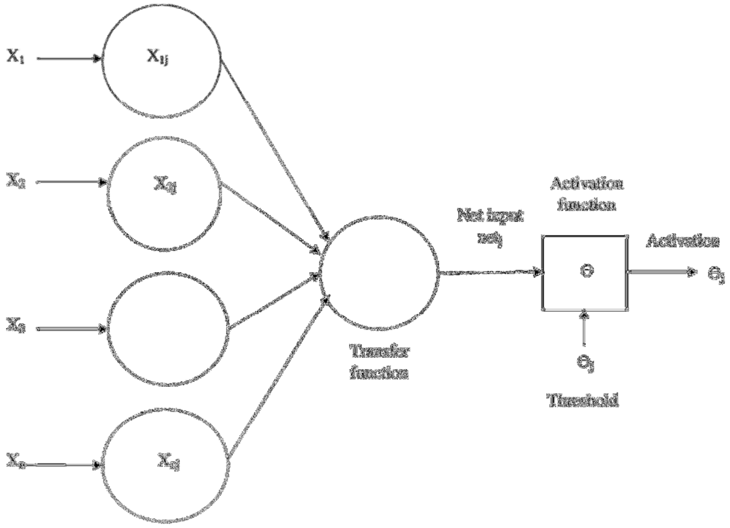

Fig 3.2: Functional composition of ANNs

For the training of multiple layer perceptron model back propagation algorithm was used. This algorithm transforms the interconnecting weights in a manner that the overall error between the tangent figures and the outcomes should reduce to a satiable limit. It has been explored by various research scholars that multiple layer perceptron

(MLP) model have ability to approximate any variable from a finite dimensional space to a figure of the desirable magnitude of accuracy. Due to the possession of this special ability the artificial neural networks are applied to any field in relation to modelling problems and queries associated with meteorology and hydrology.

ANNs are structurally framed up by the dense structure of interconnected neurons, which are typically stacked in layers. The most common application of ANN paradigms is to conduct mapping of input set to the set of outputs. In ANN model, each layer is comprised up of multiple nodes and the layers are adjoined by the set of weights which are usually interconnected. The signals which are coming as input are multiplied by respective set of weights through which they are generated and proceeded towards nodes or neurons, which in turn sums up the incoming signals and then the net input is transferred through the activation function to generate the output. The outcome of each neuron is obtained by enumerating the value of the activation function respective to the product of input vector along with weight vector and addition of the value of bias.

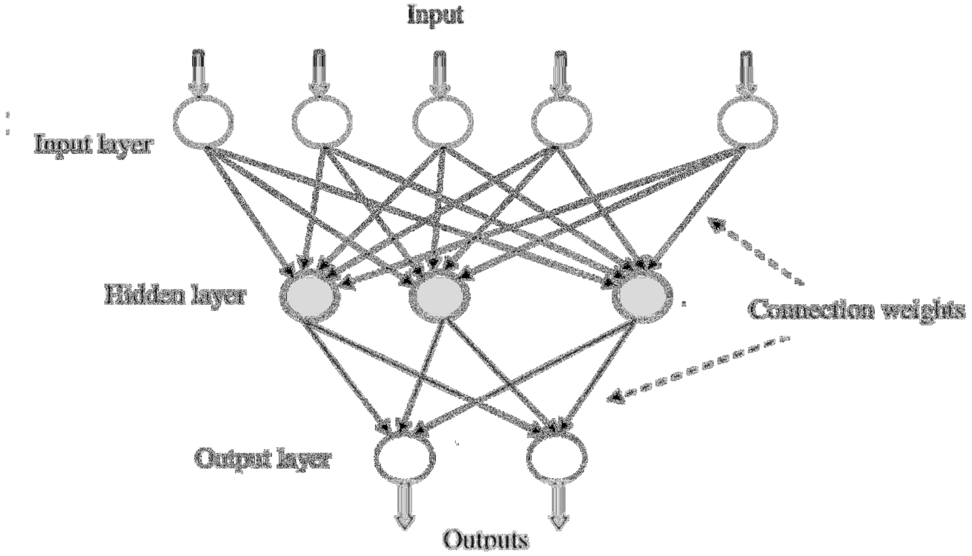

Fig 3.3 Multiple layer perceptron network

Symbolically, output is represented as a function of as described under.

$$y = f\left(\sum_{i=1}^{n} x_i\, w_i \ + b\right) \qquad \dots (3.2)$$

where, x_i(i=1,2,…..n) are the inputs and w_i (i=1,2,3…..n) are their respective weights, b is the bias, y is the outcome or output and f(..) is the activation function. The net input forwarded to node is illustrated as,

$$net = \sum_{i=1}^{n} x_i w_i \qquad \ldots (3.3)$$

Hence, transfer functions of artificial neural networks (ANNs) simulates the reaction of the phenomenon by employing the input and output parameters. A transfer function is described as the mathematical presentation of the relationship persisting between the frequencies of input with respect to output. The transfer functions in general exhibit sigmoid shape, but they can also get modified into non-linear functions, piecewise linear functions or the step functions.

3.4.2.1 Learning via multi layer feed forward networks

The most crucial action in development of an ANN model is the determination of its weight matrix via the procedure of training. Two types of learning mechanisms which preponderates are namely supervised and unsupervised. Supervised learning is a procedure where the network is trained through a set of the input pattern and its consequent output pattern. In supervised learning an external guide finds the error existed between enumerated output and the desired output during the phase of training and then the estimated error is incorporated in order to make adjustments in weights so that errors can be deduced to a desirable extent. In the case of unsupervised learning, no guide is there for training the patterns, this type of learning procedure or system learns automatically by the detection of regularities present in the input space by means of correlation, without receiving a direct feedback from a guide or a teacher.

At the present context, the present study focuses on the functional mapping, so supervised learning will be employed. Out of plenty of algorithms built for supervised learning, the back propagation technique is most promising and popular in the sense of its effectiveness and simplicity. The back propagation method is incorporated in the study in amalgamation with a special class of multiple layer perceptrons (MLP) well known as the layered feed forward networks. The MLP are generally trained by back propagation algorithm which involves the two phase's viz. forward phase and backward phase.

3.4.3 The Back propagation (BP) algorithms

The back-propagation algorithms are based upon the learning rule of the error connection; in this the network weights are manipulated by reducing the error between the actual and the observed values. The BP algorithms are an example of the iterative learning processes where all weighted parameters are initialized randomly and are updated with every iteration via the feed-forward computations and the back-propagation in relation to errors.

3.4.3.1 The Feed forward calculations

The feed forward calculations involves the receiving of input signals by input layers which are then surpassed to hidden layers and then get transferred to the output layers of network. The received signals are multiplied by the present values of the incorporated connection weights and after that the weighted inputs are summed up to provide the net input to every neuron of the succeeding layer and then the net input generated is forwarded through a transfer function in order to yield the output of neuron. The signal flow directions and the error propagation in ANN model are presented in Figure 3.4.

The procedure employed along different layers of neural network for feed forward computations is as under:

The net input transferred to f^{th} node is obtained by

$$neth_i = \sum_{i=1}^{n_i} wh_{ji} x_i \qquad \ldots (3.4)$$

Where, x_i is the number of neurons present in the input layer and wh_{ji} is the connecting weight present in between the i^{th} node of input layer of the network and j^{th} neuron belonging to the hidden layer, the outcome or the output of j^{th} node of hidden layer h_j is given by:

$$h_{ji} = f(neth_j) \qquad \ldots (3.5)$$

The net input forwarded to k^{th} node of output layer is obtained by:

$$net\ y_i = \sum_{j=1}^{n_h} wo_{ij}\ h_j \qquad \ldots (3.6)$$

Where, h_j is the number of the neurons present in the hidden layer and wo_{ij} shows the interconnecting weights in between j_{th} node of the hidden layer and k_{th} node of output layer of the network.

The outcome of the k_{th} node is illustrated by:

$$y_i = f(net\ y_i) \qquad \text{... (3.7)}$$

The error thus computed at the output layer is sent back to hidden layers and then forwarded to the input layers, in order to activate updates in relation to the connection weights.

The sum of square error E is depicted by:

$$E = \frac{1}{2}\sum_{k=1}^{n_i}(y_k - t_k)^2 \qquad \text{... (3.8)}$$

Where, $t_k$is observed output or the desired output at k^{th} neuron, where y_k is calculated output of the same neuron. Weights are transformed and updated from their previous values in order to reduce the error function. The network learning began from a random weight set. Weights in turn then updated via error back propagation technique during the training procedure. In order to attain accurate weights and better speed of learning it gives rise to multiple type of back propagations.

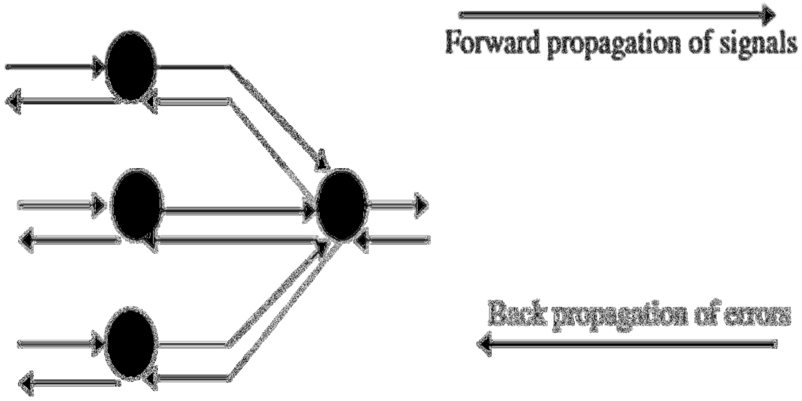

Fig: 3.4: Signal flow direction in an ANNs

3.4.3.2 The Error back propagation

The error is computed at the output layer is then forwarded back to hidden layers and then further forwarded to input layer, in order to determine the updates in relation to weights. This procedure is a derived gradient descendent procedure where, the weight updating process is performed by bending in the direction of the negative gradient together with the multidimensional aspect of the error function. During the process of training, the weights get updated via error propagation by incorporating a suitable relationship for both, the output and the hidden layers. The weight combination which yields minimum value for error function is considered as solution of the present learning problem.

3.4.4 The Activation function

The activation function is the mathematical relationship incorporated to obtain the outcome of the element which is processed. Verbally, the activation function is the functional relationship existing between internal activation level of neurons and the received outputs. The joints or connection between input and middle layer consists weights which are determined by the system of training. The weighted inputs are then aggregated via hidden layer which generates the value of output via activation function.

Activation functions of the nodes or neuron justifies the output of node provided the set of input(s). An activation function selects the best element of processing by employing the method of trial and error. There are multiple type of activation functions which are employed for the problems relating to the hydrological process. The sigmoid and the hyperbolic tangent function are the widely employed activation function in the field of hydrology and meteorology are, therefore used in this study.

Figure 3.5 shows the curve of Log-sigmoid function. The Log-sigmoid function is S-shaped curve. Equation 3.10 is defining the sigmoid curve. The value which is employed in the activation function is the threshold value; it is the value upon which the ultimate output of the network is computed. In order to obtain the network output, comparison is done between the computed net input values and the threshold values. For every application of the network there is existence of a threshold limit. If the range of output of transfer function lies from -1 to +1, the transfer function along with threshold is illustrated by Equation 3.9 and 3.10, respectively.

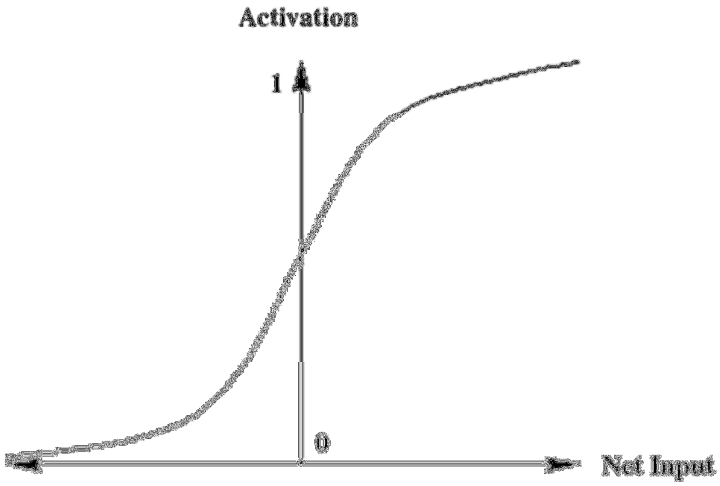

Fig3.5: The sigmoid function

$$f_{net} = 1 \; if \; net \; \geq 0 \qquad ...(3.9)$$

$$f_{net} = -1 if \; net \; < 0 \qquad ...(3.10)$$

$$S(t) = \frac{1}{1+e^{z}} \qquad ...(3.11)$$

In the topologies of multiple perceptron the TanhAxon is generally incorporated as hidden layers and output layers, it is presented by figure 3.6. The TanhAxon employs a tanh(.) function along with a bias to each neuron located in the layer, thus yielding the output ranging within -1 and 1 for every neuron. The hyperbolic tangent (tanh) function is illustrated as:

$$f_{net} = tanh(\alpha \; net) \qquad ...(3.12)$$

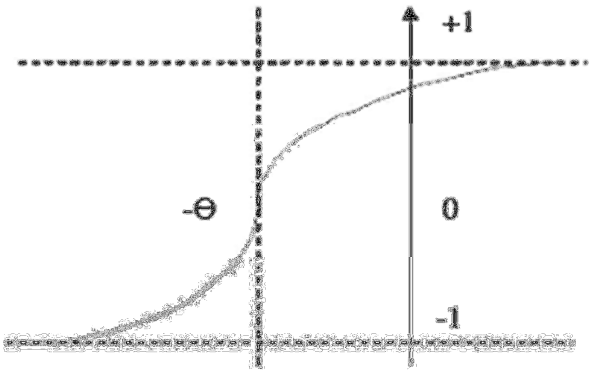

Fig 3.6 TanhAxon based on bias kind of transfer characteristic

3.4.5 Learning algorithms along with Levenberg-Marquardt back propagation

In the process of learning, in order to achieve the desired and satiable performance of the model by incorporating given set of data, the learning algorithm updates the parameter related to network. The rule of training determines that how precisely the updating of weights should be done in between successive epochs. The specialty is that learning rule along with learning parameters are associated with each layer. The corresponding fields are filled by entering the numerous elements used for processing together with the learning parameters. The correction term gets specified by the means of learning rule. Once a particular rule gets selected, the researcher should still specify that how much correction should be there to put on the weights. It takes a long time when the rate of learning is small; on the contrary if the learning rate is high then the deviations in association with adaptation and weights cannot be incorporated.

Learning algorithm is employed in order to compute the adjusted weights and network biases so that the error present between actual and observed output should be reduced. In the current context major studies are based on Levenberg-Marquardt (L-M) algorithm as this algorithm is widely famous for its greater efficiency and high speed of convergence. The L-M algorithms are considered efficient in comparison to others.

The L-M technique is the modification of classical Newton algorithm, for deducing an optimum solution for minimizing the problem. In this optimization of synaptic weights is done in order to deduct the best simulation performance in the period of training. The training of ANN focuses on minimizing the optimization of the mean squared. To minimize the function of error is the objective function of neural network training. This method incorporates approximation in the Hessian Matrix in the given Newton –kind weight update:

$$\Delta w = (J^T J + \mu I)^{-1} J^T e \qquad \text{...(3.13)}$$

Where, J is Jacobian matrix, e is the error vector, Δw is increment in the weights employed and T is the targeted output and μ is the changed parameter.

3.5 Development of the ANN models

The structure of the ANNs is determined by selecting the input variables for the forecasting, the input variables in turn affects the output as well as weighted coefficient obtained in the model. The rainfall of the current month is not only reckoned upon the current time rainfall but also relies on the rainfall occurred during previous periods. Hence, the present rainfall is regarded as the function of the present month rainfall together with the rainfall of previous periods. Therefore the lag time is an eminent factor which influences the input variables. In order to construct the proper input structure, several rainfall combinations were made. After the identification procedure of input and output variables, various ANN models were constructed for the station, by employing different combinations of current and previous month rainfall *(R_t)*which is assumed as a function of rainfall of the current month and previous (n month) lag rainfall. The developed models for ANN are presented in Table 3.1.

Table 3.1: Various models of ANNs for Almora raingauge stations

Sr. No.	Output-input variables
1	$R_t = f(R_{(t-1)})$
2	$R_t = f(R_{(t-1)}R_{(t-2)})$
3	$R_t = f(R_{(t-1)}R_{(t-2)}R_{(t-3)})$
4	$R_t = f(R_{(t-1)}R_{(t-2)}R_{(t-3)}R_{(t-4)})$
5	$R_t = f(R_{(t-1)}R_{(t-2)}R_{(t-3)}R_{(t-4)}R_{(t-5)})$
6	$R_t = f(R_{(t-1)}R_{(t-2)}R_{(t-3)}R_{(t-4)}R_{(t-5)}R_{(t-6)})$

For the purpose of successful modelling, selection of training and testing data should be there, the data is subdivided into two sets i.e. the data employed for training (Training data) and the data employed for testing (Testing data). For calibrating the model the training data is incorporated and for validating or testing of the model the testing data is incorporated. After a certain interval of time there seems the chances of over-fitting of models, and the models which are over trained are data specific and then specific to the model training. The model which is not desirable for general implication of the test data sets checks the over training of optimized models at different level of iterations by evaluating their performance. The training data sets should be comprised of all the possible combinations related to events, so that the system adjusts to be modeled with efficiency and accuracy.

The data for rainfall are depicted as R_{ij} respectively for the i^{th} year and the j^{th} month. In order to test and train the ANNs, the necessitated monthly rainfall time series should be like R_{ij} for i=1 to M year and j=1 related to N month was there for availability, where M and N are the total years and their months, respectively. As the data was used for the period of 54 years (1965 to 2018), the value of N was 648 months and value of M was 54 years. For the purpose of calibration around 38 years of data was utilized and rest 16 years data was utilized for validation of the model.

The present study is based on the training of ANNs by employing back propagation algorithm in order to achieve the minimum error function. By the trial and error procedure the single and double layers which are hidden layers neural network which processes the architecture elements are obtained.

In the present study, the hidden layers showed variation from 1 to 3 and the number of epochs in Log-SigmoidAxon, TanhAxon activation function and the Levenberg-Marquardt learning rule were 2000. The training threshold of 0.001 was assigned according to the ANN model. The criteria of root mean square error was employed for the selection of the best models. The model in which the minimum error was generated, is considered as best.

3.6 Performance Evaluation Indices of models

The task performing ability of the model is judged by the performance indices, they are basically employed in the hydrological studies. The performance assessment of the models are generally done by two ways; (i) Qualitatively and (ii) Quantitatively.

The qualitative method is the simplest method in its approach for the evaluation of any model, it is generally based upon the visual observations extracted from the graphical comparison of the actual and the predicted values, but the major limitation associated with it is the personal biasness which arises due to individual preferences, therefore this method is not viewed as reliable.

The quantitative methods are preferred due to their efficiency in the performance evaluation; the various indices that are incorporated in the assessment of performance of the models are illustrated as under:

3.6.1 Coefficient of efficiency (CE)

Coefficient of Efficiency, enumerates the goodness of fit between the actual and the observed values yielded by the model. The range of CE lies between -∞to 1,it is denoted as:

$$CE = 1 - \frac{\Sigma(Q_0 - Q_p)^2}{\Sigma(Q_0 - \bar{Q}_0)^2} \quad \text{...(3.14)}$$

Where, Q_p is predicted rainfall and $Q_0$is observed rainfall and $\bar{Q}_0$is average of observed rainfall.

3.6.2 Percentage BIAS (PBIAS)

It computes the average tendency of the simulated values to take values larger and smaller than the observed values. Optimal value of PBIAS is observed to be 0, the low values suggest the accuracy in the simulation of model.

$$\text{PBIAS (\%)} = \frac{\Sigma(Q_p - Q_0) \times 100}{\Sigma Q_0} \quad \text{...(3.15)}$$

Where, Q_p is predicted rainfall and Q_0 is observed rainfall.

3.6.3 Integral Square Error (ISE)

Integral square error is an indicator of the performance of the system and it is computed by following method

$$ISE = \frac{\sqrt{\Sigma(Q_0 - Q_p)^2}}{\Sigma Q_0} \times 100 \quad \text{...(3.16)}$$

Where, Q_p is predicted rainfall and Q_0 is observed rainfall.

3.6.4 Root mean Square Error (RMSE)

The RMSE is used to comment on the precision aspect of the model, it simply computes the difference between the observed and estimated values and it generate performance on short term basis, it generates positive figures ranging from 0 to ∞by squaring the respective errors, it is calculated as:

$$RMSE = \sqrt{\frac{\Sigma(Q_0 - Q_p)^2}{n}} \quad \text{...(3.17)}$$

Where, Q_p is predicted rainfall and Q_0 is observed rainfall.

3.6.5 Correlation coefficient

It simply measures the degree of closeness between the observed and estimated values and it is calculated as follows:

$$r = \left[\frac{\Sigma\{(Q_0 - \bar{Q}_0)(Q_p - \bar{Q}_p)\}}{\sqrt{\Sigma(Q_0 - \bar{Q}_0)^2}\sqrt{\Sigma(Q_p - \bar{Q}_p)^2}}\right] \quad \ldots(3.18)$$

Where, Q_p is predicted rainfall and Q_0 is observed rainfall,$\bar{Q}_0$ is average of observed rainfall and$\bar{Q}_p$ is average of predicted rainfall.

Results and Discussion

Chapter 4 RESULTS AND DISCUSSION

This chapter deals with development of ANN models for the prediction of monthly rainfall of Almora.

The monthly rainfall data of Almora monthly of 55 years (1965-2018) was divided into two parts out of which 38 years of data was used for training and 16 years data was used for testing to develop model to predict monthly rainfall. To evaluate the performance of developed models for prediction of monthly rainfall. Various indices were incorporated in the study like: Root Mean Square Error (RMSE), Coefficient of efficiency (CE), Percentage Bias (PBIAS), Integral Square Error (ISE) and Correlation Coefficient (r). The model was selected on the basis of RMSE, the model having the lowest value of RMSE have been selected. Indices of selected models were calculated.

4.1 Monthly rainfall Analysis of Almora

The data of monthly rainfall of 1965 to 2018 against time period is shown in Fig. 4.1. In Almora monsoon rainfall occurs during June to September. Monsoon season and annual rainfall were calculated from monthly rainfall. The time series data of monsoon season and annual rainfall are depicted in Fig. 4.2. It is observed from Fig. 4.2 that pattern of monsoon season and annual rainfall was similar.

The various statistics like mean, maximum and minimum rainfall of Almora rain gauge station are presented in Table 4.1. The long term average of monthly rainfall is shown in Fig: 4.3. The mean rainfall varied from 5.93 in the month of November to 242.5 in the month of July. The contribution to annual rainfall was maximum for the month of July and least for the month of November. The monsoon season (June, July, August, and September) contribute about 72.1% to the annual rainfall. The coefficient of skewness value ranges from -.01 to .48, maximum skewness was observed in the month of November and minimum in the month of August which was left skewed while all others are right skewed. The value of coefficient of variation varied from 34.91 in the month of august to 207.52 in the month of November. It was observed that the value of coefficient of variation in non-monsoon season months was more compared to monsoon season months.

Table 4.1 Statistics of rainfall of Almora rain gauge station

Month	Mean (mm)	Min. (mm)	Max. (mm)	SD (mm)	Coefficient of Variation	Skewness	Contribution to annual rainfall (%)
Jan	39.51	0.00	113.30	31.75	80.37	0.32	3.95
Feb	51.90	0.00	153.40	38.55	74.28	0.05	5.18
Mar	41.65	0.00	195.40	37.49	90.01	0.24	4.16
Apr	31.12	0.00	153.20	27.58	88.61	0.13	3.11
May	64.63	0.00	179.20	47.30	73.18	0.13	6.46
Jun	136.47	7.50	342.50	75.55	55.36	0.18	13.64
Jul	242.50	96.50	493.20	92.27	38.05	0.27	24.24
Aug	207.33	65.00	374.50	72.38	34.91	-0.01	20.73
Sep	134.97	8.80	463.50	97.21	72.02	0.08	13.49
Oct	23.98	0.00	210.40	36.62	152.74	0.41	2.39
Nov	5.93	0.00	51.70	12.30	207.52	0.48	0.53
Dec	20.05	0.00	107.70	25.64	127.91	0.47	2.00

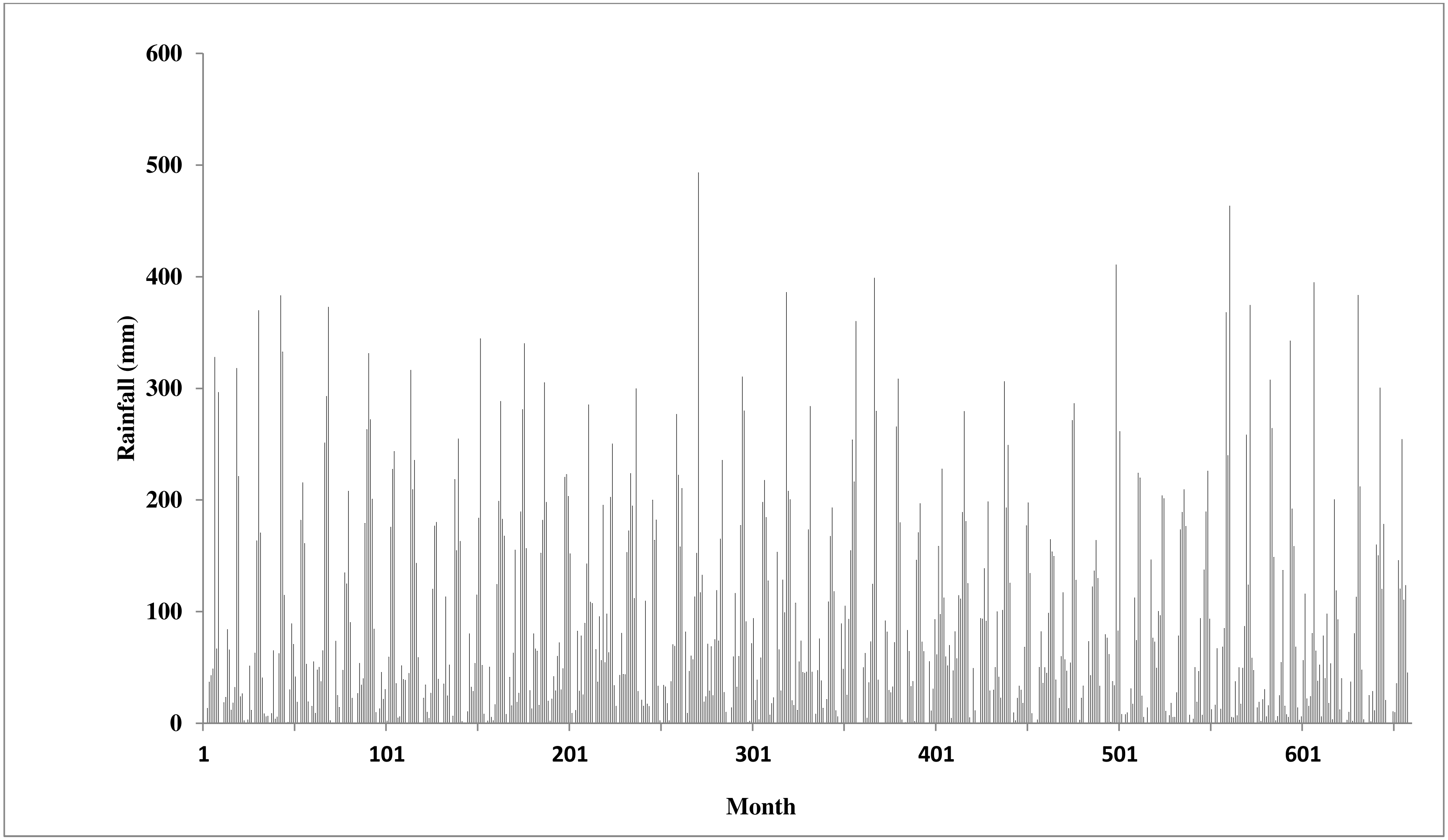

Fig. 4.1 Observed monthly rainfall of Almora rain gauge station

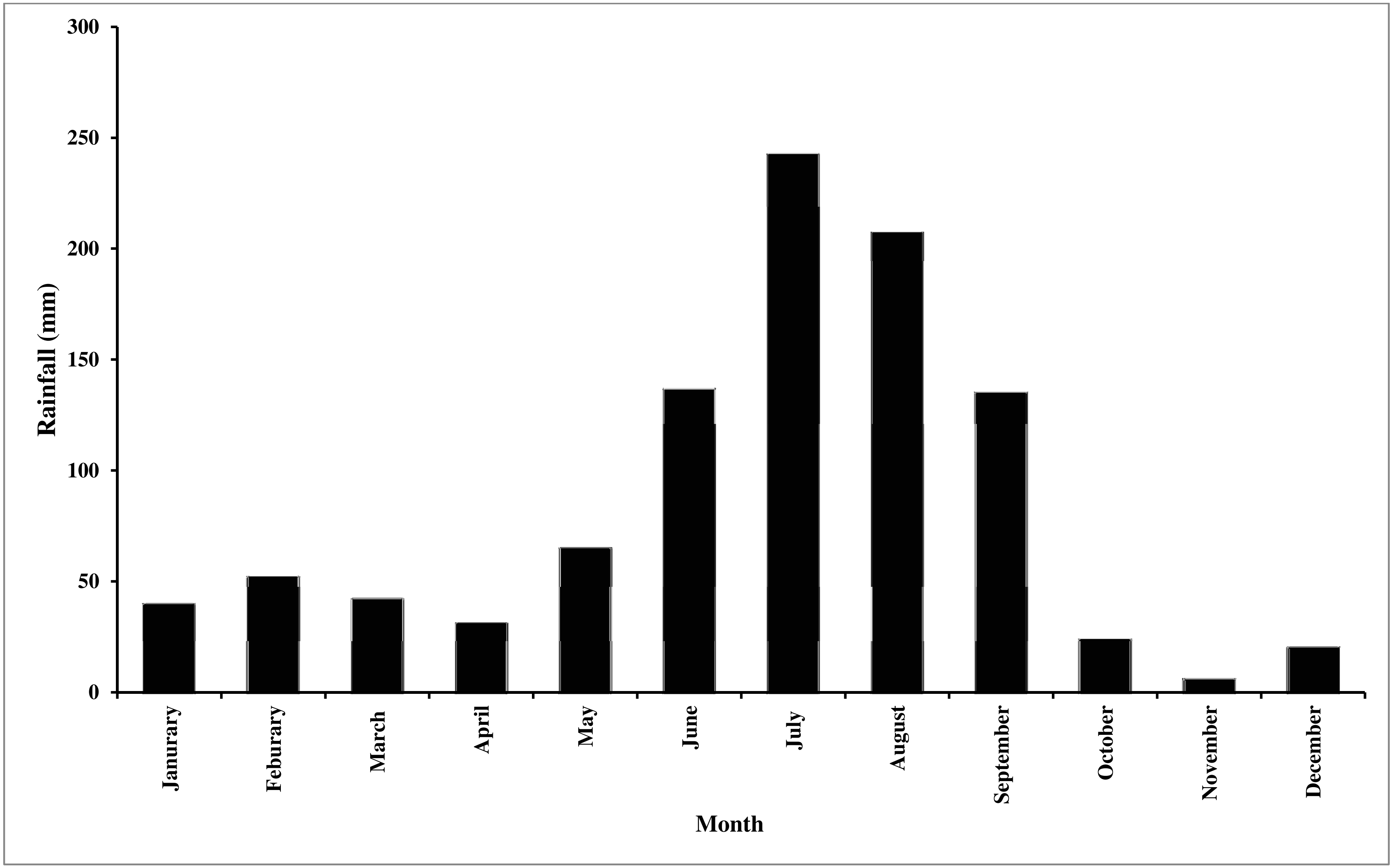

Fig.4.3 Average monthly rainfall of Almora rain gauge station

4.2 Temporal Sequence of Monthly Rainfall

The Cumulative Sum (CUSUM) technique was employed to examine the temporal sequence of annual, half yearly, seasonally and monthly rainfall. The CUSUM distribution for the annual rainfall is shown in Figure 4.3. The CUSUM plot of the rainfall during the first period i.e. from 1964 to 1976 reflects a decreasing trend with some fluctuations in between (1970-71) afterwards a positive trend was seen between 1977 to 2000, with some uncertainty in between (1986-1988).The period from 2002 to 2018 shown a decreasing trend in rainfall accompanied by some fluctuations in between (2008-2010).The period from 1964 to 1982 consisted of a period of less than average rainfall and period of 1982 to 2016 period of greater than average rainfall.

CUSUM plot was also applied to half yearly rainfall for detection of trends in half yearly rainfall average. Half yearly seasonal rainfall from the month of January to June and July to December was used. Figure 4.4 depicts the CUSUM plot of half yearly rainfall and it is observed that, in the months of July to December, the trend line was increasing from 1964 to 1966, with some uncertainity during 1968-70, then a decreasing trend is observed from 1971 to 1976 after that an increasing trend is observed from 1976 to 1996 with fluctuations in (1984-96). Thereafter the trend showed decreasing trend from 1996 to 2018, with uncertainties in between. The trend in case of the months January to June showed a constant increase from 1964 to 2005 after which a gradual declination in trend is observed from 2006 to 2018. Similar pattern was observed in monsoon season rainfall (June to September), whereas trend is different in half yearly rainfall and October to January and February to May season rainfall.

Cumulative sum was applied to seasonal rainfall to steady seasonal trends. The rainfall was divided into three seasons: June to September, October to January, and February to May. The cumulative sum values of seasonal rainfall are scattered as compared to the annual and half yearly cumulative sum values, which is evident from the Fig. 4.5. The trend of season February to May rainfall shows that there was a sudden decreased in the slope from 1964 to 1977 with few uncertainty in 1971 to 1973 and after that there is increase in slope till 1990, after 1990 the value almost remain constant till 2018 with few expectations.

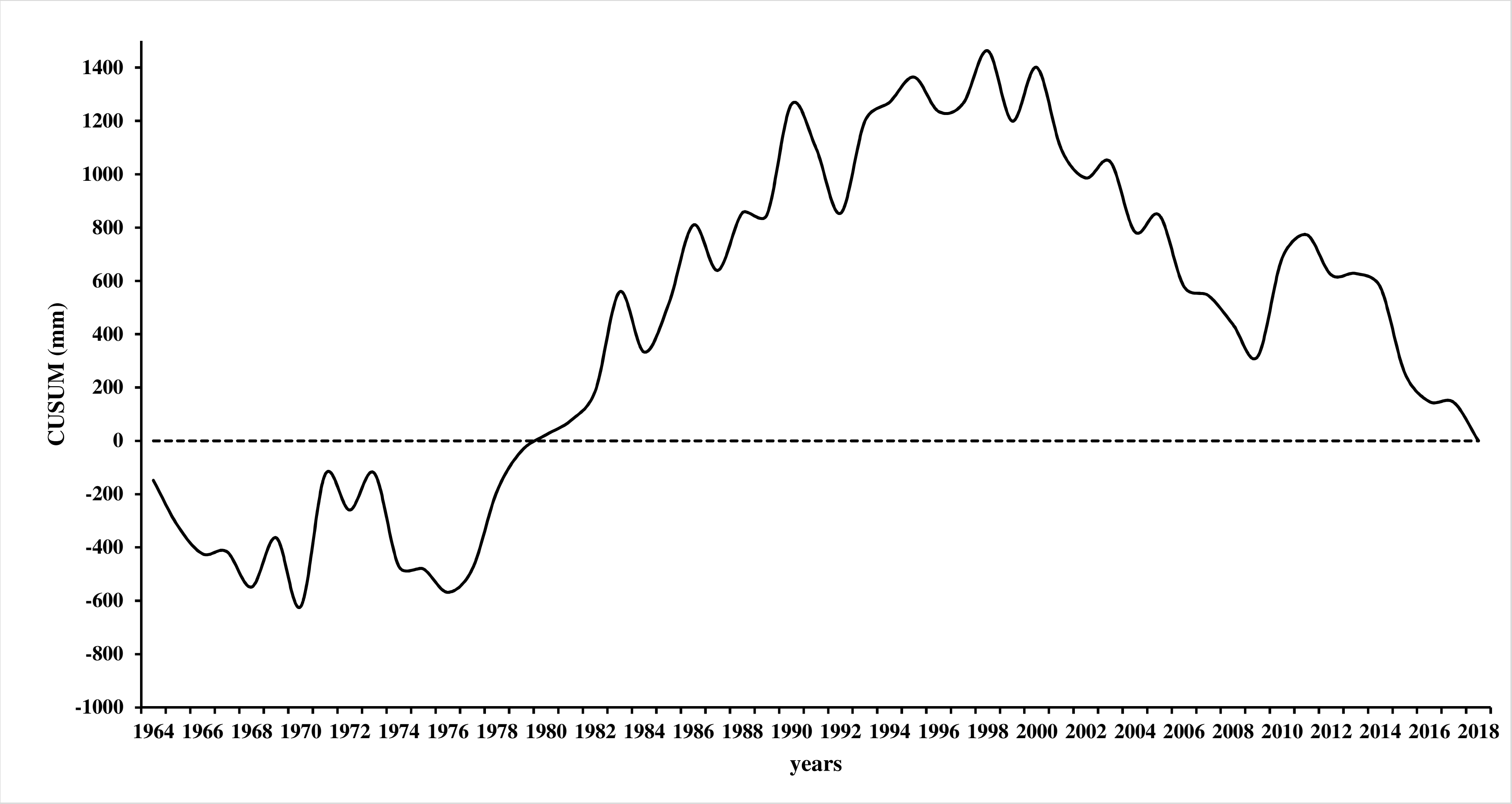

Fig. 4.3 A CUSUM plot of annual rainfall

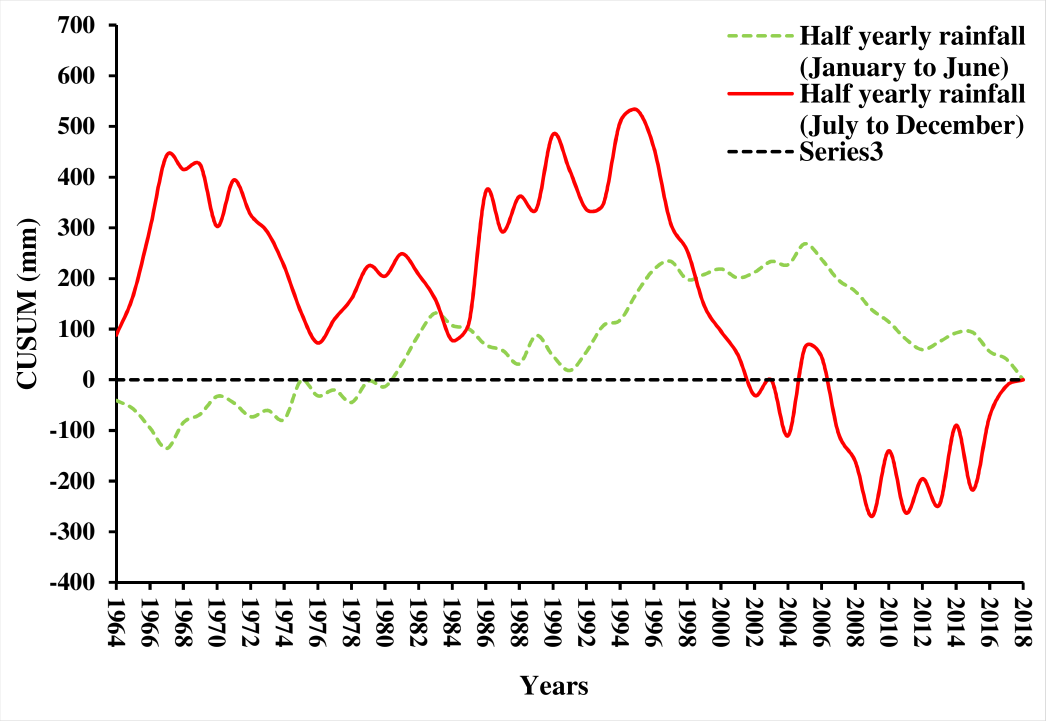

Fig. 4.4 A CUSUM plot of half yearly rainfall

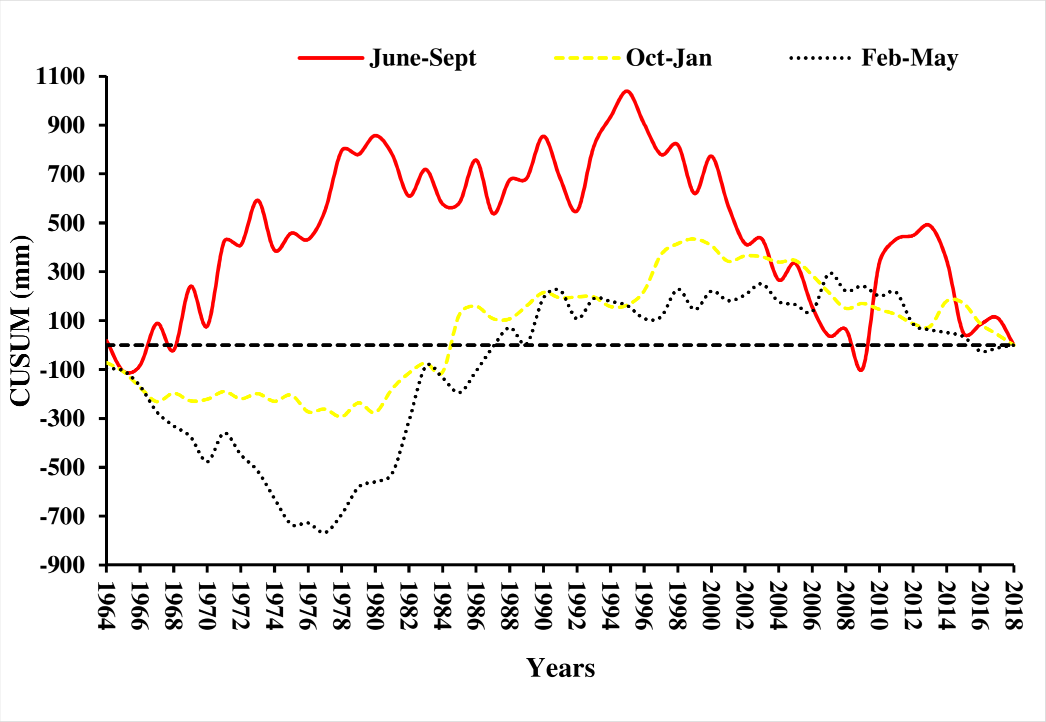

Fig. 4.5 A CUSUM plot of Seasonal rainfall

For June to September season, the trend of season June to September rainfall showed a constant increase from 1964 to 2000, having some fluctuations in between 1984 to 1985 and 1990 to 1991. Then a decreasing trend was observed between 2000 to 2018. The trend of season October to January season rainfall showed an increasing trend from 1964 to 1998, having fluctuations during 1976-78 and thereafter a negative trend was observed from 1998 to 2008. An increase in trend was seen from 2008 to 2014, then trend reflected decreasing pattern from 2014-18.

Cumulative sum was applied to all the month from January to December and different trend were observed. CUSUM for January, February, March, April, May, June, July, August, September, October, November and December are shown in Fig. 4.6, 4.7, 4.8, 4.9, 4.10, 4.11, 4.12, 4.13, 4.16, 4.17, 4.18 and 4.19 respectively.

Figure 4.6 is depicting CUSUM for the month of January and it is observed from the plot that the CUSUM for the January rainfall shows increasing trend between 1964 to 2008 with fluctuations in between(1964-66), (1970-74), (1978-1982), (1986-88), (1998-2006)afterwards an decreasing trend is observed between 2008 to 2018, with some fluctuations in between (2012-2014).

Figure 4.7 depicts the CUSUM for the month of February, it is observed that the rainfall shows a decreasing trend from 1964 to 2000, with uncertainity in the periods between (1964-66), (1966-68), (1978-80), (1986-88), (1990-92), afterwards an increasing trend is observedfrom (2002-18), with fluctuatons in between (2002-04), (2006-2008) and (2008-12).

Figure 4.8 shows CUSUM for the rainfall of March, it was observed that there is decreasing trend of rainfall between 1964-76 with some fluctuations in between (1966-70). Then an increase in trend is observed during the period of 1976-92, with uncertainty lying in the period of (1986-88), afterwards a decreasing trend pattern is observed from 1992 to 2018, with fluctuation in between (2004-08).

Figure 4.9 is presents the CUSUM of the rainfall for the month of April. It is observed that there is a decreasing trend from the period of 1964 to 1982, with fluctuations in between (1968-72). From 1982 to 2018, the trend is increasing, accompanied by fluctuations in between the periods (1988-96), (1998-2000), (2004-06).

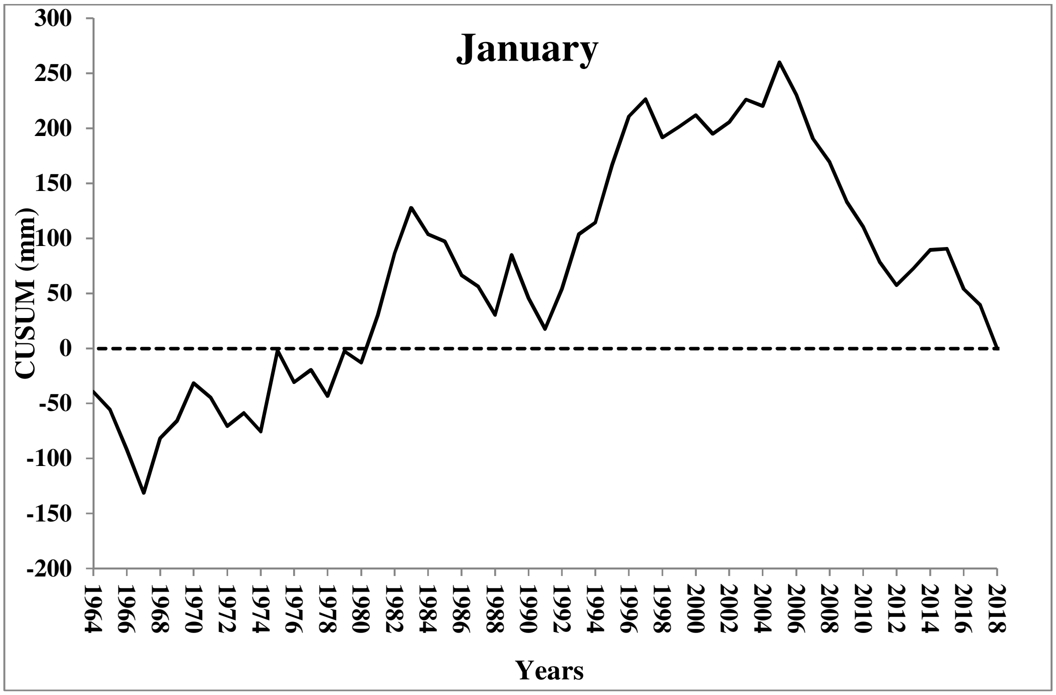

Fig. 4.6 A CUSUM plot ofJanuary rainfall

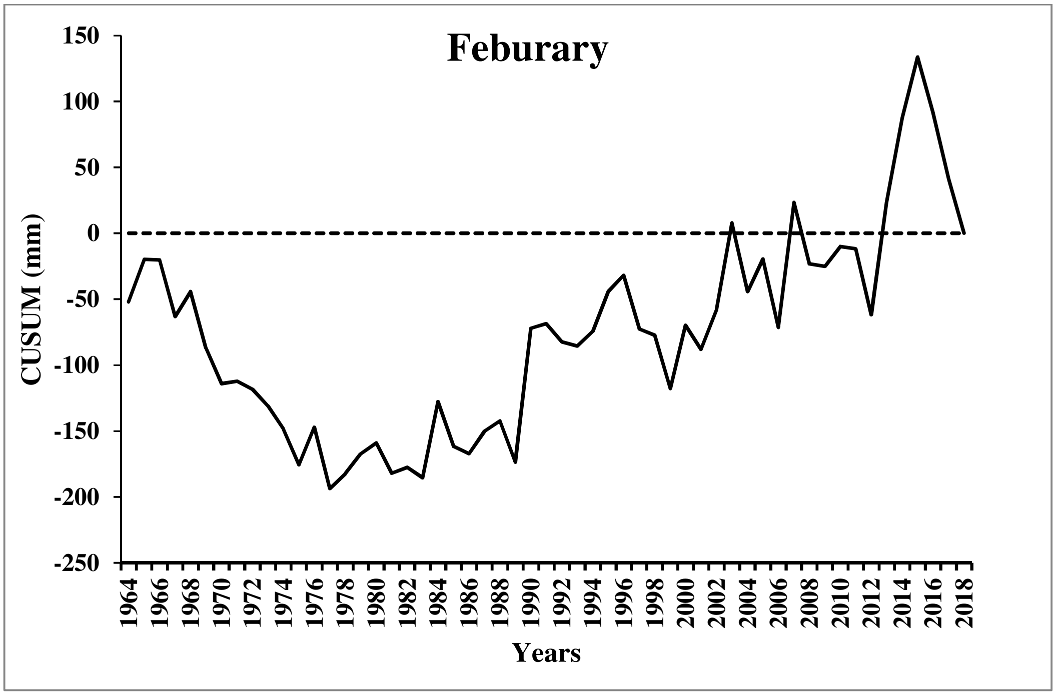

Fig. 4.7 A CUSUM of February Rainfall

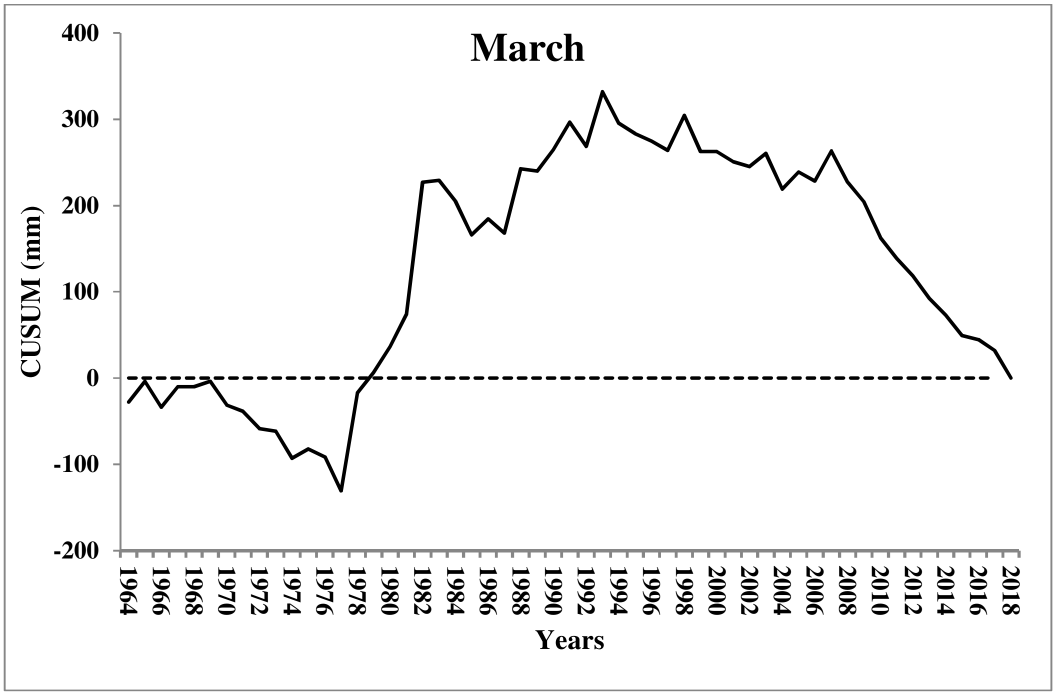

Fig. 4.8 A CUSUM of March Rainfall

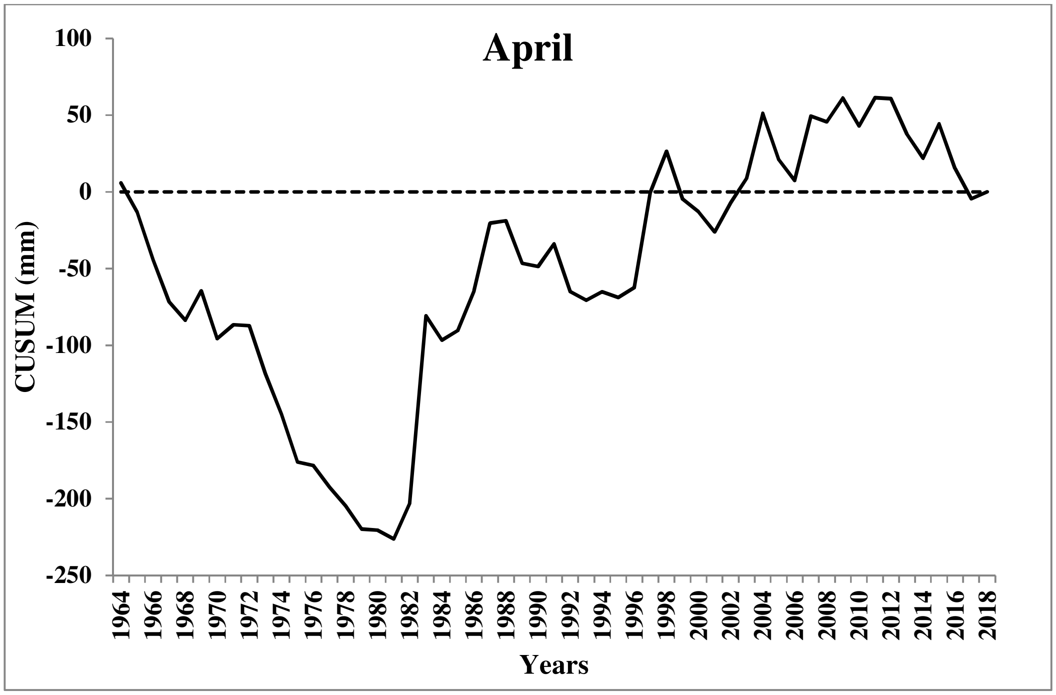

Fig. 4.9 A CUSUM plot of April Rainfall

A CUSUM plot of the rainfall for the month of May is presented in Figure 4.10, it is inferred that a decreasing trend is observed between the periods of 1964 to 1976, with fluctuations in between (1968-70). An increasing trend is observed during the period of 1976 to 2010, accompanied by frequent fluctuations during the periods of 1994 to 1996 and 2004 to 2006, after that a decreasing trend is observed between 2010 to 2014.

Figure 4.11depicts the CUSUM of the rainfall for the month of June, it is inferred from the graph that, rainfall showed a decreasing trend from 1964 to1970 afterwards an increase in trend is seen from 1970 to 1990, with fluctuations in (1980-82) and (1984-86). A decrease in trend is seen during 1990 to 2010 with fluctuation observed during (2000-02). An increase in trend is seen in 2010 to 2018, with minor fluctuations in between.

Figure 4.12 presents the CUSUM plot of rainfall for the month of July. It is seen from the plot that the rainfall showed a decreasing trend from 1964 to 1984, with fluctuation in between (1978-80), an increasing trend was observed between (1984-96), with uncertainity between (1988-90) and (1992-94). A decreasing trend is observed between 1996-2008, with fluctuation in (2002-04). An increasing trend is observed during 2008 to 2018.

The CUSUM plot of rainfall for the month of August is shown in Figure 4.13. An increasing trend is observed in 1964 to 1976, thereafter a decreasing trend of rainfall is seen between1976 to 1986. An increase in trend was observed between 1988 to 1996 afterwards, the trend is observed as decreasing between 1998 to 2018, with fluctuation in between 2010 to 2012.

The CUSUM plot of rainfall for month of September is shown in Figure 4.14. A decreasing trend is observed during 1964 to 1992, with fluctuation in between (1968-70), (1982-84) from the plot. An increase in trend is observed during the period of (1992 to 2010) afterwards, the trend showed decreasing pattern between 2012 to 2016.

The CUSUM plot of rainfall for the month of October is presented by Figure 4.15, it is seen that the rainfall showed a decreasing and increasing trend after regular interval. Thus there is no clear cut trend.

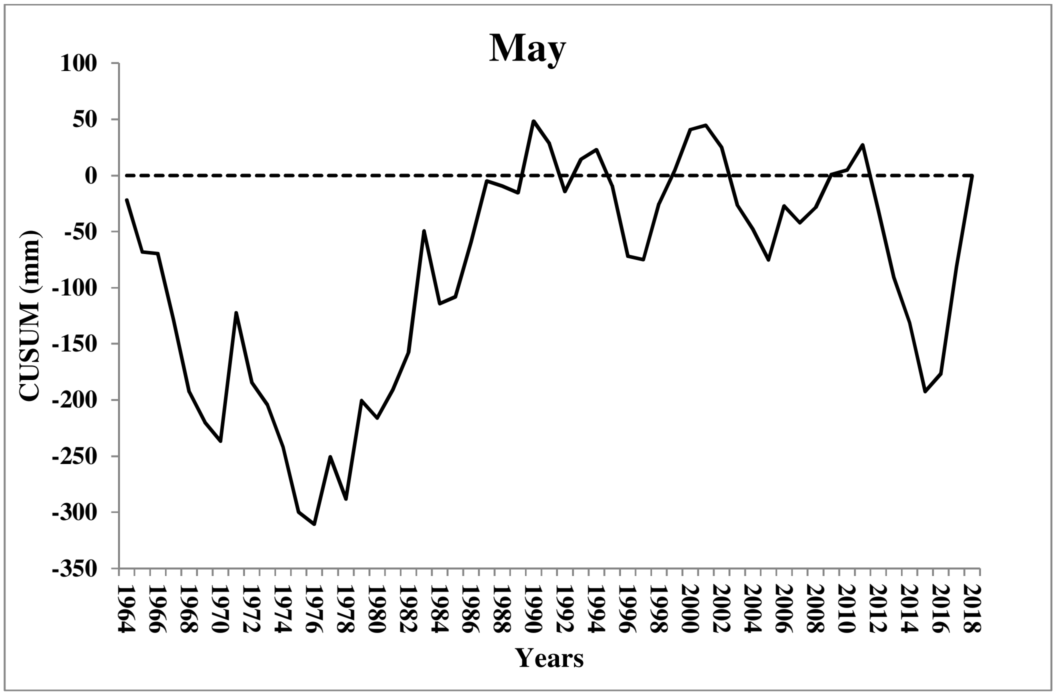

Fig. 4.10 A CUSUM plot of May Rainfall

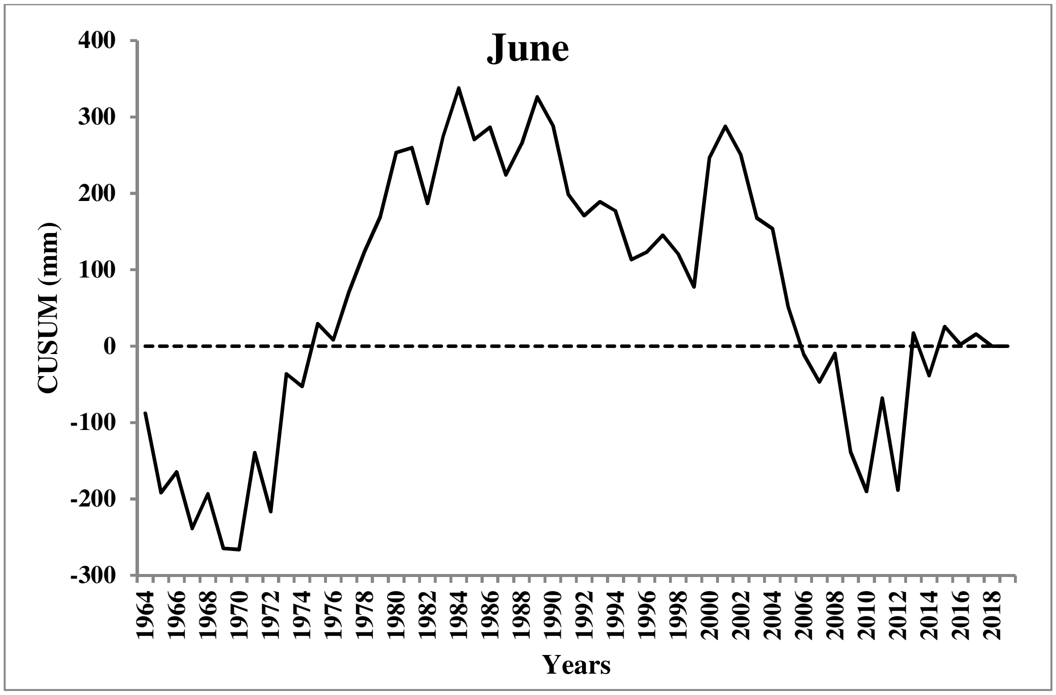

Fig. 4.11 A CUSUM plot of June Rainfall

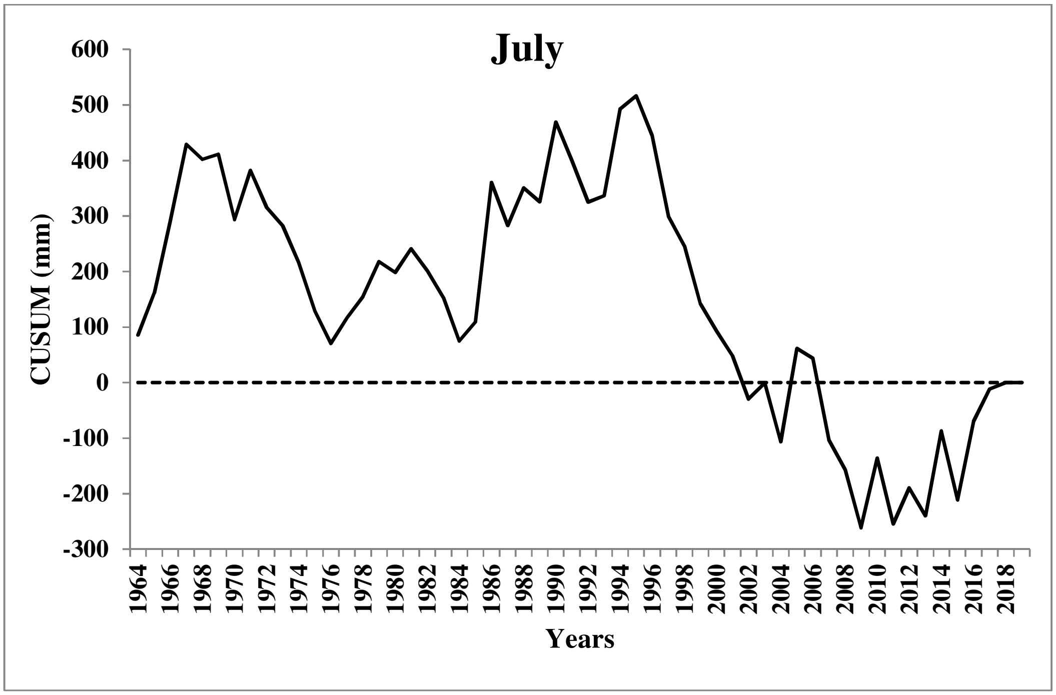

Fig. 4.12 A CUSUM plot of July Rainfall

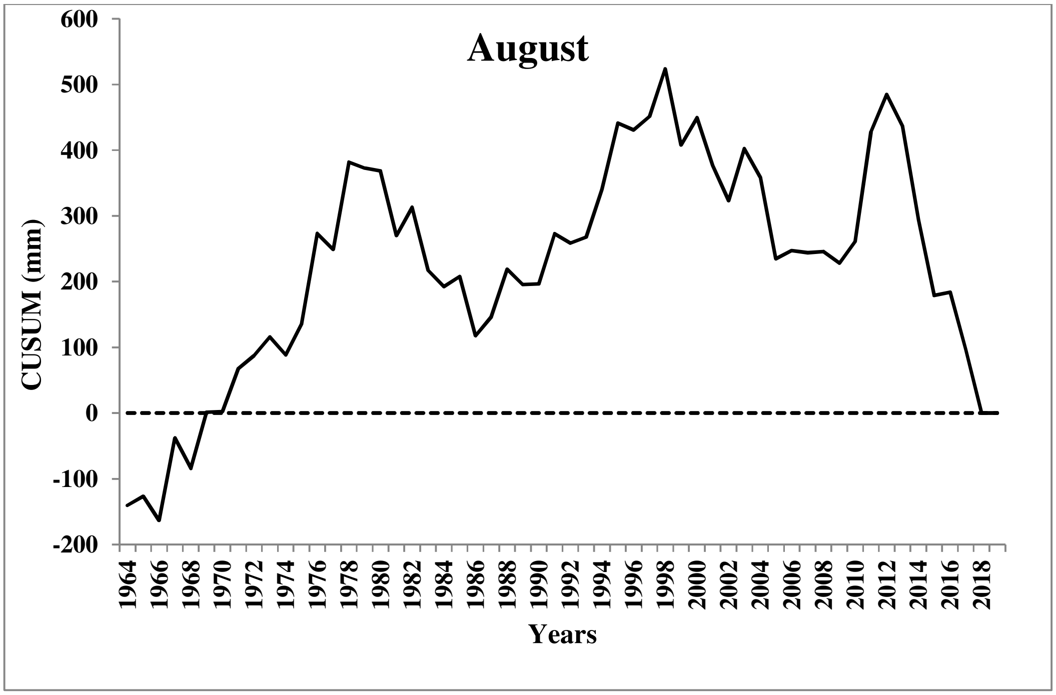

Fig. 4.13 A CUSUM plot of August Rainfall

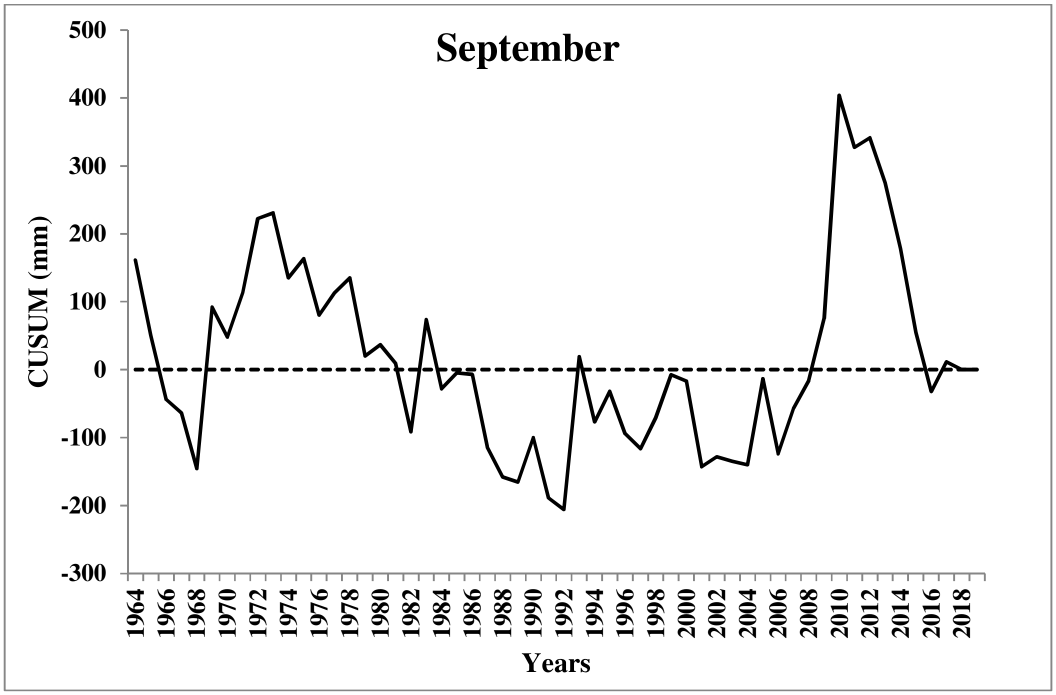

Fig. 4.14 A CUSUM plot of September

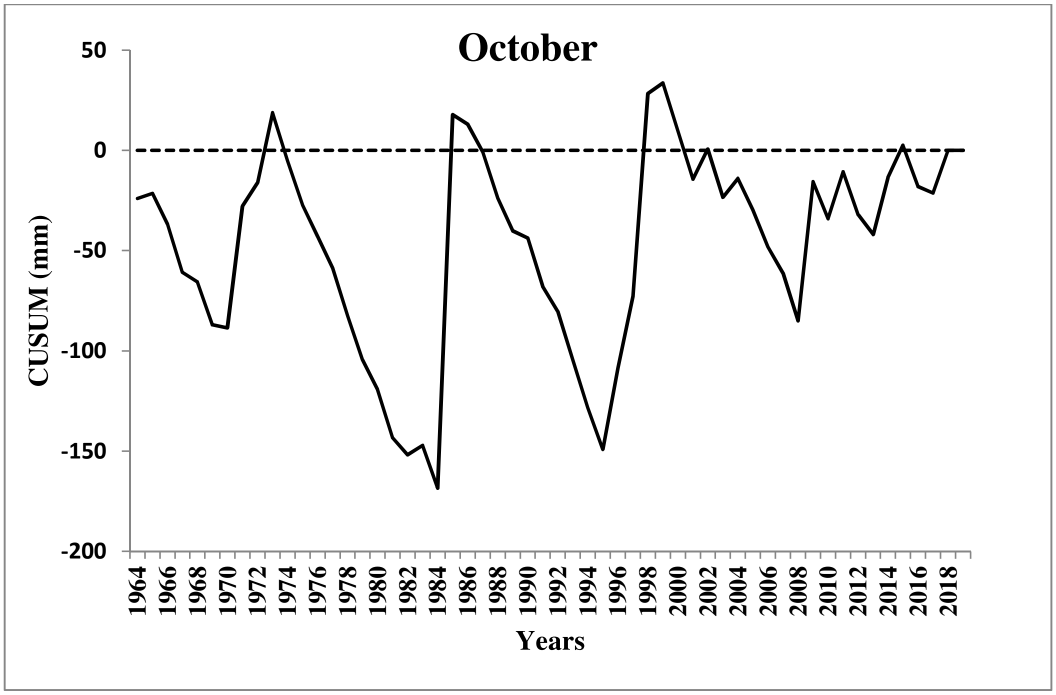

Fig. 4.15 A CUSUM plot of October

Figure 4.16 presents the CUSUM of rainfall for the month of November. It is observed that the rainfall shows decreasing trend during 1964-1976 after that an increasing trend is observed during 1976 to 2008 with fluctuations in between (1986-88),(1996-98) thereafter the trend line shows decreasing trend from 2008 to 2018.

The CUSUM plot of rainfall for the month of December is shown in figure 4.17. It is observed that the rainfall has decreasing trend during 1964-1976. An increasing trend is observed during 1976 to 1992 after that a negative trend is observed from 1992 to 2018, with fluctuations during (1994-96) and 2008 to 2016.

It is observed that in general, the pattern of trend of June, July, August and September is similar to the trend of June to September seasonal rainfall and the trend pattern of November and December is similar to October to January rainfall, the trend of February, April and May seasonal rainfall is similar to the trend of February to May seasonal rainfall.

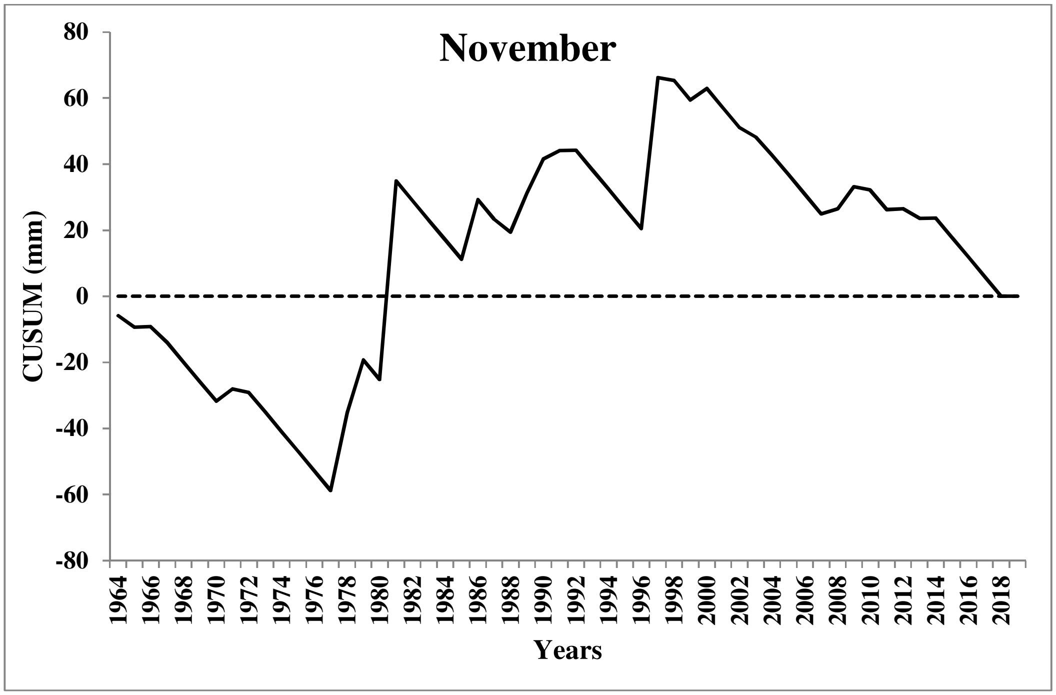

Fig. 4.16 A CUSUM plot of November Rainfall

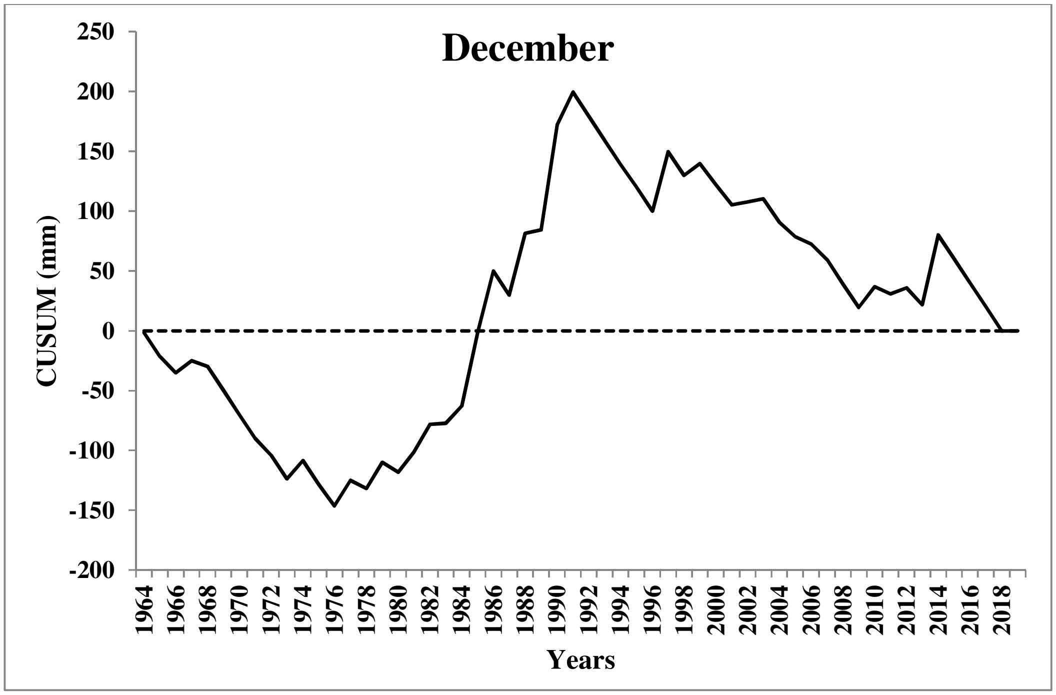

Fig. 4.17 A CUSUM plot of December Rainfall

4.3 Development of Model for Rainfall Prediction

In this study, ANN models with six inputs were developed for monthly rainfall prediction of Almora. The six inputs used in development of models are as follows: past one month rainfall, past one month and two month rainfall, past one month, two months and three months rainfall, past one month, two months, three months and four months rainfall, past one month, two months, three months, four months and five months rainfall and past one month, two months, three months, four months, five months and six months Different models were developed by changing the number of hidden layer and by changing the number of neuron. One to four hidden layers were used and the number of neurons used was one to ten.

Best model was selected by trial and error on the basis of root mean square error; The model which gave the minimum value of RMSE is selected as the best model. .001kept as the threshold values of root mean square error. For the development of model, transfer function used were Log-Sigmoid Axon and Tanh Axon learning rule was Levenberg Marquardt. In the development of model epoch were kept constant as 2000. Now the best model for each transfer function was selected on the basis of root mean square error. The architecture of ANN models and Root mean square value for the developed models are given in Table 4.2.

4.3.1 Performance evaluation of models by qualitative assessment

For model evaluation one of the basic methods is qualitative assessment. In qualitative assessment visual comparison between the observed rainfall values and the computed rainfall values is used. The scatter plot and time series plot of rainfall are used in visual comparison. The best models were used to develop the scatter plot and time series of rainfall. The best model was selected on the basis of lowest RMSE and thus this model is used in all the assessment.

4.3.1.1 Evaluation based on rainfall time series plot performance

The comparison of monthly computed time series and the observed time series for training period by MO-1, MO-2, MO-3, MO-4, MO-5, MO-6, MB-1, MB-2, MB-3, MB-4, MB-5 and MB-6 model are show in Fig. 4.18, 4.19, 4.20, 4.21, 4.22, 4.23, 4.24, 4.25, 4.26, 4.27, 4.28 and 4.29 respectively. The comparison of monthly computed time series and the observed time series for testing period byMO-1, MO-2, MO-3, MO-4,

MO-5, MO-6, MB-1, MB-2, MB-3, MB-4, MB-5 and MB-6 model are shown in Fig. 4.30, 4.31, 4.32, 4.33, 4.34, 4.35, 4.36, 4.37, 4.38, 4.39, 4.40 and 4.41 respectively.

As the study was carried forward it was seen that in MO-6 model there was a good match between the observed and computed rainfall in comparison to MO-1, MO-2, MO-3, MO-4and MO-5 models during calibration and validation period. MO-6 model predict value of computed rainfall closer to the observed value in comparison of MO-1, MO-2, MO-3, and MO-4and MO-5 models. The performance of MO-6 model is much better than the MO-1, MO-2, MO-3, and MO-4and MO-5 models as it can be seen from the analysis. From the visual observation of the plot it is observed that in case ofMO-3 model estimation of peak rainfall is better in comparison to MO-1, MO-2, MO-4, and MO-5and MO-6 models.

It was also seen from the plot that for high magnitude values MO-6 model under predict monthly rainfall. Also, in model MO-6 time of occurrence of peaks is almost same for observed rainfall and computed rainfall, and it is better in comparison to MO-1, MO-2, MO-3, and MO-4and MO-5 models. In Model MO-6 the predicated rainfall followed the trend of computed rainfall as shown in Fig. 4.23.

Further it is observed that in MB-6 model there is a good match between the observed and computed rainfall in comparison to MB-1, MB-2, MB-3, MB-4 and MB-5 models during calibration and validation period. MB-6 models predict value of computed rainfall closer to the observed value and do not under predict the value as is the case in MB-1, MB-2, MB-3, and MB-4and MB-5 models. The performance of MB-6 models was much better than the MB-1, MB-2, MB-3, and MB-4and MB-5 models as is seen from the analysis. From the visual observation of the plot it was observed that in no model was able to estimate peak rainfall as closer as MO-3 models.

It was also seen from the plot that for high magnitude values MB-6 model under predict monthly rainfall. In Model MB-6 the predicated rainfall followed the trend of computed rainfall as shown in Fig.4.29. However, MO-6 model predict the monthly rainfall close to the observed rainfall in comparison to MB-6 model that means best model among all the model is MO-6 Model.

4.3.1.2Performance evaluation based on Scatter plots

Scatter plots was used to test the accuracy of ANN models. The closer the values to the best fit line, the model will be considered as the best model among all the other models. The scatter plot between the observed value and the computed value of MO-1, MO-2, MO-3, MO-4, MO-5 and MO-6 models for training and testing period are shown in the Fig. 4.42, 4.43, 4.44, 4.45, 4.46, 4.47 for training period 4.54, 4.55, 4.56, 4.57, 4.58 and 4.59 for testing period respectively. From the figure it is observed that model MO-3 and MO-6 have values around the best fit line in comparison to MO-1, MO-2, MO-4 and MO-5 models. It is evident from the analysis the performance of model MO-3 and MO-6 is good in comparison to MO-1, MO-2, MO-3 and MO-5 models.

The scatter plot between the observed value and the computed value of MB-1, MB-2, MB-3, MB-4, MB-5 and MB-6 models for training periods are shown in the Fig. 4.48, 4.49, 4.50, 4.51, 4.52, 4.53 respectively and for testing periods in Figure 4.60, 4.61, 4.62, 4.63, 4.64 and 4.65 respectively. From the figure it is observed that model MB-1 and MB-6 have values around the best fit line in comparison to MB-2, MB-3, MB-4 and MB-5 models. It is evident from the analysis the performance of model MB-1 and MB-6 is good in comparison to MB-2, MB-3, MB-4 and MB-5 models.

Table 4.2 Artificial Neural Network models network with root mean square error

Model	**Input**	**Output**	**ANN Network**	**RMSE**	
				Training	**Testing**
S Log Sigmoid Axon Transfer Function					
MO-1	R_{t-1}	R_t	1-8-8-1	78.28	90.20
MO-2	**R_{t-1},R_{t-2}**	R_t	2-7-1	74.72	87.41
MO-3	**R_{t-1},R_{t-2}, R_{t-3}**	R_t	3-10-10-1	67.91	63.31
MO-4	**R_{t-1},R_{t-2}, R_{t-3}, R_{t-4}**	R_t	4-6-6-1	64.15	71.37
MO-5	**R_{t-1},R_{t-2}, R_{t-3}, R_{t-4},R_{t-5}**	R_t	5-6-1	67.62	65.81
MO-6	**R_{t-1},R_{t-2}, R_{t-3}, R_{t-4},R_{t-5}**, R_{t-6}	R_t	6-8-8-1	62.89	61.35
Tanh Axon Transfer Function					
MB-1	R_{t-1}	R_t	1-9-1	77.56	75.95
MB-2	**R_{t-1},R_{t-2}**	R_t	2-7-7-1	74.20	78.27
MB-3	**R_{t-1},R_{t-2}, R_{t-3}**	R_t	3-9-9-1	65.31	76.67
MB-4	**R_{t-1},R_{t-2}, R_{t-3}, R_{t-4}**	R_t	4-10-10-1	66.41	76.14
MB-5	**R_{t-1},R_{t-2}, R_{t-3}, R_{t-4},R_{t-5}**	R_t	5-9-9-1	66.34	69.91
MB-6	**R_{t-1},R_{t-2}, R_{t-3}, R_{t-4},R_{t-5}**, R_{t-6}	R_t	6-9-9-9-1	63.14	73.65

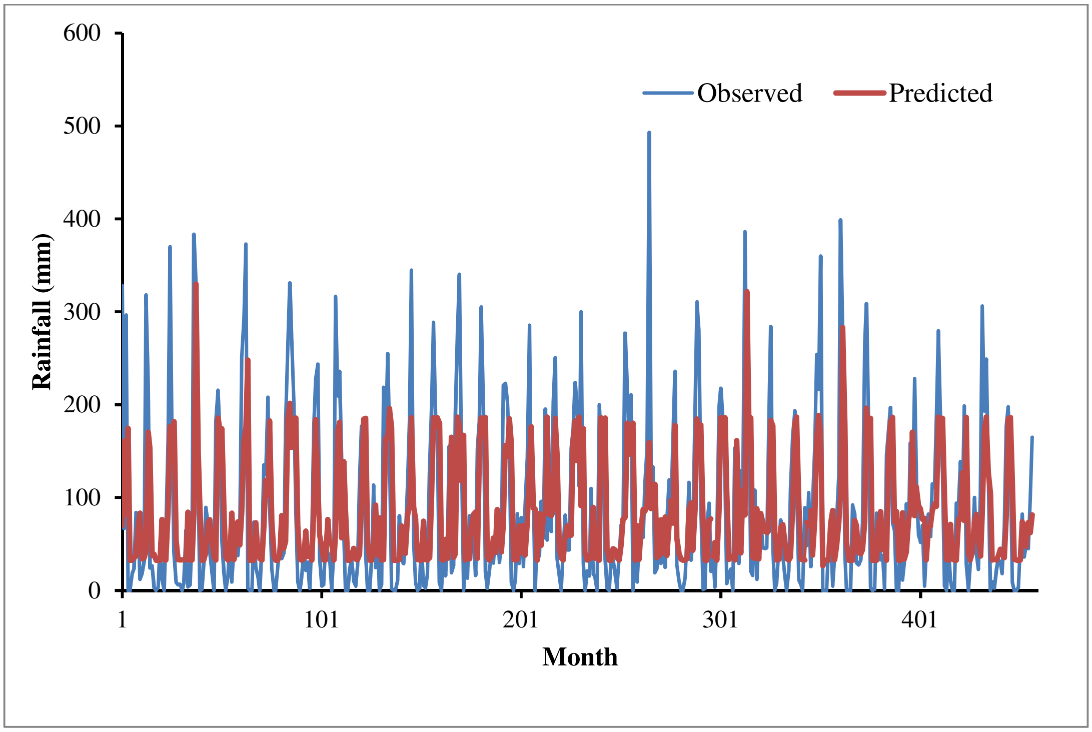

Fig. 4.18 Observed and computed rainfall using MO-1 model during training period

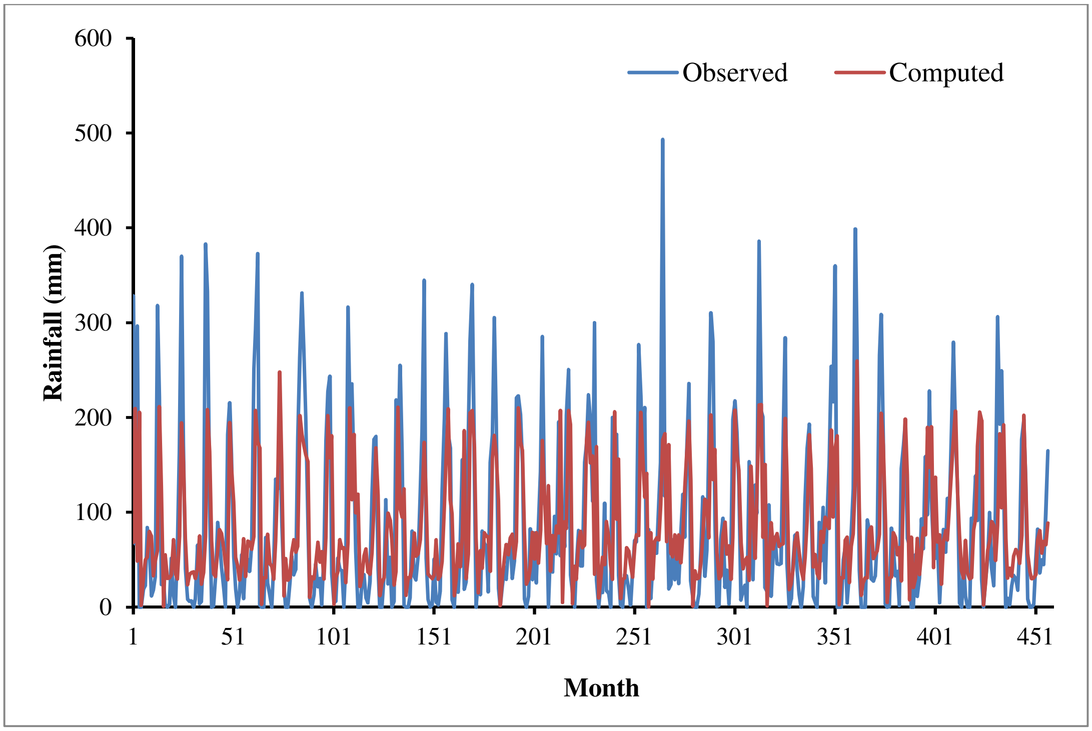

Fig. 4.19 Observed and computed rainfall using MO-2 model during training period

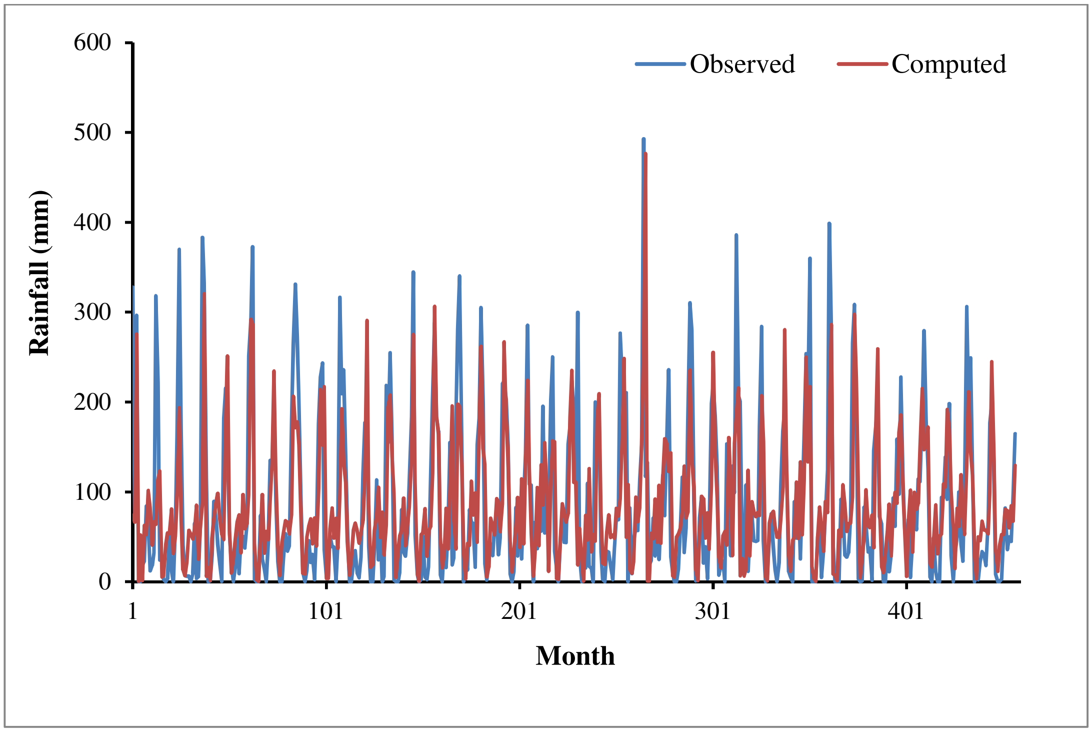

Fig. 4.20 Observed and computed rainfall using MO-3 model during training period

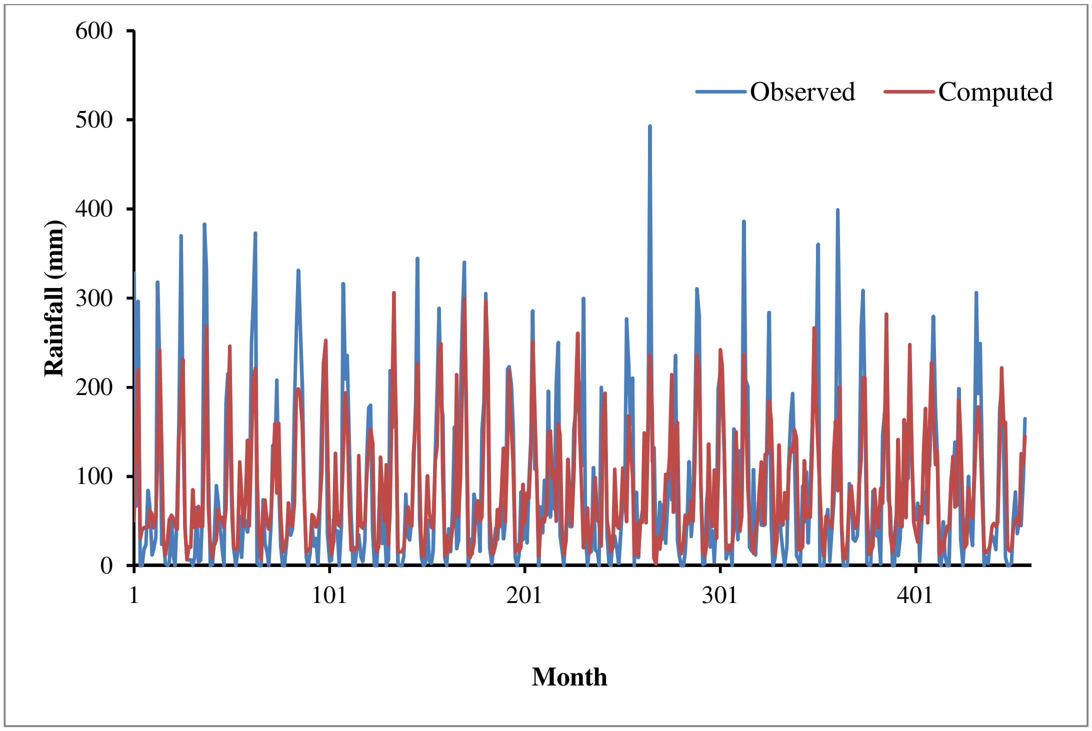

Fig. 4.21 Observed and computed rainfall using MO-4 model during training period

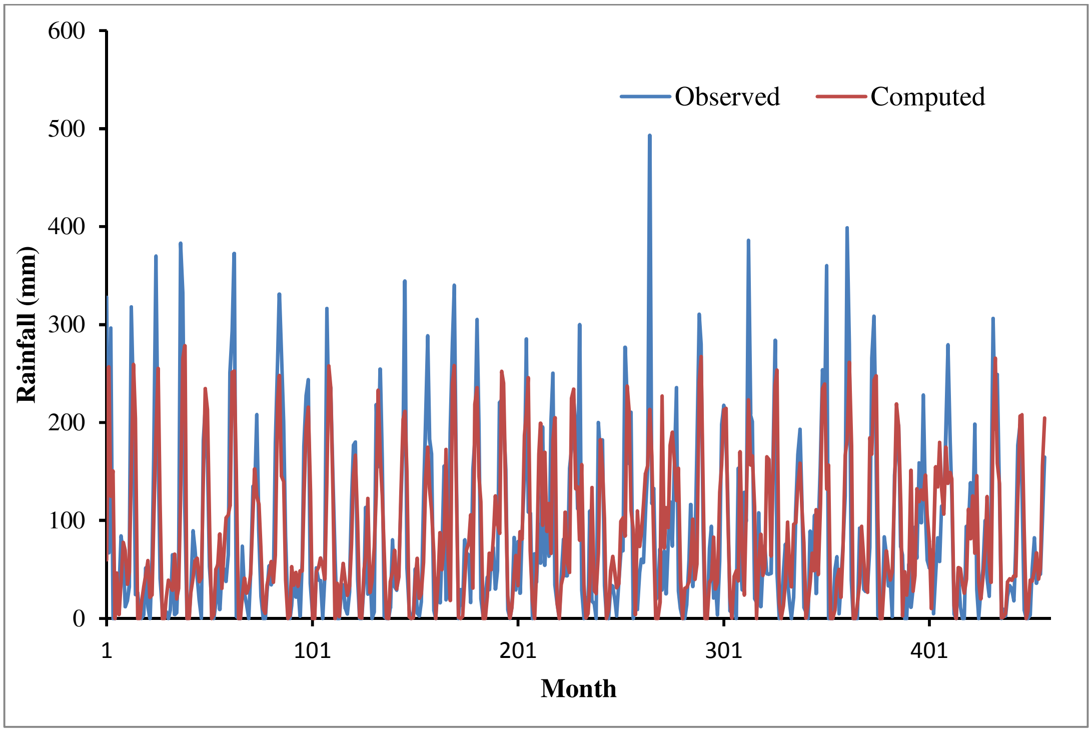

Fig. 4.22 Observed and computed rainfall using MO-5 model during training period

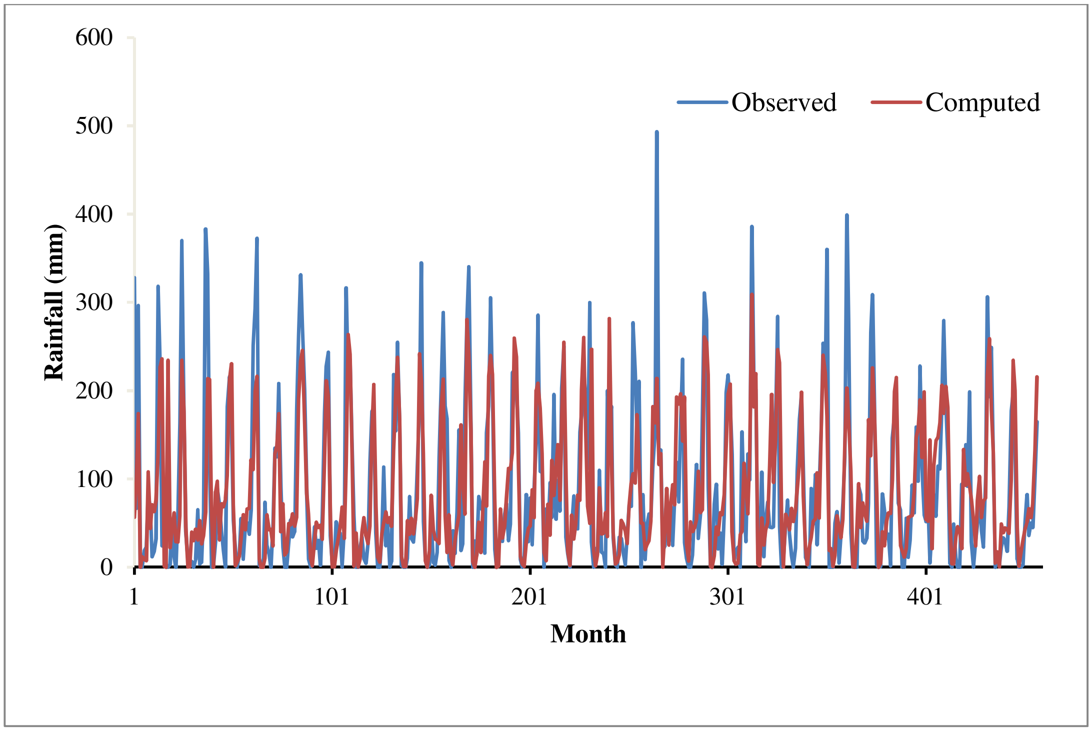

Fig. 4.23 Observed and computed rainfall using MO-6 model during training period

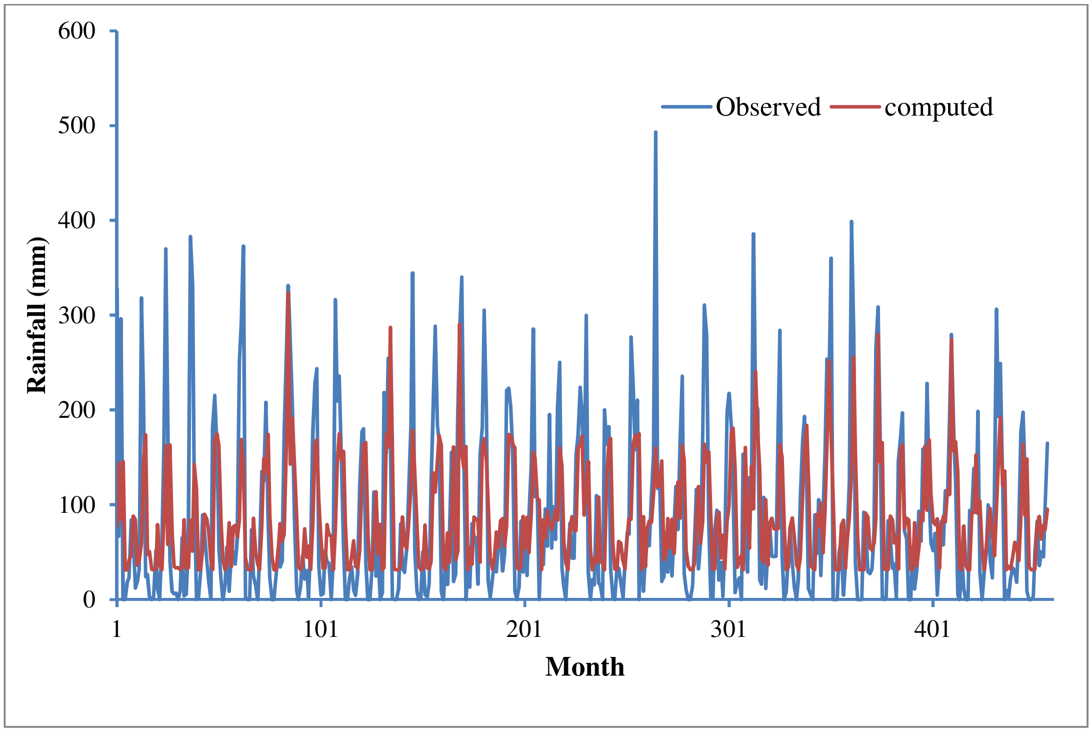

Fig. 4.24 Observed and computed rainfall using MB-1 model during training period

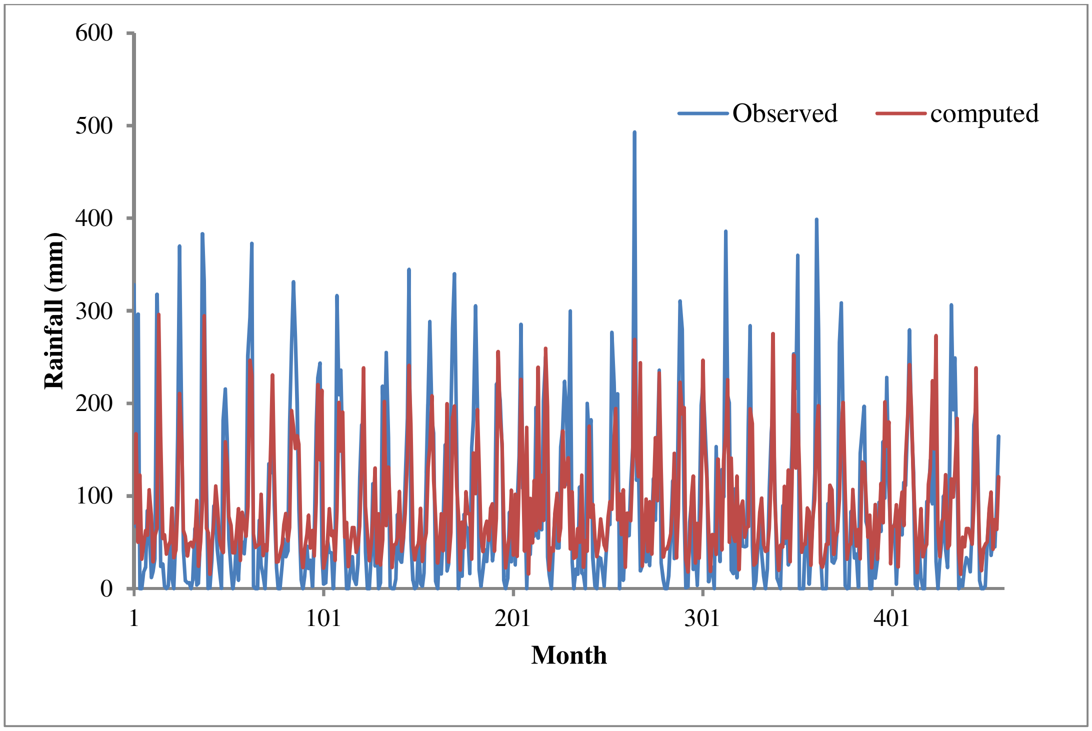

Fig. 4.25 Observed and computed rainfall using MB-2 model during training period

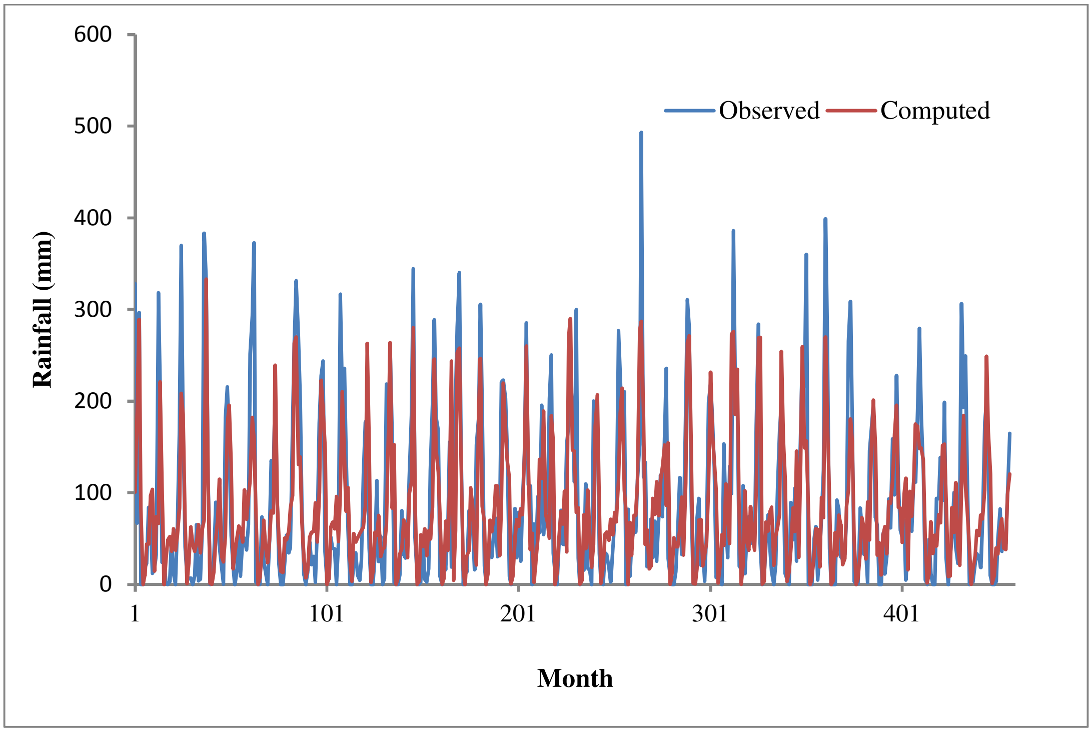

Fig. 4.26 Observed and computed rainfall using MB-3 model during training period

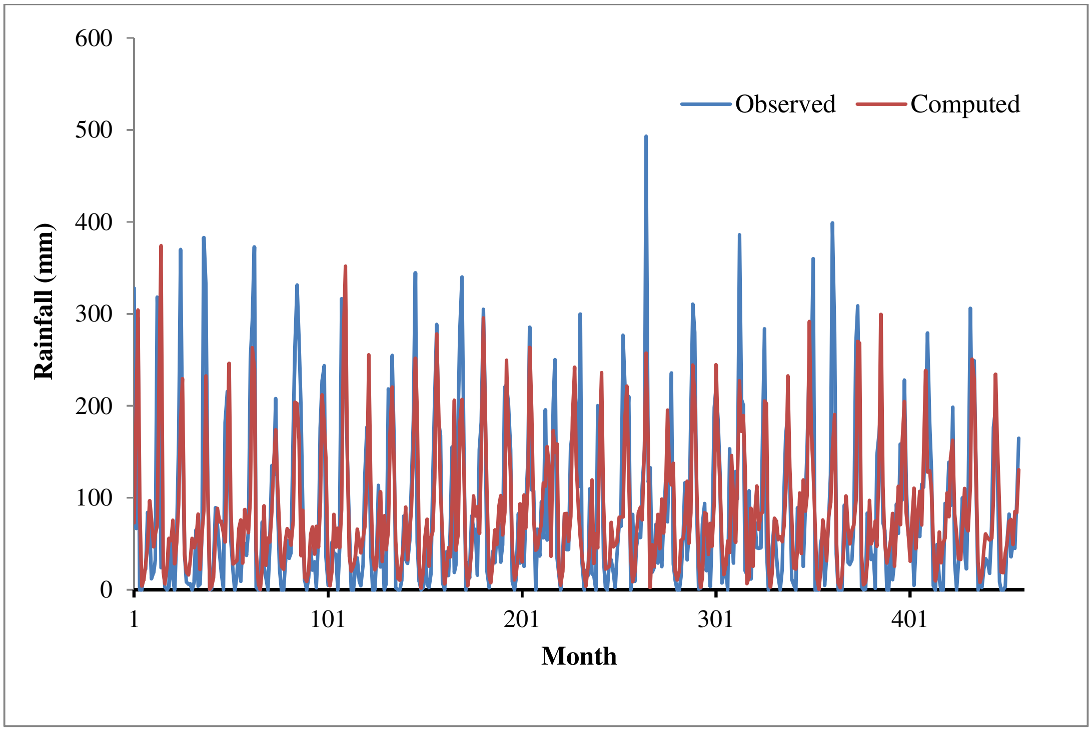

Fig. 4.27 Observed and computed rainfall using MB-4 model during training period

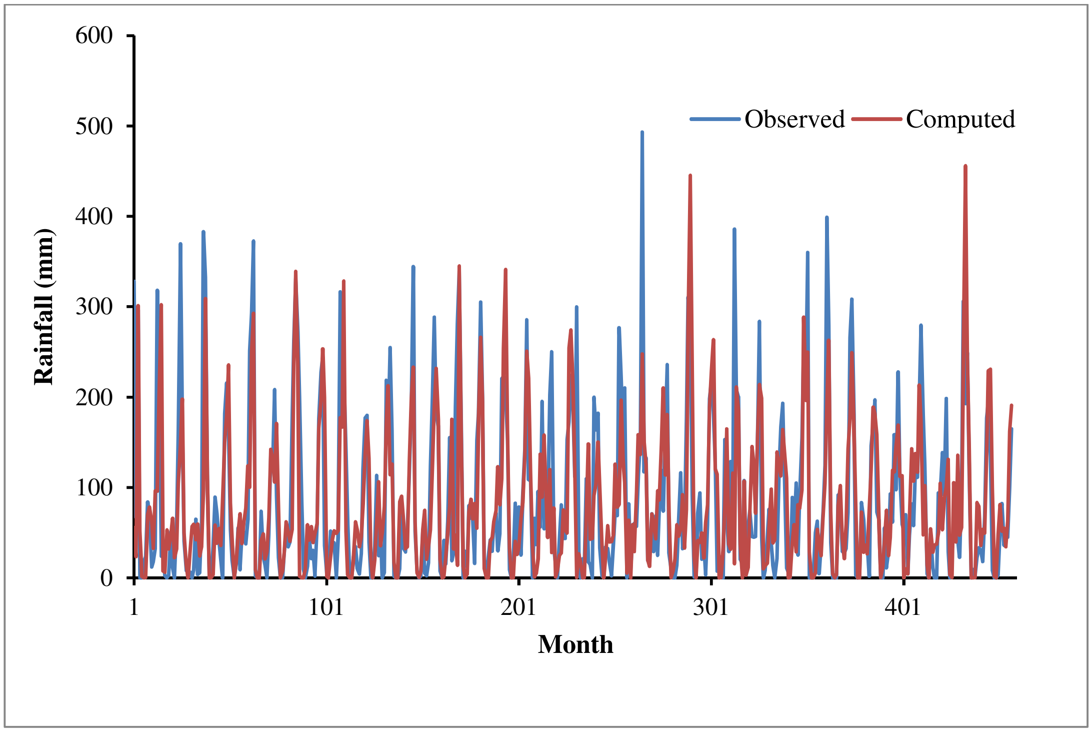

Fig. 4.28 Observed and computed rainfall using MB-5 model during training period

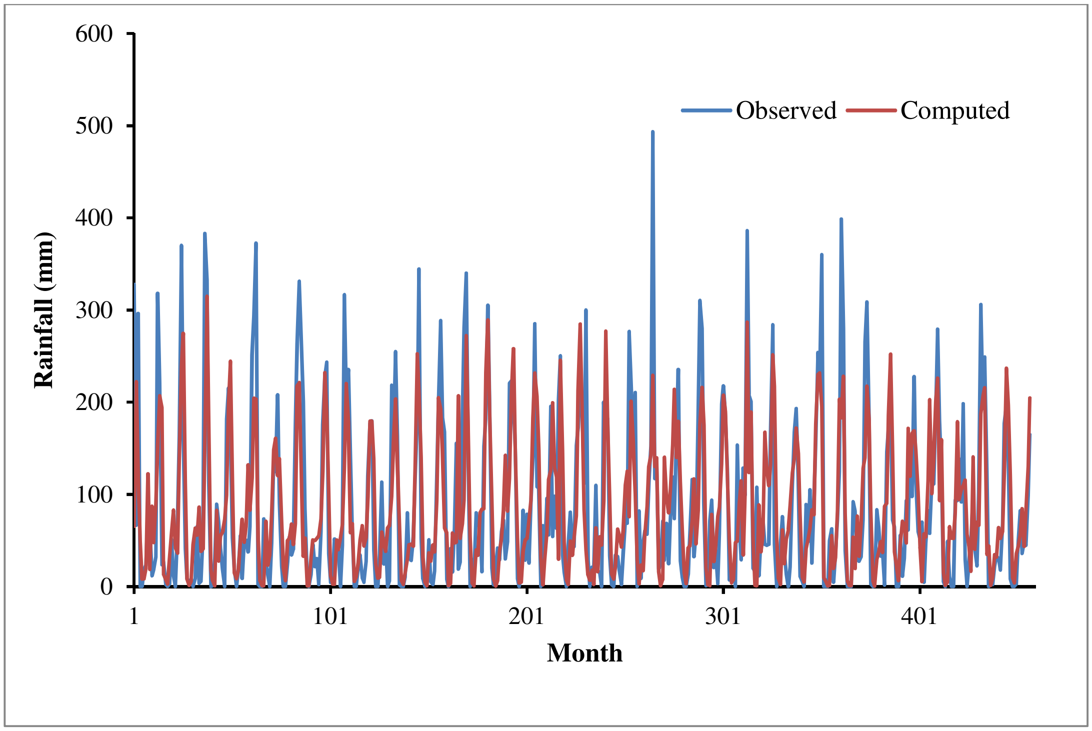

Fig. 4.29 Observed and computed rainfall using MB-6 model during training period

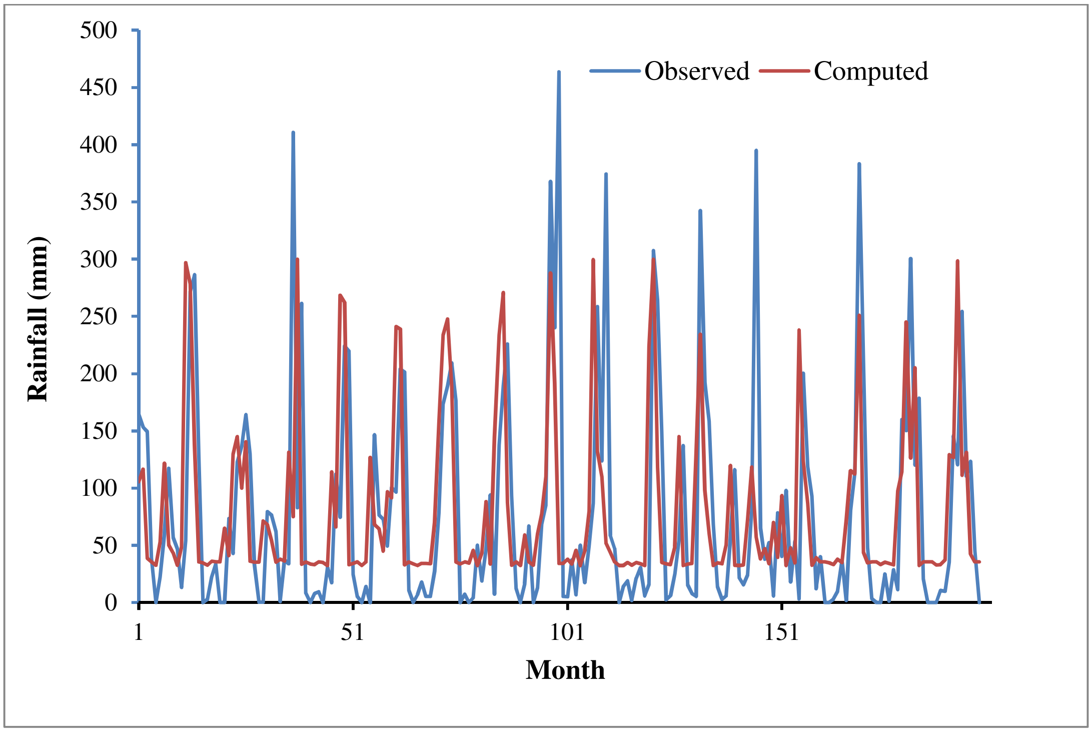

Fig. 4.30 Observed and computed rainfall using MO-1 model during testing period

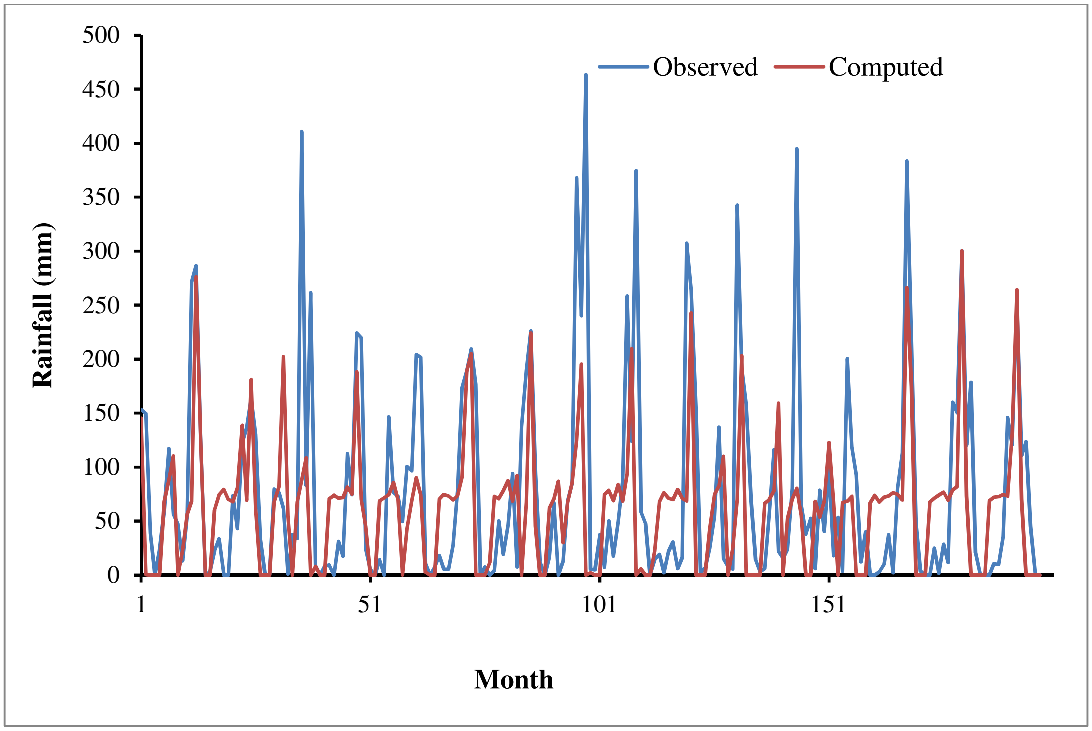

Fig. 4.31 Observed and computed rainfall using MO-2 model during testing period

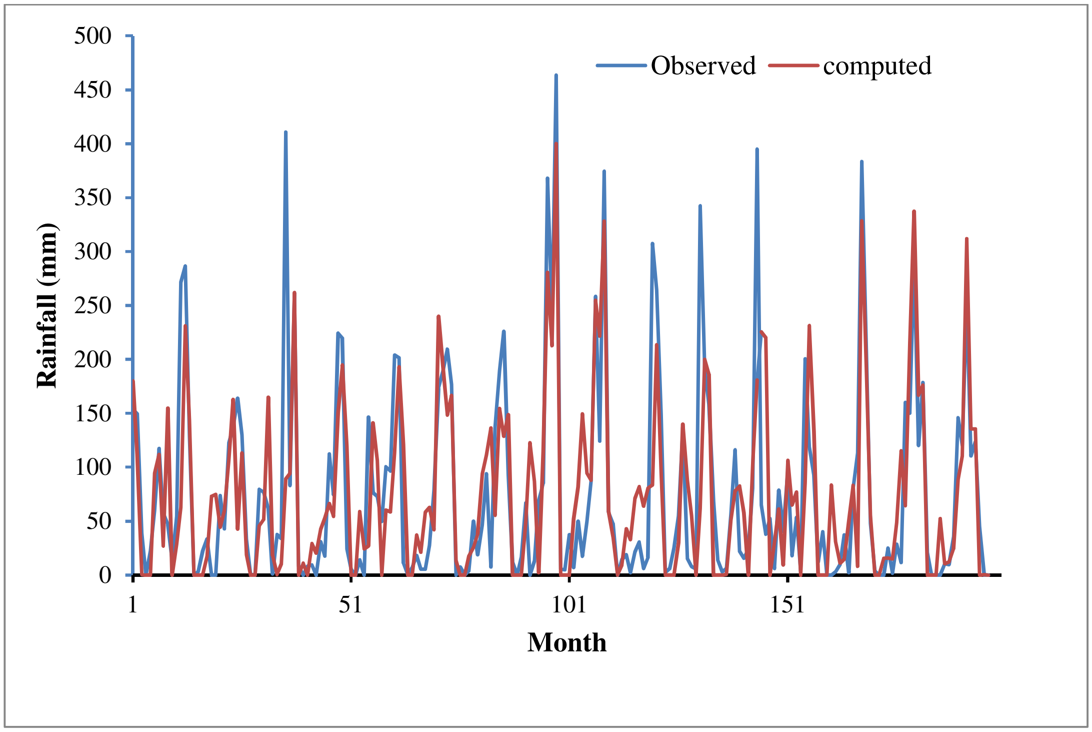

Fig. 4.32 Observed and computed rainfall using MO-3 model during testing period

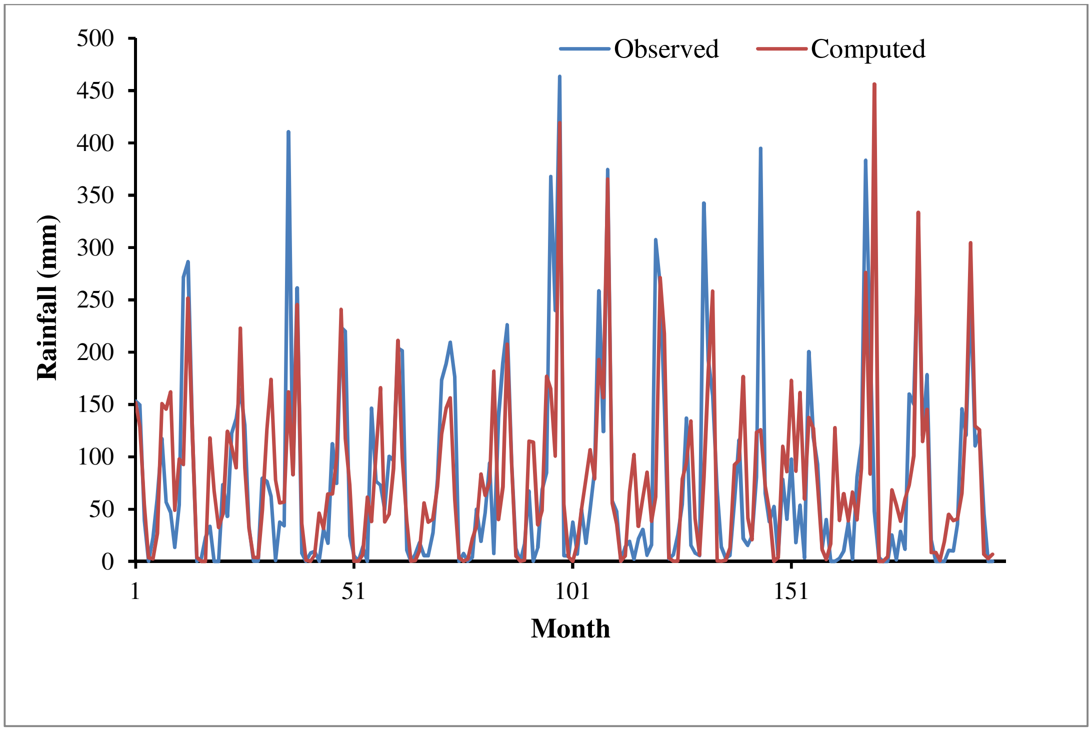

Fig. 4.33 Observed and computed rainfall using MO-4 model during testing period

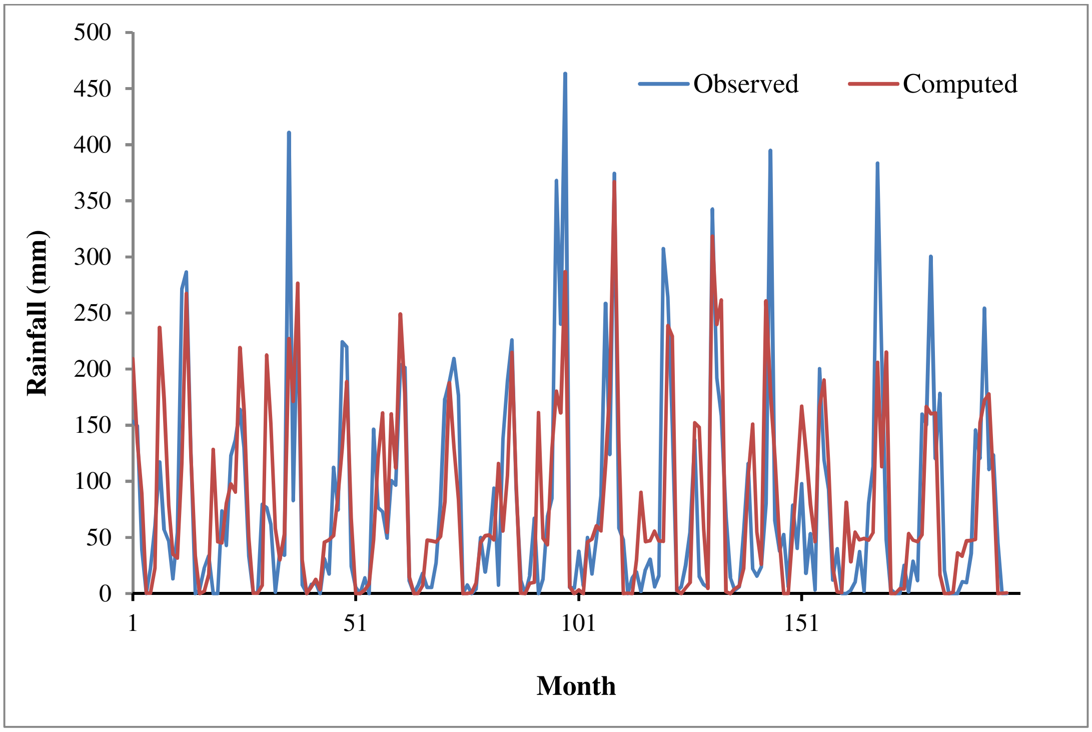

Fig. 4.34 Observed and computed rainfall using MO-5 model during testing period

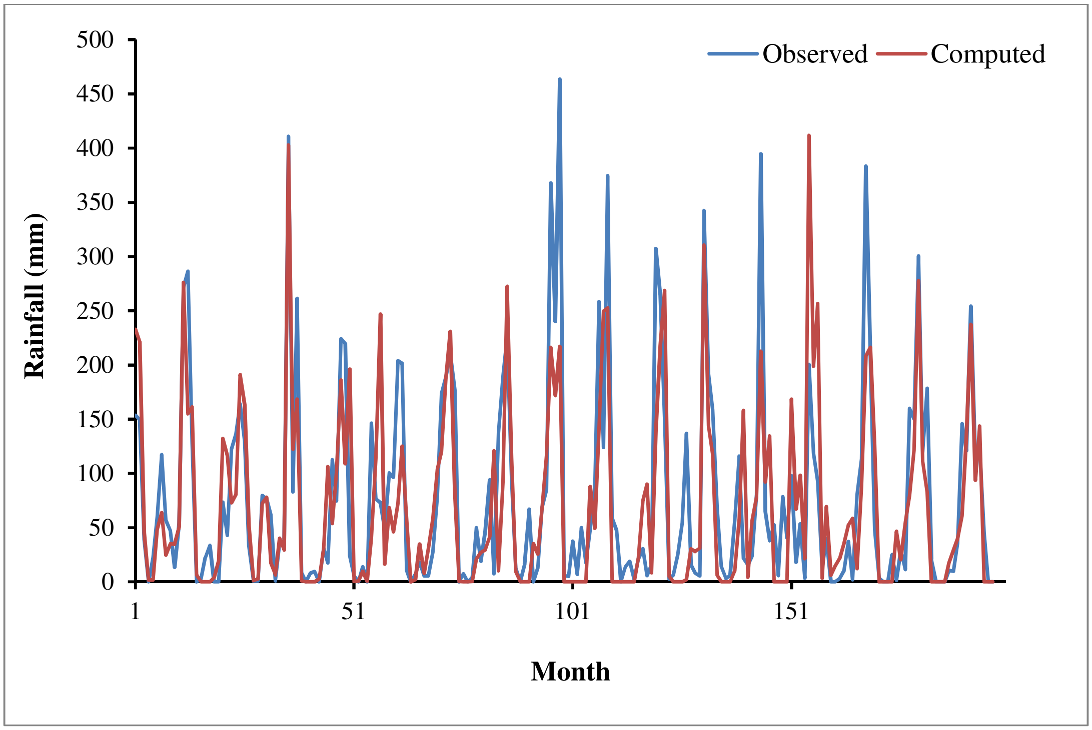

Fig. 4.35 Observed and computed rainfall using MO-6 model during testing period

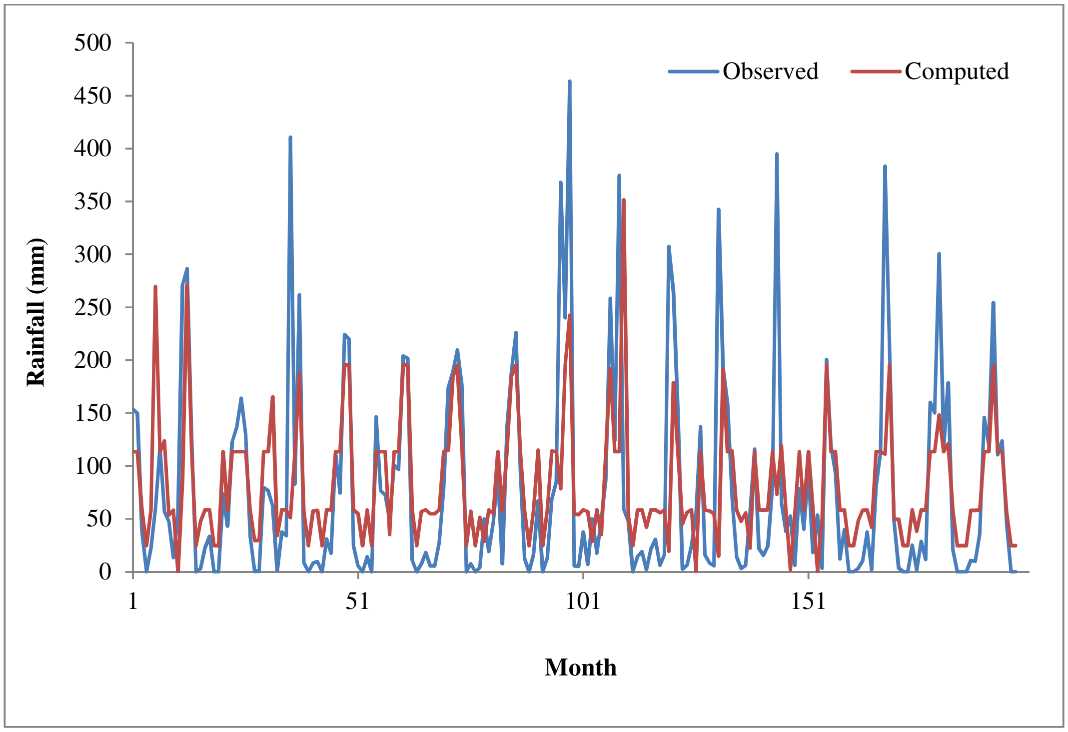

Fig. 4.36 Observed and computed rainfall using MB-1 model during testing period

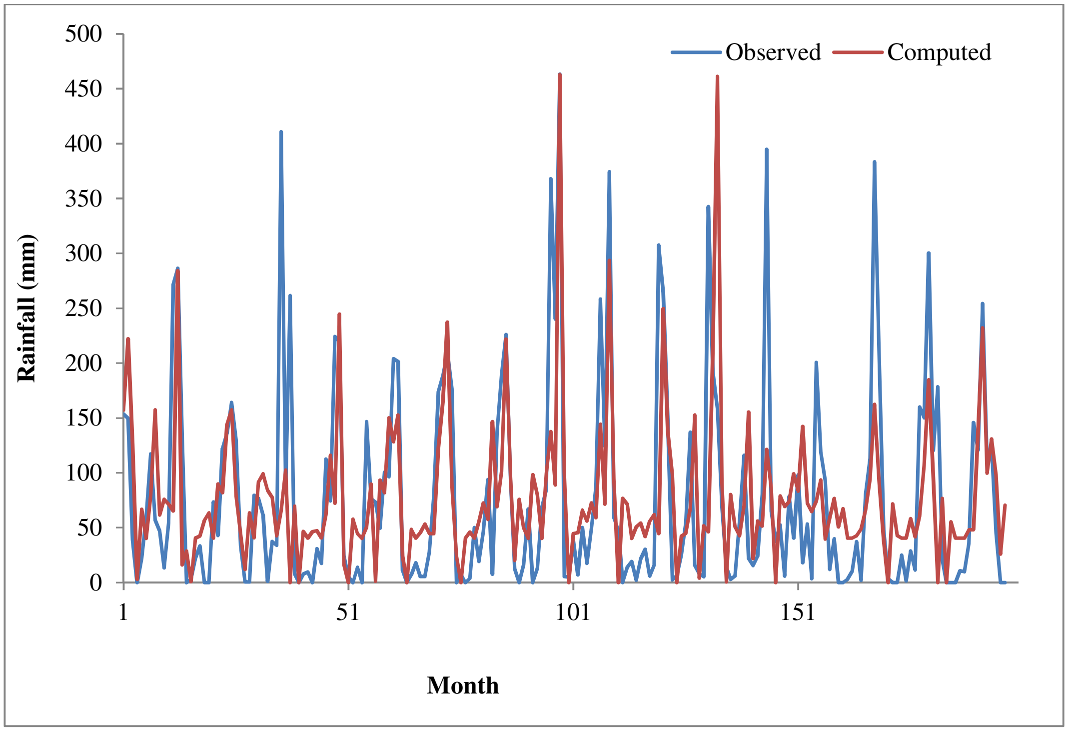

Fig. 4.37 Observed and computed rainfall using MB-2 model during Testing period

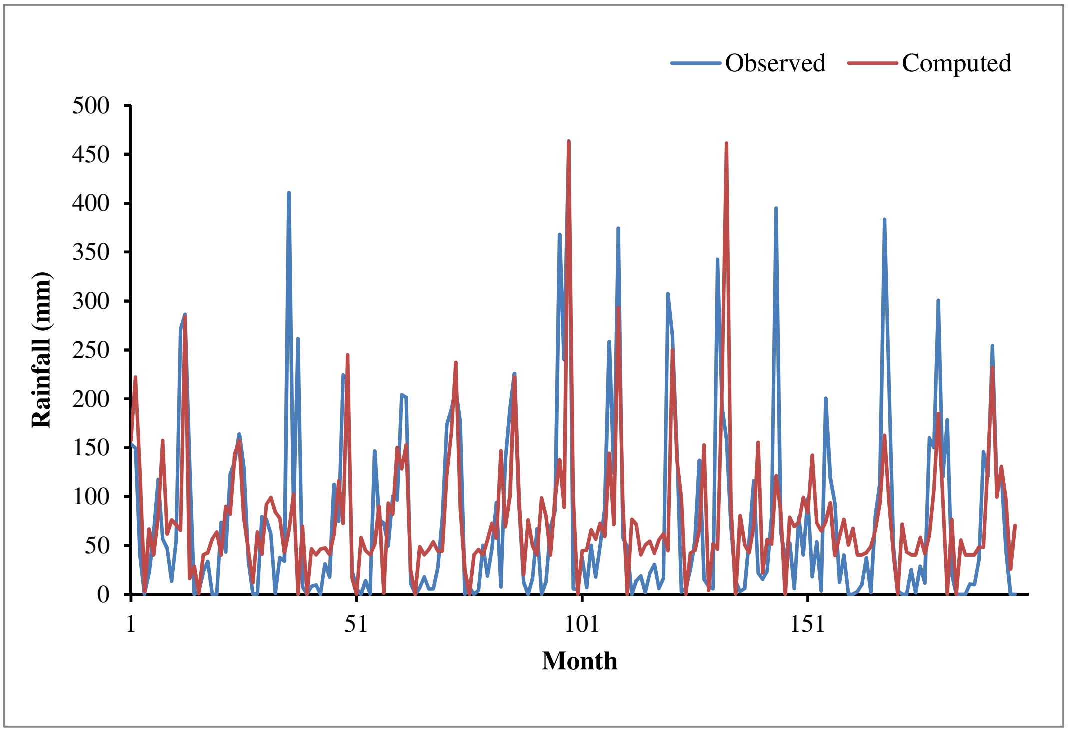

Fig. 4.38 Observed and computed rainfall using MO-3 model during Testing period

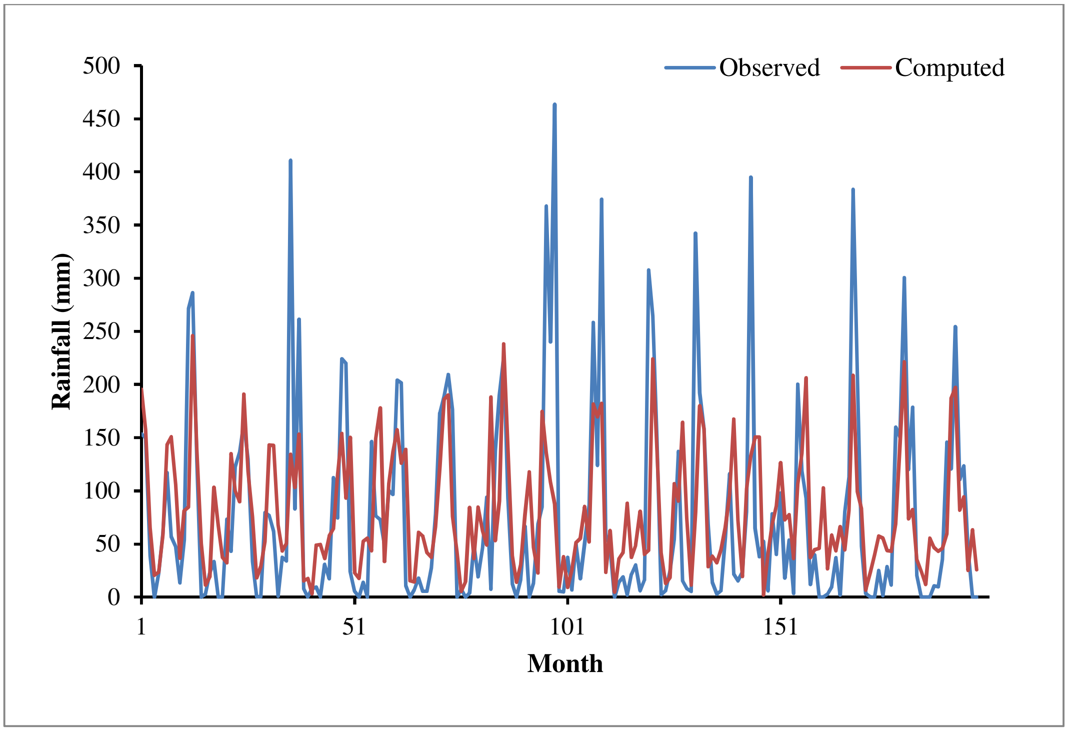

Fig. 4.39 Observed and computed rainfall using MB-4 model during testing period

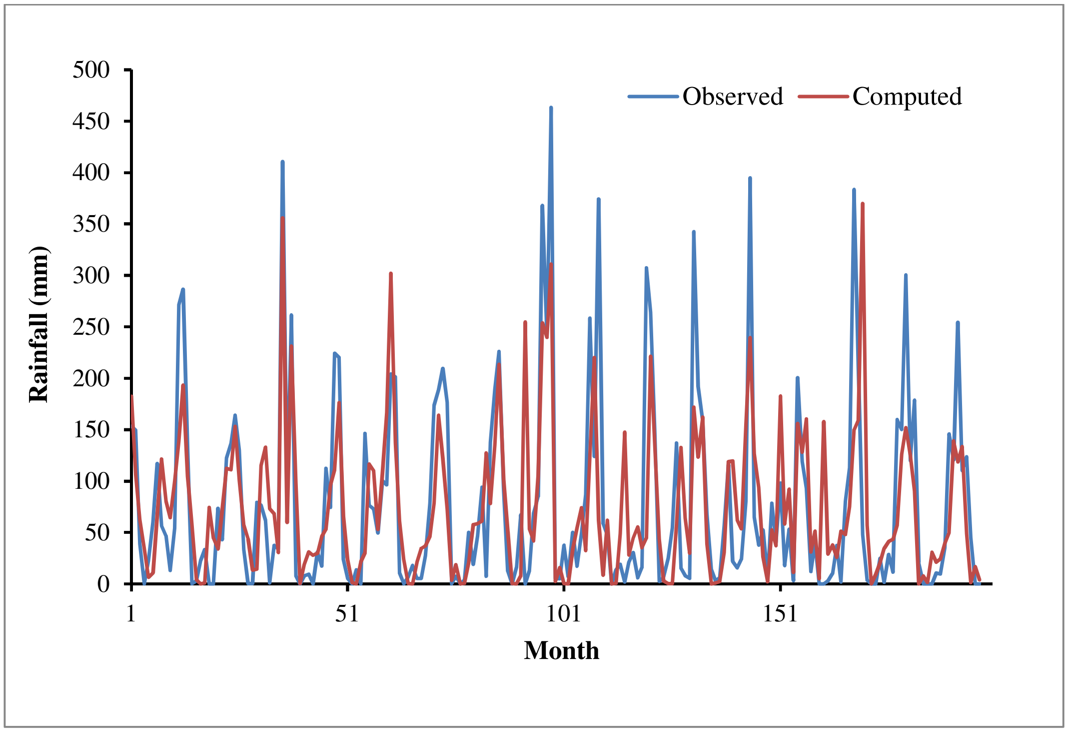

Fig. 4.40 Observed and computed rainfall using MB-5 model during Testing period

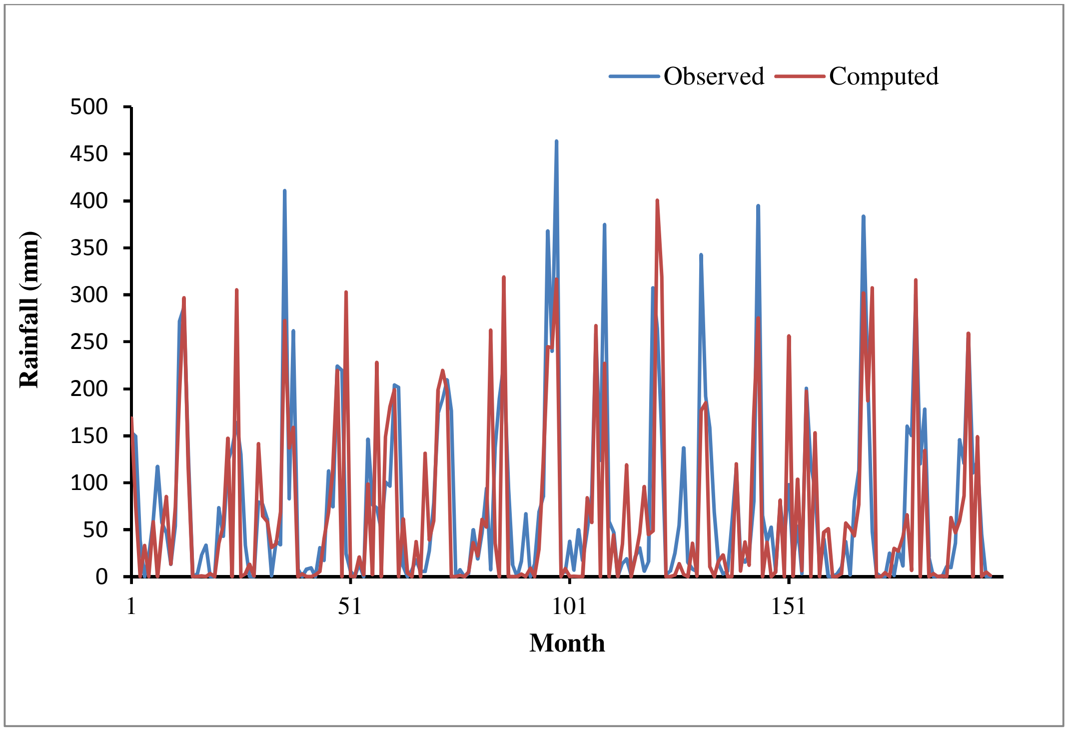

Fig. 4.41 Observed and computed rainfall using MB-6 model during Testing period

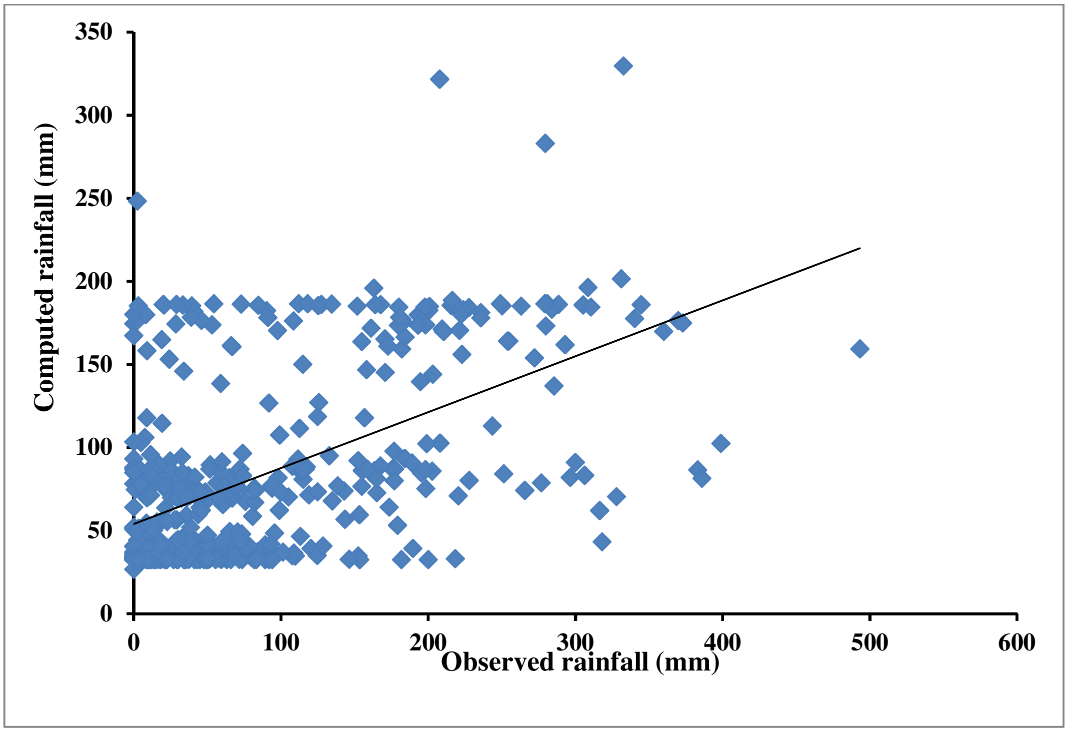

Fig. 4.42 **Scatter plot of observed and computed rainfall using MO-1 model during training period**

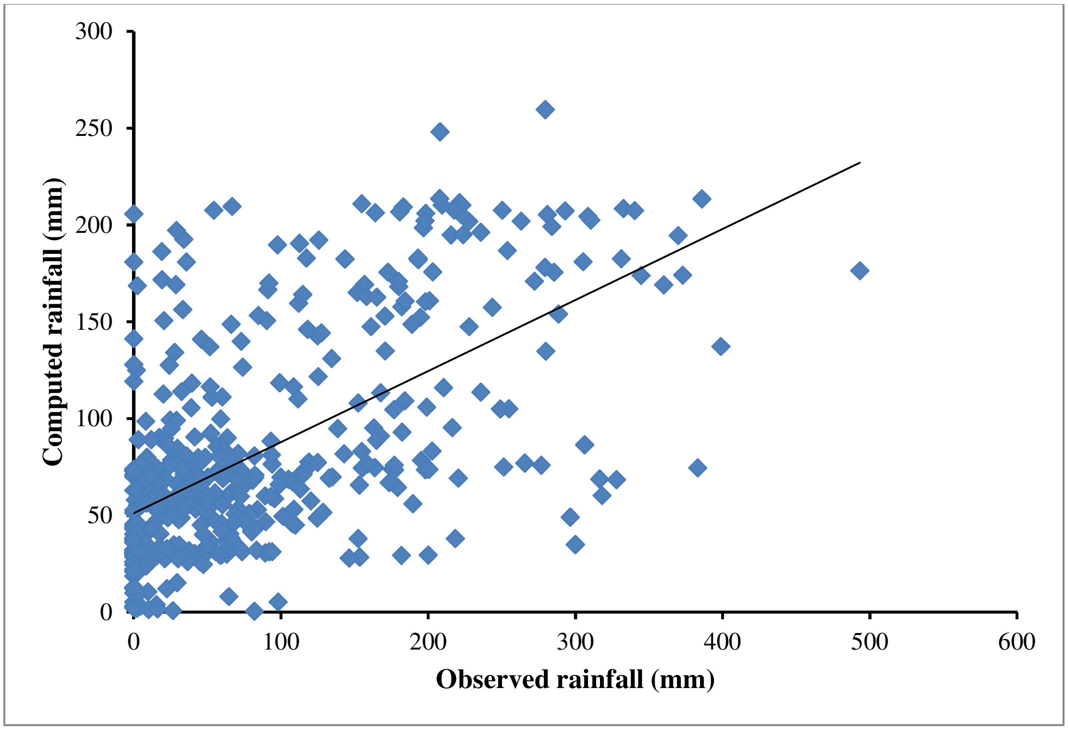

Fig. 4.43 **Scatter plot of observed and computed rainfall using MO-2 model during training period**

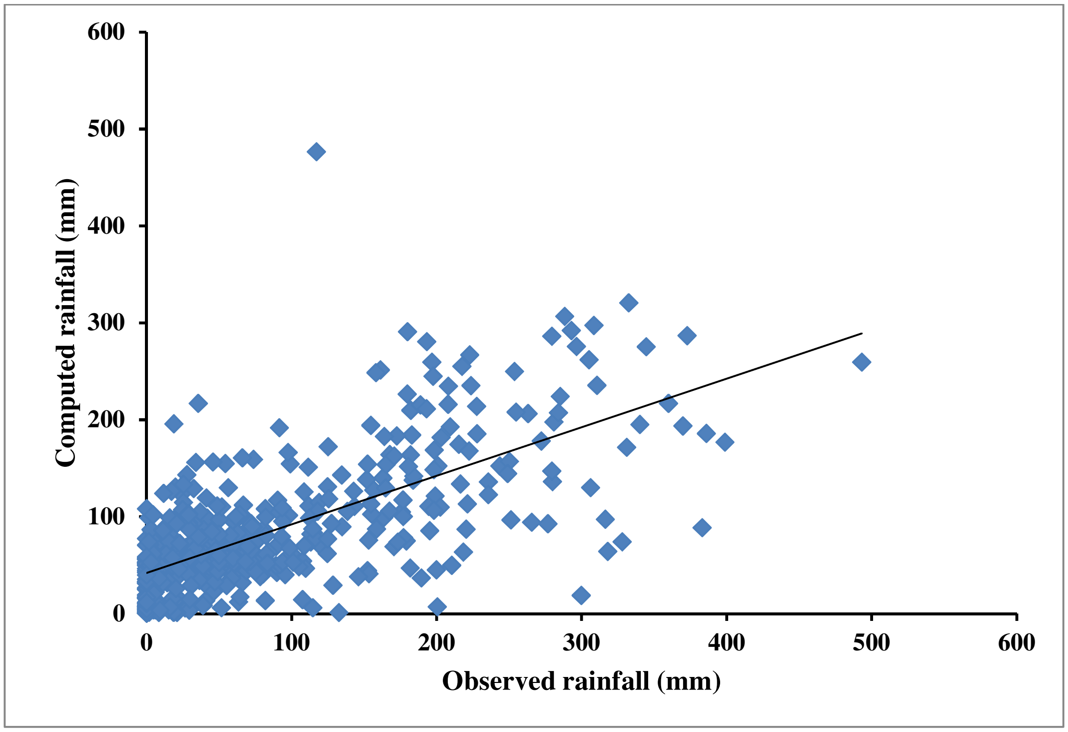

Fig. 4.44 **Scatter plot of observed and computed rainfall using MO-3 model during training period**

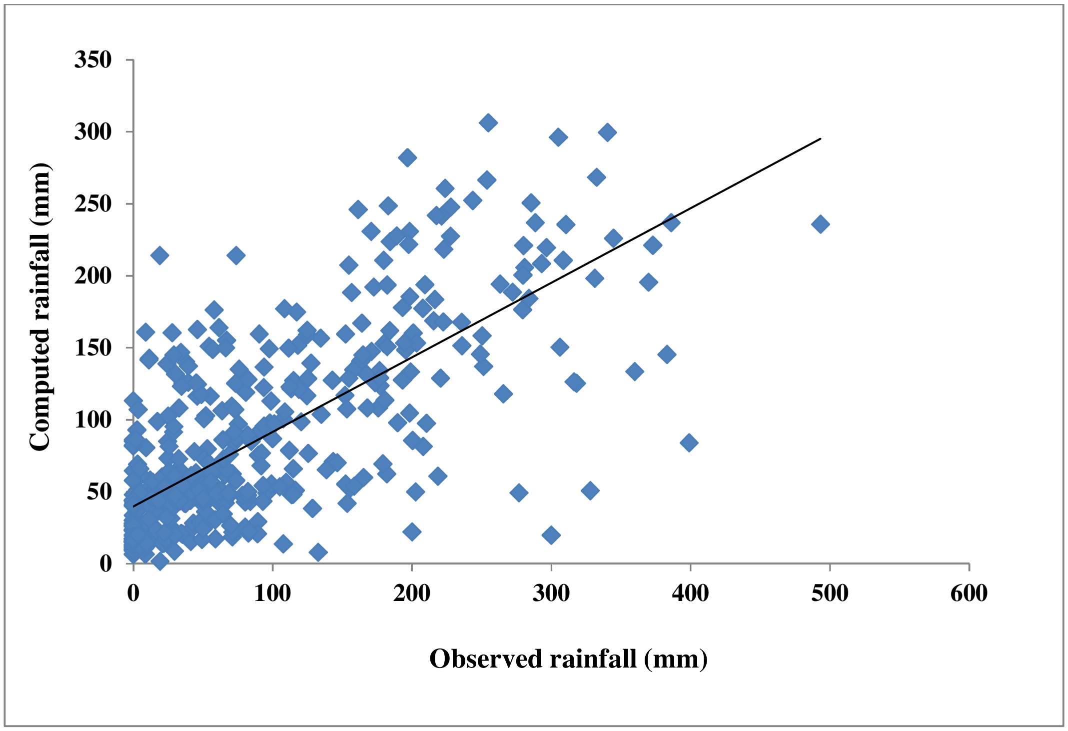

Fig. 4.45 **Scatter plot of observed and computed rainfall using MO-4 model during training period**

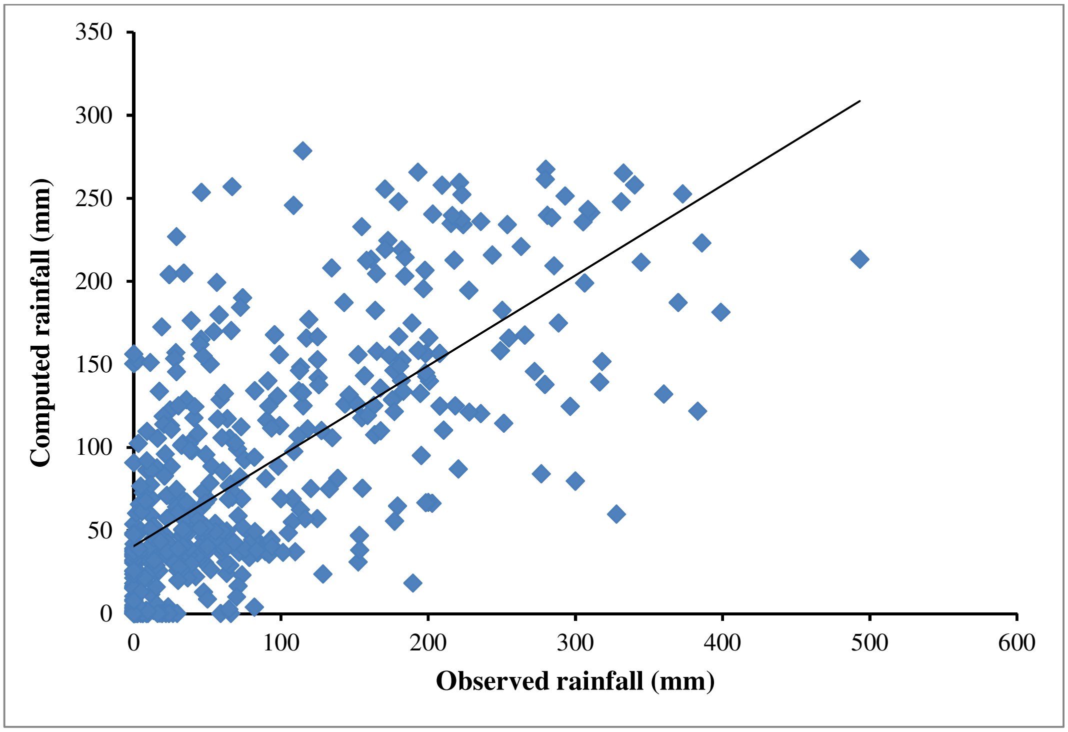

Fig. 4.46 **Scatter plot of observed and computed rainfall using MO-5 model during training period**

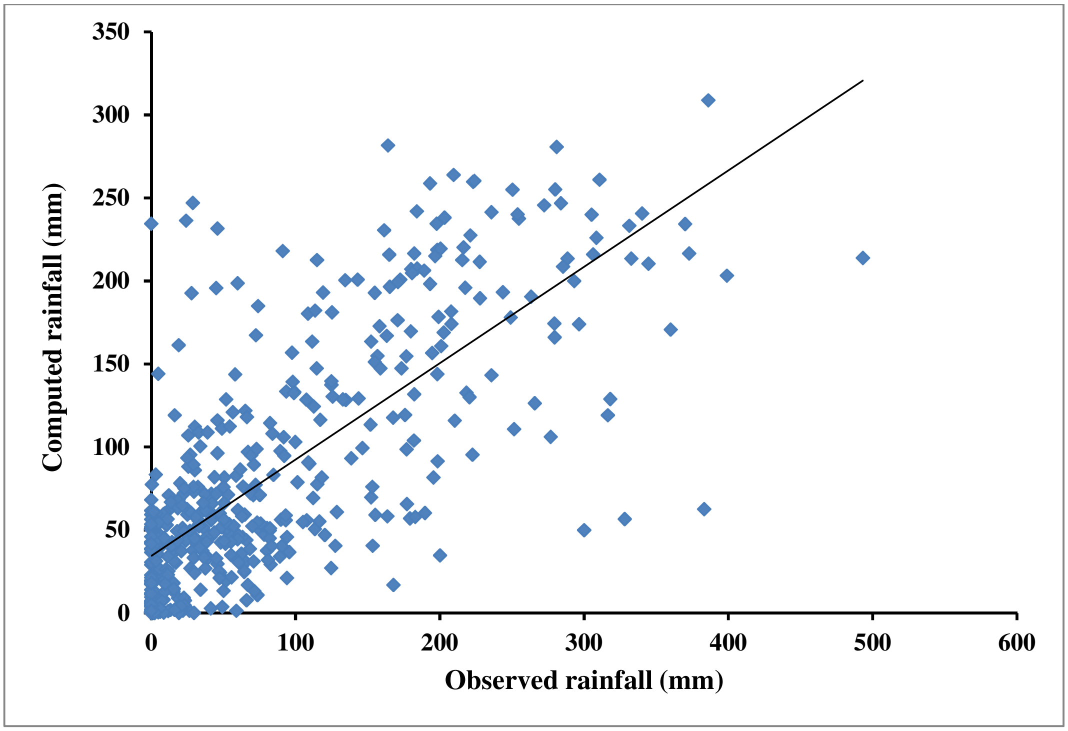

Fig. 4.47 **Scatter plot of observed and computed rainfall using MO-6 model during training period**

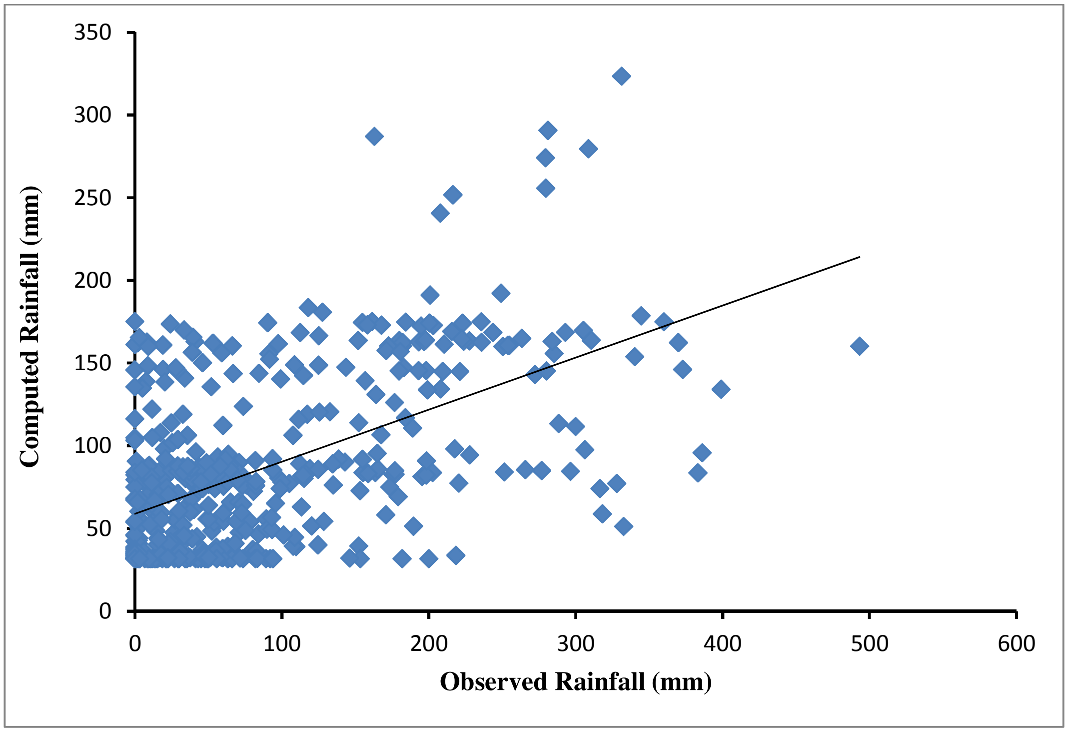

Fig. 4.48 **Scatter plot of observed and computed rainfall using MB-1 model during training period**

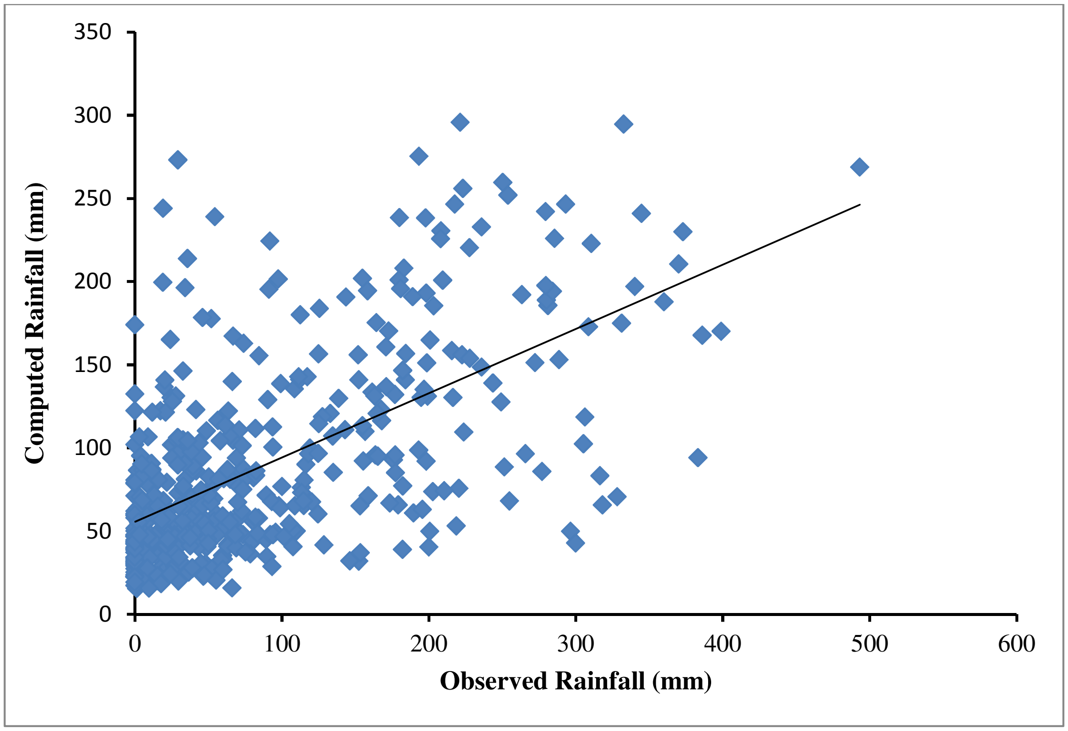

Fig. 4.49 **Scatter plot of observed and computed rainfall using MB-2 model during training period**

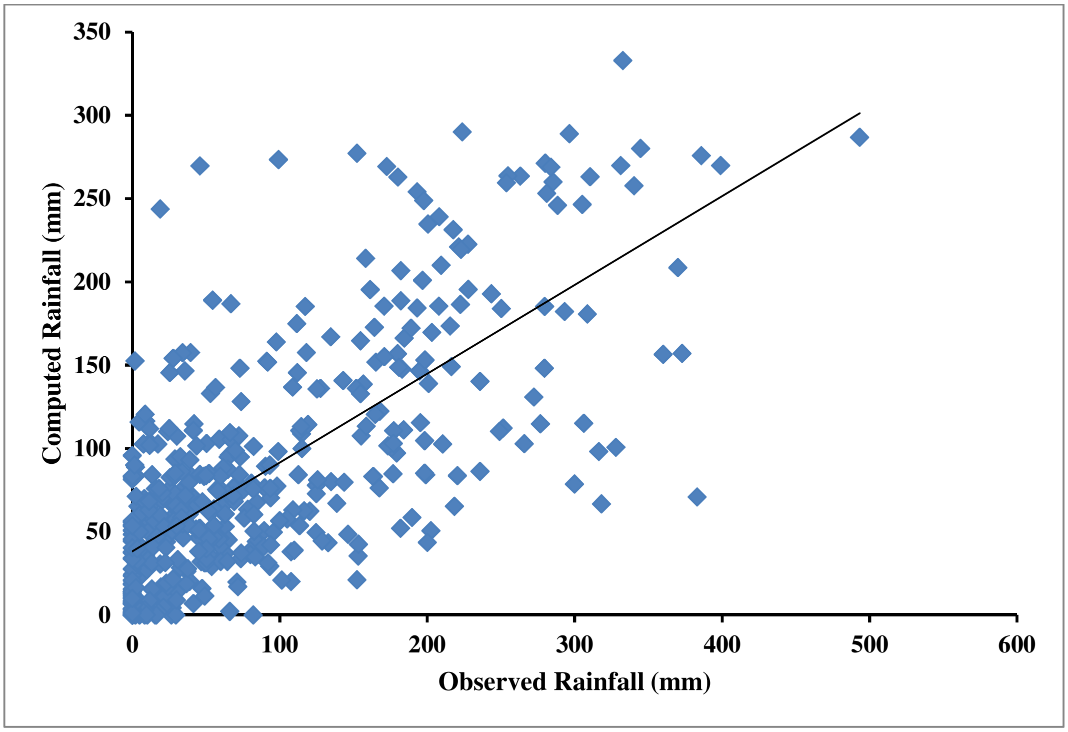

Fig. 4.50 **Scatter plot of observed and computed rainfall using MB-3 model during training period**

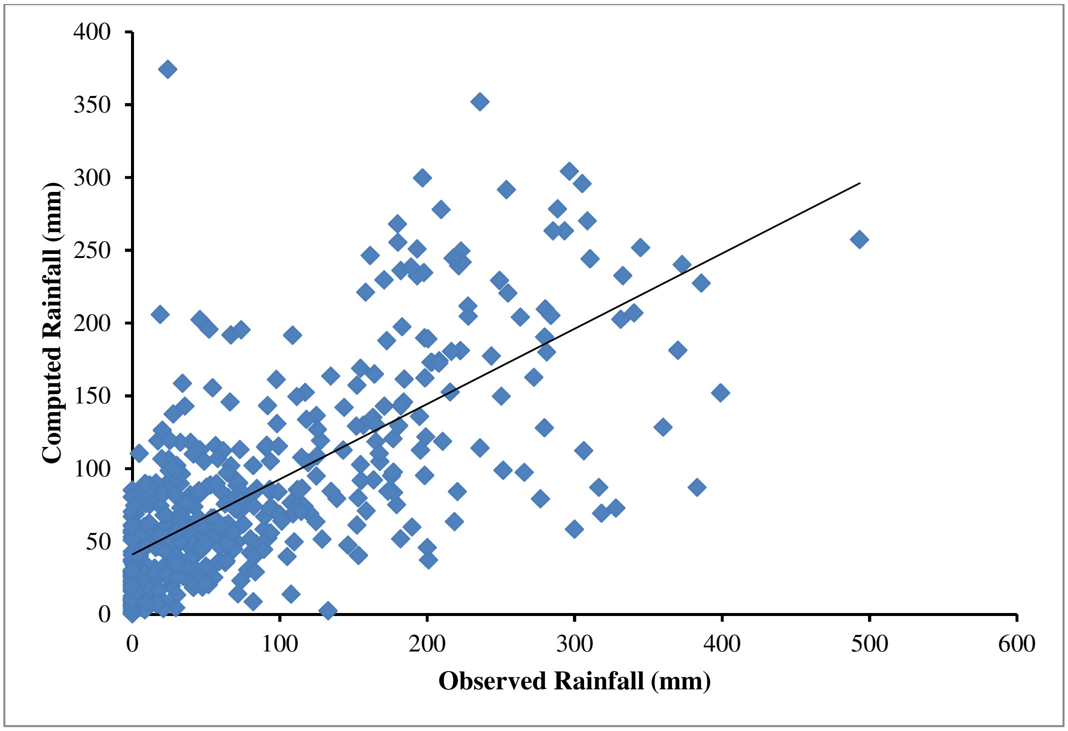

Fig. 4.51 **Scatter plot of observed and computed rainfall using MB-4 model during training period**

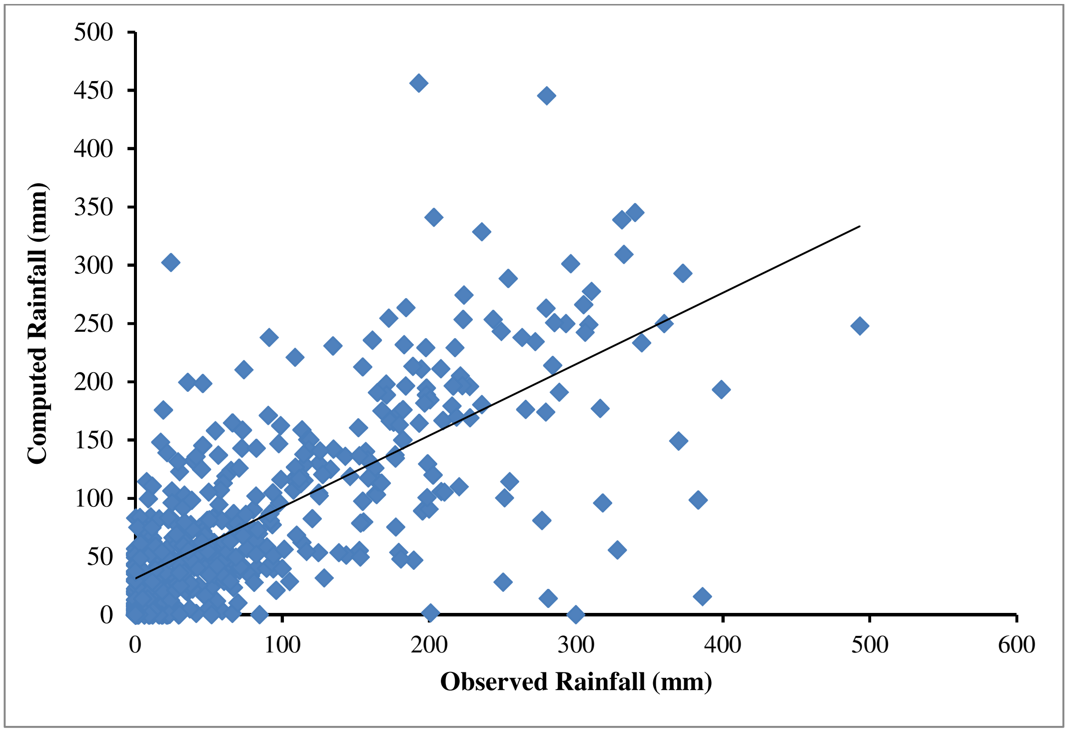

Fig. 4.52 **Scatter plot of observed and computed rainfall using MB-5 model during training period**

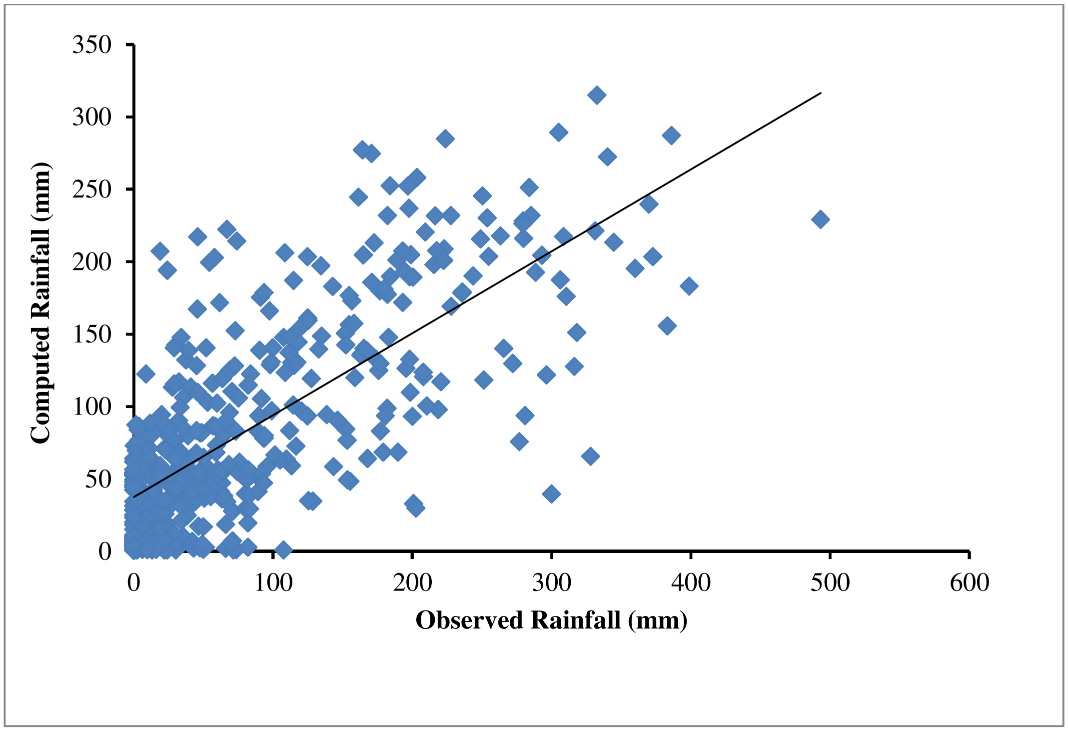

Fig. 4.53 **Scatter plot of observed and computed rainfall using MB-6 model during training period**

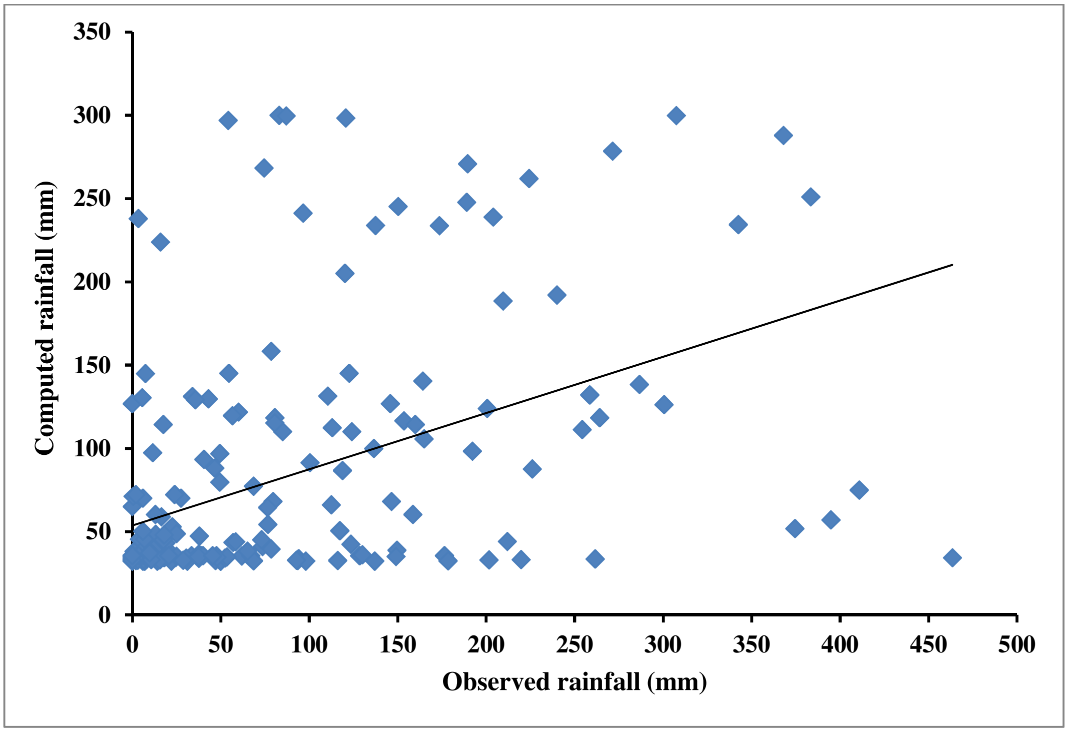

Fig. 4.54 Scatter plot of observed and computed rainfall using MO-1model during testing period

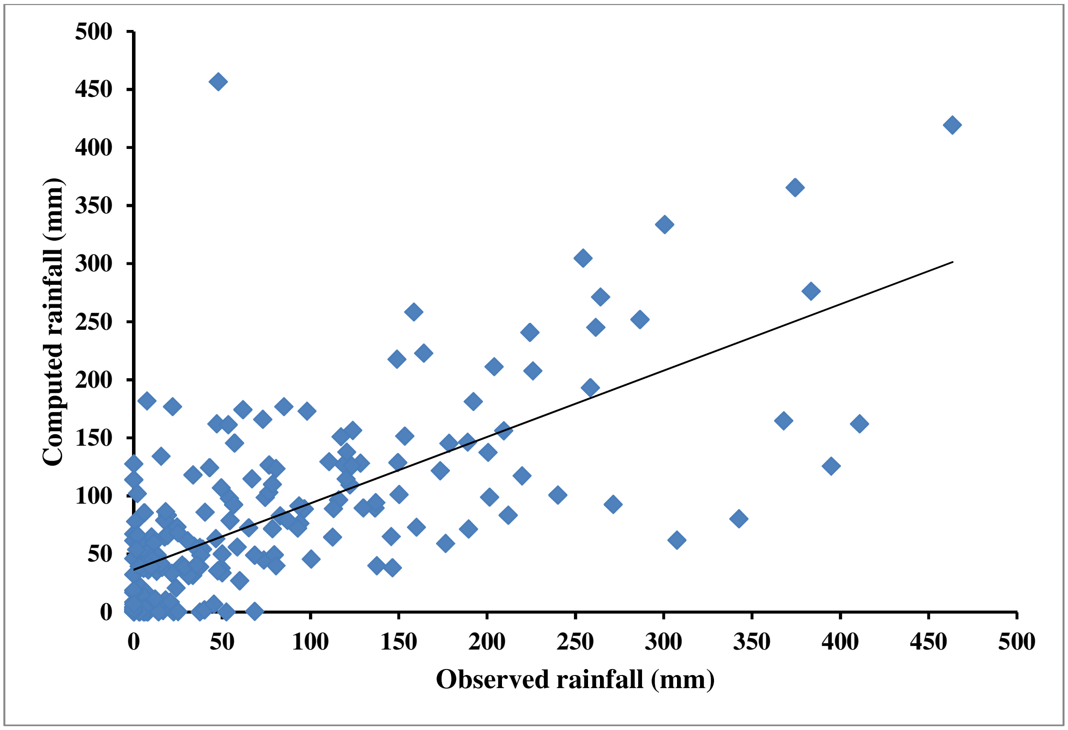

Fig. 4.55 Scatter plot of observed and computed rainfall using MO-2model during testing period

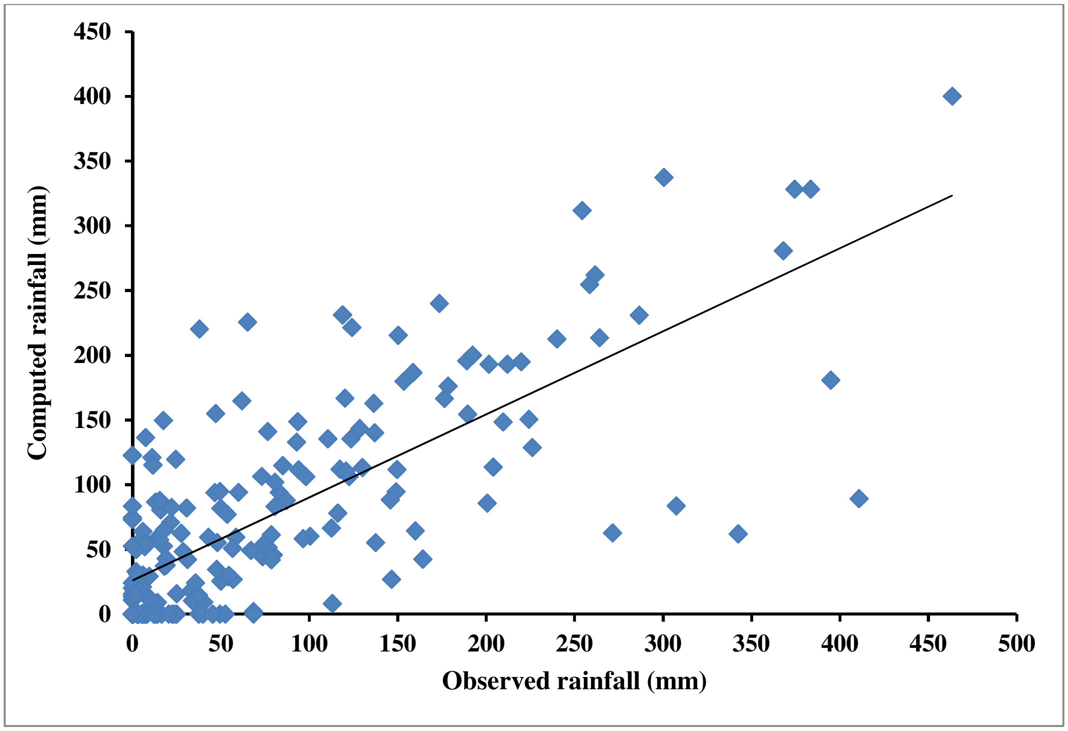

Fig. 4.56 **Scatter plot of observed and computed rainfall using MO-3model during testing period**

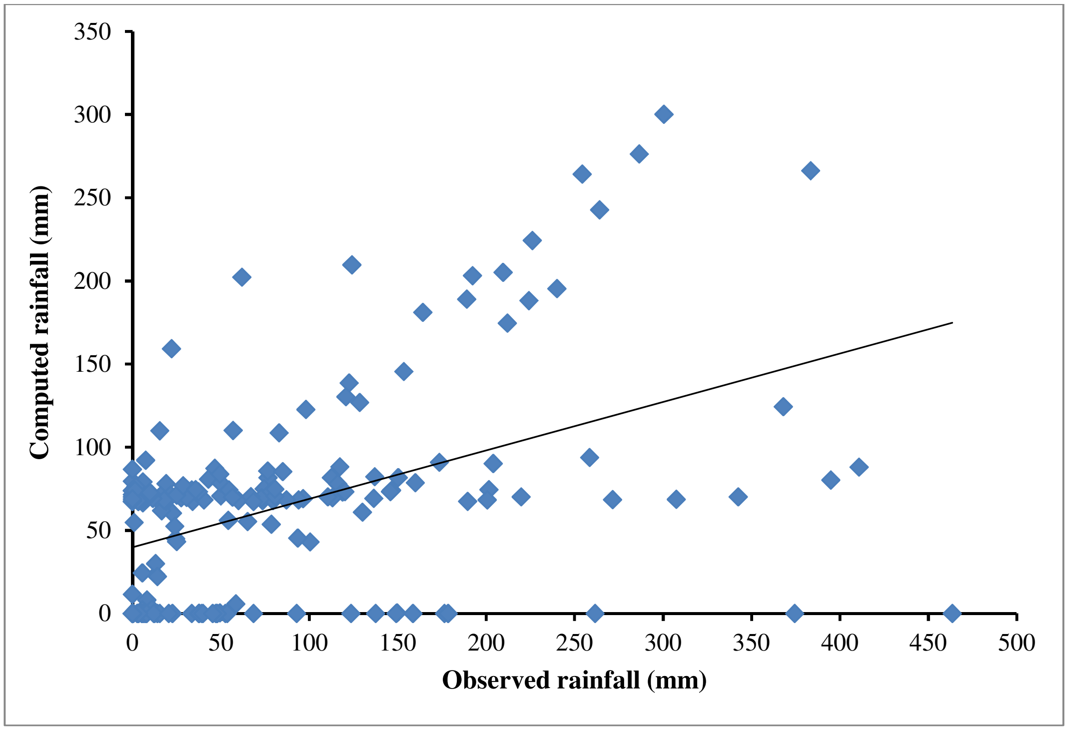

Fig. 4.57 **Scatter plot of observed and computed rainfall using MO-4model during testing period**

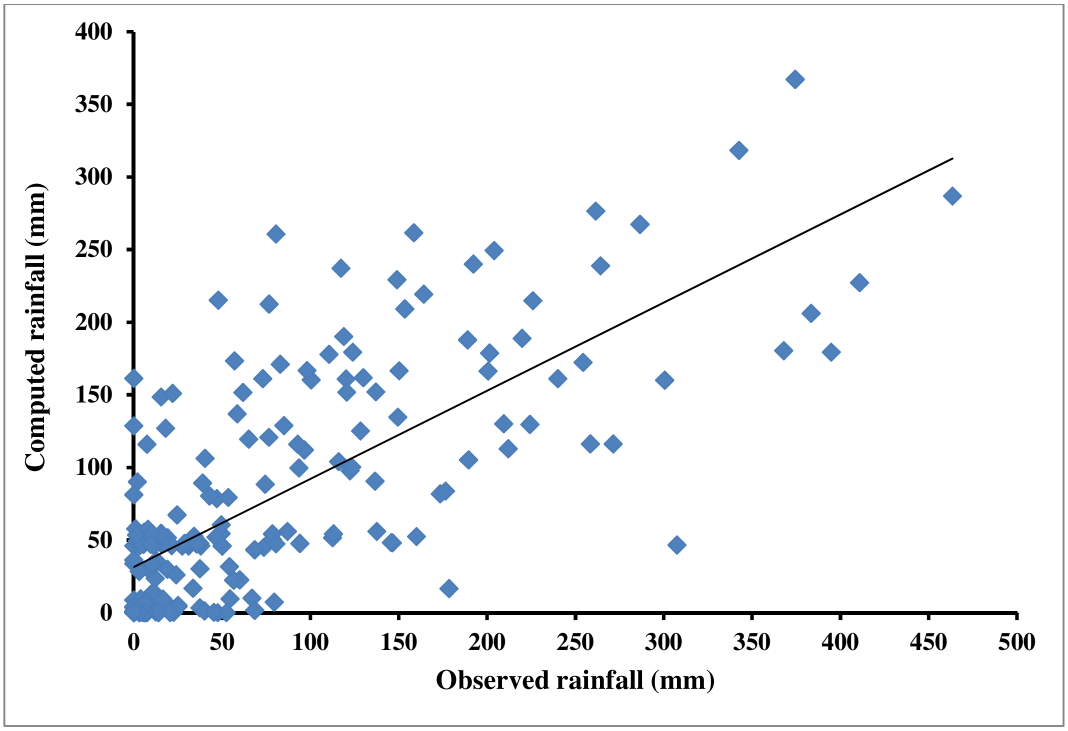

Fig. 4.58 **Scatter plot of observed and computed rainfall using MO-5model during testing period**

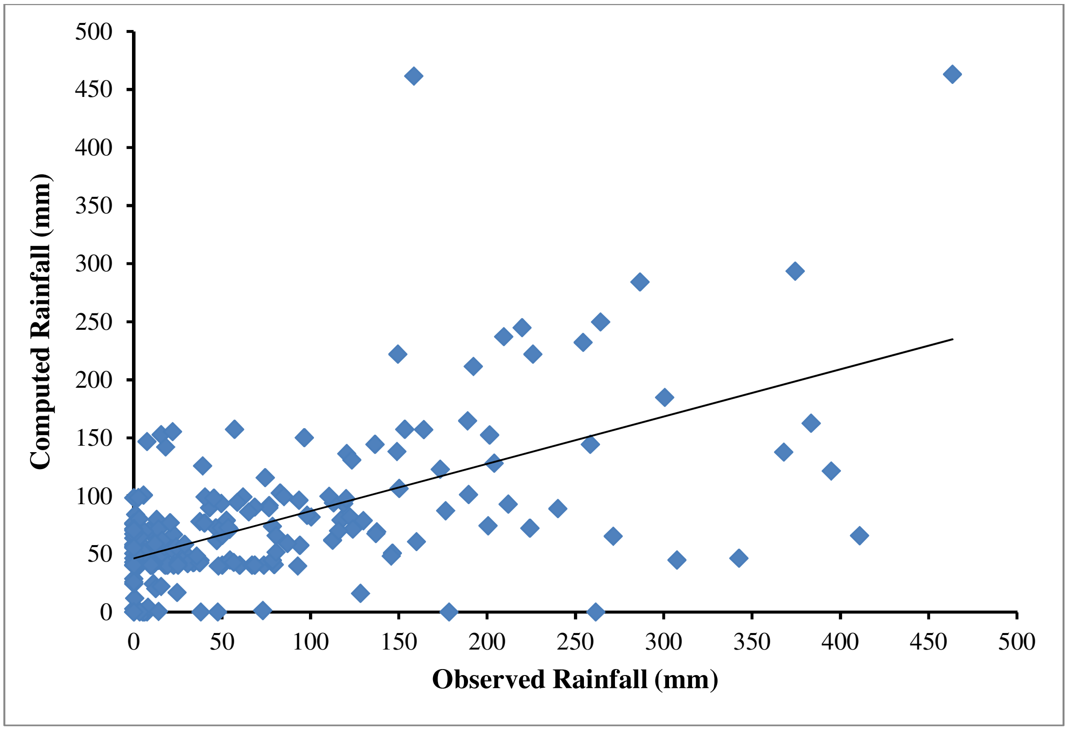

Fig. 4.59 **Scatter plot of observed and computed rainfall using MO-6model during testing period**

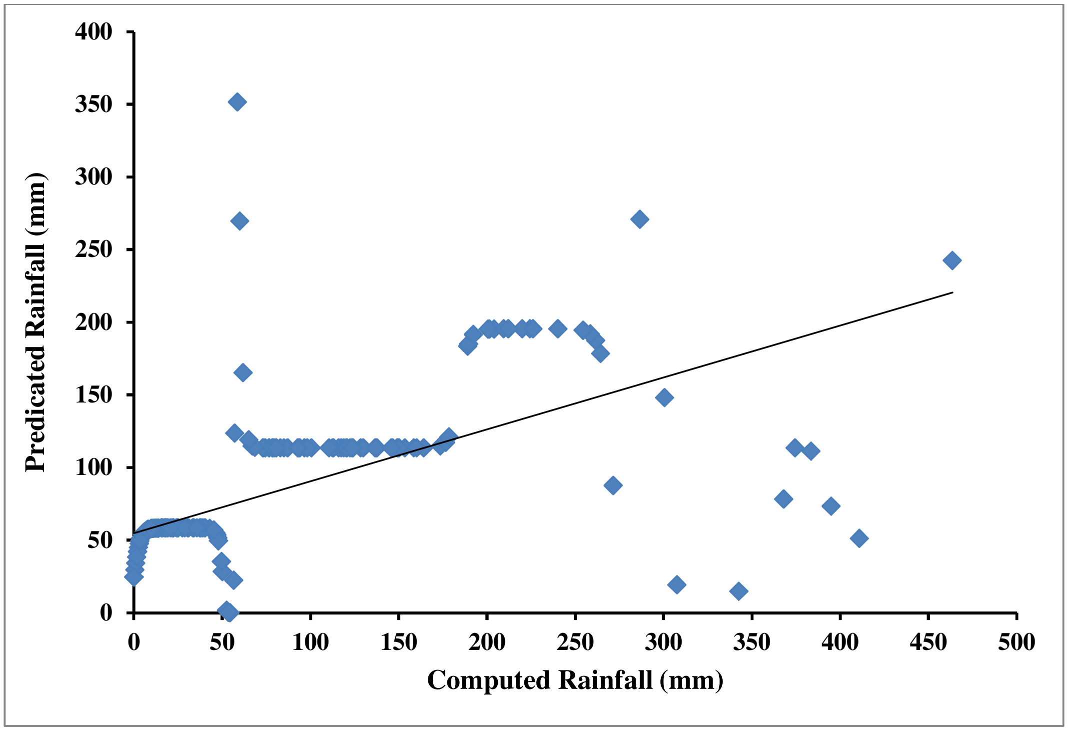

Fig. 4.60 Scatter plot of observed and computed rainfall using MB-1model during testing period

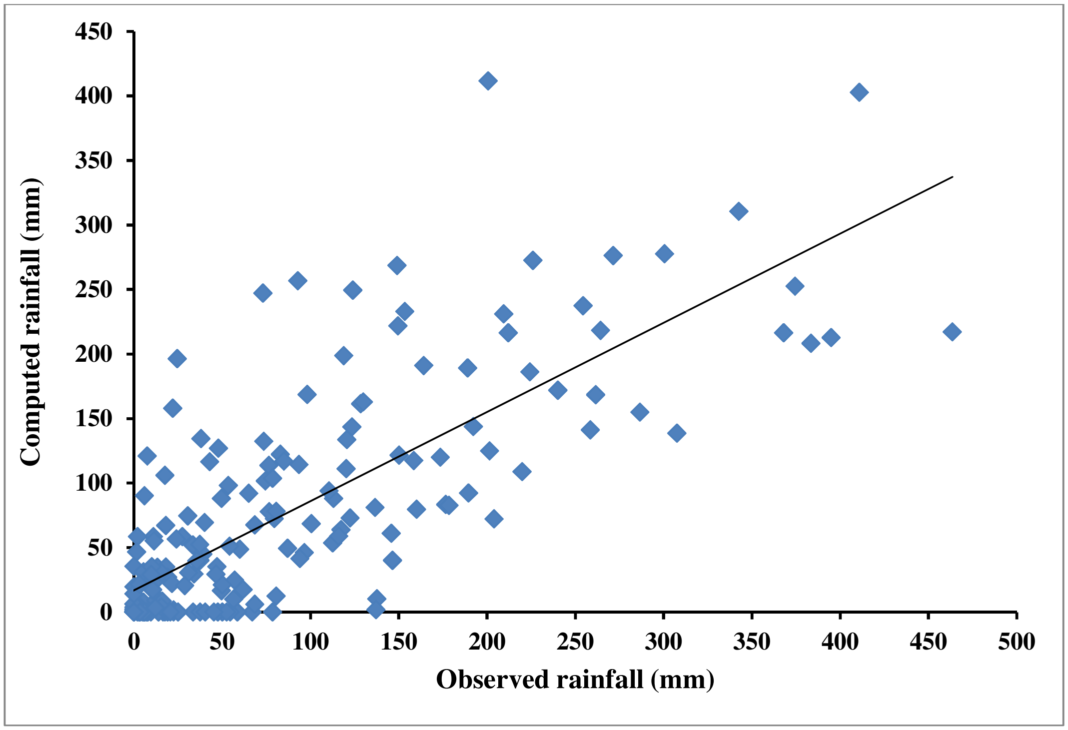

Fig. 4.61 Scatter plot of observed and computed rainfall using MB-2model during testing period

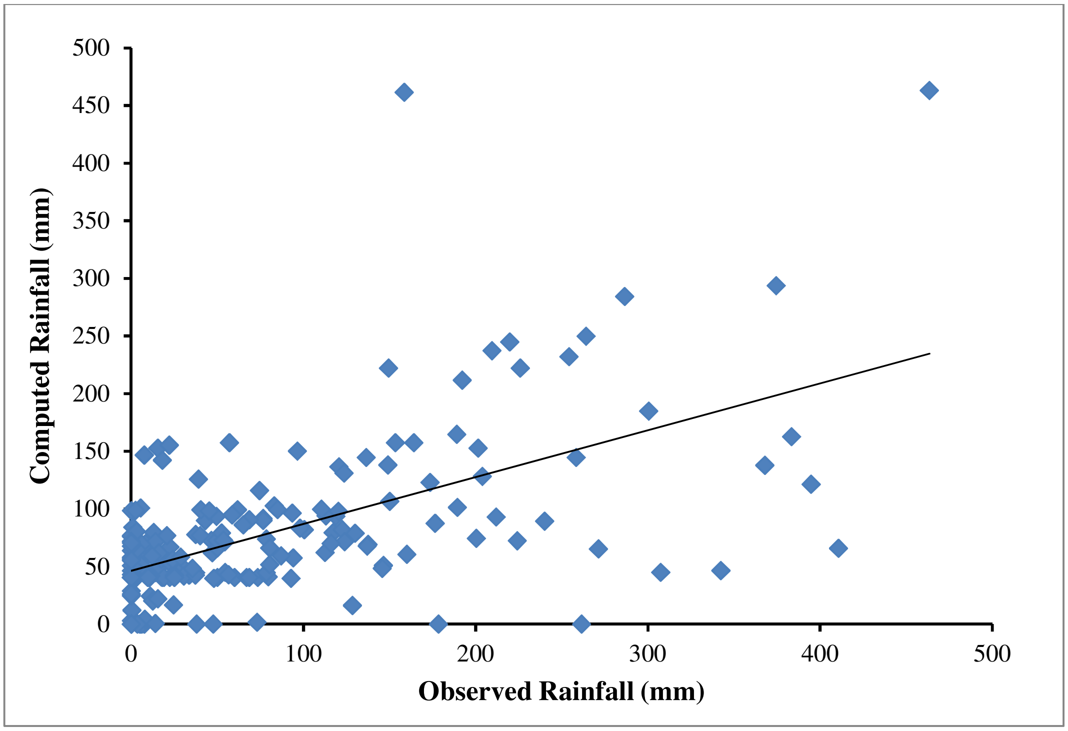

Fig. 4.62 **Scatter plot of observed and computed rainfall using MB-3model during testing period**

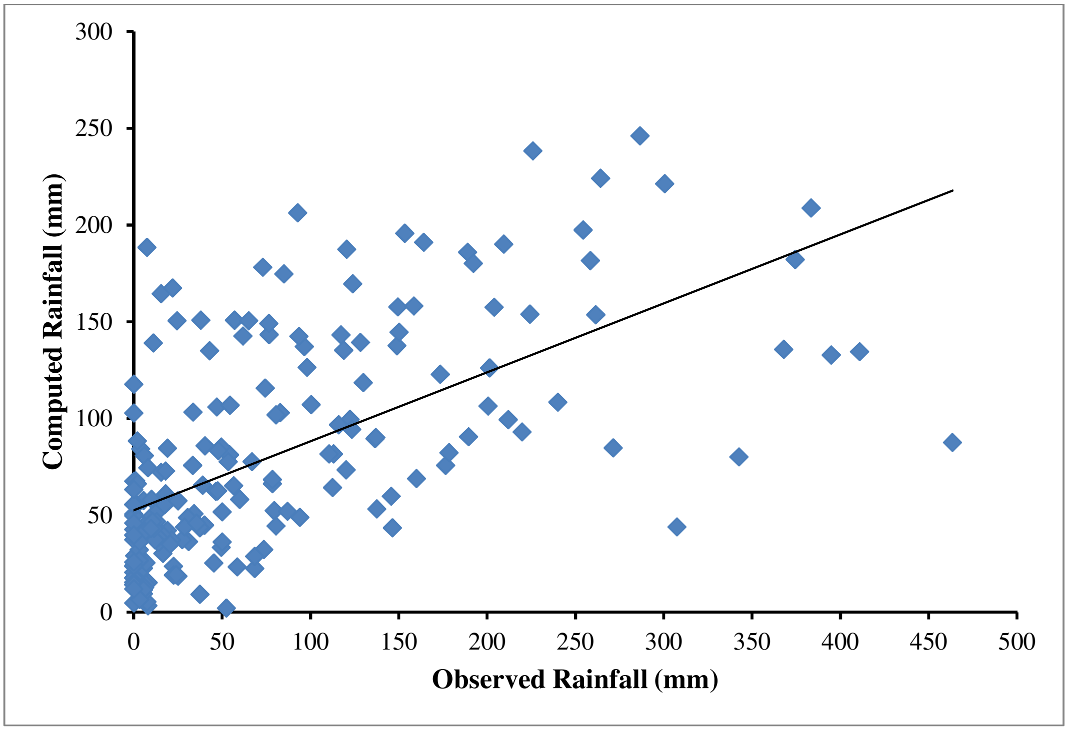

Fig. 4.63 **Scatter plot of observed and computed rainfall using MB-4 model during testing period**

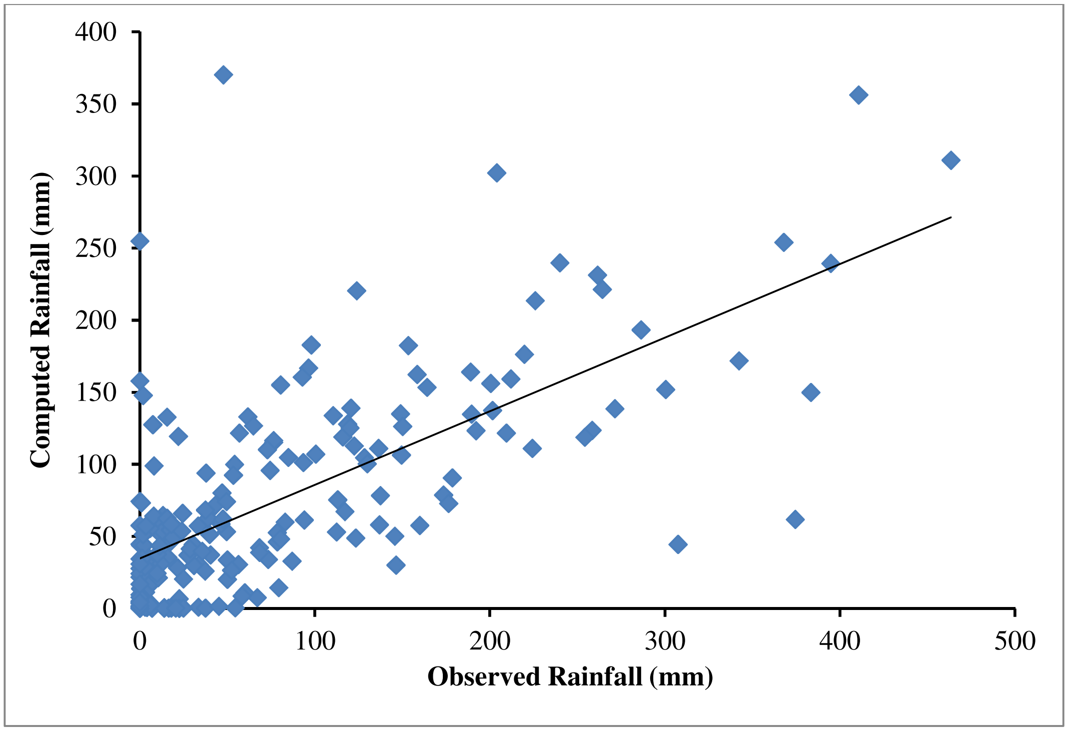

Fig. 4.64 **Scatter plot of observed and computed rainfall using MB-5 model during testing period**

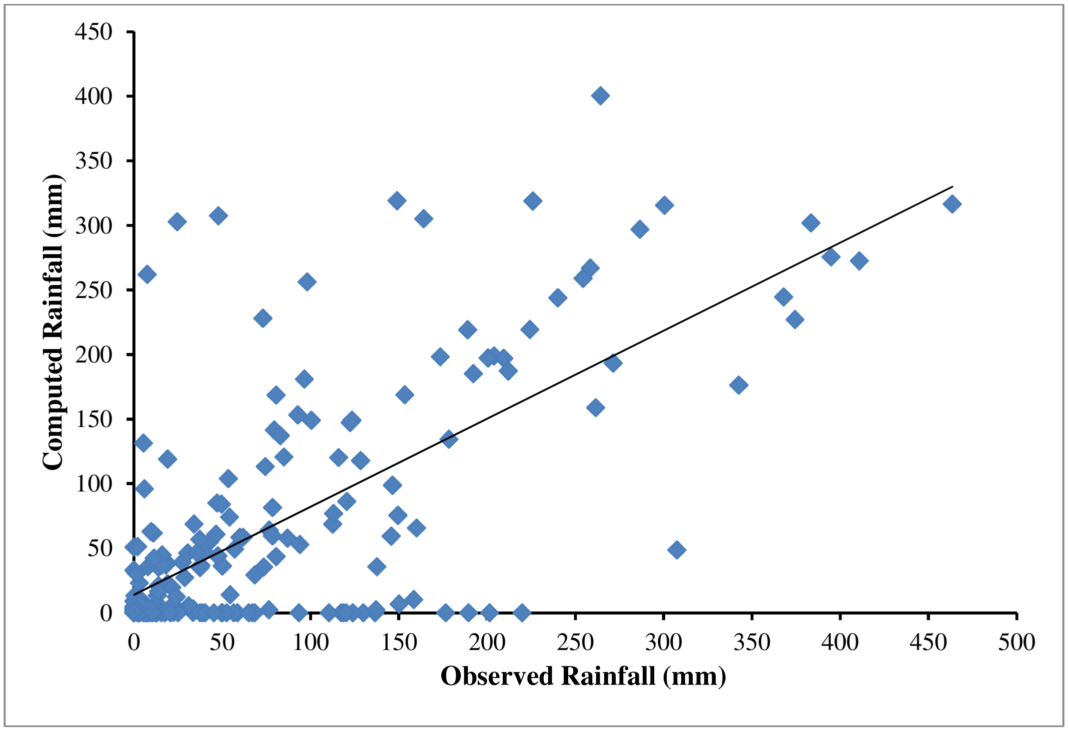

Fig. 4.65 **Scatter plot of observed and computed rainfall using MB-6 model during testing period**

4.3.2 Performance Evaluation of models by Quantitative assessment

For the evaluation of the model's quantitative assessment is considered better as it is also free from personal bias. Root Mean Square Error (RMSE), PBIAS, Integral Square Error(ISE), Coefficient of Efficiency (CE), Correlation Coefficient (r) were calculated using Equation 3.14 to Equation 3.18 respectively. In Table 4.3 and Table 4.4 the value of all the indices for training and the testing period are given respectively.

Further it is observed that RMSE for the selected models varied from 62.89mm to78.21mm and 61.35mm to 90.209mm for training and testing period respectively. The value of PBIAS varies from -3.87 to 3.02 and -14.04 to 3.67 for training and testing period respectively. The value of Integral Square Error varies from 3.42 to 4.23 and 5.77 to 8.14 for training and testing period respectively. The value of Coefficient of Efficiency varies from 0.29 to 0.54 and 0.1 to 0.58 for training and testing period respectively. The value of Correlation Coefficient varies from 0.54 to 0.73 and 0.45 to 0.77 for training and testing period respectively.

The models having maximum values of Coefficient of Efficiency and Correlation Coefficient and minimum value of Root Mean Square Error, PBIAS and Integral Square Error are considered as the best models among all the other models. MO-6 model was considered as the best model among all the other model at the selected station.

In MO-6 model the value of Root Mean Square Error was 62.89 and 61.35 for training and testing period respectively, value of PBIAS was -2.14 and -9.36 for training and testing period respectively, value of Integral Square Error was 3.45 and 5.99 for training and testing period respectively, Coefficient of Efficiency was 0.54 and 0.58 for training and testing period respectively, Correlation Coefficient was 0.73 and 0.77 for training and testing period respectively.

Thus, from comparison of qualitative and quantitative evaluation of models it is observed that MO-6 model is the best model among all the other model. In MO-6 model the present month rainfall depends on the present month rainfall one, two, three, four, five and six lag month rainfall. From the above discussion it was observed that those networks with a higher lag give better result in comparison to those with lower lag. Thus, it can be said that monthly rainfall series have long term dependence. This study shows that model MO-6 can predict the monthly rainfall accurately for Almora gauge station and can be used to interpolate the missing data.

Table 3 Performance evaluation indices of ANN model for Training Period

Model	Network architecture	Number of epochs	RMSE	P Bias	ISE	CE	r
MO-1	1-8-8-1	2000	78.21	-1.87	4.23	0.29	0.54
MO-2	2-7-1	2000	74.75	-1.27	4.04	0.35	0.6
MO-3	3-10-10-1	2000	67.91	-1.68	3.67	0.46	0.68
MO-4	4-6-6-1	2000	64.15	-2.08	3.47	0.52	0.72
MO-5	5-6-1	2000	67.64	1.19	3.66	0.47	0.7
MO-6	6-8-8-1	2000	62.89	-2.14	3.45	0.54	0.73
MB-1	1-9-1	2000	77.56	-0.37	4.2	0.36	0.55
MB-2	2-7-7-1	2000	74.2	3.02	4.01	0.36	0.6
MB-3	3-9-1	2000	65.31	-2.43	3.56	0.5	0.71
MB-4	4-10-10-1	2000	66.41	-0.66	3.59	0.49	0.7
MB-5	5-10-10-1	2000	66.34	-2.5	3.6	0.49	0.71
MB-6	6-9-9-9-1	2000	63.16	-0.68	3.42	0.54	0.73

Table 4 Performance evaluation indices of ANN model for Testing Period

Model	Network architecture	Number of epochs	RMSE	Pbias	ISE	CE	r
MO-1	1-8-8-1	2000	90.20	1.81	8.14	0.1	0.45
MO-2	2-7-1	2000	87.41	-1.6	7.02	0.35	0.47
MO-3	3-10-10-1	2000	63.31	2.39	5.77	0.56	0.75
MO-4	4-6-6-1	2000	71.37	3.67	6.51	0.44	0.68
MO-5	5-6-1	2000	65.81	0.82	6.06	0.52	0.73
MO-6	6-8-8-1	2000	61.35	-9.36	5.99	0.58	0.77
MB-1	1-9-1	2000	75.95	5.9	6.93	0.36	0.6
MB-2	2-7-7-1	2000	78.27	-0.175	7.143	0.32	0.58
MB-3	3-9-1	2000	76.67	-3.54	6.99	0.35	0.6
MB-4	4-10-10-1	2000	76.14	3.07	6.94	0.36	0.6
MB-5	5-10-10-1	2000	69.91	-4.039	6.94	0.46	0.68
MB-6	6-9-9-9-1	2000	68.65	-4.04	6.38	0.53	0.71

Summary and Conclusions

Chapter 5 SUMMARY AND CONCLUSION

For prediction of monthly rainfall for Almora Artificial Neural Networks models were developed using monthly rainfall data. The monthly rainfall data of Almora was divided into two parts, 38 years of data was used for calibrations of the modeland 16 years was used for verificationsof developed models.

Artificial Neural Networks (ANNs) based monthly models were developed for the rainfall by employing different inputs like rainfall of past one month, rainfall of past two month, rainfall of past three month, rainfall of past four month, rainfall of past five month and rainfall of past six month for prediction of monthly rainfall of current month. Various topologies of ANNs were constructed with alterations in number of hidden layers, the number of processing elements and activation functions which varied from 1 to 3 and number of neurons varied from 1 to 10.For the development of models, two transfer functions namely Log sigmoid Axon and TanhAxon along with Levenberg-Marquadt learning rule were employed in the development of models. The threshold limit of the root mean square error was fixed at 0.001. The trial and error method was used to determine the number of processing elements and the hidden layers. The number of epochs were fixed ass 2000. The value of root mean square error (RMSE) was used for the selection of the best optimized neural network structure.

The performance of the model was qualitatively evaluated by visually observing scatter plots andrainfall time series graphs and quantitative evaluation of models was done by employing various indices viz. Root Mean Square Error (RMSE),PBIAS, Integral Square Error (ISE), Coefficient of efficiency (CE) and correlation coefficient (r), for the prediction of monthly rainfall, the models having higher correlation coefficient (r) and coefficient of efficiency (CE) and lower values ofRoot mean square error (RMSE), PBIAS, Integral Square Error (ISE) were considered as the better fit of the model.

The following conclusions are drawn from the analysis of results are presented as following:

1. It is observed that 72.1 per cent of rainfall occurred during monsoon months (June to September) at Almora.
2. The monthly rainfall of all the months except that of August is right skewed.
3. The period from 1964 to 1982 consisted of a period of less than average rainfall and period of 1982 to 2016, period of greater than average rainfall. Similar pattern was observed in monsoon season rainfall (June to September), whereas trend is different in half yearly rainfall and October to January and February to May season rainfall.
4. It is observed that in general, the pattern of trend of June, July, August and September is similar to the trend of June to September seasonal rainfall and the trend pattern of November and December is similar to October to January rainfall, the trend of February, April and May seasonal rainfall is similar to the trend of February to May seasonal rainfall.
5. It was observed from the comparison of time series graph representing the observed and predicted monthly rainfall values that a better match in the outcomes was found in the case of MO-6 model when compared with the other model. The monthly rainfall predicted by employing MO-6 model was in accordance with the trend of observed rainfall.
6. The monthly rainfall which was predicted by MO-6 along with MB-6 model showed that the network with a higher lag reflected better performance in comparison with the lower lag models.
7. The outcomes yielded by comparison of scatter plots between observed and predicted monthly rainfall proclaimed that the model MO-6 was having smaller scatter near to the line of best fit when compared with other models, besides that the predicted monthly rainfall of MO-6 models were more closer to the best fit line as compared to other models.
8. The quantitative evaluation of the model yielded that the MO-6 model built up by network architecture of 6-8-8-1 have higher value for the correlation coefficient i.e. 0.73, coefficient of efficiency i.e. 0.54 and lowest values were reported for Root Mean Square Error (RMSE) i.e. 62.89, PBIAS (2.14) and Integral Square Error (ISE) i.e. 3.45, in case of training period. Whereas, in case of testing period,

the values of Correlation coefficient (r) and Coefficient of efficiency (CE) was observed high as 0.77 and 0.58 respectively and lowest values were reflected for Root Mean Square Error (RMSE) i.e. 61.35, PBIAS (-9.36) andIntegral Square Error (ISE) i.e. 5.99 for the testing period.

9. The findings of the study suggeststhat MO-6 Artificial Neural Networks (ANNs) model can be successfully employed for the monthly rainfall prediction at Almora raingauge station of Uttarakhand.

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ABSTRACT

Artificial Neural Networks model using different inputs were developed for monthly rainfall modelling of Almora. The 70% of monthly rainfall data from 1964 to 2018 was used for calibration and 30% for validation. Different topologies of models were constructed with change in number of hidden layers, processing elements and activation functions. The numbers of hidden layers varied from 1 to 3 and numbers of neurons from 1 to 10. Log-Sigmoid Axon & Tanh Axon transfer functions with back propagation algorithm and Levenberg-Marquardt learning rule were used. The performance of the models was evaluated qualitatively using rainfall time series graphs and scatter plots and quantitatively by employing Correlation coefficient, Root mean square error, Coefficient of efficiency, Integral square error and Pbias indices. The models having higher value of Coefficient of efficiency, Correlation coefficient and lower values of Root mean square error, Integral square error and Pbias were considered to be the best fit model. Based on the selected criteria, the performance of ANN model with 6-8-8-1 architecture with Log-SigmoidAxon transfer function with back propagation and Levenberg-Marquardt learning rule having past 1, 2, 3, 4, 5 and 6 months rainfall as inputs was found better than the other models.

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शोध का शीर्षक : "कृत्रिम तंत्रिका संजाल का उपयोग करके अल्मोड़ा के लिये मासिक वर्षा का प्रतिरूपण"

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सारांश

अल्मोड़ा के मासिक वर्षा प्रतिरूपण के लिए विभिन्न आदानों का उपयोग करते हुए कृत्रिम तंत्रिका संजाल मॉडल विकसित किए गये। १९६४ से २०१८ मासिक वर्षा के आंकड़ों का ७०% प्रशिक्षण के लिए और ३०% सत्यापन के लिए उपयोग किए गये। छिपी हुई परतों, प्रसंस्करण तत्वों और सक्रियण कार्यों की संख्या में परिवर्तन के साथ मॉडल के विभिन्न टोपोलॉजी का निर्माण किया गया था। छिपी हुई परतों की संख्या १ से ३ तक और न्यूरॉन्स की संख्या १ से १० तक भिन्न होती है। लॉग-सिग्माइड एक्सॉन और टैन एच एक्सॉन स्थानांतरित फलनों के साथ बैक प्रोपेगेशन एल्गोरिथ्म और लेवेनबर्ग-मार्क्वार्ड सीखने के नियम का उपयोग किया गया था। मॉडल के प्रदर्शन का मूल्यांकन गुणात्मक रूप से वर्षा समय श्रृंखला ग्राफ और बिखराव भूखंडों का उपयोग करके किया गया तथा सहसंबंध गुणांक, रूट माध्य वर्ग त्रुटि, दक्षता का गुणांक, इंटीग्रल वर्ग त्रुटि और पि बायस सूचकांकों को नियोजित करके मात्रात्मक रूप से मूल्यांकन किया गया। दक्षता और सहसंबंध गुणांक के उच्च्च मूल्य वाले और रूट मीन वर्ग त्रुटि, इंटीग्रल वर्ग त्रुटि और पि बायस न्यूनतम मूल्य मॉडल को सबसे अच्छा योग्य मॉडल माना गया । चयनित मापदंड के आधार पर, लॉग-सिग्माइडएक्सन ट्रांसफर फ़ंक्शन के साथ ६-८-८-१ स्थापत्य के साथ एएनएन मॉडल का प्रदर्शन बैक प्रोपेगेशन और लेवेनबर्ग-मार्क्वर्ट अधिगम नियम के साथ १,२,३,४, ५ और ६ मासिक वर्षा आदानों के रूप में अन्य नमूनों की तुलना में बेहतर पाया गया।

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