DEVELOPMENT OF RAINFALL-RUNOFF EMPIRICAL MODELS IN BANAS RIVER BASIN, RAJASTHAN, INDIA

Ph.D. Thesis

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by

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DECLARATION

I **Sunil Kumar Vyas**, declare that this thesis titled, **"Development of Rainfall-Runoff Empirical Models in Banas River Basin, Rajasthan, India"** and the work presented in it, are my own. I confirm that:

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This is to certify that the thesis entitled **"Development of Rainfall-Runoff Empirical Models in Banas River Basin, Rajasthan, India"** being submitted by **Sunil Kumar Vyas, ID: 2011 RCE7134**, is a bonafide research work carried out under our supervision and guidance in the fulfillment of the requirement of the award of the degree of **Doctor of Philosophy** in the Department of Civil Engineering, Malaviya National Institute of Technology, Jaipur, India. The matter embodied in this thesis is original and has not been submitted to any other University or Institute for the award of any other degree.

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Date:

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Date: ___________

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Abstract

The transformation of rainfall occurred within a catchment into runoff, is a highly complex natural phenomenon, influenced by many local topographic, geographic, geologic, and sociologic factors, but the main and the principle factor that affects the runoff is the local areal and temporal rainfall and its distribution. The quantitative relation between the rainfall occurred and the corresponding runoff in a catchment is called rainfall-runoff model. Since, the rainfall records of longer period are available and are easy to be collected than runoff data, there is a need to develop the rainfall-runoff model, which compensates the lack of runoff data for evolving effective water management strategies.

Regression technique is being used from past, but from past few decades soft computing techniques are also used for rainfall-runoff modelling, as a substitute of regression technique. Artificial Neural Networks (ANN), Genetic Algorithms (GA) and Fuzzy Logic (FL) or combination of any two are major soft computing techniques, which are commonly used, to yield an approximate solution to a problem for quick solution.

For the fulfilment of the objectives of the present study, the study area (Banas River Basin) was divided in 9 sub-basins, based on the ridge lines of the sub-basins. A dam catchment from each sub-basin was selected for rainfall-runoff analysis and model development. Total effective rainfall over each selected dam catchment was computed, by applying Thiessen's Polygon weighted technique, on the affecting raingauge monthly rainfall data. Total effective runoff from the dam catchment, was computed using net dam inflow with addition of total evaporation from the water bodies in the catchment and itself, in the particular month. The total effective rainfall and corresponding total effective runoff for 20 years data from 1996 to 2015, converted in mm

depth and then used for model development

Entire data was divided into four parts adopting four-fold hold out technique; one part on rotation at a time was used for validation purpose and the remaining three parts for training of the sub-model, the sub-models were named as 1V, 2V, 3V and 4V. Three performing metrics namely correlation of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), were used for comparing the training and validation performance of the developed sub-models. Simple ranks were allotted to each performing metric according to its value providing equal importance to each metric in training and validation process, average out the allotted ranks and then obtained final ranks, were used for comparing the prediction accuracy of the developed sub-models. The best one out of these four developed sub-models would be the model having the best rank.

Using regression and soft computing techniques four types of rainfall-runoff empirical models namely, first and second order polynomial regression models, ANN and ANFIS soft computed models have been prepared. Then a decision support tool having the option of selection of a model type, giving liberty to the model user was also prepared.

The results show that as the order of the regression model is increased, there is an improvement in the prediction accuracy during training and validation. The ranking of all performance metrics taken together demonstrate that the ANN and ANFIS models are superior to the regression models. The value of runoff predicted by ANN and ANFIS are very closer to the actual runoff as compared to, the first and second order regression models in most of the time periods. The value of the statistical parameters, i.e. mean, standard deviation and skewness for the runoffs, predicted by ANFIS and ANN are also closer to the parameters of the actual runoff, which also shows their consistency and good prediction accuracy.

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List of Symbols and Abbreviations

BP	Back Propagation Algorithm
ANN	Artificial Neural Networks
ANFIS	Adaptive Neuro Fuzzy Inference System
MFNN	Multilayer Feedforward Neural Network
BPNN	Back Propagation Neural Network
LMBNN	Levenberg-Marquardt Back propagation Neural Network
GA	Genetic Algorithms
FL	Fuzzy Logic
p_{norm}, $p_{\max}$ and $p_{\min}$	Normalized, maximum and minimum value of variable p respectively
T_i	Target or actual value of runoff for ith pattern
P_i	Predicted value of runoff for ith pattern
$\overline{P}, \overline{T}$	Mean of model predicted and actual value of runoff
N	Number of data pairs
e	Network error evaluated as difference between T_i and P_i
$\overline{e}$	Mean of e
y	Dependent or response variable
$x_1, x_2, x_3, \ldots\ldots\ldots\ldots, x_n$	Independent or regressor variables

$\beta_1, \beta_2, \beta_3, ..., \beta_k$	Partial regression coefficients
ε	Random error
$\beta_i, \beta_{ii}, \beta_{ji}$	Linear, quadratic and interaction coefficients
MAE	Mean absolute error
R	Correlation coefficient
R^2	Coefficient of determination
$RMSE$	Root mean square error
w_n	Weight of connection from one layer neuron to the other layer neuron
b	Bias at any layer neuron
X_i	Total effective rainfall
Y_i	Total effective runoff

Introduction

1.1 General

Water is the most precious resource for the sustenance of life on earth, and is necessary for human beings next to air. It is the most critical and finite natural resource for the survival of mankind, making it necessary to assess the realistic available water and utilize in most efficient and economic way. As per the report of National Commission for Integrated Water Resources Development Plan (1999), Ministry of Water Resources (MOWR) the average annual surface runoff in the different river basins of India is assessed to be about 4000 cubic km and 80 % of it is generated during the monsoon period i.e. between June to September. The annual rainfall distribution in India varies, from less than 25 cm in Great Thar Desert in Rajasthan to about 1150 cm in Meghalaya Hills. Similarly, the ratio of maximum discharge to the minimum discharge at particular site in a river is also very large in perennial rivers. The variations in river flows during monsoon and non-monsoon months are also quite considerable, and due to limited provision for water storage, a large portion of the runoff goes waste in the monsoon months. The above features lead to occurrence of flood-drought-flood syndrome in various parts of the country.

As per Tahal Report on Integrated Water Resources Plan for Rajasthan (2014), Rajasthan state receives an average annual rainfall of 60.4 cm and monsoon rainfall is 53.1 cm. The rainfall intensity and its pattern in the state are highly erratic and sporadic, the extreme hydrological events i.e., floods and droughts are more frequent with scarce underground resources. The rivers in Rajasthan are mostly Monsoon flowing Rivers. Hence, a system of basin planning is necessary to preserve, conserve and utilize available water most economically in the state.

For the efficient management of water, it requires rainfall-runoff modeling and forecasting for its optimal planning, that needs low as well as high inflow modeling. The low inflow modeling is used for determining the assured water available during water scarcity periods, while the high inflow modeling is used for determining the surplus water available in the flooding period.

The rainfall-runoff model involves the conversion of rainfall occurred within a catchment into runoff, a highly complex natural phenomenon that passes through different inter-related processes and influenced by many local topographic, geographic, geological and sociological factors. The conversion of rainfall into runoff is shown in the Figure 1.1.

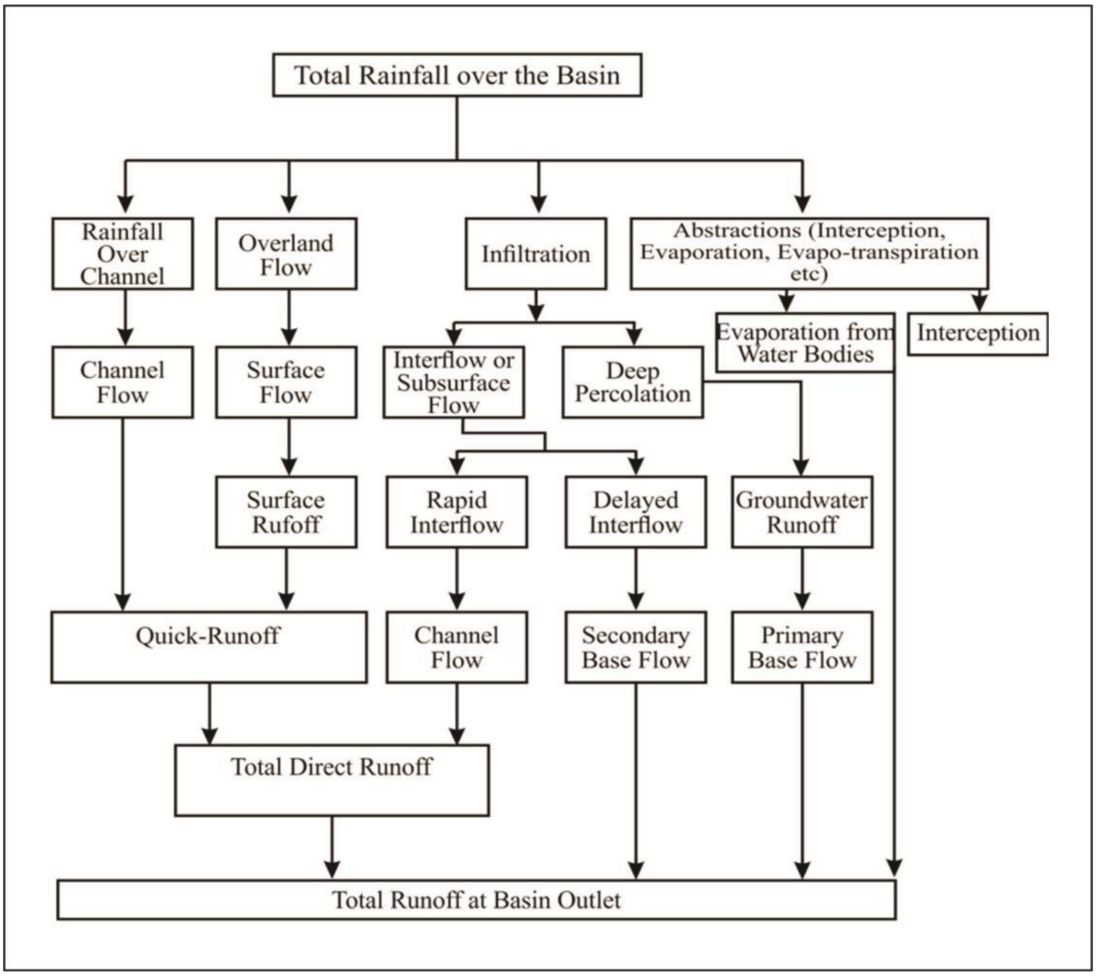

Figure 1.1: Flow chart of rainfall-runoff model (Punmia & Pandey, Laxmi Publications, New Delhi)

In the present thesis an attempt has been made to review the literature available on the methodology and development of rainfall-runoff empirical models, using conventional regression and soft computing techniques, including Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS), forecasting with a view to prepare a concise reference on the subject. Four types of rainfall-runoff empirical models namely first and second order polynomial, ANN and ANFIS models have been developed, compared in terms of the model performing parameters namely co-relation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE) with sum of ranking.

1.2 Rainfall-Runoff Modeling

Hydrological modeling is mathematical or computed simulation of natural hydrological phenomena, considered as a single or group of processes or systems, undergoing continuous changes with time. The simulation of natural process in mathematical modeling needs a certain amount of conceptualization for adopting the computational procedure of the model. It requires extensive datasets for calibration of various parameters and checking its validation and is used for prediction purpose at later stage. Various techniques used in hydrological model development and the selected model developing technique should provide a forecasted value as well as the forecasting error, that can be compared by selecting certain performing metrics based on predicted and actual values.

Hydrological systems are so complex that no exact physical laws have yet been formulated, for explaining the natural phenomenon completely and with precision. In reality, all hydrological systems are non-linear, stochastic and time variant processes. A number of hydrological models are available and are in use for analytic purposes but the effectiveness of a model depends on the degree to which the model simulates the natural process.

Although rainfall-runoff model is primarily dependant on natural parameters, but the human intervention to the system also influences the situation in one or the other way. The runoff transformed from the occurred rainfall in a specified area depends on different local topographic, geographic, geologic, and sociologic factors. Many factors contribute in the rainfall-runoff process but the main and the principal factor that affects the runoff is the local areal rainfall and its distribution.

Based on the approach used in the model development, the rainfall-runoff models may be divided into two major groups namely, (i) Empirical models and (ii) Conceptual models.

In empirical approach the principal objective is to estimate the value of the dependent variable from the independent variables only, while in the conceptual approach the principal objective is not only to arrive at an estimated value of the dependent variable from the values of other parameters, but also, to study the degree of their mutual dependence. The conceptual rainfall-runoff models explain mathematically the processes of the hydrological cycle, based on the physical laws responsible for each process but the calibration of these processes is not easy and in many cases it depends on the field survey for data, which are scarce. The use of basin averages for relevant parameters and their non-linear behaviour also give additional difficulties. Due to these characteristics, the implementation of the conceptual model often render difficult and financially burdensome. The empirical rainfall-runoff models are obtained by establishing a stable relationship between the rainfall as input and runoff as output variables. It is a black box model where the variables are the part of the structure of the expression which may or may not be dimensional homogeneousness.

The available different model developing techniques may be divided in two types namely, conventional regression technique and soft computing techniques. Due to the unstructured, non-linear and complex natural behavior of the rainfall-runoff model, the computation of runoff becomes difficult in conventional regression computing. On the other hand soft computing techniques are becoming very popular with the development in the computer field, which harnesses reasoning, intuition, consciousness and wisdom possessed by human beings. Soft computing aims at exploiting given tolerance of precision, the trivial and uncertain nature of the problem to yield an approximate solution to a problem in quick time. Soft computing method involves use of Artificial Neural Network (ANN), Genetic Algorithms (GA), Fuzzy Logic (FL) and Adaptive Neuro Fuzzy Inference System (ANFIS). Artificial Neural Network (ANN) is inspired by learning ability of the human brain which is able to imbibe the subtle relationships between the dependent and independent variable whose interactions are unknown, non-linear or too complex to represent. Genetic Algorithms (GA) represents a stochastic search and optimised computational tool that revolves around the evolutionary theories of natural genetics and natural selection. Fuzzy Logic (FL) helps in solving real life problems which are always in some way or the other prone to ambiguity and uncertainty. ANFIS is a combination of ANN and Fuzzy Logics that have also been successfully used for developing rainfall-runoff models.

Updating the latest knowledge with appropriate data communications, operations and processing system procedures are being adopted for more accuracy.

In short, the accuracy and timeliness of developed model depend on the amount and reliability of hydrological and meteorological information, the procedure on which the forecasts are based, speed of processing and the time taken to disseminate the forecast to the users.

1.3 Research problem - Rainfall-Runoff Empirical Modeling in Banas River Basin

The study area (Banas River Basin) as shown in the Figure 1.2, is the largest river basin in Rajasthan with a total catchment area of 47060 sq. km. which is 13.4 % of the state area. There are 9 major dams, 36 medium dams and 1282 minor irrigation structures in Banas River basin.

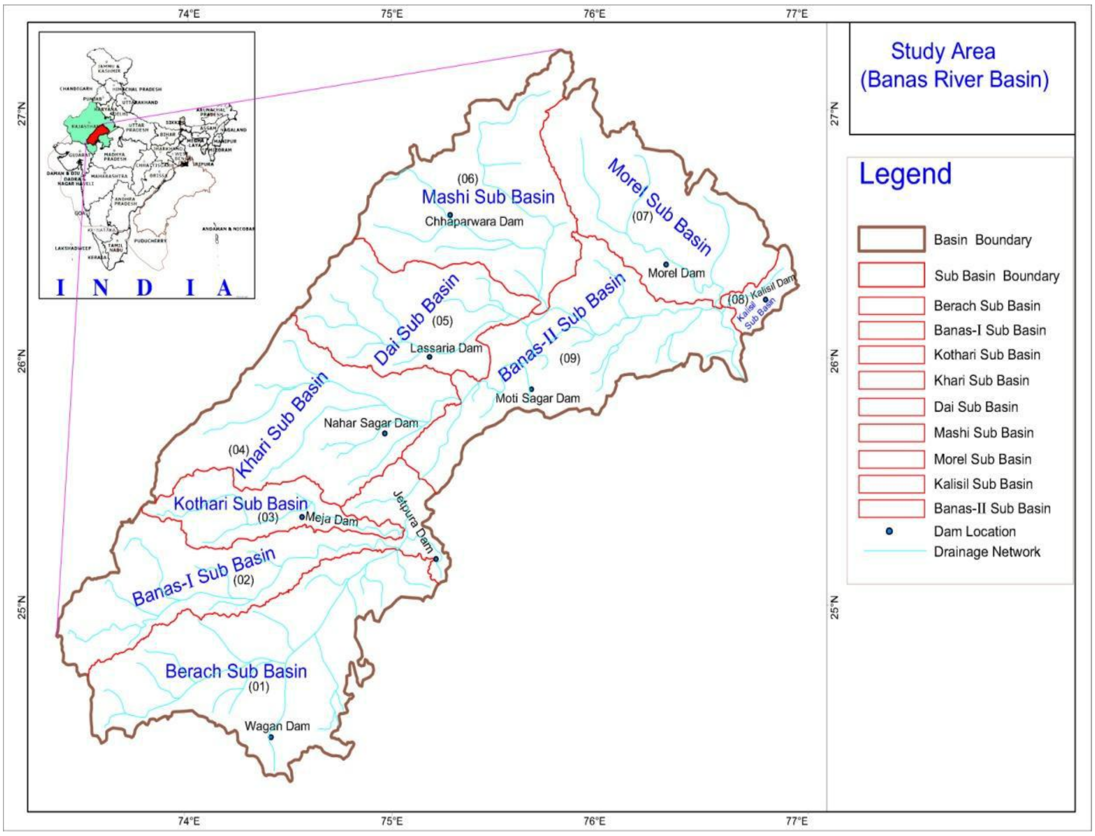

Figure 1.2: Map of the Study Area (Tahal 1998)

Following three inter-related problems are normally found in the rainfall-runoff modeling : -

a) Rainfall data is measured accurately but the runoff data is not reliable as it is being collected by less skilled personnel.

b) The temporal and spatial variability in the hydrologic data influences the models reliability and accuracy, which are directly used as input in all types of models.

c) Assumptions and simplifications, inherent to any modeling which is site or region specific, lead to over simplification of the variability.

1.4 Need and importance of the present study

The availability of water resources, particularly during the non-monsoon period generally remains unaltered. Also, there is generally a gradual reduction in the availability of water during the monsoon period due to various factors such as deforestation, urbanization etc. Thus, the water requirement is increasing and its availability is reducing. Hence in order to manage the precious water resource, there is a need for a detailed thorough analysis of rainfall and corresponding runoff.

Since the rainfall records of longer period are available and easy to be collected than runoff data, there is a need to develop the rainfall-runoff model based on the local physical characteristics and climatic factors of the catchment, to compensate the lack of runoff data for evolving effective water management strategies. Presently, Water Resources Department, Rajasthan is using Strange's Table for computing runoff for future planning of the area. No scientific research has been undertaken in any of the river basin in Rajasthan which improves the water resources planning in the state.

Hydrological data and their statistical analysis play a significant role in the planning of water resources projects, whereas the rainfall and its corresponding runoff forecasts are necessary for the efficient operation of these projects. The observed historic data provide possible range and some probable situations. Such exercises are relevant in the evaluation of the economic viability of the project and formulating guidelines for reservoir operations.

Rainfall and its corresponding runoff forecasts are formulated round the year to plan or modify the operating procedures keeping in view the available storage and the water requirement. Rainfall-runoff modeling is very much needed in the planning of seasonal utilization of water and developing periodic regulation schedule. When this forecasting is extended to cover the river flow throughout the year, then it also provides useful information for reservoir operation.

Rainfall-runoff models developed for different time periods for a river are significant for addressing various aspects of economy and ecology. The quantitative aspects include water supply for domestic, industrial and agricultural purposes, hydro-electric power generation and navigation. Chemistry and biology of the river water and ecosystems constitute the qualitative aspects.

Thus, timely evaluation and forecasting of the river-flows is of great help and important in decision making processes for appropriate water use. The demand for the information regarding rainfall and its corresponding runoff with required prediction accuracy may vary from case to case. It is desirable to have a prior estimate of water available that could be drawn from reservoirs for various uses in several months in future, particularly for drought prone regions. The wide range of application further stresses on the necessity and need for rainfall-runoff model studies.

1.5 Objectives of the present study

Following three objectives are identified for the present study ‘Development of rainfall-runoff empirical models in Banas River basin’:

a) To develop an empirical relationship between monthly rainfall and its corresponding runoff by employing regression and soft computing techniques for the study area.

b) To compare the effectiveness of the conventional regression techniques and soft computing techniques using three different performance metrics namely co-relation coefficient, root mean square error and mean absolute error.

c) To develop a decision support tool that can provide liberty to the model user, to modify the developed model for the use under different climatic condition and basin characteristics, with the effect of temporal variation.

1.6 Limitations of Rainfall-Runoff modeling

Utility of rainfall-runoff empirical model depends on its timeliness and accuracy. Hence, an adequate data network as well as its well distribution is very much desired in runoff forecasting. The data network includes hydrological and hydro-meteorological observations on the basis of an optimal design of such stations.

In case of larger river systems, it becomes very difficult to separate out the contributions from various sources. Many a times the contribution from glaciers, groundwater reservoirs, irrigation recharge etc. cannot be estimated precisely. It gets further complicated with the existence of major regulatory structures. Due care must be taken to separate out the effects of regulatory structures. Similarly, the effects of local factors, duration and localized intense rainfall with areal distribution, are also to be dually considered.

1.7 Organization of the thesis

This dissertation has been divided into 6 chapters. A brief overview of the contents of each chapter is summarized as below:-

Chapter 1: The chapter introduces the basic idea of rainfall-runoff modeling and the research problem. Need for the study, research objectives and its limitations have been dealt in this chapter.

Chapter 2: The chapter titled as literature review covers the model concept and classification of the various hydrological models, with analysis and forecasting techniques are discussed. The literature related for the development of rainfall-runoff empirical models using regression and soft computing techniques, used in the present study namely, first order and second order polynomials, Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) are discussed. The referred previous studies related to rainfall runoff modeling are also critically analysed in this chapter.

Chapter 3: General characteristics of Banas River basin are summarized in this chapter. In this chapter general geography, geomorphology, geology and Hydrogeology of the basin are included. Climatologic and weather statistics are also discussed. The soil cover and the present land use pattern being followed in the basin are also included in this chapter.

Chapter 4: Components of the rainfall-runoff model and its procedural development are explained in this chapter. The required data for the model and the scope of the application of the developed models, with limitations are also discussed in this chapter. Methodology selected for model development and for checking its consistency, using different model performance metrics and statistical parameters are explained here.

Chapter 5: The final results and related interpretations, obtained after developing the rainfall-runoff empirical models, in different sub-basins are presented here.

Chapter 6: The overall summary of the study with the conclusions drawn from it and the recommendations for future work are discussed in this chapter.

Appendix I: Marked Catchment area and Thiessen's polygons drawn for the selected dam catchments are appended here.

Appendix II: The computed total effective rainfall values, its corresponding total effective runoff values and mean annual evaporation data for the selected dam catchments are appended here.

Literature Review

2.1 Introduction

Rainfall and the corresponding runoff are of immense importance in hydrology. Runoff with its spatial and temporal distributions is directly used in water resources projects. Efforts for establishing quantitative relationship between rainfalls occurred and the resulting surface or sub-surface runoff in different regions is being attempted since long. The quantitative relationship established between the rainfall and the corresponding runoff is termed as “rainfall-runoff model”.

2.2 Hydrological Cycle and its components

The regular cyclic movement of the water i.e., evaporation of water from oceans and land surface, transpiration from vegetative surface in the form of water vapour gets lifted up and stored in the clouds in the atmosphere until it condenses and precipitates in the form of rainfall on the land surface or in the ocean. The precipitated water may be intercepted by local vegetation, become overland flow over the ground surface called surface runoff, infiltrate or flow below the soil sub-surface called sub-surface runoff, discharges into streams as surface runoff. The infiltrated water may join groundwater, later emerge out as spring and seeps into streams to form surface runoff and finally flow into the sea or evaporate into the atmosphere as the hydrologic cycle continues. Although the concept of hydrologic cycle seems to be simple, in actuality it is complex and intricate phenomena. It is not just one large cycle but it is composed of many inter-related cycles of local, regional and continental scale.

The water balance or the continuity equation considering only the land phase of the hydrological cycle is given by

$$I - O = \pm \Delta S \qquad (2.1)$$

where, I is the input to the system in the form of rainfall, O is output from the system in the form of evaporation, transpiration, interception, stream and groundwater flow and is the change in soil moisture or water storage.

2.3 Factors affecting rainfall-runoff model

The rainfall occurs within a catchment and the conversion of this rainfall into runoff depends on many local climatic, morphological, morphometric, hydro-geological and human influencing factors that may directly or indirectly influence the rainfall-runoff model. The general factors, described by McMohan and Arenas (UNESCO, 1982) that affect the rainfall-runoff modeling are attached at Appendix-III.

2.4 System approach, modeling concept and classification of rainfall–runoff models

2.4.1 The system

A hydrological system or rainfall runoff model is a structure or space volume surrounded by defined boundaries that receive measurable water as rainfall with other measurable input variables. It internally operates on them and then gives output as runoff in a measured variable form.

2.4.2 Concept of rainfall-runoff models and its classification

The concept of overall areal or geographical distribution of the rainfall and its corresponding generated runoff can be summed up in a rainfall-runoff model and this rainfall-runoff modeling concept can be represented in a flow chart form. The brief view of the rainfall-runoff modelling concept is already represented in a flow chart as shown in Figure 1.1.

Existing rainfall-runoff models can be classified based on randomness of the variables, consideration of physical processes, superposition criteria, spatial variation and technique used. The general classification of the rainfall runoff models is shown in Figure 2.1 and a brief introduction of the models are as follows-

(1) Empirical /Input-output/ Black box models identify a relationship between the input as rainfall and output as runoff, without attempting to describe the transformation processes. In other words it is developed without any consideration of the physical processes happening in the catchment. The model is merely based on the analysis of concurrent rainfall and its corresponding runoff time series.

(2) A statistical model is based on the approach involving functional relationship between rainfall and its corresponding measured runoff data. Various statistical methods have been developed, extensively in hydrology with the support from developed basic statistical theories applied in other fields.

(3) A stochastic model has some component of random character, having a probability distribution with time. Identical rainfalls may result in different runoffs, if the same is run through the model under identical conditions.

(4) A deterministic model is one in which no uncertainties in runoff prediction are admitted, so that two equal sets of rainfalls always yield the same runoff if run through the model under identical conditions. The model has no component with stochastic behaviour i.e. the variables are free from random variation and have no distribution in probability.

(5) A physically based mathematical models/ conceptual model is based on some consideration of the physical processes in the catchment. In a conceptual model physically sound structures and equations are used together with semi-empirical relations. However, the physical significance is not so clear that the parameters can be accessed from direct measurements. It is necessary to estimate the parameters from calibration, applying concurrent input and output time series. A conceptual model which is usually a lumped type model is often called a grey box model.

(6) A lumped model is a model where the catchment is regarded as one unit. The input variables and parameters represent average values for the entire catchment.

(7) A fully physically or geographically based distributed model describes the system using the basic equations governing the flows of energy and water in the catchment. A fully physically based model in practice also has to be a fully distributed model which takes into account the spatial variations in all variables and parameters. Representative Elementary Watershed (REW) approach gives an alternate blueprint for geometrically distributed models.

(8) If there is a linear relation between the rainfall and its corresponding runoff then it is called linear model.

(9) If the estimated runoff variable has non-linear function of independent variable rainfall then it is called non-linear model. It may be polynomial of any degree, exponential or logarithmic.

(10) The rainfall-runoff models developed using the conventional regression theories are known as conventional regression models.

(11) The rainfall-runoff models developed using the soft computing techniques i.e. ANN, Genetic Algorithm, Fuzzy Logics or its combination are known as soft computing models.

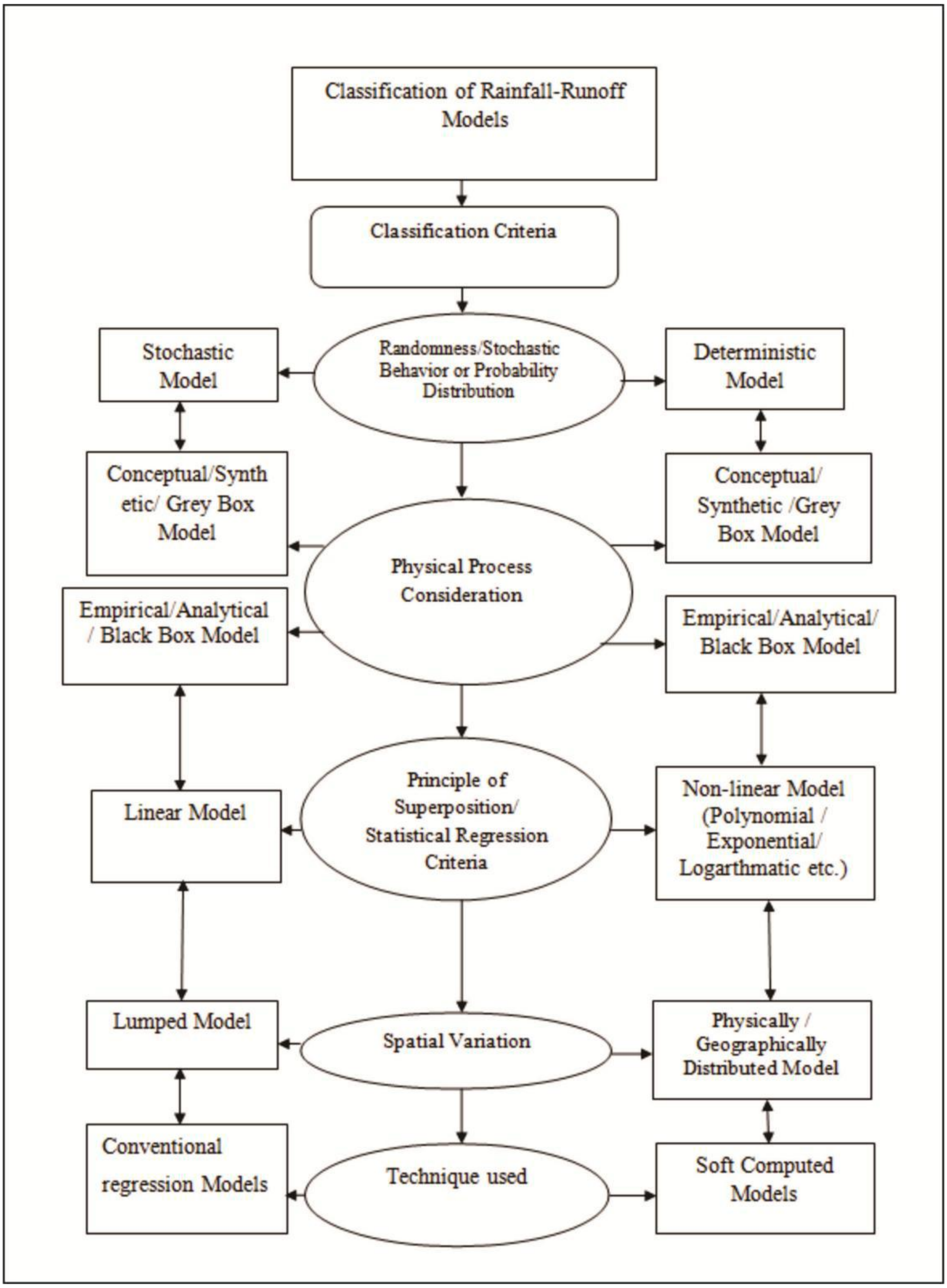

Fig. 2.1: Classification of rainfall-runoff models

A fully geographically distributed hydrologic model considers the local properties of the catchment and shows the individuality in the results hence it is more practical. .

2.5 Regression analysis

Regression analysis is a statistical tool with the help of which one can estimate or predict the unknown values of the dependent variable from known values of independent variables and it is based on the principle of least sum of square errors between the actual and the computed dependent variable.

2.5.1 Rainfall-runoff empirical modelling using first and second order regression

A mathematical relationship established between an independent variables and a dependent variable in an equation form using regression analysis is called regression models. If there is a dependent variable y which is dependent on k independent variables viz., $x_1, x_2, x_3, \ldots\ldots\ldots\ldots, x_k$.

First order polynomial regression model is based on Multiple Linear Regression (MLR) analysis containing one or more number of independent variables that affects the dependent variable which can be expressed as: -

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_k x_k + \varepsilon \qquad (2.2)$$

where, y is the dependent variable, β_0 is the intercept, $\beta_1, \beta_2, \ldots\ldots\ldots\ldots, \beta_k$, are the partial regression coefficients, $x_1, x_2, \ldots\ldots\ldots\ldots, x_k$ are independent variables and ε is the random error.

If there are m sets of observations $x_{1i}, x_{2i}, \ldots\ldots\ldots\ldots, x_{ki}$, y_i (i=1, 2,………, m), then the model for the i^{th} observation is:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots\ldots\ldots\ldots + \beta_k x_{ki} + \varepsilon_i, \; i = 1, 2, \ldots\ldots\ldots, m \qquad (2.3)$$

Alternatively, in matrix forms the above equation can be written as

$$Y = X\beta + \varepsilon \tag{2.4}$$

Where,

$$X = \begin{bmatrix} 1 & x_{11} & x_{21} & \cdots & x_{k1} \\ 1 & x_{12} & x_{22} & \cdots & x_{k2} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1m} & x_{2m} & \cdots & x_{km} \end{bmatrix}, Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_m \end{bmatrix}, \ \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \vdots \\ \beta_m \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \vdots \\ \varepsilon_m \end{bmatrix} \tag{2.5}$$

The second order polynomial regression model is a quadratic relation between one or more independent variables and the corresponding dependent variable which can be expressed as:-

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{j=1}^{i-1} \sum_{i=2}^{k} \beta_{ji} x_j x_i + \varepsilon \tag{2.6}$$

where, y is dependent variable and β_i, β_{ii}, β_{ji} are the linear, quadratic and interaction effects and β_0 is the intercept term. The terms x_i , x_j , x_k represent the independent variables.

The coefficients of the regression model can be computed by using the principle of least squares. Using this principle the unknown coefficients of the regression line can be evaluated as:

$$\beta = \left[X^T X\right]^{-1} \left[X^T Y\right] \tag{2.7}$$

In the first order multiple linear regression model the matrix X has the values of independent variables x_i , matrix Y has the values of the dependent variable and the matrix β has the unknown linear coefficients. In the case of second-order polynomial multiple regression models, the matrix X has the quadratic terms of x_i^2, the interaction terms $x_j x_i$ and matrix β contain the unknown quadratic and interaction coefficients β_{ii} and β_{ji} respectively.

2.6 Artificial Neural Network

A biological neuron is the main processing unit in the human brain. An Artificial Neural Networks (ANN) is a massively parallel information processing system inspired from the inter-disciplinary subjects as neuroscience, computer science and mathematics. It is a symbiotic of the human cognition using mathematical functions in a computing environment for solving the complex real life's uncertainties. It is very much helpful in the research field for dealing the problems which are ill-conditioned, containing noisy or incomplete data and related to real life dynamic environments.

The ANN works on the following rules:-

I. Processing of available information occur at number of single elements which are called neurons. Schematic diagram of an artificial neuron with its mechanism and processing of the available information is shown in Figure: 2.2.

II. Signals are carried from neuron to neuron through connection links and the strength of each connection link is represented by its associated synaptic weight.

III. Each neuron applies a typical transformation called an activation function to its net input to determine its output signal.

IV. The error between the actual and the predicted output values should be minimum, and for that the error correction learning rule is applicable for each iteration.

An artificial neuron resembles the biological neuron, is a mathematical model that receives the essential signals as neuron input vector $x_1, x_2, \ldots\ldots\ldots \ldots\ldots, x_n$, controls their relative signal strength by giving a multiplication factor called synaptic weights $w_1, w_2, \ldots\ldots\ldots \ldots\ldots\ldots, w_n$ and applying the summation function to combine the weighted signals with an additional bias weight b . The combined sum of weighted signals $\sum_{i=1}^{n}(w_i x_i) + b$ is finally acted upon by a transfer function to produce the output vector of a neuron $f\left(\sum_{i=1}^{n}(w_i x_i) + b\right)$.

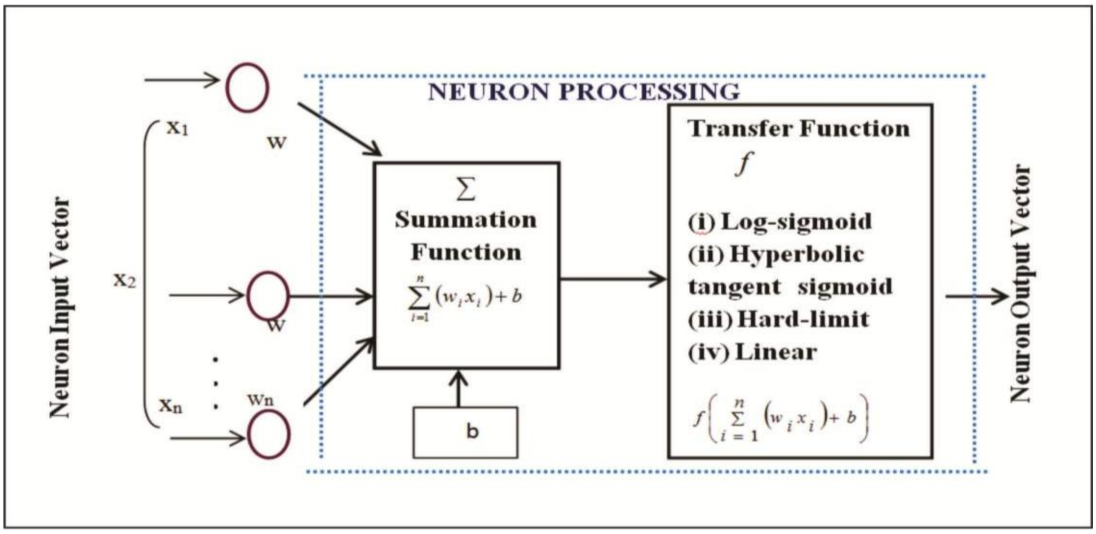

Fig. 2.2: Schematic diagram of artificial neuron and its processing mechanism

The general characteristics of adopted ANN, i.e. architecture, learning algorithm and transfer functions including back-propagation neural network is attached at Appendix- III.

2.7 Adaptive Neuro Fuzzy Inference System

Adaptive Neuro Fuzzy Inference System (ANFIS) works in two stages firstly using fuzzy inference or fuzzy rule based system than use the adaptive neural network. The fuzzy inference system involves membership functions, logical operations and if then rules. Gaussian membership function is a popular method for specifying the fuzzy sets due to its smooth of curve shape and non-zero value at all points. The two most popular fuzzy systems are Mandani- type and Sugeno-type that is used in the present study. An adaptive neural network is a multi layered feed-forward network consisting of neurons connected by directional links. The learning rule specifies how the parameters of adaptive neurons should be changed to minimize a prescribed measured error. ANFIS uses input output data sets to construct a fuzzy inference system whose membership functions are tuned using learning algorithm and then the system is trained with data pairs by an adaptive neural network. Adaptive Neuro Fuzzy Inference System (ANFIS) combines the advantages of fuzzy logic (FL) and artificial neural network (ANN) on a conceptual and structural basis. ANN and ANFIS soft computing techniques have been successfully used for developing rainfall runoff relation in the past.

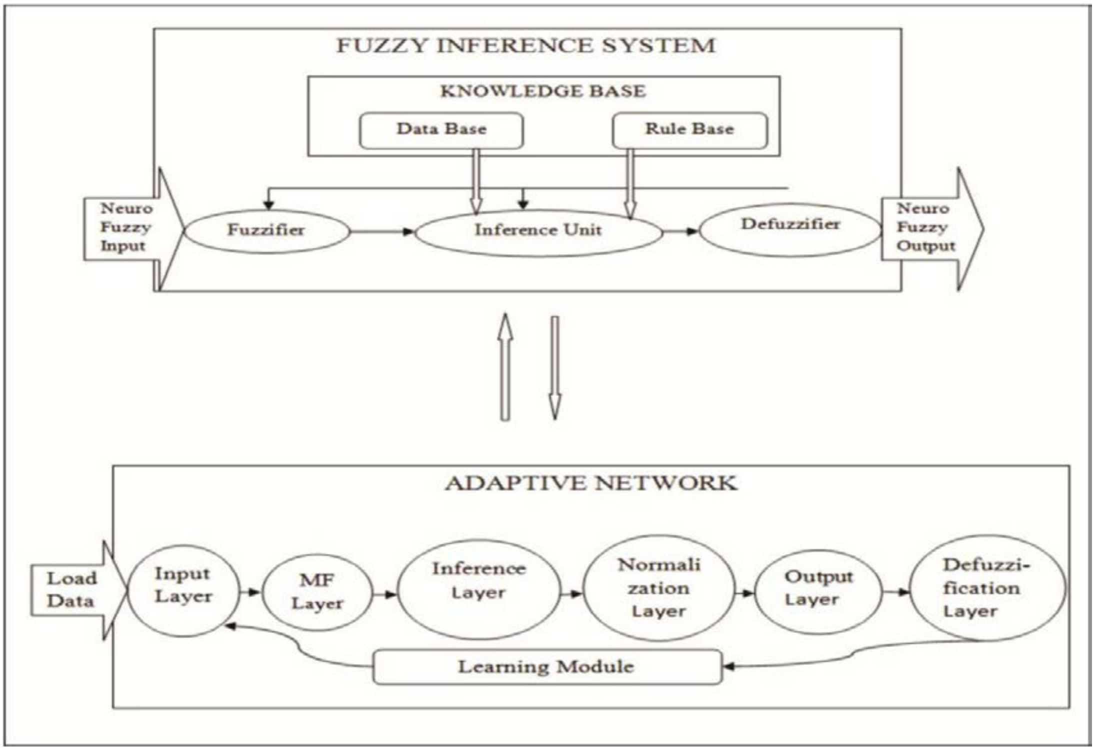

Fig. 2.3: Schematic diagram of an adaptive neuro fuzzy inference system (ANFIS)

2.8 Performance metrics and ranking technique

For checking the performance and predictive accuracy of the developed models using different techniques following three performance metrics namely Co-relation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for the training and validation data sets were computed.

These are given by :-

$$R = \frac{\sum_{i=1}^{N}\left(T_i - \overline{T}\right)\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{N}\left(T_i - \overline{T}\right)^2 \sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2}} \tag{2.8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(T_i - P_i\right)^2} \tag{2.9}$$

$$MAE = \frac{\sum_{i=1}^{N} |T_i - P_i|}{N} \tag{2.10}$$

Where, T_i and P_i are the corresponding individual target or actual and predicted values of runoff, $\bar{T}$ and $\bar{P}$ denote the mean of actual and predicted runoff values, N is the number of data pairs used for the computation in training or validation.

These performance metrics are most important and widely used for judging the prediction accuracy of the conventional regression and soft computing models.

Karl Pearson's co-relation coefficient (R) represents the degree of association between the dependent and independent variables. The range of the correlation coefficient is in between -1 and +1. If the correlation coefficient is 0, then there is no association between the variables. If R is positive or negative, then the variables are associated directly or inversely. If the value of R lies between ± 0.00 to ± 0.20 no relation, ± 0.21 to ± 0.40 weak relation, ± 0.41 to ± 0.60 moderate relation, ± 0.61 to ± 0.80 strong relation,± 0.81 to ± 1.00 very strong relation between the independent variable rainfall and the dependent variable runoff. It is over sensitive to the extreme values in comparison to the values near to the mean value and this value significantly influences the slope of the regression line, but is insensitive to additive and proportional errors. Data normalization and making data in a certain range before using for model development, reduces the over sensitivity of the extreme values and thus reduce the effect of these in model development.

Square of the correlation coefficient is called as coefficient of determination (R^2), that interprets the percentage dependence of the dependent variable on the independent variable or the percentage fineness of the computed regression equation and it varies from 0 to 1. Higher the value of determination coefficient, higher is the degree of relationship between the independent and dependent variable.

The root mean square error (RMSE) and mean absolute error (MAE) are the most important and widely used performance metrics for judging the prediction accuracy of the conventional regression and soft computing models. They compare the observed or the target value with the values predicted by the model and it measures the prediction accuracy of the model in terms of variance. Lower the RMSE and MAE, the better is the prediction accuracy of the model.

The developed model should have maximum value of R near to 1 with the minimum value of RMSE and MAE near to 0 for getting the better model. Sometimes the model has maximum R value but it does not give the minimum value of RMSE and MAE. It represents that there is a variance in the actual and the predicted values of runoff, so the model is not perfect. A single performance metric cannot provide an unbiased model prediction.

Simple ranking procedure may be adopted for each training and validation performing metric for comparing the different types of models. Where data is limited then K-fold holdout technique can be used for getting best results.

2.9 Studies related to rainfall-runoff modeling

Many studies for determining a relation between rainfalls occurred and its corresponding runoff in a catchment, various different rainfall-runoff models were developed in the past at different places in the world, using conventional regression and soft computing techniques as an application.

2.9.1 Regression analysis applications

***Reddy and Vedula* (1981)** compared the applicability of different stream-flow generating models using the same historic data of monthly stream-flows into upper Cauvery river basin and found that the Thomas- Fiering model was the best to preserve the mean, standard deviation and lag one correlation of historic stream-flows.

***Varma and Haque* (1990)** developed a stochastic model for generation of daily rainfall sequences by analyzing the rainfall data at Mokhada rain gauge station.

Srinivasan and Thandaveshwara **(1995)** fitted lower order periodicauto-regressive/ autoregressive moving average (PAR/PARMA) models to the monsoon-dependent river flows of Karnataka in Southern India measured at Chunchanakatte (Cauvery river), Akkihebbal (Hemavathy river) and Unduwadi (Lakshmanathirtha river) and showed that the above models do not seem to perform satisfactorily in the modeling of highly variable monsoon dependent river flows.

Gorantiwar and Majumdar **(1998)** analyzed the stream-flow sequences of some streams in West Bengal, India and modelled the stream-flow using autoregressive model of first order.

Milly and Dunne **(2001)** reported an increasing trend in precipitation over the Mississippi River basin in recent decades while ***Larson and Schwein*** **(2004)** asserted that there was no statistically significant trend over the Missouri River basin for the period 1895-2001.

Mallikarjuna and Rao **(2001)** developed a relationship between rainfall and other meteorological parameters such as relative humidity, wind velocity; temperature and sunshine hours for the Tirupati area of the drought prone Rayalaseema region through multiple correlation and regression analysis

Mallikarjuna and Vishnuvardhan **(2002)** generated monthly rainfall sequences independently for the four raingauge stations of Kalangi basin located in Andhra Pradesh and concluded that the Thomas-Fiering model for the independent generation of synthetic sequences of rainfall may be used in the design of water resources system of Kalangi Basin.

Sudhisri et al **(2002)** developed rainfall-runoff models for Upper Kolab Catchment of Orissa for annual, pre-monsoon, monsoon and post-monsoon seasons and found the rainfall runoff relation having high correlation coefficient.

. ***Hamed*** **(2008)** reviewed the trends in U.S. Rivers and found three rivers to have increasing trends, one to have a decreasing trend, and the remaining eight do not have a trend statistically significance at the significance level of 0.05.

Baig, M.A. et al. **(2008)** developed empirical relations between rainfall and runoff for monsoon period for the Bahuda river basin in Andhra Pradesh, India. The multiple correlation and regression analysis was also carried out to forecast the maximum daily rainfall during monsoon season using antecedent meteorological indices i.e. humidity, wind velocity and temperature. It was also concluded that the synthetic sequences of runoff may be generated using the Thomas-Fiering model for the development and management of water resources projects of the Bahuda basin.

John F. Joseph and H. Ernest Falcon **(2012)** studied the hydrologic trends and correlations in South Texas River Basin and found the majority of trends and correlations were statistically significant at the level 0.05 and all relationships were positive or increasing

2.9.2 Artificial Neural Network (ANN) applications

Zhu et al. **(1994)** predicted upper and lower bounds on the flood hydrograph in Butter Creek, New York, NY, USA. Data for ANN testing and validation were generated from a nonlinear storage model. Model performance was strongly influenced by the training dataset and it was concluded that while the ANN did well during interpolation, predictions made by it outside the range of the training dataset were not encouraging. The process of trying to make ANN model adaptive it was repeated with each new data pairs. It was also found that as the lead-time for forecasting increased, ANN performance deteriorated.

Campolo et al. **(1999)** developed a neural network model to analyze and forecast the behaviour of the river Tagliamento, Italy during heavy rain periods and observed that one layer of hidden neurons was sufficient to perform the input-output transformation for both short-range and long-range prediction.

Sajikumar and Thandaveswara **(1999)** developed a nonlinear rainfall-runoff model using short lengths of data. The model was demonstrated as a monthly rainfall-runoff model and it was concluded that temporal back-propagation neural network model was the most efficient of the black box models.

***Tokar and Johnson* (1999)** reported that ANN models provided higher training and testing accuracy as compared to regression and simple conceptual models. They trained and tested the ANN models with wet, dry, and average-year precipitation and temperature data and found the ANN model that was trained on wet and dry data had the highest prediction accuracy. It was also concluded that the length of training record had a much smaller impact on network performance than the types of training data.

***Zealand et al.* (1999)** investigated the utility of artificial neural networks for short term forecasting of streamflow for the Winnipeg River system, Canada and compared the performance with conventional approaches and concluded that ANNs outperformed the conventional models.

***Coulibaly et al.* (2000**) used multi-layer feed forward ANN with early stopped training approach and Levenberg Marquardt back-propagation algorithm, for daily reservoir inflow forecasting. It was reported that the ANN methodology has better prediction accuracy than the other conventional methods.

***Birkundavyi et al.* (2002)** investigated the performance of neural networks as potential models that are capable of forecasting daily stream-flows of Mistassibi River, Quebec, Canada and concluded that ANN models outperform the deterministic model and were superior to the classic autoregressive models.

***Rajurkar et al.*(2002)** used ANN on the daily rainfall runoff model for Narmada catchment in Central India and found that ANN led to higher prediction accuracy than the other linear and non-linear models.

***Jain and Prasad* (2003)** investigated the suitability of some deterministic and statistical techniques along with artificial neural networks technique to model an event-based rainfall-runoff process using the data derived from Salado Creek at Bitters Road, San Antonio, Texas, USA. It was found that the ANN models consistently outperformed conventional models, barring a few exceptions, and provided a better representation of an event- based rainfall-runoff process.

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Rajurkar et al. **(2004)** modelled rainfall-runoff process by coupling a simple linear model with ANN using the data from two large sized catchments in India and five other catchments used earlier by the World Meteorological Organization (WMO) for inter-comparison of the operational hydrological models. The substitution of the previous days runoff, by a term that represents the runoff estimated from a linear model and coupling the simple linear model with the ANN proved very useful in modeling the rainfall-runoff relationship in the non-updating mode.

Lin and Chen **(2004)** developed radial basis function network (RBFN) to formulate a rainfall-runoff model and applied to an actual reservoir watershed. The results revealed that the RBFN can be successfully applied to build the relation of rainfall and runoff.

Riad et al. **(2004)** used rainfall-runoff data at the Aghbalou station for developing rainfall-runoff model using ANN

Srinivasulu and Jain **(2006)** investigated and compared the effectiveness of back propagation, real coded genetic algorithm, self-organizing map neural network training methodologies using streamflow data and the daily rainfall derived from Kentucky River basin and it was obtained that neural networks trained using real coded genetic algorithm were able to outperform the prediction accuracy of back propagation neural networks and self-organizing maps.

Wu and Chou **(2006)** have developed model for forecasting the downstream water levels on the basis of water levels recorded at the upstream in Yangtze River of China using the conventional linear regression and artificial neural network both. It was found that the ANN model was giving better predicted values than the conventional linear regression model.

Chen and Adams **(2006)** proposed a hybrid rainfall-runoff modelthat integrated artificial neural networks and conceptual models. The flood hydrographs at the three individual sub-catchments were compared using conceptual methods and they were superimposed nonlinearly using ANNs and linearly using regression.

Sarkar, A. et al. (2006) developed ANN runoff models to simulate and forecast daily runoff for part of the Satluj basin of India. It was observed that the runoff at the upstream sites are required to be included in the input in addition to rainfall and temperature in the simulation and forecasting of the catchment runoff resulting from rainfall and snowmelt contribution to improve the performance of the models.

Sedki et al. **(2009)** applied artificial neural network for developing soft computing models using four years rainfall data, taking past four days daily rainfalls as four input layer neurons and runoff as one output neuron for the semi-arid catchment region of Morocco. The number of hidden layer neurons was varied for getting the best relation by trial and error. Value of root mean square error (RMSE) and coefficient of determination (R^2) were used as model performing parameters. It was found that the hybridized neural network model was better performing than the simple back-propagation neural network.

Machado et al. **(2011)** formulated three ANN models based on monthly rainfall and corresponding runoff and compared them with the conceptual model at the monthly time scale. It was found that ANN models provided better results in comparison to the conceptual models.

Huang and Wang **(2011)** developed ANN rainfall-runoff model for Liujiang River in China using the observed rainfall and corresponding monthly streamflow. The auto regressive integrated moving average (ARIMA) Model was compared with the single neural network, radial basis function neural network and hybrid artificial neural network-genetic algorithm on the basis of three statistical metrics namely, the normalized mean squared error (NMSE), Pearson relative coefficient (PRC) and mean absolute percentage error (MAPE).

Chen et al. **(2013)** have also developed rainfall-runoff model for typhoon using Artificial Neural Network.

Asadi et al. **(2013)** studied the complex rainfall-runoff interactions using 12years time series data and analysed by ANN with Levenberg- Marquardt Back Propagation (LMBP) algorithm and finally compared the results with the actual runoff data. It was found that Levenberg-Marquardt Neural Networks (LMNN) methodology presented in the paper showed faster training, good ability to imbibe complex rainfall-runoff processes and higher accuracy in comparison to the studies performed earlier.

Liu and Chung **(2014)** studied the water stage during typhoon selecting seven events using artificial neural networks on a local river located in Taiwan and observed that the hydrodynamic model required more time in simulating the water stages than the neural network models and also provided less accuracy compared to the artificial neural network.

Chandre Gowda and Mayya **(2014)** developed streamflow forecasting model in natural rivers taking the rainfall data of the current time, rainfall lagged by one and two days, the streamflow data lagged by one and two days. The study showed that the ANN modeling using back propagation training was effective in modelling of complex hydrological phenomena.

Chandwani et al. **(2015)** concluded in their study that as the interactions between the rainfall and its corresponding runoff in a catchment is complex, so the conventional mathematical techniques used for developing rainfall-runoff model in the form of regression equations do not provide a perfect representation of the rainfall runoff phenomenon and soft computing approach may be more fruitful. The synaptic weights used in artificial neural networks attribute the relative importance of the various inputs on the predicted output value. Rainfall-runoff models developed by hybridization of different soft techniques i.e., ANN with Fuzzy Logic enrich the original procedure, cover up their individual limitations and give better results.

2.8.3 Adaptive neuro fuzzy inference system (ANFIS) applications

***Jang* (1995)** developed an adaptive network based on fuzzy inference system that identified asset of parameters through a hybrid learning rule combining the back propagation gradient descent and least square method.

***Mason et al.* (1996)** used Radial Basis Function (RBF) neural networks for accelerating the training procedure as compared to regular back-propagation techniques and it was concluded that, while RBF networks did provide for faster training, such network required the solution of linear system of equations that may become ill conditioned, especially if a large number of cluster centres are chosen. It was found that RBF networks could be trained much faster than multiple layer perceptor (MLP) networks using back propagation.

***Kim et al.* (2000)** used first order Sugeno fuzzy ANFIS technique for developing rainfall runoff hydrograph simulation in Bocheong river basin in South Korea, taking several lags in inputs and compared with the Quasi-Newton neural network system. ANFIS based models showed the most accurate prediction capability and RMSE was found to be lower than that for ANN Model.

***Swain and Umamahesh* (2004)** developed an ANFIS model to forecast ten daily flows into the Hirakund reservoir on Mahanadi river in Orissa, India using ten daily precipitation over the whole catchment using first order Sugeno fuzzy model and found that the ANFIS modelling technique was able to model the streamflow process with reasonable accuracy which could be used for real time forecasting of streamflows.

***Bateni et al.* (2006)** used ANFIS for prediction of runoff in terms of rainfall and evaporation as inputs for the 7^{th} basin of 12 Mopex river in United States and showed that the ANFIS model provided a good prediction of runoff as compared to traditional methods. They used first order Sugeno fuzzy model and the multi layer feed forward back propagation neural network. The computed statistical parameters i.e., MAE, RMSE and determination coefficient (R^2) showed that ANFIS model provides a good runoff prediction.

Jacquin and Shamseldin **(2006)** used Takagi Sugeno fuzzy inference systems to develop rainfall-runoff model using daily averaged values of precipitations used as inputs and it was resulted that fuzzy inference systems were a suitable alternative to the traditional methods for modelling the non-linear relationship between rainfall and runoff.

Tutmej et al. **(2006)** found that neuro fuzzy model was capable of generalisation, which would not be possible if fuzzy logic based approaches were used alone.

Firat **(2007)** studied applicability of ANFIS, ANN and generalised regression methods for forecasting of daily river flow in Seyhan catchment in southern Turkey and demonstrated that ANFIS model was superior to the ANN and traditional models. ***Hasan*** **(2006)** found out that ANFIS can construct an input-output mapping based on a given initial fuzzy system and available input-output data pairs by using learning procedure.

Shingare et al. **(2010)** have developed rainfall-runoff models using conventional, fuzzy and ANFIS approach for Upper Damodar Valley region in Jharkhand, India and concluded that ANFIS requires fewer input parameters and was capable of generalisation which is not possible in fuzzy logic based approaches used alone.

2.9 Summary

In all the above enumerated studies the main objective was to find out a relationship between rainfall and corresponding runoff in any form like an equation, table, graph, or soft computed relation, on the basis of some available records of rainfall and its corresponding runoff including the effects of other variable parameters. There were essentially two approaches followed for the development of rainfall-runoff models, namely the empirical approach and the rational approach. In the empirical approach the runoff had been expressed as a percentage of rainfall and the wide divergence between the actual and the calculated runoff values were sought to be minimized by introducing constants for catchment characteristics and temporal seasonal variations in rainfall and runoff.

While in the rational approach runoff was expressed as a residual of rainfall after the deduction of loss due to evaporation, transpiration and other precipitation abstracts. In determining the losses in rational approach the various other factors affecting the rainfall and runoff like as temperature, wind velocity, atmospheric pressure, humidity, hours of sunshine, solar radiation etc. have also been brought in some studies by some hydrologist. Most of them have assumed that all the factors depend directly on temperature or the local terrain. The water infiltration into the subsoil was not considered as a loss and was considered as a sub-surface runoff in the form of regeneration that meet the original stream after some time lag in the down-stream.

The Levenberg-Marquardt (LM) back-propagation algorithm provides higher prediction efficiency as well as fast learning rate to the Multilayer Feed-forward Neural Networks (MFNN), hence ANN using LM algorithm is a good model developing tool and vastly used in the modeling of nonlinear complex physical phenomenon, wherein the conventional regression models do not yield the desired accuracy and predictability. In most of the ANN studies one hidden layer was used and its neurons have been determined by adopting trial and error technique. ANN and ANFIS soft computing techniques have also been successfully used for developing the rainfall runoff models in the past.

A single generalised equation cannot be prepared or applied for each catchment because every catchment has unique physical parameters. Previously developed models can give satisfactory results in the regions for which they were derived and they cannot be directly applied in the other regions for getting the accurate results. For getting precise results, the model should be revised by the local data considering all local physical parameters. The model may be algebraic or soft computed that depends on the local physical characteristics and climatic factors of the catchment.

In the light of the above points, the determination of the rainfall-runoff relation or the rainfall-runoff model should be based on the actual physical relationship between rainfall and corresponding runoff rather than on a mathematical interpretation of any data. Moreover, since, the rainfall records of longer period are available and are easy to collect than runoff data, there is a need to develop the rainfall-runoff empirical models including the effect of the local physical parameters and climatic factors of the catchment, which compensates the lack of runoff data for evolving effective water management strategies. Presently in Rajasthan, Strange's Table is being used for determining runoff or indirectly the available yield from the occurred rainfall in the catchment for future planning of the area, that necessitates the use of more scientific methods for runoff computation in the study area. It was also found that the rainfall runoff empirical models using soft computing techniques are an easy approach and give better results in stipulated time.

2.10 Research gap

The literature survey has revealed that soft computing techniques are also popularly used with the conventional regression techniques and are now a preferred choice for the researchers for modeling unknown, complex or nonlinear functional relationships related to physical phenomena. ANN technique and hybrid of ANN with Fuzzy Logic or Genetic Algorithm are better performing in comparison to conventional regression technique. Moreover, this methodology has not been so far employed for modeling rainfall-runoff models in Banas River Basin.

Study Area

3.1 Introduction

This chapter presents the general physical characteristics including the surface water-flow directions, geography, location and sub-division, geomorphology and geology with general soil layer, land use pattern of the study area. Climatological characteristics of the study area including special weather phenomena and the general statistics of various weather parameters have also been discussed.

3.2 Geography of the area

3.2.1 General

The selected study area is Banas River Basin which is located in east-central Rajasthan in India, between the latitudes $24^{o}15^{'}$ and $27^{o}20$'N, and, longitudes $73^{o}25$' and $77^{o}00$'E. It is surrounded by the Luni Basin in the west, the Shekhawati, Banganga and Gambhir Basins in the north, the Chambal Basin in the east, and the Mahi and Sabarmati Basins in the south. The Basin extends over the parts of Jaipur, Dausa, Ajmer, Tonk, Bundi, Sawai Madhopur, Karauli, Udaipur, Rajsamand, Bhilwara and Chittorgarh districts of Rajasthan.

The total catchment area of the Banas basin is 47060 sq. km. Orographically the western part of the basin is marked by hilly terrain belonging to the Aravali chain. East of the hills lies an alluvial plain with a gentle eastward slope. The ground elevations in its western hilly part ranges from 850 to 1123 m, while in the alluvial plain, elevation ranges from 280 to 850 m above mean sea level.

The study area have been divided in 9 sub-parts called as sub-basins on the basis of the general geographical/topographic characteristics and the water flow direction in the particular sub-basin. The locations of the sub-basins with their surrounding sub-basins situated in Banas River Basin have been marked and shown at **Figure 3.1**. The names of sub-basins are –

(1) Berach sub-basin (2) Banas part-I sub-basin
(3) Kothari sub-basin (4) Khari sub-basin
(5) Dai sub-basin (6) Mashi sub-basin
(7) Morel sub-basin (8) Kalisil sub-basin
(9) Banas part-II sub-basin.

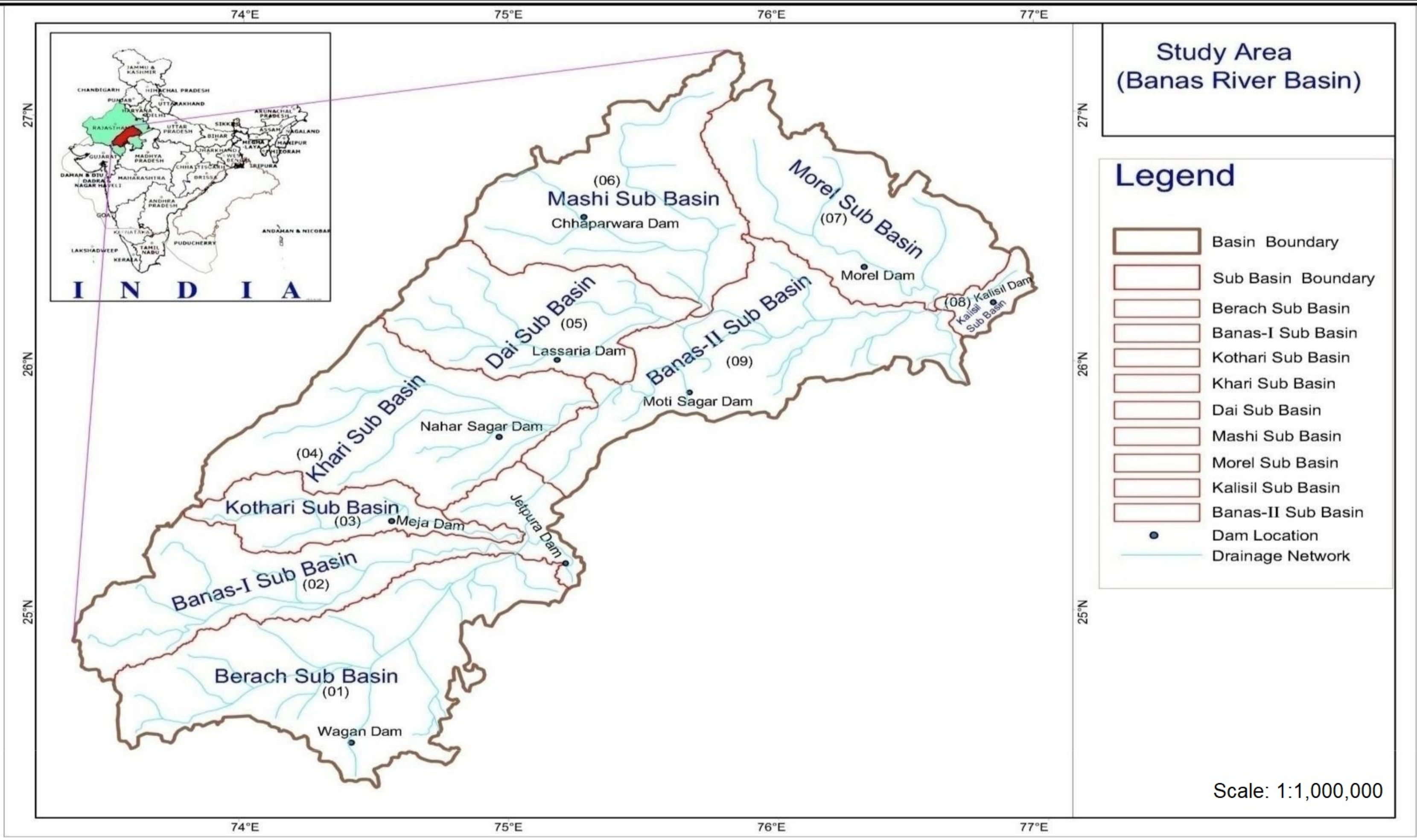


Fig. 3.1: Sub-basins of Banas River Basin

(Tahal Report 1998 - Study on the planning of water resource of Rajasthan

3.3 Geomorphology of the area

3.3.1 General

As per geomorphology, the study area may broadly be divided into three units, i.e., rocky uplands, pediplain and alluvial plain.

3.3.2 Rocky uplands

The upper elevated part of the study area is rocky uplands that comprises of both hill ranges and isolated residual hills. The western and northern boundaries of the study area are formed by the Aravali hill range, extending in NE to SW direction, having a maximum elevation of about 1200 m above mean sea level (msl). There is blown sand and the area in the east of the Aravali range is noticed as flat to undulating topography, with small isolated ridges or hills, running in NE to SW direction, distributed throughout the area.

3.3.3 Pediplain

The middle medium elevated part of the study area is pediplain which comprises of buried and barren pediments. It is almost flat and is a gently sloping hard rock terrain. In buried areas the rocks are highly weathered and have a considerably thick soil cover, supporting agricultural activities. On the other hand the barren areas have no soil cover and cannot support agriculture. Sheet and gully erosion is a severe problem in this area and it is observed mainly along or near tributaries of Banas River.

3.3.4 Alluvial plain

The lowest part of the study area is having alluvial plains. The alluvial plain rises to an elevation from 280m to 850 m above mean sea level (msl) and slopes are towards the north. The alluvium is confined to river valleys only. It has been deposited in the form of small isolated valley fills. Width of the alluvial plain widens in the flow direction of the stream. It is maximum near the confluence with the other rivers. The thickness of the alluvial deposits thin out towards the west where the plain is higher and more irregular, whereas it thickens out in the east and north side portion of the study area.

There are extensive dune fields which normally aligned from east to west and also from north east to south west. They impart a hillock appearance to the topography. The blown sands occur both as obstacle dunes and as free dunes. Obstacle dunes are sand falls seen along the river courses and on the windward sides of north east to south west trending hill ranges. Gully erosion and badland topography have developed here. Free dunes are mainly confined to the northern banks of the Banas River.

3.4 Geology of the area

3.4.1 General

The geology of the study area reveals that the exposed rocks are of diverse types, ranging from the oldest Archaean metamorphic to sub-recent alluvium and wind-blown sands.

3.4.2 Geological sequence and structure of the rocks in the area

The study area is occupied with three categories of rock formations i.e., hard rock formations like gneiss, phyllite, schist and quartzite, sedimentary formations like sandstone, shale and limestone and unconsolidated formations of alluvium overlain with windblown sand deposits. About 70% area of the basin is hard rock, 20 % is alluvium and 10% area is sedimentary rock that is occupied by pre-cambrian rocks.

The pre-cambrian rocks are tectonically disturbed to a great extent as is evidenced by the presence of major and minor faults, folds, joints and fractures. The major tectonic element in these rocks is the presence of a series of sub-parallel NE-SW trending faults.

Groundwater exploration shows that there is a high proportion of coarser material like Kankar in the vicinity of the present river course, a condition that extends up to the central part of the valley fill. Gravels, pebbles and boulders are found in the abandoned buried channels.

3.5 Hydrogeology of the area

3.5.1 General

Hydrogeology is the geology of groundwater, especially concerning the physical, biological and chemical properties of its occurrence and movement.

The study area is built naturally like a belt that stretches from north-east down through the basin's eastern border and bends westwards along the northern border of Berach Sub-basin. The main hydro-geological formation is phyllite & schist. There are also patches of gneisses in the southeast and hills at the western edge of the basin. At the north-eastern part of the sub-basins of the study area, the slope of the Banas River is moderate and it accommodates plains of younger alluvium.

3.6 Climatology of the area

3.6.1 General

As per the India Meteorological Department (IMD), Rajasthan has been divided in two meteorological sub-divisions named as Western Rajasthan and Eastern Rajasthan. The study area is falling within the Eastern Rajasthan subdivision.

Based on Koppen’s classification of climatic patterns, the study area may be classified as tropical steppe, semi-arid and hot. The year may be divided into four seasons. The winter season from November to the beginning of March, is followed by the hot summer season, from March to June including the pre-monsoon season from April to June. The period from July to mid-September constitutes the southwest monsoon season and the period from the second half of September to end of October as the post-monsoon season. The brief idea about the local climatic factors affecting the rainfall and corresponding runoff is follows.

3.6.2 Temperature

Temperature increases from March to June and on the onset of the southwest monsoon in the second half of June it lowers. After the monsoon recedes by mid-September, the temperature again increases slightly during the day, reaching a secondary maximum in October. From November onwards both day and night temperatures decrease rapidly up to January which is the coldest month. The annual range of temperature, i.e., the difference between extreme maximum and minimum temperatures, may be over 45^{o}C.

3.6.3 Rainfall

Rainfall distribution in the basin differs very much in magnitude, time and space. It also depends on the intensity of monsoon season and local areal parameters. The major part of the rainfall in the area is due to the southwest monsoon in the months of July, August and September and a small part of rainfall occur in the remaining months. The rainfall in the pre-monsoon period from April to June and the post-monsoon period that is October, is very less in comparison to the monsoon period.

3.6.4 Cloudiness

Skies are generally moderate to heavily clouded during the southwest monsoon season, being overcast on some days. During the rest of the year, skies are normally clear to lightly clouded, although the cloudiness sometimes also occurs during the winter due to the western disturbances.

3.6.5 Winds

Winds are generally light to moderate except in summer and during the early part of the southwest monsoon season. Winds strengthen slightly on some days. The summer winds blow from northwest-southwest directions. Westerly to south-westerly winds prevail during the monsoon season. In the post-monsoon and winter months, winds are mostly from directions lying between west and north.

3.6.6 Relative humidity

Relative humidity of the area during the southwest monsoon season is generally over 60% and during the rest of the year, the air is normally dry. The relative humidity during summer afternoons drops to as low as 20% and in morning it is usually more humid.

3.6.7 Evaporation

Evaporation varies from month to month. It is the highest in the months of May and June when the heat received is maximum while minimum in the month of December and January. The mean annual evaporation from the selected dam catchments is shown in **Table 3.1**.

Table 3.1: Mean annual evaporation in the selected dam catchments

S. No.	Name of sub-basin	Name of selected dam	Mean annual evaporation from dam catchment in MCM
1	Berach	Wagan	1.63
2	Banas I	Jetpura	0.48
3	Kothari	Meja	3.71
4	Khari	Nahar Sagar	5.49
5	Dai	Lassaria	9.8
6	Mashi	Chhaparwara	2.67
7	Morel	Morel	14.26
8	Kalisil	Kalisil	0.89
9	Banas II	Moti Sagar	1.28

3.6.8 Special weather phenomena

Depressions originating in the Bay of Bengal during the southwest monsoon season move across the central part of the country and during their last stages sometimes affect the study area and cause heavy rainfall in the area. In the hot season, dust storms or thunderstorms occur frequently, some of them accompanied by squalls and occasionally by hail, particularly in the early part. Thunderstorms also occur during the monsoon season.

3.6.9 Statistics of weather parameters in the area

The overall statistical parameters of the climatic factors in the study area are shown in the **Table 3.2**.

Table 3.2: Statistics of weather parameters in the study area

Weather parameter	Minimum	Maximum	Mean	Standard deviation	Coefficient of variation
Mean maximum temperature in ^{o}C	32.11	33.20	32.77	0.19	0.01
Mean minimum temperature in ^{o}C	17.50	20.66	19.05	0.71	0.04
Annual rainfall in mm	341.80	868.20	588.80	92.40	0.16
Monsoon months rainfall in mm	326.50	810.60	544.50	87.10	0.16
Rainy days in days/yr	18.00	37.00	29.00	3.50	0.312
Wind speed in km/hr	1.40	8.50	4.74	1.29	0.27
Sunshine hours in hr/day	7.90	8.38	8.11	0.16	0.02
Relative humidity in %	43.65	55.10	50.54	2.26	0.04
Annual evaporation in mm	1677.6	2281.0	2105.6	9.83	0.05

Source: IMD monthly dataset (1990-2009), Rainfall statistics based on IMD, RD and WRD dataset (1957-2010)

3.7. Soil cover in the area

3.7.1 General

Soil is made up of part of finely grinded rock particles, grouped according to size as sand and silt in addition to clay and organic material such as decomposed plant matter. Each component and their size play an important role. The largest particles are sand which determine the aeration and drainage characteristics, while the tiniest are sub-microscopic clay particles are chemically active and bounded with water and plant nutrients. The ratio of these sizes determines the soil type which may be sand, clay, loam, clay-loam and so on which directly affect the water percolation rate in the area.

3.7.2 Percentage soil covers in the surface area

Soil cover in most of the sub-basins is predominantly sandy loam. The general soil texture distribution found in the study area is shown in **Table 3.3**.

Table 3.3: Soil texture distribution in the study area

Soil texture	Area (sq.km)	% of Study Area
Clay	7584.22	16.12
Clay Loam	6372.73	13.54
Loam	2685.02	5.71
Loamy Sand	7333.16	15.58
Sand	6455.29	13.72
Sandy Clay Loam	1519.13	3.23
Sandy Loam	13943.90	29.63
Silt Loam	1166.82	2.48
Total	47060.27	100

Source: State Remote Sensing Application Centre, Jodhpur.

3.8 Land use pattern in the area

Major part of the basin is under agricultural use. Wheat and Bajra are the predominant crops where wheat is grown in Rabi season and Bajra in Kharif season. **Table 3.4** shows the different land use patterns followed in the study area.

Table 3.4: Land use percentages in study area

Land use pattern	Area (sq.km.)	% of Study Area
Built Up	243.45	0.52
Kharif crop only	6049.91	12.86
Rabi crop only	8159.44	17.34
Double/ tripple	5513.21	11.72
Current fallow land	19249.47	40.90
Deciduous forest	806.3	1.71
Scrub/Degraded forest	1147.33	2.44
Other wasteland	4041.57	8.59
Gullied	36.72	0.08
Scrub land	1271.83	2.7
Water bodies	531.7	1.13
Total	47060.27	100

Source: National Remote Sensing Centre

3.9 Socio-economic situation of the area

Roughly 93.3 lacs people out of the total population 148.9 lacs live in the rural area and the remaining in the urban area. The growth rate of population in the area has been higher than the national average. The pace of urbanisation has also been high which resulted in mushrooming growth of kutchi basties in shanty towns. The problem of proper sanitation and sewerage is also acute.

The Rajasthan state also ranks lower on the human development index than the other states. Inspite of an impressive increase in level of literacy and number of hospitals and educational institutions both in public and private sector, sizeable section of the population remains deprived of these facilities. The area is poor in industrial development and the development is concentrated around the district head quarters.

The female literacy rate and the enrolment of girls in primary and upper primary schools are very low and dropout rate is high especially in the rural area. As the area has less gender development and empowerment index, women continue to have lower status than men resulting in frequent atrocities against them.

After independence, a uniform system of tenancy land revenue and settlement was introduced in the state. Agriculture and animal husbandry are the main occupation of a majority of people in the area. Agriculture is mostly dependent on the monsoon, which is not only erratic and uncertain but also a short span. The major Kharif crops are Bajra, Jowar, Maize, pulses, Guar and the Rabi crops are wheat, Gram etc. The area has made substantial improvement in crop production, especially after the Green Revolution.

The area is rich in animal wealth and has distinction of having cows, buffaloes, sheep, goat, horse, donkey, camel, pigs and poultry. The available mean annual virgin water yield of the area is 5097.26 MCM while the water demand in the area is 545.88 MCM per year.

Methodology

4.1 Introduction

As discussed in the literature review, rainfall-runoff empirical models adopting regression and soft computing techniques, with the use of general statistical principles are easy to approach and give better results in minimum time. Rainfall-runoff empirical models are based on a simplified representation of the hydrologic processes and the balances of incoming and outgoing water from the catchment on a monthly time step. The general physical characteristics of the study area have been discussed in the ThirdChapter and it is well known that major part of the rainfall occurs in the monsoon period and hence these models will be developed for that period only. This chapter presents the model structure, modeling methodology and model consistency checking procedure for the developed models. Further developments and the improvements of the model structure with the extension of their applicability to the basin will also be discussed here.

4.2 Model structure

The transformation of rainfall which occurs within a catchment into runoff, is a highly complex natural phenomenon, influenced by many factors including topographic, geographic, geologic, and sociologic factors.But the main factor that affects the runoff is the local areal and temporal rainfall and its distribution. The quantitative relation between the rainfall and the resulting runoff in a catchment, without accounting the physical laws responsible for governing the natural processes is called rainfall-runoff empirical model. It is a black box model for rainfall and runoff in which we have an expression between them that may or may not be dimensionally homogeneous.

For developing the rainfall-runoff empirical models in a catchment following three main components are required:-

(1) Occurrence of rainfalls at different places in the catchment with its temporal distribution.

(2) Runoff generated from the catchment at the selected site.

(3) Water evaporated from the catchment.

Before deriving different relations between rainfall and its corresponding runoff, developing the rainfall-runoff empirical models, the values of rainfall and corresponding runoff are converted in the same unit and, are normally expressed in mm of water depth that is assumed to be uniformly spread over the entire catchment area.

4.3 Collection and pre-processing of modeling data

4.3.1 Collection of data

The Banas River Basin is the largest river basin in Rajasthan State in India is selected for the present study. The geographical and geomorphological map of the area, climatological and hydro-geological characteristics of the area was collected for determining the generalized basic nature of the catchment. The locations of the existing dams and the rain-gauge stations in the Banas river basin were also collected. The monthly rainfalls observed at the different rain-gauge stations in the previous 20 years from 1996 were collected from the Water Resources Department of Rajasthan, Indian Meteorological Department and the Revenue Department of Rajasthan. The water-inflows observed in the existing dams in the corresponding 20 years were collected from Water Resources Department. The catchment area of the dams and total evaporation from the dam catchments of the study area were also collected. The mean annual evaporated water from the dam itself and other water bodies in the catchment, in the months of July, August and September was also collected and shown in **Table 3.1**.

4.3.2 Division of basin and selection of dams for model development

As the study area is very large having a catchment area of 47060 sq. km., it was divided in 9 sub-basins, on the basis of the general geographic characteristics and water flow directions as Berach sub-basin, Banas I sub-basin, Kothari sub-basin, Khari sub-basin, Dai sub-basin, Mashi sub-basin, Morel sub-basin, Kalisil sub-basin and Banas II sub-basin. Since each sub-basin has different average characteristics like climate, topography, land use pattern, soil layer, agro-climatic zone, average groundwater level etc., it behaves as a micro climate for that area and due to that the rainfall-runoff model for the individual sub-basin will be different.

The rainfall-runoff empirical models developed for each sub-basin will differ from one another as individual sub-basin has a unique micro-climate.

The general behaviour of all the dam catchments located in the same sub-basin would be same as there is the same type of micro-climate in the entire sub-basin. So, it was assumed that any dam catchment which is fully located in a sub-basin would represent the general behaviour of that sub-basin. Hence for developing the rainfall-runoff empirical models in 9 different sub-basins, one dam catchment is selected from each sub-basin for analysis and modeling. The longitude and latitude with catchment area of the selected discharge gauging sites in these sub-basins is mentioned in **Table 4.1**.

Table 4.1: Brief description of the discharge gauging sites

S. No.	**Name of sub-basin**	**Name of selected dam or discharge measuring site**	**Longitude** (E)	**Latitude** (N)	**Catchment area (in sq. km)**
1	Berach	Wagan	$74^{O}28'$	$24^{O}29'$	354.0
2	Banas I	Jetpura	$75^{O}10'$	$25^{O}15'$	146.9
3	Kothari	Meja	$74^{O}32'$	$25^{O}25'$	1641.2
4	Khari	Nahar Sagar	$74^{O}58'$	$25^{O}48'$	576.8
5	Dai	Lassaria	$75^{O}09'$	$26^{O}02'$	2335.6
6	Mashi	Chhaparwara	$75^{O}15'$	$26^{O}45'$	746.6
7	Morel	Morel	$76^{O}30'$	$26^{O}25'$	3289.9
8	Kalisil	Kalisil	$76^{O}48'$	$26^{O}21'$	347.9
9	Banas II	Moti Sagar	$75^{O}47'$	$25^{O}57'$	154.0

4.3.3 Preparation of modeling data

For getting the effect of the rainfalls of individual raingauge stations in and around the catchment, Thiessen Polygon averaging technique was adopted. The catchment area along with the location of each selected dam and the nearby rain-gauge stations were marked and then Thiessen's polygons were drawn for determining the influence factor or the weightage of the individual rain-gauge station situated in the catchment. The marked catchment area and its corresponding drawn Thiessen's polygon for the selected dams situated in the different sub-basins are shown in

Appendix-I.

The raingauge stations and its influencing factors for the selected discharging site, computed by Thiessen technique is mentioned in **Table 4.2**.

Table 4.2: Details of rain-gauge stations and their computed influence factors affecting the discharge gauge site

S. No.	Name of sub-basin	Name of selected dam or discharge measuring site	Name of raingauge stations with influence factor
1	Berach	Wagan	Badi Sadri (0.52), Dungla (0.48)
2	Banas I	Jetpura	Mandalgarh (1.0)
3	Kothari	Meja	Raipur (0.27), Mandal (0.20), Amet (0.19), Devgarh (0.10), Sahara (0.06), Nimbahera (0.18),
4	Khari	Nahar Sagar	Shahpura (0.51) , Banera (0.49)
5	Dai	Lassaria	Sarwar (0.39), Ajmer (0.25), Nasirabad (0.24), Kishangarh (0.12)
6	Mashi	Chhaparwara	Dudu (1.0)
7	Morel	Morel	Dausa (0.17), Jamuaramgarh (0.23), Bonli (0.11) Chaksu (0.20), Sanganer (0.16), Niwai (0.13)
8	Kalisil	Kalisil	Sapotara (0.63), Karauli (0.37)
9	Banas II	Moti Sagar	Deoli (1.0)

As the available rainfall data of each rain-gauge were measured in mm in daily data form so these were summed up for the individual month i.e. for July, August and September for the selected years i.e. from 1995 to 2015. Using Thiessen's technique the rainfalls at different rain-gauge stations were averaged out for getting their effective rainfall contribution in the catchment with the help of their influencing factors computed for the individual rain-gauge station. For getting the summative effect of all the rainfalls occurred at different raingauge station in the catchment in the particular time period the total weighted rainfall was computed. The total effective monthly and monsoon weighted average rainfall measured in mm for the month of July, August, September and monsoon period is the sum of the product of the influencing factor and rainfall measured at the particular rain-gauge stations. This computed total effective rainfall may be assumed to have uniformly occurred over the catchment and it contributes runoff in the specified time period. These computed month-wise total effective rainfall data which were used for the development of rainfall-runoff empirical models in the different sub-basins, is given in **Appendix-II**.

As the total stored water capacity of the selected dams at the end of the monsoon months i.e. the cumulative water inflow in MCM up to the end of that month for the selected years from 1995 to 2015 was available, so the monthly water volume received from the dam catchment was determined by subtracting the water volume of previous month from the current month. The average evaporation of water from the catchment through soil and water surface, in the month of July, August and September was computed with the help of the mean annual evaporation from the selected dam catchments shown in **Table 3.1** and the month-wise percentage distribution of the annual evaporation in the previous years in Rajasthan shown in **Appendix-II**. Summing up of these two water volumes would be the total volume of water or the total runoff volume in million cubic meters, obtained from the selected catchment. Assuming that this water inflow to receive in the dam or the runoff from the dam catchment had been uniformly received from the entire catchment, the computed volume of water was divided with the catchment area of the dam in the specified period and converted in water depth in mm.

These computed month-wise total effective runoff data which were used for the development of rainfall-runoff empirical models in the different sub-basins, is also appended in **Appendix-II**.

The sub-surface percolation losses were very less in comparison to the evaporation losses as the most of the study area was pediplain having hard rock. Though the small quantity of water percolates through sub-soil and meets the original stream after a time lag in the down-stream in the form of regeneration, so its effect have already included into the water inflow in the dam. Hence it was assumed that sub-surface percolation would not provide significant effect on the model development.

Above computed data of previous 20 years from 1996 to 2015 i.e. the total effective rainfall taken in mm and its corresponding total effective runoff also taken in mm, for the selected dam catchments had been used for further data analysis and development of rainfall-runoff empirical models in the basin.

4.3.4 Splitting data and sub-model preparation by using k-fold holdout technique

When the data is limited than the available data can be fruitfully used for model development applying the k-fold holdout technique. In this technique entire data is divided in to k (1, 2, 3 …, k) parts, from these k parts, one part is kept for testing and the remaining (k-1) parts under for training. By using this technique the developed model undergoes training k times and each part from one to k, gets a chance to undergo for testing. This technique gives equal importance to the each data for training as well as validation and none of the data is left behind during training and validation process. This k-fold holdout technique was employed by **Mojarad et. al (2010)** for the validation of cancer progression data in the analysis of the network performance.

As the rainfall and its corresponding runoff data was limited to 20 years so the four-fold holdout technique was used in the present study. The entire 20 years rainfall and its corresponding runoff data were divided into two subsets namely, training dataset and validation dataset..

The rainfall and corresponding runoff of 15 years data at a time were used for training purpose and the remaining 5 years data for validation. As per four-fold holdout technique, the entire data was partitioned into four parts having five years data each. The first, second, third and fourth part having five years data each at a time, were used for validation and the remaining fifteen years data were used in training of the model. According the part of data used as validation the sub-models were respectively named as 1V, 2V, 3V and 4V. Thus in the learning or training process each sub-model i.e. 1V, 2V, 3V and 4V was trained using 15 years training data, and then it was checked by the remaining five years validation data for assessing the generalization ability of the developed model. Hence 1V sub-model was prepared by learning or training it with the second, third and fourth part of the data and validated from the first part of the data. 1V, 2V, 3V and 4V sub-models were prepared using first and second order regression, ANN and ANFIS techniques.

4.3.5 Finding best model from the sub-models using performance metrics and simple ranking technique

For finding best model and checking the performance as well as the predictive accuracy of the developed models using different technique, three performance metrics namely Co-relation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for the training and validation data sets were computed. Some sub-models give good value of R in training but not providing good value of R in validation and the same thing is for RMSE and MAE.

Higher the value of R better is the prediction accuracy of the model. As R is over sensitive to the extreme values in comparison to the values near to the mean value and this value significantly influences the slope of the regression line, but is insensitive to additive and proportional errors. RMSE and MAE compare the observed or the target value with the values predicted by the model and measures the prediction accuracy of the model in terms of variance. It represents that there is a variance in the actual and the predicted values of runoff, so the model is not perfect and a single performance metric cannot provide an unbiased model prediction. Lower the RMSE and MAE, the better is the prediction accuracy of the model.

Hence the developed model should have maximum value of R near to 1 with the minimum value of RMSE and MAE near to 0 for getting the best model.

Data normalization and making data in a certain range before using for model development also reduces the over sensitivity of the extreme values and thus reduce the effect of these extreme values in model development.

Some-times the sub-model has maximum value of R but it does not give the minimum value of RMSE and MAE in training. Hence for obtaining the best model from the available four sub-models a simple ranking technique as suggested by **Armaghani et al. (2016),** was adopted for assessing the best model from the available sub-models prepared by adopting fourfold hold out technique. Ranks varying from 1 to 4 to each training and validation performing metric based on its computed value, was given to the each sub-model and then averaged out the allotted ranks, providing equal importance to each performing metric for getting the best model. The sub-model achieving best rank in all the four sub-models would be the best model fit in the selected catchment for the used specific technique i.e. first order regression model, second order regression model, ANN model and ANFIS model.

4.3.6 Data normalization

As enumerated by **Arbib (1995) and Shamseldin *et al. (*2002)**, the activation function or transfer function provides non-linearity in the multi-layer perceptrons and increase the ability of the network to deal critically with input-output relations that are either undefined or complex in nature. The non-linear activation functions commonly used for the backpropagation neural network are logistic sigmoid or tangent hyperbolic. The output range of these activation functions is bounded and, therefore, demands pre-processing of the training data so that they fall within the minimum-maximum range of the activation function. An individual scaling of input and output patterns is usually done to maximize the variance in the available data **(Kalogirou, 2003)** for obtaining good results and significantly reducing the computation time (**Nawi*et al.*,2013; Sola and Sevilla, 1997)**. The data normalization also helps the neural networks to efficiently learnfeatures comprising of different identities by minimizing the bias within the network towards a particular feature **(Priddy. and Keller 2005),** to ensure that all features get same significance during the training phase **(Maier*et al.*,2000)**.

The training data was pre-processed or normalized to minimize the bias towards a particular feature before using it for model development and so in the present study the normalized rainfall and corresponding normalized runoff values were linearly transformed within a bounded range [-1, 1] by following formulae

$$pn = \frac{2*\left(p - p_{\min}\right)}{p_{\max} - p_{\min}} - 1 \qquad (4.1)$$

where, p_n is the normalized value of the variable p which may be rainfall or runoff, maximum value is $p_{\max}$ and minimum value is $p_{\min}$.

After training or model development and its validation, the values obtained as its output are again de-normalized to the actual values using re-normalizing formulae:

$$p = \frac{1}{2}\left(p_n + 1\right)\left(p_{\max} - p_{\min}\right) + p_{\min} \qquad (4.2)$$

4.4 Development of four types of models using different modeling techniques - Regression, Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS)

Harnessing conventional regression and soft computing techniques four different types of models, namely first order rainfall-runoff empirical model, second order rainfall-runoff empirical model, ANN rainfall-runoff empirical model and ANFIS rainfall-runoff empirical model have been developed using the above normalized rainfall and its corresponding runoff data.

4.4.1 Rainfall-runoff empirical model using regression technique

For getting the first order polynomial regression model, all the four first order regression sub-models i.e. 1V, 2V, 3V and 4V were developed and validated by computing the performing metrics i.e. R, RMSE and MAE for training as well as validation process. Ranks from 1 to 4 to the each training and validation performing metrics was given to each sub-model, giving equal importance to each training and validation performing metrics and then averaged out the allotted ranks for getting the best first order polynomial regression model. Similar procedure was also adopted for the selection of the best fit second order polynomial rainfall-runoff empirical regression model.

4.4.2 Rainfall-runoff empirical model using Artificial Neural Networks

Artificial Neural Networks (ANN), for instance, inspired by capabilities of the human brain to learn from the training rainfall and corresponding runoff data, transfer the information from input layer of four neurons representing the rainfalls in July, August, September and monsoon, to the output layer of four neurons representing runoffs in July, August, September and monsoon, through the inter-connected hidden layer neurons varied from 2 to 11, in the form of synaptic weights and biases with transfer functions. The systematic updating of the neural network synaptic weights and biases for multi-layer feedforward neural network (MFNN) is accomplished by the Levenberg Marquardt (LM) back-propagation training algorithm. A tangent hyperbolic sigmoid transfer function (tansig) that is known for providing complexity in the relation and hence speeding up the training process has been used in the hidden layer. A linear transfer function (purelin) has been used in output layer to facilitate comparison of actual and predicted runoff.

Studies conducted in the past for determining the optimal number of hidden layers have indicated that, any complex non-linear function can be approximated to an acceptable degree of accuracy by a single hidden layer of ANN and an increase in the number of neural network hidden layers may not result in significant performance improvements, so one hidden layer was taken.

A trial and error approach has been adopted to determine the optimal number of hidden layer neurons, gradually increasing from 2 to 11 having 50 epochs each and that one architecture which provides the best set of performing metrics for training as well as validation process for each sub-modal i.e. 1V, 2V, 3V and 4V have been selected. Further procedure was same as followed in the regression models. Accordingly ranks to each performance metric were allotted to each sub-modal, then averaged out and found the best ANN model out of the four ANN sub-model which one was getting best rank.

4.4.3 Rainfall-runoff empirical model using Adaptive Neuro Fuzzy Inference System

Adaptive Neuro Fuzzy Inference System (ANFIS) works in two stages firstly making fuzzy rules or membership functions then secondly use the adaptive neural network. It uses rainfall and runoff training data sets to construct a fuzzy inference system whose membership functions are tuned using learning algorithm and then the system is trained with data pairs by an adaptive neural network. It combines the advantages of fuzzy logic (FL) and artificial neural network (ANN) on a conceptual and structural basis.

In ANFIS also four sub-modals i.e. 1V, 2V, 3V and 4V were prepared using subtractive clustering technique. The genfis2 function has been used to generate fuzzy inference system (FIS) and the radius of the cluster was varied from 0.05 to 0.7, to optimize the performance metrics computed for training as well as validation of each sub-modal of ANFIS model. Further procedure remained same as followed in the regression and ANN models and got the ANFIS model which was getting best rank out of the four sub-modals.

Neural Network and Adaptive Neuro-Fuzzy Inference System toolbox included in the software MATLAB R2011b (Version 7.13.0.564) were used to implement ANN and ANFIS respectively.

4.4.4 Evaluating performance of the different techniques used in modal development

For comparing performance of the techniques used in the model development, ranks were again allotted to each training and validation performing metrics obtained for each first order polynomial regression model, second order polynomial regression model, ANN model and ANFIS model. The final rank would represent the performance of the model using different techniques.

4.4.5 Development of a decision support tool

A decision support tool for the individual sub-basin could be prepared and that will be helpful in computing the runoff in mm per unit area, using the computed total weighted rainfall in mm in the catchment and selecting the used technique. All the developed four models using different techniques were harnessed and a decision support tool for predicting runoff in mm per unit area would have prepared. A typical decision support tool prepared for Mashi sub-basin using Chhaparwara catchment characteristic is shown in **Figure: 5.46**.

The flow chart of the methodology followed in this research work is shown in the **Figure: 4.1.**

4.5 Methodology flow chart

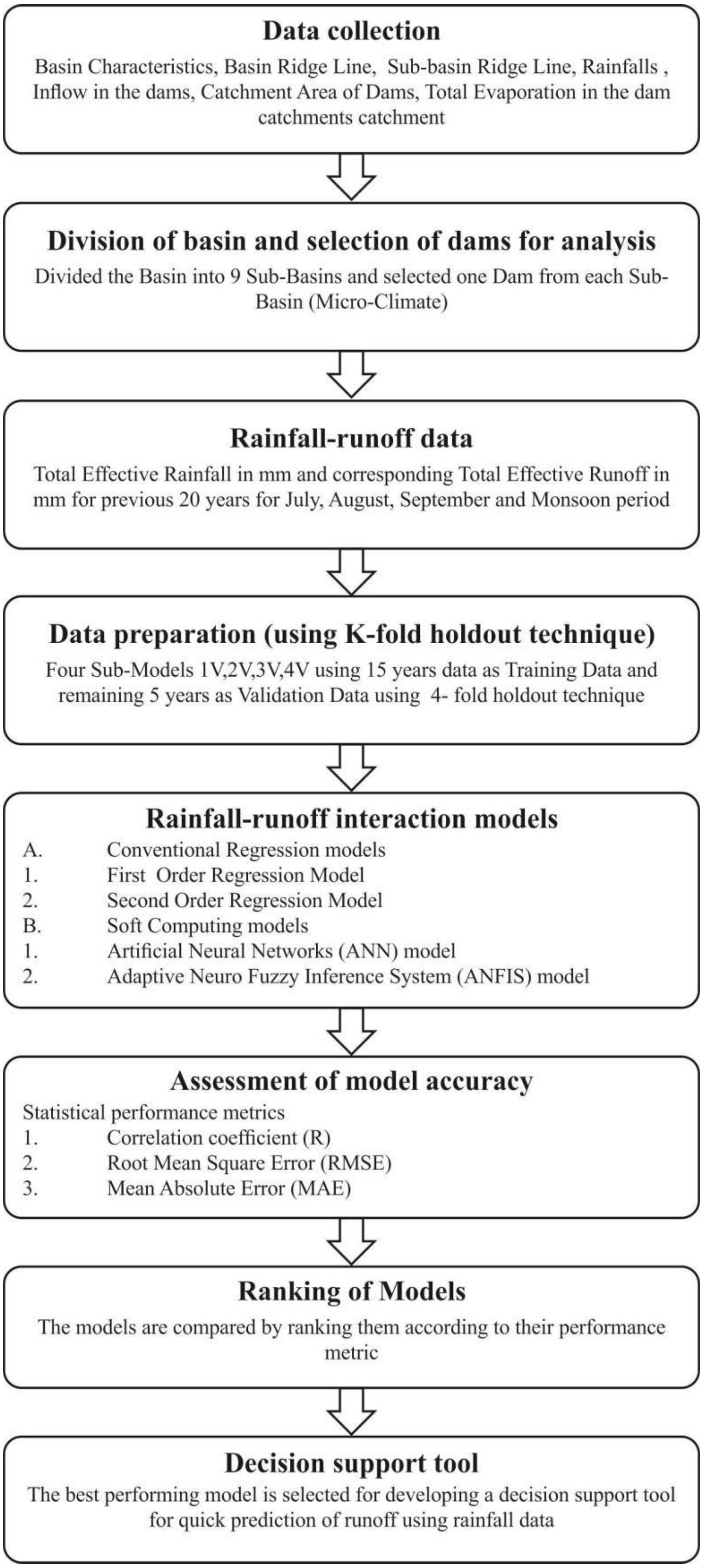


Figure 4.1: Flow chart of research methodology

4.6 Formulation and testing of Hypothesis

Following two hypothesis were laid for the development of rainfall runoff empirical models -

1. Null hypothesis H_0: There is no association between the total effective rainfall and corresponding total effective runoff in the Banas River Basin.
2. Null hypothesis H_0: There is no significant relation between the total effective rainfall and corresponding total effective runoff in the basin.

A relation between total occurred effective rainfall (X) and its corresponding total effective runoff (Y) can be developed using conventional regression analysis, which is based on the principle of least sum of squares of errors between the actual and predicted runoffs. For checking the significance of the developed relation the co-relation coefficient which also represents the strength of the relation was computed. It was also one of the model performance metrics that were used for checking the accuracy of the developed model i.e., R, RMSE and MAE.

As the value of R represent the degree of association, between the rainfall and its corresponding runoff as well as the strength of the developed relation. If the value of R is 0, then there is no association between rainfall and its corresponding runoff values in the catchment. If R is positive or negative, then the rainfall and its corresponding runoff values are associated directly or inversely related to each other. The range of the R value for rainfall-runoff empirical model varies between 0 and 1.

Various possible graphs were plotted between total effective rainfall and corresponding total effective runoff pairs, with their correlation coefficient for each dam catchment selected from different sub-basins. As the data pairs are less than 30 so Student’s t-distribution test was applied for testing the significance of hypothesis. The significance of the developed rainfall-runoff empirical relationship was tested by applying t-test with the help of computed R-value.

The ‘t’ statistic value for (N-2) degree of freedom is computed by

$$t = \frac{R}{\sqrt{\frac{1-R^2}{N-2}}} \tag{4.3}$$

Where, *R* is the correlation coefficient and N is the number of pairs of observations which is 15 in this study. On the basis of threshold 't' value, the corresponding threshold R values, at different significant level, for different degree of freedom were computed and tabulated in the **Table 4.3**. If the calculated t statistic or the corresponding R is more than the value of threshold 't' or the corresponding threshold R as in Table 4.3, then the null hypothesis is rejected and the alternate hypothesis accepted, which infers that there is a certain association and also a statistical relationship between the total effective rainfall and corresponding total effective runoff at various significance levels. Comparing the computed values of R and the corresponding threshold value R the significance level of the developed rainfall-runoff relation or the rainfall-runoff empirical model was decided.

Table 4.3: Student's critical 't' values and corresponding threshold correlation coefficient (R) at different significant levels

No of observations (N)	Degrees of freedom (N-2)	Significance level									
		0.20		0.10		0.05		0.02		0.01	
		t	R	t	R	t	R	t	R	t	R
12	10	1.37	0.40	1.81	0.50	2.23	0.58	2.76	0.66	3.17	0.71
13	11	1.36	0.38	1.80	0.48	2.20	0.55	2.72	0.63	3.11	0.68
14	12	1.36	0.36	1.78	0.46	2.18	0.53	2.68	0.61	3.06	0.66
15	13	1.35	0.35	1.77	0.44	2.16	0.51	2.65	0.59	3.01	0.64

4.7 Data requirement and application scope of the developed models

The developed models are intended for areas having less availability of hydrological data, like Rajasthan and in some other regions of the world. For updating the developed models following hydrological input data on monthly and monsoon time periods are required-

(1) Areal rainfall and its distribution

(2) River inflow at the outlet of the catchment

(3) Areal evaporation from the catchment area

(4) Catchment area and its general characteristics

The models are based on the water balance at a selected catchment scale so any other water taken from or come into a catchment from an adjacent catchment has also be taken into account.

4.8 Limitations of the developed models

It is assumed that the total effective rainfall and evaporation distribution is more or less homogeneous in the entire catchment. If there is high spatial variation of rainfall, the model does not perform efficiently. The water percolated into the subsoil is considered as a subsurface runoff, which meets in downstream in the form of regeneration. Too small catchment also may give difficulties, in that case the groundwater and the topographic boundaries may not coincide. These models are not applicable if there are large water bodies such as lakes in the catchment and if significant frost and snow occur. In the latter case temperature input is also essential.

The amount and the nature of data or the information comprising the training dataset are critical for the successful performance of the neural networks. ANN is less capable in extrapolating the predictability beyond the data range used during training period so the validation part of the model is also as important as the training part.

Results and Discussion

5.1 Introduction

In the previous chapters the literature related to the present study and the methodology adopted in developing the different rainfall- runoff empirical models, using conventional regression and soft computing techniques were discussed. General local characteristics of the study area have also been discussed in the previous chapter. This chapter presents the sub-basin wise results obtained in the study area with their interpretation and their applicability in the basin. A decision support tool was prepared on the basis of the results obtained in developing the models (adopting different techniques) have also been discussed in the present chapter. In the study efforts have been made to make such a model, which is able to calculate runoff quickly, with the help of the rainfall and its distribution only.

5.2 General observations on rainfall and runoff in the study area

Computation of available water or runoff at different locations is required for proper regulation of existing and proposed water resources projects. It was observed that the availability of the runoff data are generally not long enough, while the rainfall data are generally available for relatively longer duration , so rainfall can be taken as the basis for estimating runoff and the estimated runoff can directly be used for different hydrologic purposes in the study area. The trends of runoff can also be worked out from the existing rainfall trends with the help of the developed rainfall-runoff models.

After observing the available rainfalls in the Banas river basin for the last 50 years it has been found that 80 to 90 percent of rainfall occurs from starting of July to end of September which is also known as monsoon period. There exists a long extended dry period before the beginning of each successive rainy season in the entire study area. The potential evapotranspiration exceeds the amount of water received from rain, for a large period of the year in most of the dam catchments. There are only two or three monsoon water spells in a year, in the study area. The rainfall distribution within all the selected dam catchments varies from place to place and from time to time also. There is a great variability in the incidence of monthly and monsoon rainfalls, with time and space within a single year.

In developing the rainfall-runoff empirical models it had been tried to connect the total effective rainfall over the catchment with the total effective runoff received from the catchment. For finding out a formula for getting the runoff measured in the mm depth from catchments in the monsoon months a clear idea of the factors influencing runoff and their relative importance is necessary. Depending on the nature and importance of the runoff influencing factors of the catchment, all the factors may be divided in two kind i.e. constant factors and variable factors. The factors like area, shape and slope of the catchment are considered as constant factors as these provide constant effect on the volume of water generated from the catchment. The factors like rainfall intensity, rainfall distribution and evaporation losses provide variable effect on the volume of water received from the catchment at its outlet point.

The general characteristics of the study area showed that water flow direction is different at different places in a catchment and it also changes at the ridge line of the individual sub-basins. The maximum surface area of the study area is hard rocky like gneiss, phyllite, schist and quartzite, with higher proportion of coarser material like as kankar, gravels and pebbles in the vicinity of river course. The soil texture of the study area is sandy loam or clay underlained by fine sand or clay which acts as hard rock aquifers that do not lend themselves to good yields and large scale groundwater storage. The maximum area is pediplain comprised of buried or barren pediments and uncultivated also. Due to rocky surface the storm water could not percolate deeply; surface runoff is generated and very less quantity of water pours into the groundwater. Although the higher proportion of coarser material present in the river courses and the local sandy texture of soil generates sub-surface runoff but the underlained fine sand or clay present in the soil strata restricts the sub-surface runoff into deep percolation or groundwater recharge. The sub-surface percolated water meets the stream in the downwards constituting regenerated runoff. As such the deep percolated water was assumed as negligible and the effect of groundwater was not considered in the development of rainfall-runoff empirical models.

The surface water area due to storage of the water in the tributaries, main stream, water bodies in the dam catchment and its submergence is very small in comparison to the remaining soil cover area in the catchment, so the water evaporated from the water surface is very less in comparison to the water evaporated from the soil surface area. The other water losses are very less in comparison to the evaporation losses, hence only the water evaporated through soil and water bodies in the catchment have been considered.

5.3 Rainfall-runoff empirical models in different sub-basins in the study area

The transformational behaviour of rainfall into runoff within a catchment depends on many local topographic, geographic, geologic and sociologic factors that might be of constant or variable nature with respect to time.

The study area was divided in 9 sub-basins because each sub-basin has individual geographical, topographic and hydrogeologic characteristics which differ from the other sub-basins. Each sub basin behaves in unique manner and has unique micro-climate that differs from other sub-basins.

For developing the rainfall-runoff empirical models in the study area, one dam from each sub-basin was selected for data analysis and model development. As the selected dam catchment is a part of the individual sub-basin, hence the general physical characteristics and the general behaviour of the dam catchment is assumed to resemble with the characteristics and general behaviour of the sub-basin.

5.3.1 Regression Models

When different graphs were plotted between the values of total effective rainfall and corresponding total effective runoff, it was found that second order polynomial rainfall-runoff empirical relation showed the better value of correlation coefficient and determination coefficient, then the linear rainfall-runoff relation.

The developed first order rainfall–runoff empirical equations with their R^2, RMSE and MAE for different months for the 9 selected dam catchments from different subbasins are shown in **Table 5.1A and 5.1B.** The comparison of actual runoff with the runoff predicted by first order regression model from different selected dam catchments is shown in **Figure- 5.1 to Figure- 5.9**.

In Table 5.1 and Table 5.2**,** X represents the total effective rainfall in millimetre occurring in the catchment and Y is the runoff in millimetre reaching at the discharge site of any marked catchment area.

The developed second order rainfall–runoff empirical equations with their related R^2, RMSE and MAE for different months for the 9 selected dam catchments from different sub-basins are shown in **Table 5.2A and 5.2B.** The comparison of actual runoff with the runoff predicted by second order regression model from different selected dam catchments is shown in **Figure- 5.10 to Figure- 5.18**.

Table 5.1-A: First order rainfall-runoff regression models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected Dam	Month	First order regression equation	R^2	RMSE	MAE
1	Berach	Wagan	July	$Y = 0.1355X - 11.8299$	0.62	11.01	8.98
			Aug.	$Y = 0.0583X + 1.5717$	0.25	22.14	15.71
			Sept.	$Y = 0.0552X - 2.2479$	0.22	6.64	4.45
			Mons.	$Y = 0.1808X - 55.5599$	0.92	10.98	9.31
2	Banas I	Jetpura	July	$Y = 0.1054X - 10.8793$	0.46	16.27	11.75
			Aug.	$Y = 0.1146X + 5.9270$	0.58	22.78	16.62
			Sept.	$Y = -0.0019X + 1.9247$	0.02	4.95	3.23
			Mons.	$Y = 0.0626X + 55.0923$	0.29	15.88	13
3	Kothari	Meja	July	$Y = 0.0003X + 0.2489$	0.03	0.30	0.2
			Aug.	$Y = 0.0023X + 0.4189$	0.48	0.83	0.52
			Sept.	$Y = 0.0014X + 1.3941$	0.04	3.36	2.38
			Mons.	$Y = 0.0017X + 0.9258$	0.18	3.25	2.21
4	Khari	Nahar Sagar	July	$Y = 0.0793X - 8.7230$	0.52	8.70	7.02
			Aug.	$Y = 0.0730X - 4.700$	0.77	6.62	4.67
			Sept.	$Y = 0.0045X + 2.2994$	0.07	2.96	2.15
			Mons.	$Y = 0.0160X + 8.4772$	0.12	13.63	11.42
5	Dai	Lasasaria	July	$Y = 0.0204X - 0.4710$	0.21	1.82	1.46
			Aug.	$Y = 0.0218X - 0.858$	0.56	1.53	1.22
			Sept.	$Y = 0.0004X + 0.1715$	0.03	0.31	0.21
			Mons.	$Y = 0.0016X + 3.0465$	0.03	1.96	1.78

Table 5.1-B : First order rainfall-runoff regression models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected Dam	Month	First Order Regression Equation	R^2	RMSE	MAE
6	Mashi	Chhaparwara	July	$Y = 0.0179X + 0.0004$	0.41	1.68	1.3
			Aug.	$Y = 0.0230X + 2.6593$	0.12	7.27	5.78
			Sept.	$Y = 0.0109X + 0.0151$	0.29	2.39	1.45
			Mons.	$Y = 0.0153X + 3.2000$	0.13	9.91	8.11
7	Morel	Morel	July	$Y = 0.0203X - 1.4243$	0.18	3.71	2.41
			Aug.	$Y = 0.0238X - 1.8112$	0.64	1.87	1.51
			Sept.	$Y = 0.0018X + 1.5056$	0.01	3.59	2.44
			Mons.	$Y = 0.0058X + 2.8144$	0.21	4.67	3.48
8	Kalisil	Kalisil	July	$Y = 0.2646X - 27.375$	0.88	13.30	11.53
			Aug.	$Y = 0.0688X + 2.0886$	0.26	23.10	17.65
			Sept.	$Y = 0.0611X - 2.6684$	0.25	6.34	3.97
			Mons.	$Y = 0.1776X - 28.9369$	0.65	21.92	18.37
9	Banas II	Motisagar	July	$Y = 0.0999X + 12.5923$	0.21	25.16	20.48
			Aug.	$Y = 0.0535X + 2.6700$	0.46	14.51	11.52
			Sept.	$Y = 0.0019X + 0.8061$	0.09	1.81	1.17
			Mons.	$Y = 0.0165X + 43.8950$	0.11	26.68	24.02

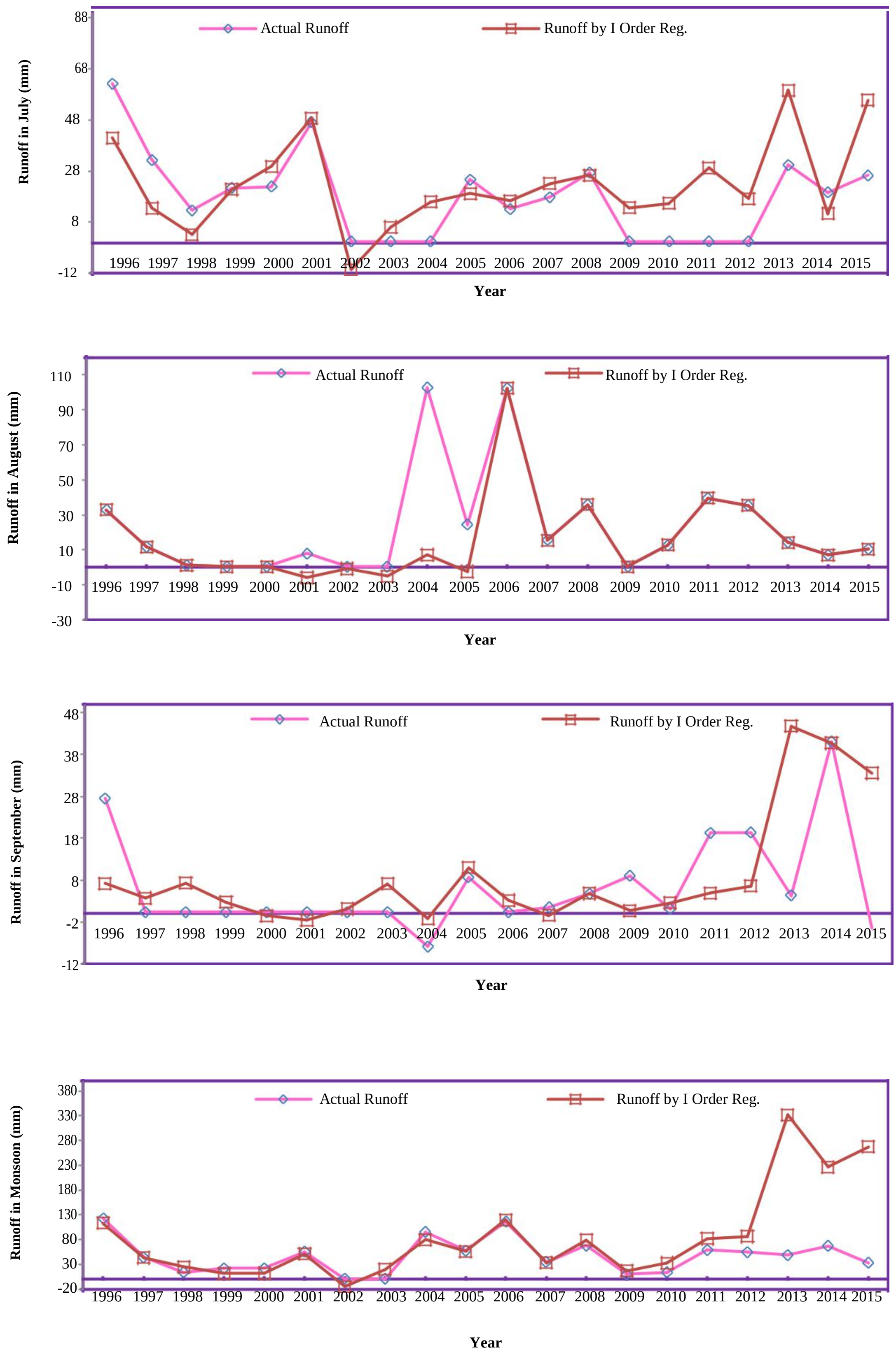


Fig. 5.1: Comparison of actual runoff and runoff predicted by first order regression model for Wagan Dam Catchment

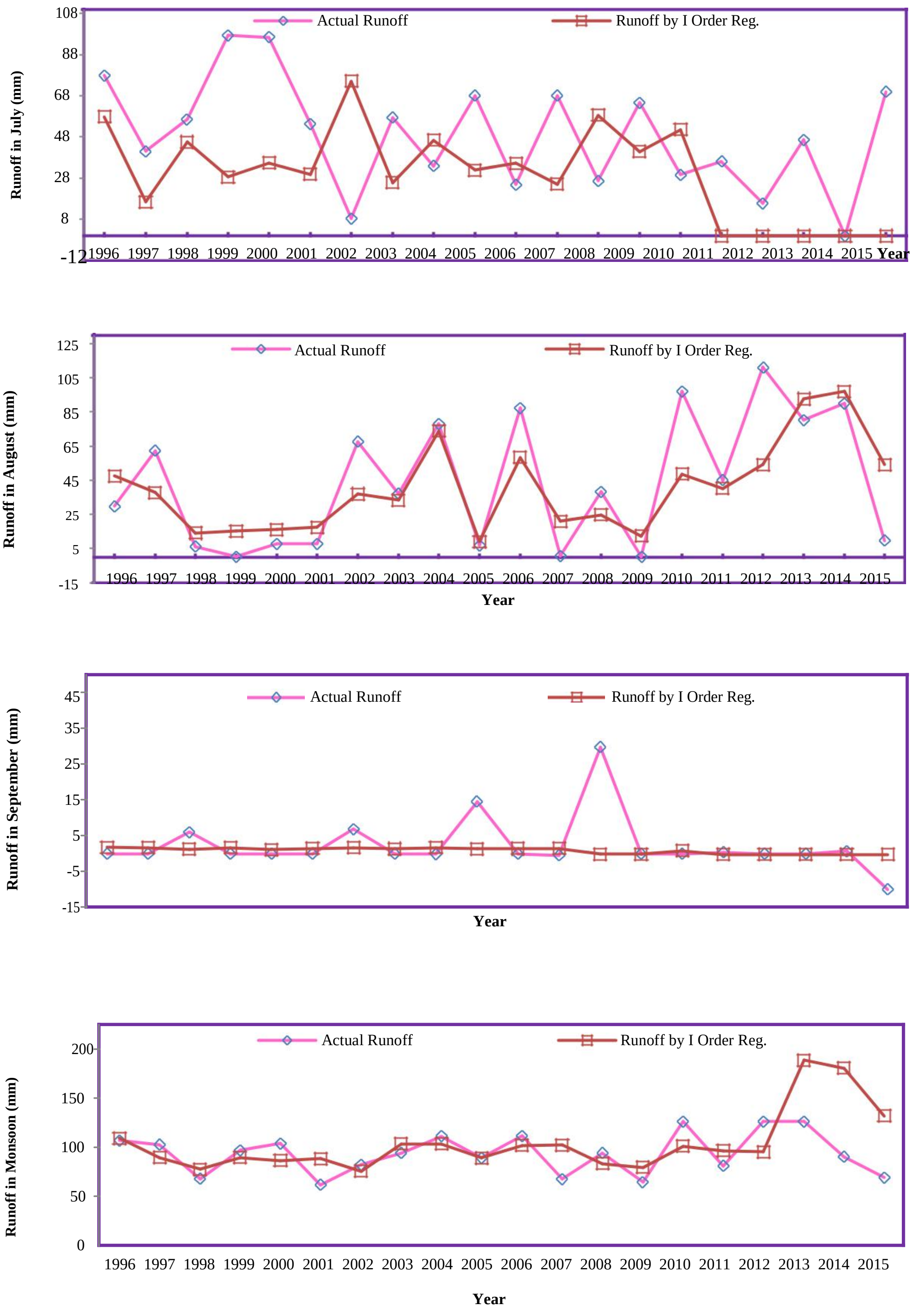


Fig. 5.2 Comparison of actual runoff and runoff predicted by first order regression model for Jetpura Dam Catchment

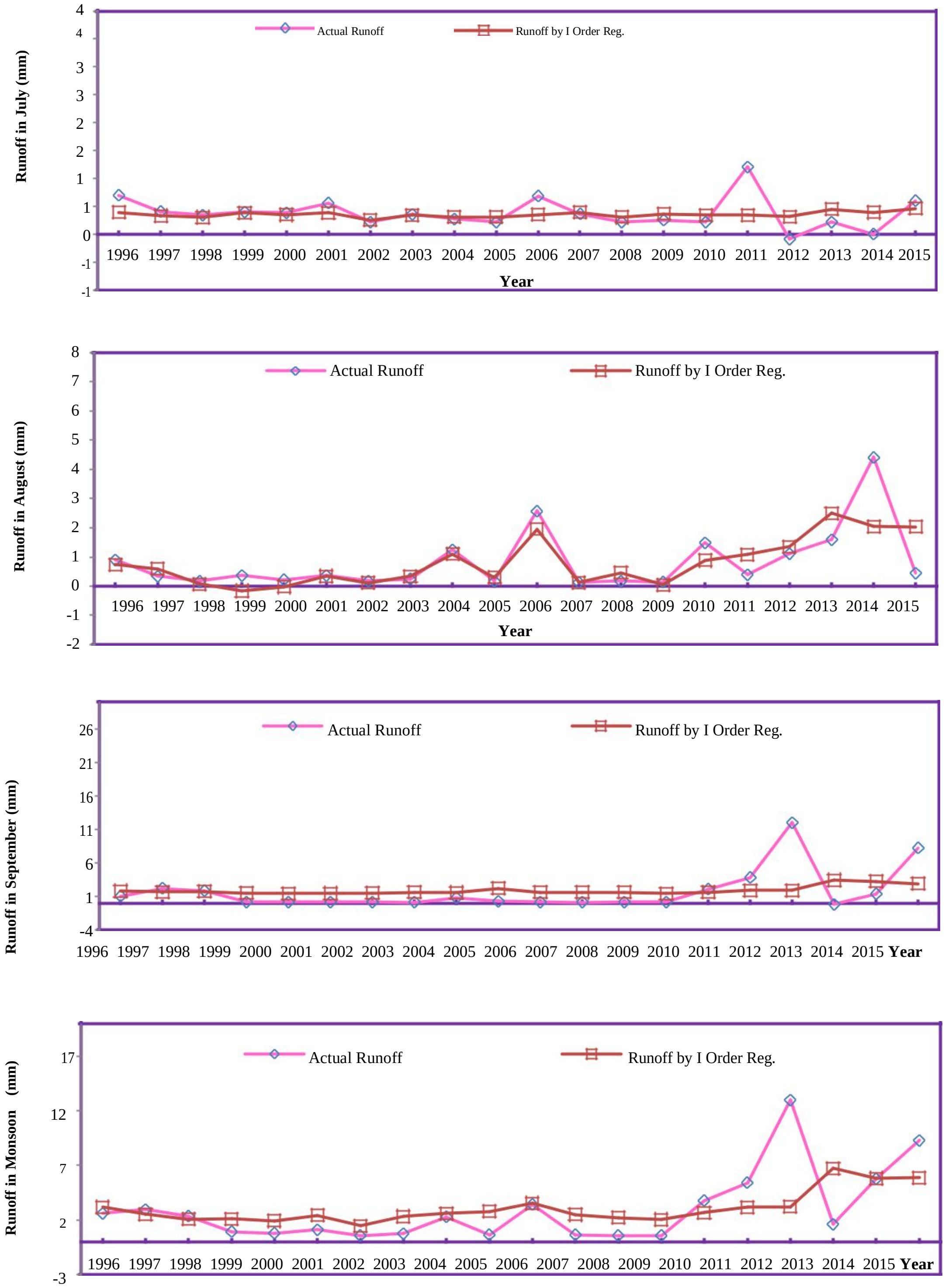


Fig. 5.3: Comparison of actual runoff and runoff predicted by first order regression model for Meja Dam Catchment

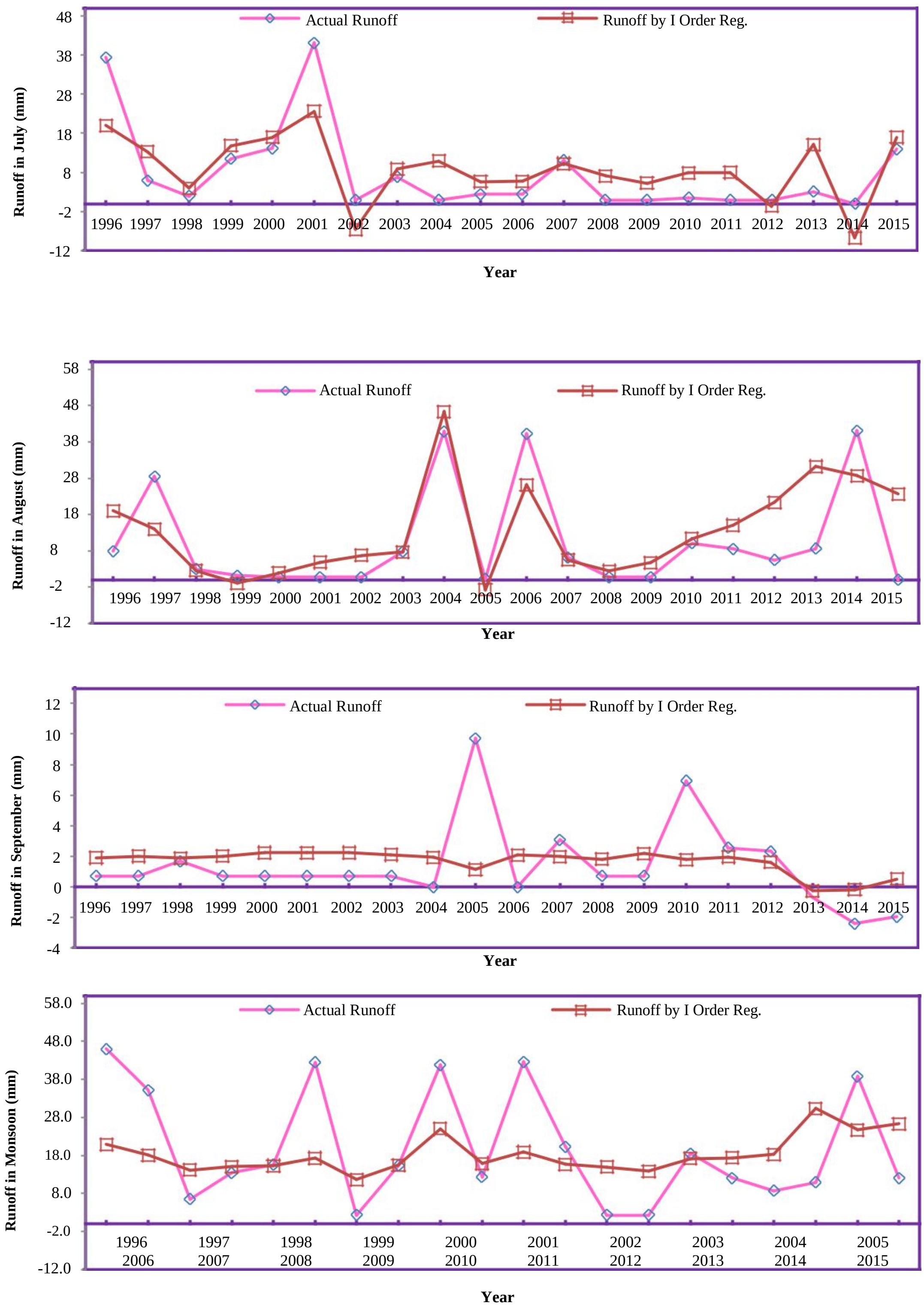


Fig. 5.4: Comparison of actual runoff and runoff predicted by first order regression model for Nahar Sagar Dam Catchment

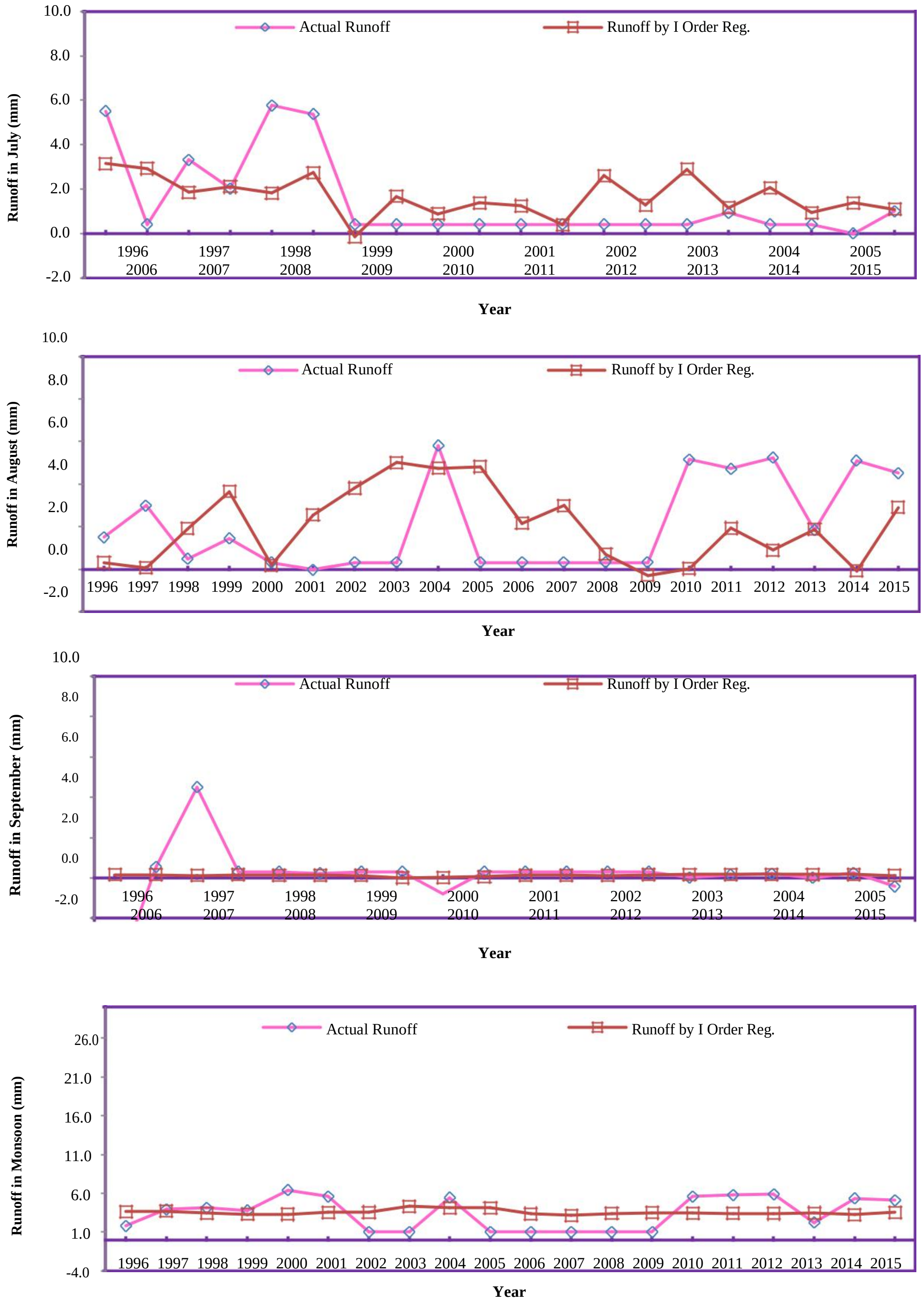


Fig. 5.5: Comparison of actual runoff and runoff predicted by first order regression model for Lassaria Dam Catchment

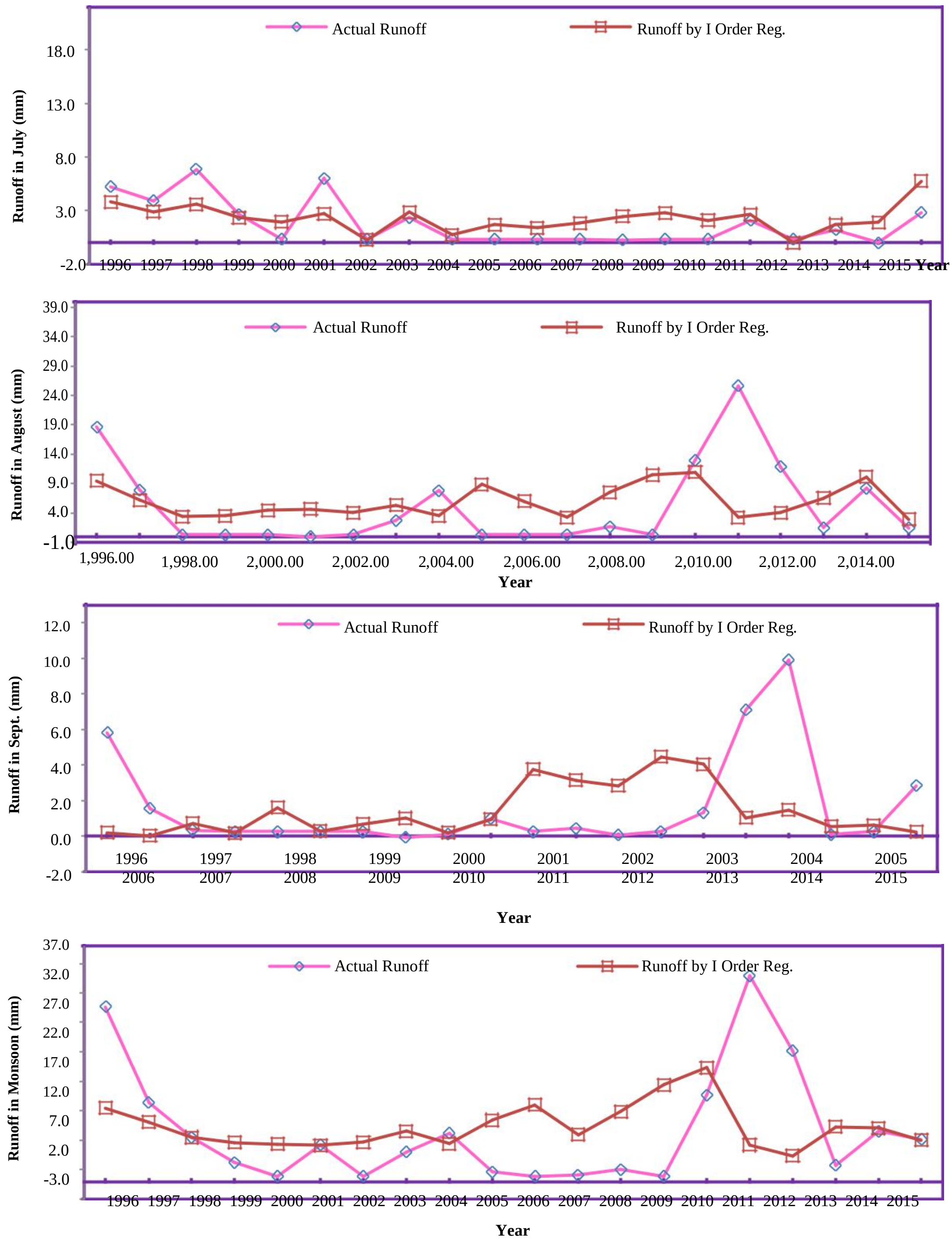


Fig. 5.6: Comparison of actual runoff and runoff predicted by first order regression model for Chhaparara Dam Catchment

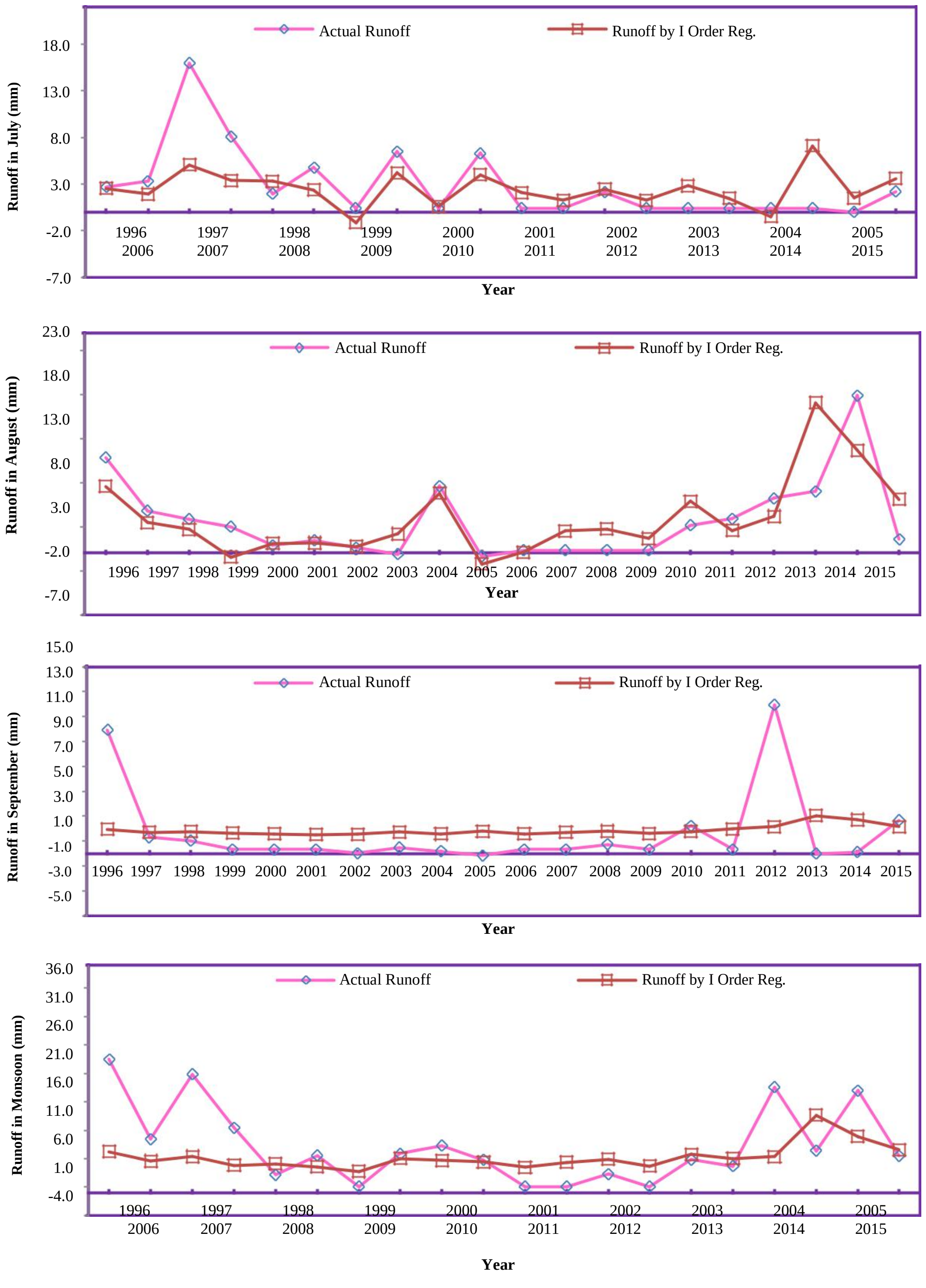


Fig. 5.7: Comparison of actual runoff and runoff predicted by first order regression model for Morel Dam Catchment

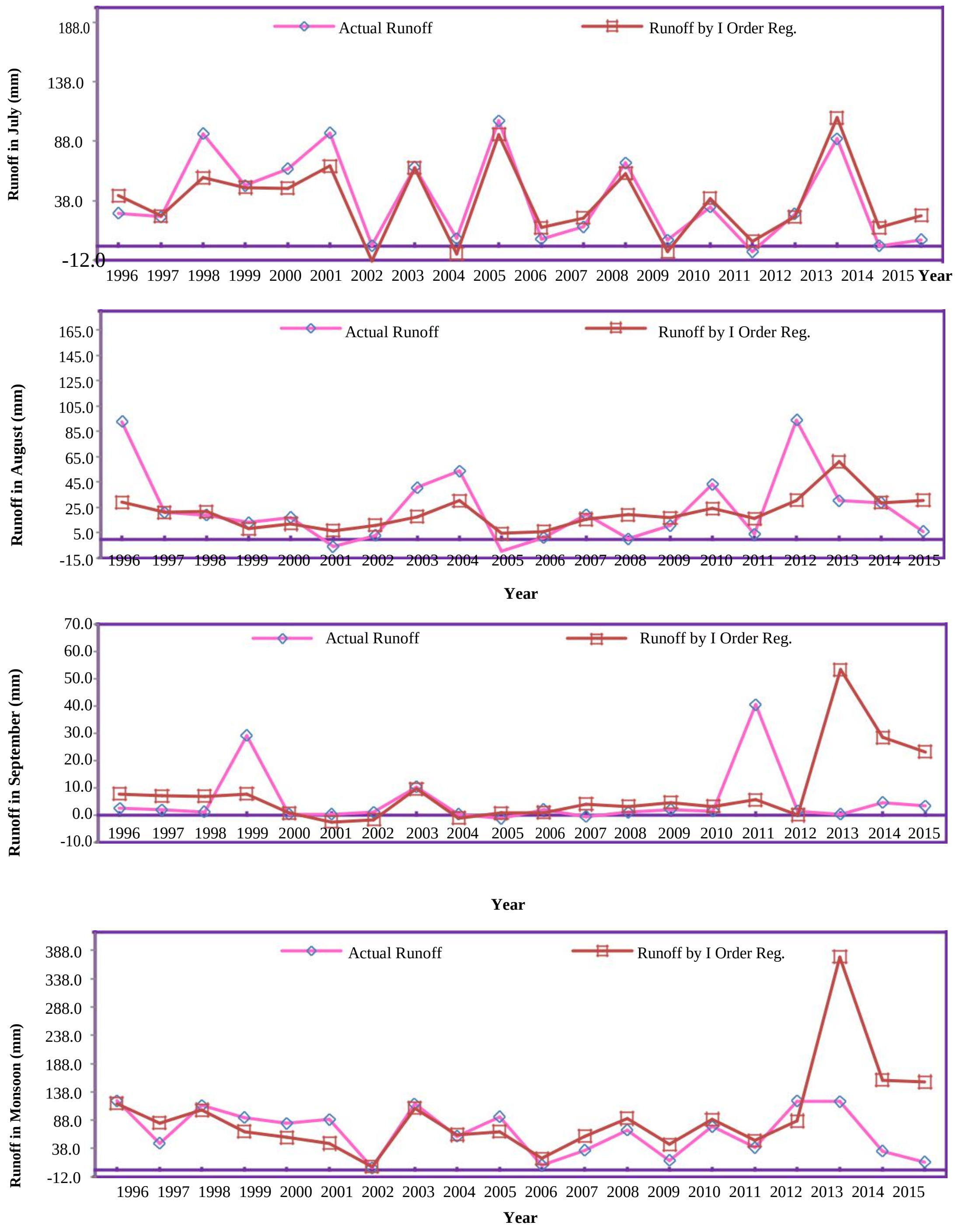


Fig. 5.8: Comparison of actual runoff and runoff predicted by first order regression model for Kalisil Dam Catchment

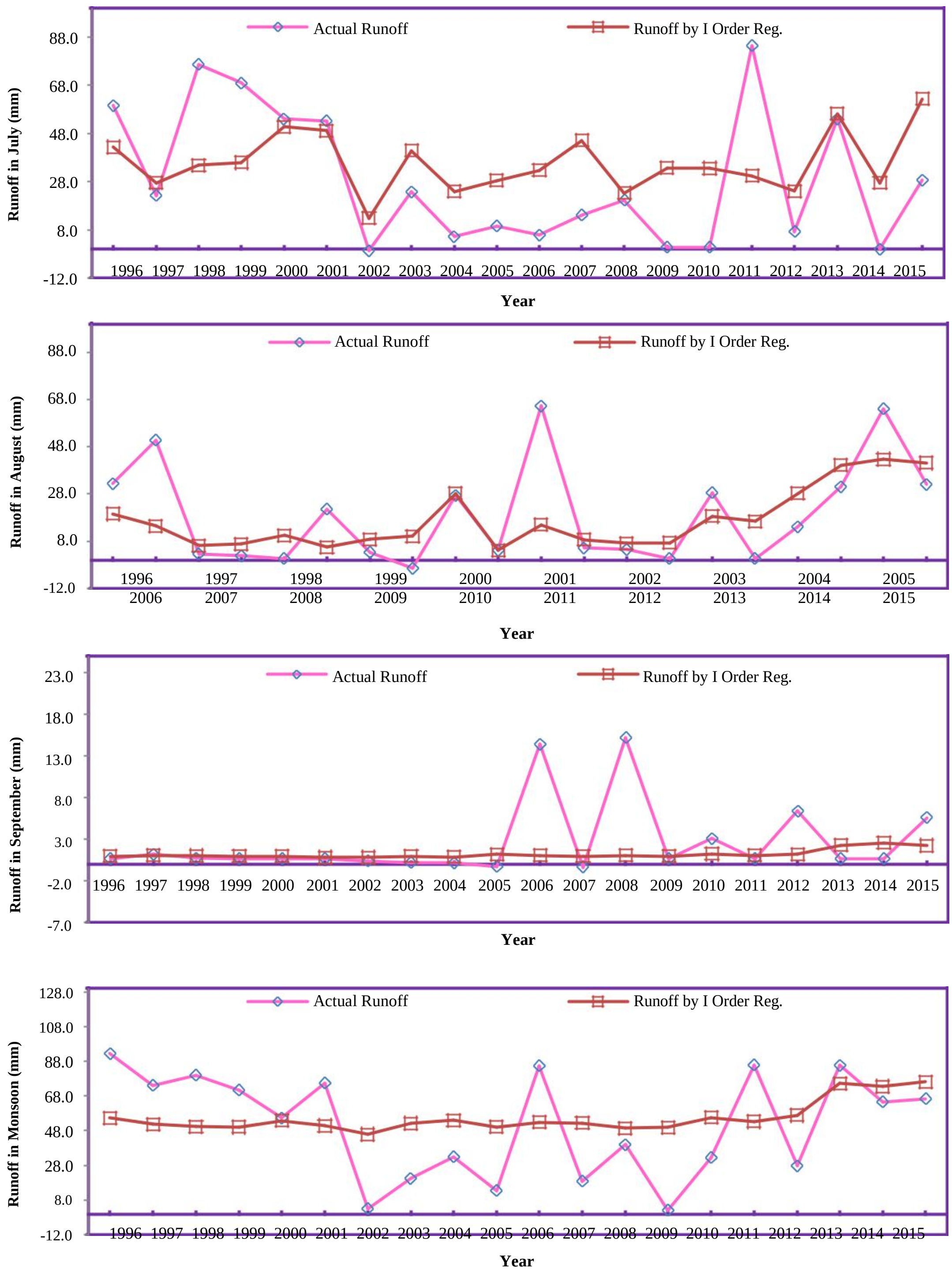


Fig. 5.9: Comparison of actual runoff and runoff predicted by first order regression model for Motisagar Dam Catchment

Table 5.2-A: Second order rainfall-runoff regression models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected Dam	Month	Second order regression equation	R^2	RMSE	MAE
1	Berach	Wagan	July	$Y = 0.00026X^2 + 0.0103X + 0.1037$	0.67	10.15	8.25
			Aug.	$Y = -0.00031X^2 + 0.0327X - 35.0896$	0.34	26.17	18.20
			Sept.	$Y = 0.00003X^2 + 0.0634X - 2.5618$	0.22	6.64	4.45
			Mons.	$Y = -0.00008X^2 + 0.0224X - 51.34$	0.62	19.82	15.40
2	Banas I	Jetpura	July	$Y = 0.00042X^2 + 0.4X - 17.0850$	0.69	14.04	11.50
			Sept.	$Y = -0.00021X^2 + 0.297X - 18.0237$	0.19	7.18	4.29
			Aug.	$Y = 0.00006X^2 + 0.0254X + 0.4403$	0.57	22.78	16.60
			Mons.	$Y = 0.000005X^2 + 0.0170X + 82.1832$	0.06	20.58	18.30
3	Kothari	Meja	July	$Y = 0.0000006X^2 + 0.0001X + 0.2078$	0.38	0.12	0.09
			Aug.	$Y = -0.0000009X^2 + 0.0036X - 0.7593$	0.49	0.83	0.53
			Sept.	$Y = -0.00001X^2 + 0.0190X - 1.0323$	0.04	3.36	2.38
			Mons.	$Y = 0.0000026X^2 + 0.0120X - 6.2935$	0.18	3.25	2.21
4	Khari	Nahar Sagar	July	$Y = 0.00042X^2 - 0.0928X + 3.0210$	0.72	4.97	3.70
			Aug.	$Y = -0.00004X^2 + 0.10X - 7.7366$	0.79	6.46	4.72
			Sept.	$Y = -0.00002X^2 + 0.008X + 1.1383$	0.35	1.74	1.27
			Mons.	$Y = -0.00008X^2 + 0.154X - 33.0427$	0.48	10.52	8.64
5	Dai	Lasasaria	July	$Y = 0.00002X^2 + 0.0147X - 0.2355$	0.21	1.82	1.44
			Aug.	$Y = -0.00007X^2 + 0.04X - 2.0183$	0.59	1.48	1.26
			Sept.	$Y = -0.00002X^2 - 0.0096X + 0.2582$	0.03	1.35	0.71
			Mons.	$Y = -0.00001X^2 + 0.0147X + 0.674$	0.08	1.9	1.68

Table 5.2-B: Second order rainfall-runoff regression models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected Dam	Month	Second order regression equation	R^2	RMSE	MAE
6	Mashi	Chhaparwara	July	$Y = 0.00025X^2 - 0.0268X + 0.7274$	0.66	1.34	0.98
	Mashi	Chhaparwara	Aug.	$Y = -0.00023X^2 + 0.109X - 1.9927$	0.20	6.91	5.28
	Mashi	Chhaparwara	Sept.	$Y = 0.00005X^2 + 0.0310X - 0.7917$	0.35	2.30	1.64
	Mashi	Chhaparwara	Mons.	$Y = -0.000050X^2 + 0.0681X - 8.2979$	0.28	7.84	5.84
7	Morel	Morel	July	$Y = -0.00008X^2 + 0.0615X - 5.5462$	0.23	3.58	2.55
	Morel	Morel	Aug.	$Y = -0.00003X^2 + 0.0422X - 2.8817$	0.61	2.97	2.02
	Morel	Morel	Sept.	$Y = -0.00004X^2 + 0.0356X - 1.7766$	0.36	2.84	2.09
	Morel	Morel	Mons.	$Y = 0.000011X^2 + 0.0288X - 4.9730$	0.44	3.95	3.14
8	Kalisil	Kalisil	July	$Y = 0.00035X^2 + 0.122X - 11.5120$	0.86	12.45	9.92
	Kalisil	Kalisil	Aug.	$Y = -0.00020X^2 + 0.240X - 21.4720$	0.48	19.55	13.9
	Kalisil	Kalisil	Sept.	$Y = -0.00005X^2 + 0.043X + 2.8183$	0.09	11.09	7.65
	Kalisil	Kalisil	Mons.	$Y = 0.00003X^2 + 0.213X - 37.1869$	0.66	21.89	18.4
9	Banas II	Moti Sagar	July	$Y = 0.00001X^2 + 0.134X - 2.6716$	0.29	22.04	17.3
	Banas II	Moti Sagar	Aug.	$Y = 0.00002X^2 + 0.036X + 4.5351$	0.46	14.51	11.5
	Banas II	Moti Sagar	Sept.	$Y = -0.00005X^2 + 0.046X - 0.7529$	0.15	4.47	3.24
	Banas II	Moti Sagar	Mons.	$Y = -0.00003X^2 + 0.0875X + 18.3045$	0.17	25.81	23.5

Fig. 5.10: Comparison of actual runoff and runoff predicted by second order regression model for Wagan Dam Catchment

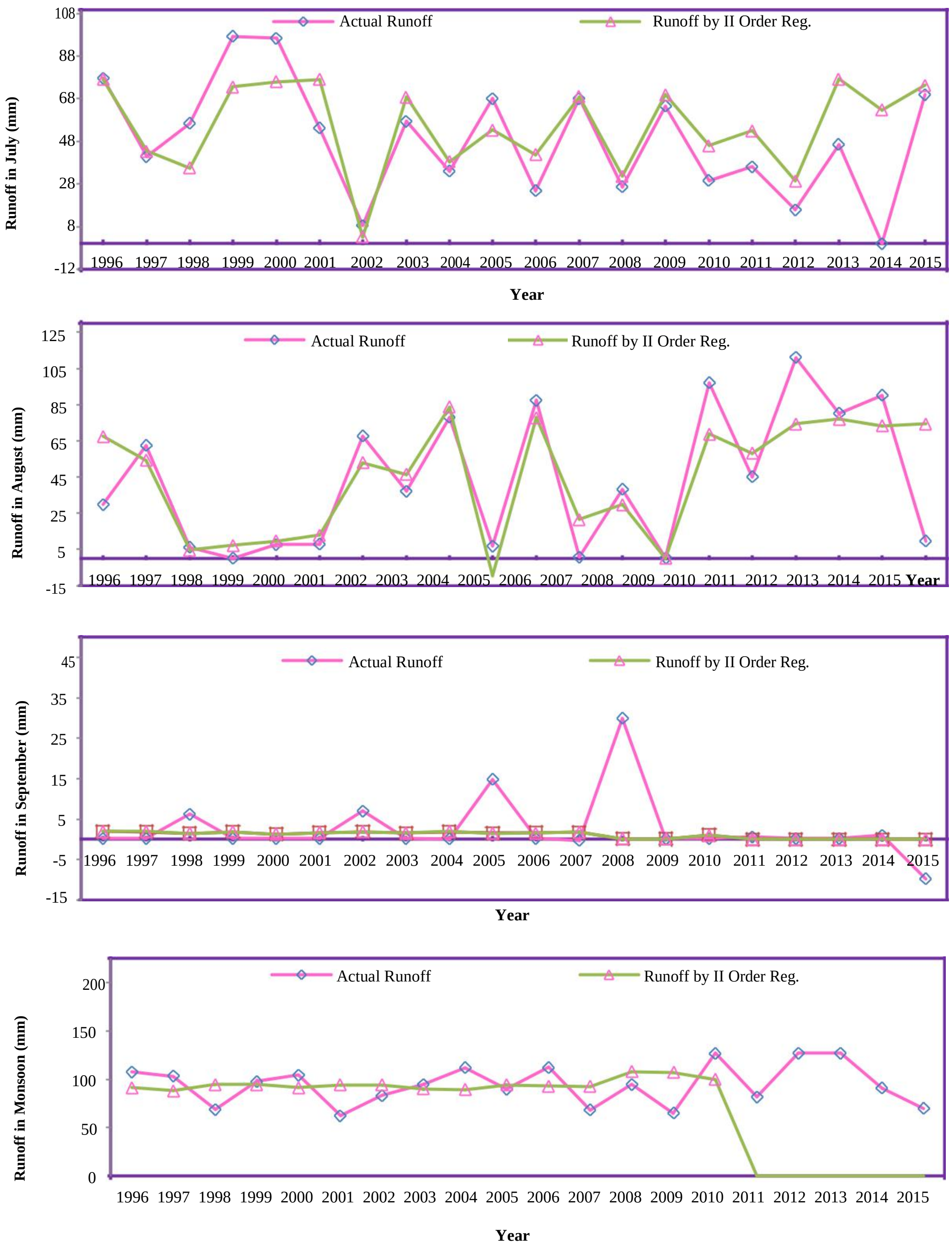


Fig. 5.11: Comparison of actual runoff and runoff predicted by second order regression model for Jetpura Dam Catchment

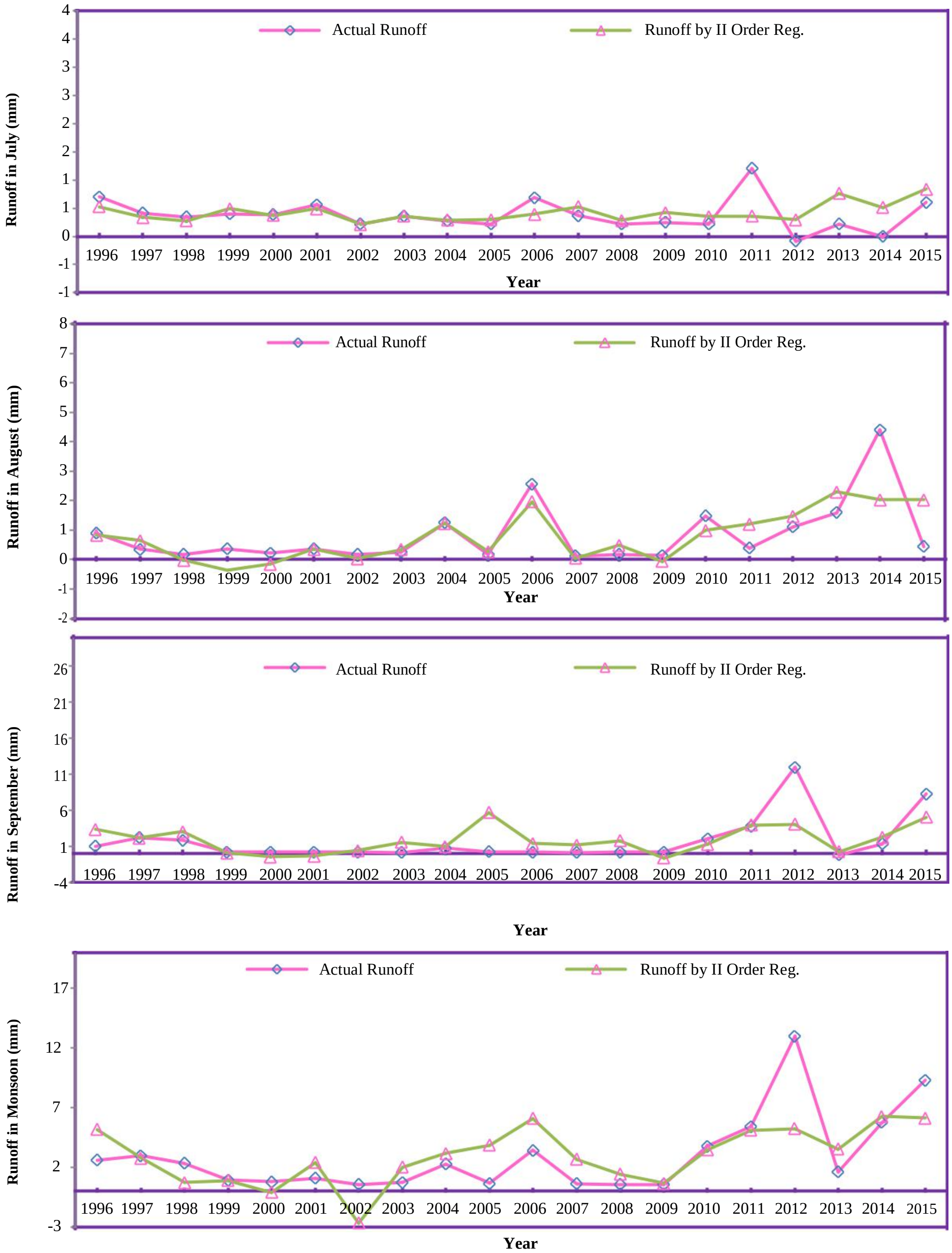


Fig. 5.12: Comparison of actual runoff and runoff predicted by second order regression model for Meja Dam Catchment

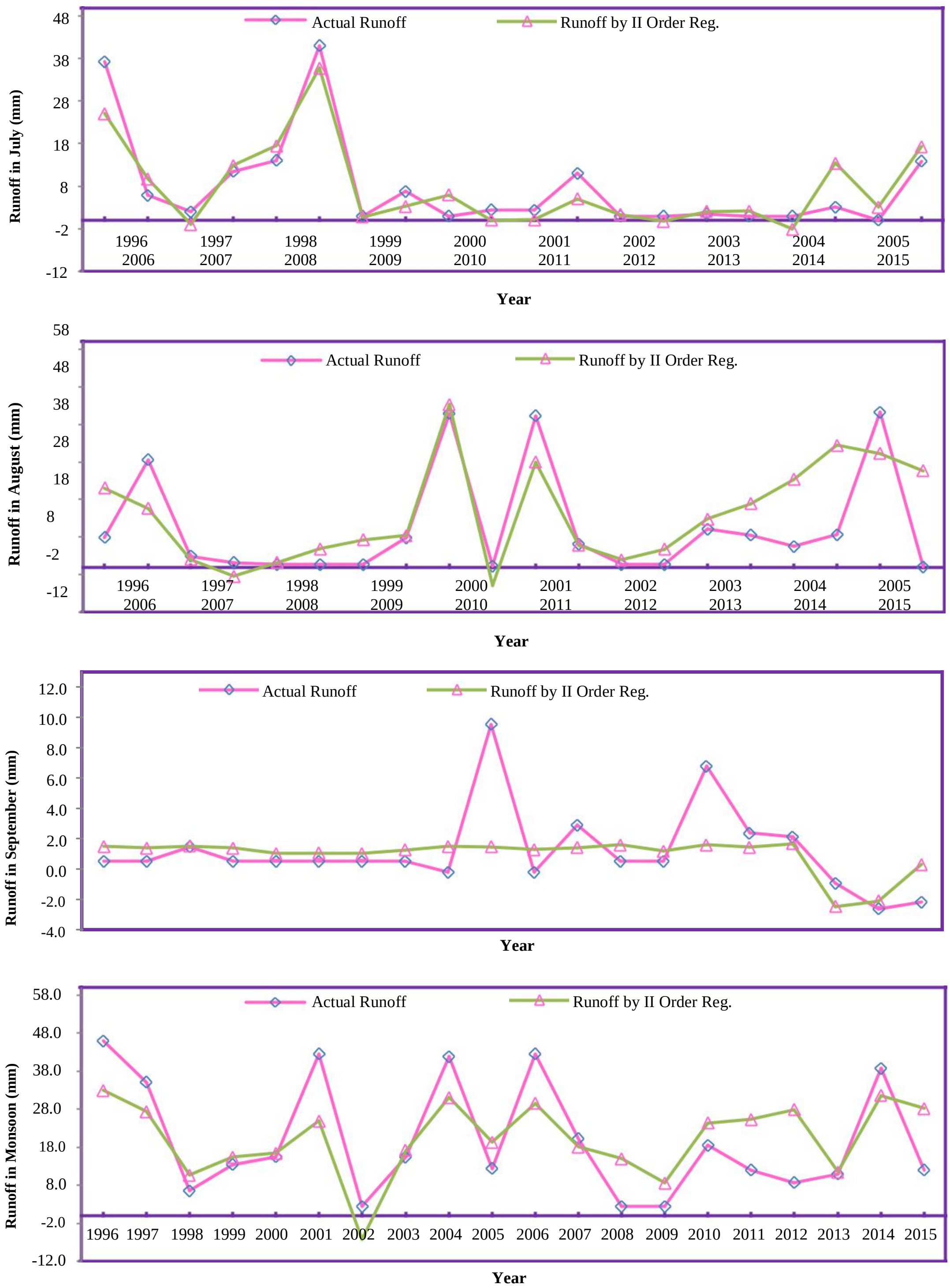


Fig. 5.13: Comparison of actual runoff and runoff predicted by second order regression model for Nahar Sagar Dam Catchment

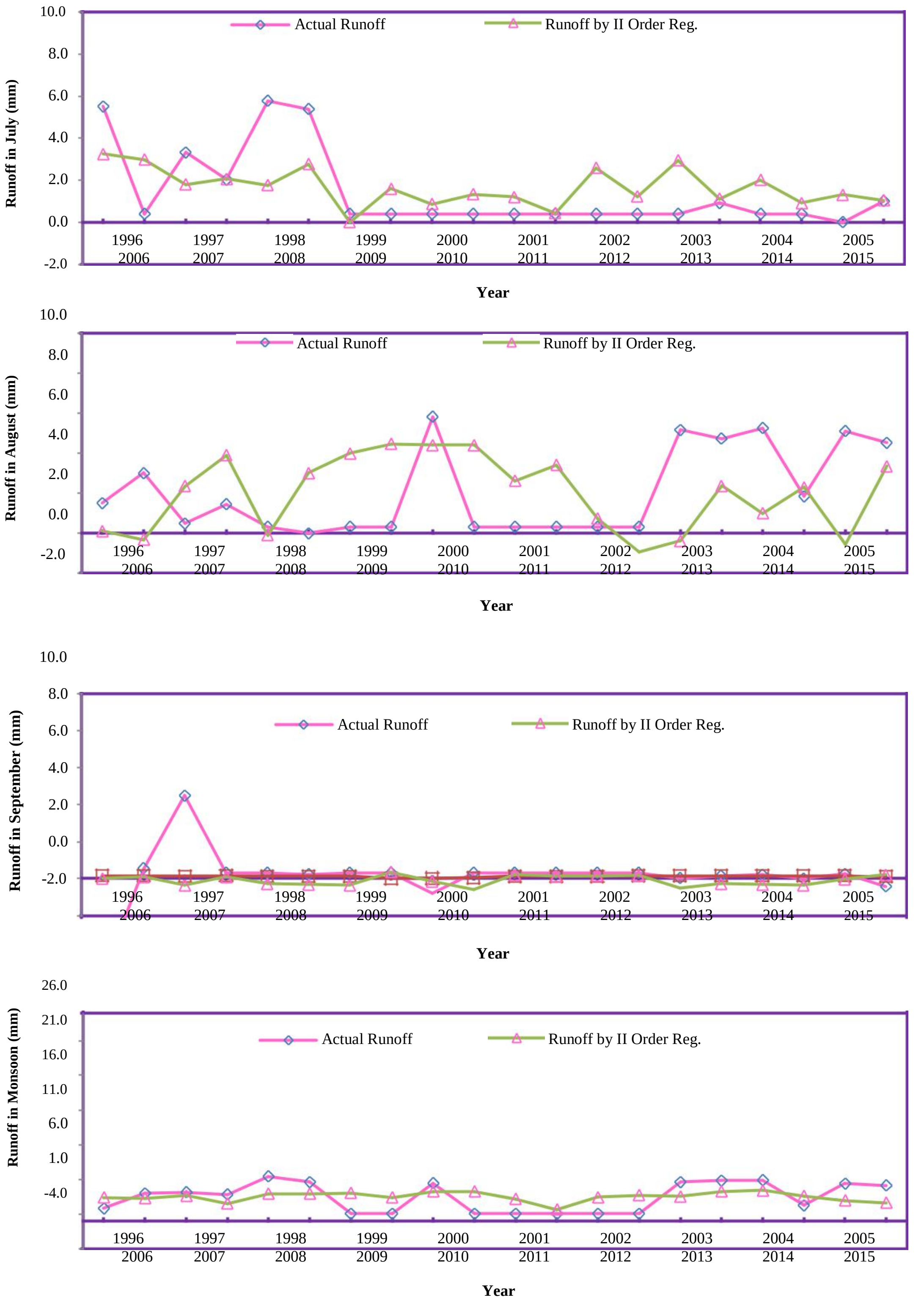


Fig. 5.14: Comparison of actual runoff and runoff predicted by second order regression model for Lassaria Dam Catchment

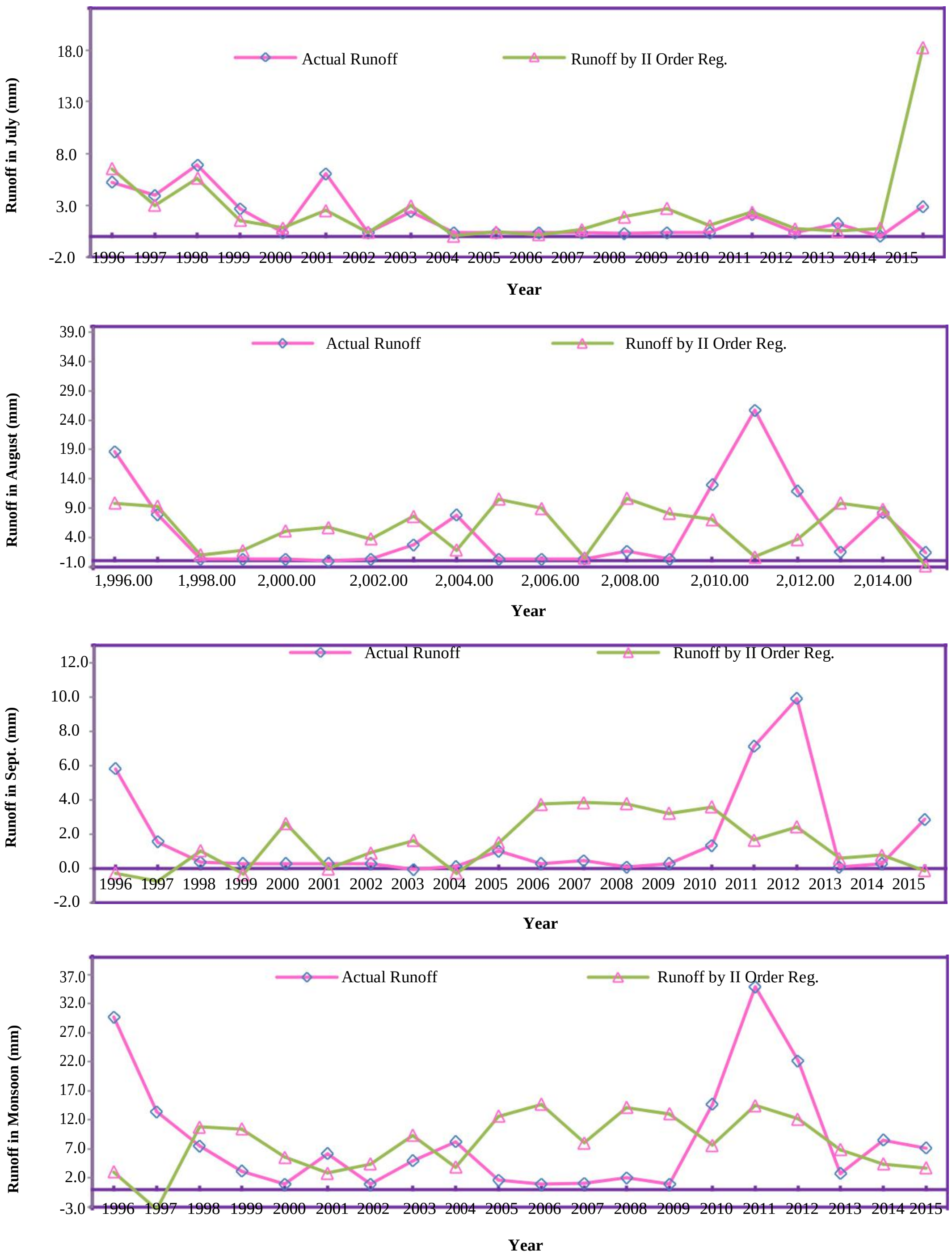


Fig. 5.15: Comparison of actual runoff and runoff predicted by second order regression model for Chhaparwara Dam Catchment

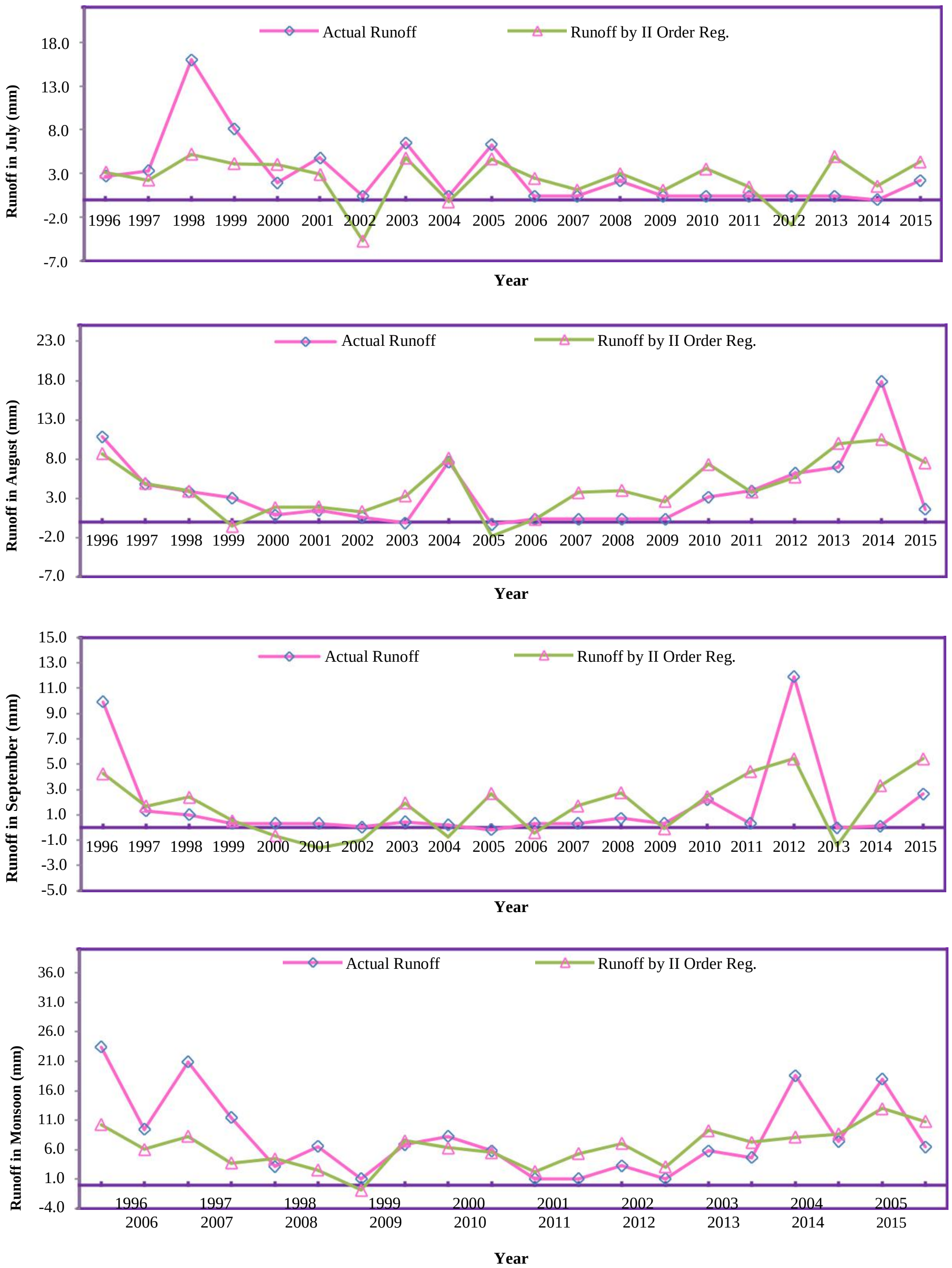


Fig. 5.16: Comparison of actual runoff and runoff predicted by second order regression model for Morel Dam Catchment

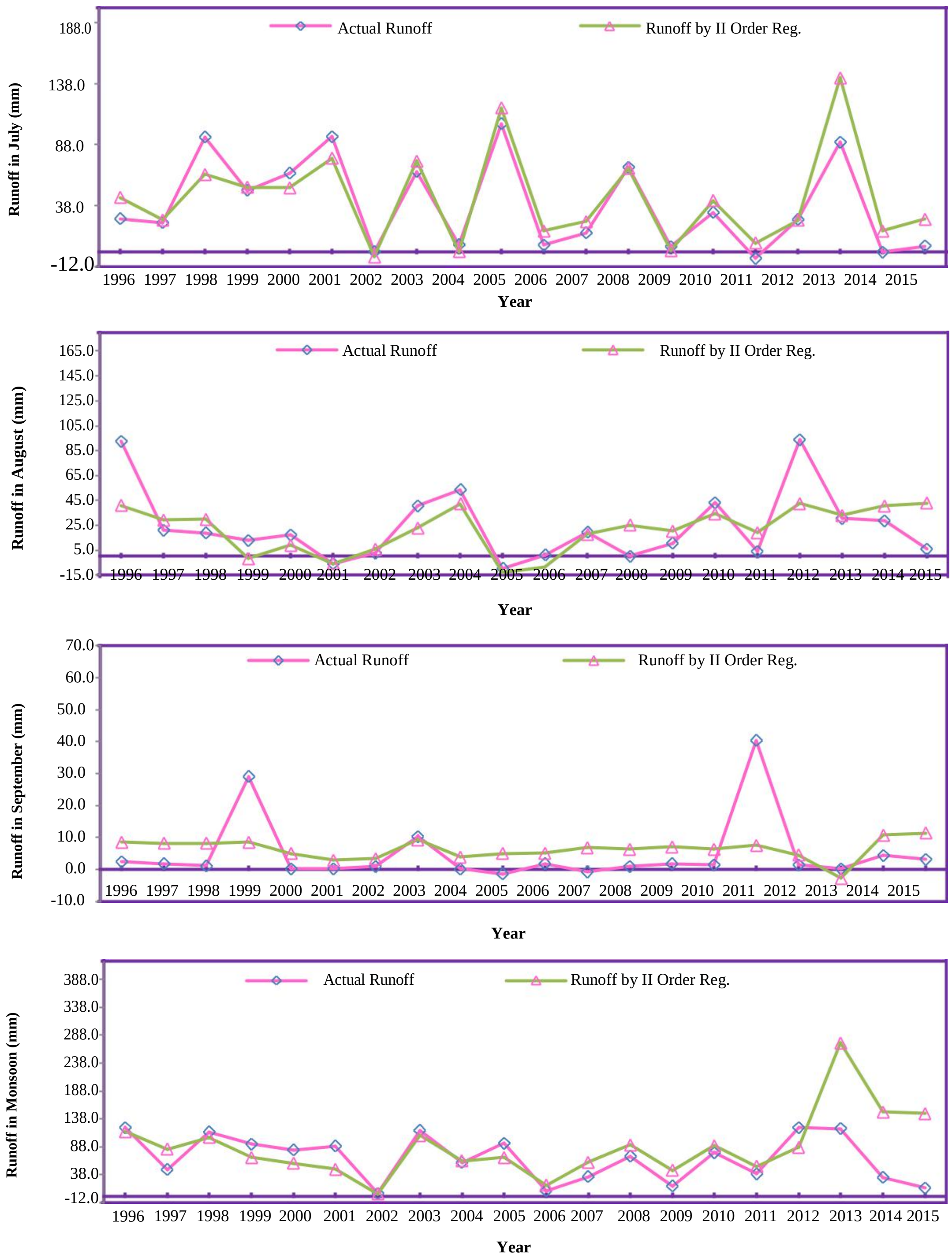


Fig. 5.17: Comparison of actual runoff and runoff predicted by second order regression model for Kalisil Dam Catchment

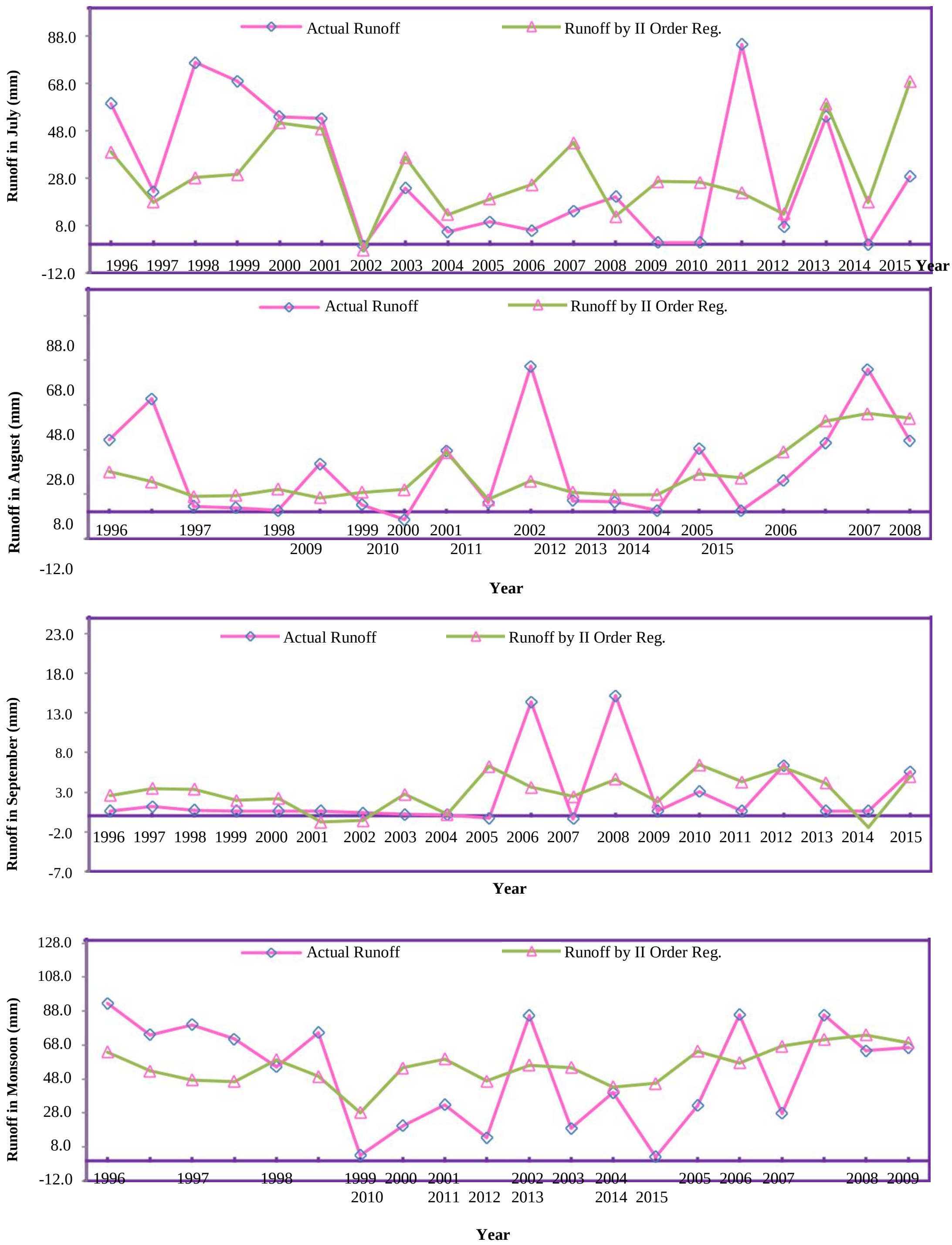


Fig. 5.18: Comparison of actual runoff and runoff predicted by second order regression model for Motisagar Dam Catchment

5.3.2 Soft computing models

The architecture of ANN model comprised of three layers namely, an input layer having 4 neurons representing the rainfalls, a hidden layer containing 2 to 11 varying number of neurons, and an output layer having 4 neurons representing runoffs. The Hyperbolic tangent sigmoid function (viz. *Tansig*) was used for transferring the information from input layer to hidden layer and the linear function (viz. *Purelin*) for transferring the information from hidden layer to the output layer. The training of the ANN model using Levenberg-Marquardt back-propagation algorithm (LMBNN) was repeated using a different set of randomly initialized weights and biases.

Similarly for making sub-clustering of the training data in ANFIS, the radius of the cluster was varied from 0.05 to 0.7 with a trial and error approach, to optimize the performance metrics for training as well as validation in ANFIS models.

The training and validation both are important in the preparation of a model, so ranks were allotted to each training and validation performance metric providing equal importance, in the preparation of each sub-model. The adopted simple ranking technique would become very fruitful in comparing the sub-model performance and finding the best model from the four sub-models as well as in comparing the performance of the used different techniques.

The value of the performance metrics obtained in training and validation process for ANN model for the selected dam catchments situated in different sub-basin are shown in **Table 5.3A and 5.3B**. The comparison of actual runoff with the runoff predicted by ANN model from different selected dam catchments is shown in **Figure- 5.19 to Figure- 5.27**.

The value of the performance metrics obtained in training and validation process for ANFIS models for the selected dam catchments situated in different sub-basins are shown in **Table 5.4A and 5.4B**. The comparison of actual runoff with the runoff predicted by ANFIS model from different selected dam catchments is shown in **Figure- 5.28 to Figure- 5.36**.

Table 5.3-A: Performance metrics of ANN models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected Dam	Month	Training			Validation		
				R^2	RMSE	MAE	R^2	RMSE	MAE
1	Berach	Wagan	July	0.7	0.44	5.82	0.82	3.26	6.77
			August	0.99	0.22	1.23	0.89	7.79	11.58
			September	0.94	0.31	1.95	0.29	1.33	4.52
			Monsoon	0.97	0.07	4.06	0.8	7.13	14.32
2	Banas I	Jetpura	July	0.89	0.19	5.46	0.97	16.48	8.56
			August	0.98	0.91	3.51	0.96	3.07	7.13
			September	0.96	0.09	0.78	0.96	10.63	5.11
			Monsoon	0.72	0.76	7.13	0.65	1.85	14.49
3	Kothari	Meja	July	0.99	0.00	0.02	0.93	0.19	0.13
			August	0.99	0.00	0.06	0.87	0.46	0.38
			September	0.98	0.01	0.24	0.56	0.43	0.59
			Monsoon	0.98	0.01	0.25	0.99	0.15	0.74
4	Khari	NaharSagar	July	1.00	0.01	0.09	0.38	1.59	3.16
			August	1.00	0.01	0.04	0.97	2.82	4.74
			September	1.00	0.01	0.01	0.47	0.57	1.73
			Monsoon	1.00	0.03	0.07	0.97	1.80	6.14
5	Dai	Lassaria	July	0.86	0.05	0.41	0.9	0.03	0.64
			August	0.96	0.08	0.23	0.99	0.26	0.30
			September	0.98	0.07	0.10	0.99	0.13	0.06
			Monsoon	0.97	0.02	0.18	0.94	0.16	0.43

Table 5.3-B: Performance metrics of ANN models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected Dam	Month	Training			Validation		
				R^2	RMSE	MAE	R^2	RMSE	MAE
6	Mashi	Chhaparwara	July	0.99	0.01	0.05	0.89	1.27	0.88
			August	0.99	0.01	0.15	0.87	1.49	2.72
			September	1.00	0.00	0.03	0.90	1.33	0.64
			Monsoon	0.99	0.01	0.13	0.93	4.02	3.04
7	Morel	Morel	July	1.00	0.00	0.01	0.52	4.02	3.5
			August	1.00	0.00	0.00	0.93	3.46	1.55
			September	1.00	0.00	0.01	0.41	0.36	0.87
			Monsoon	1.00	0.00	0.00	0.52	0.20	2.42
8	Kalisil	Kalisil	July	0.98	0.02	3.04	0.96	23.22	14.53
			August	0.97	0.04	3.46	0.76	13.89	13.99
			September	0.98	0.03	1.02	0.14	3.22	3.14
			Monsoon	0.99	0.06	1.70	0.96	12.56	18.99
9	Banas II	Moti Sagar	July	0.98	0.03	2.42	0.65	29.81	18.93
			August	0.92	0.00	4.40	0.07	13.32	18.93
			September	0.97	0.00	0.51	0.08	4.23	2.28
			Monsoon	0.99	0.03	1.77	0.73	20.71	13.27

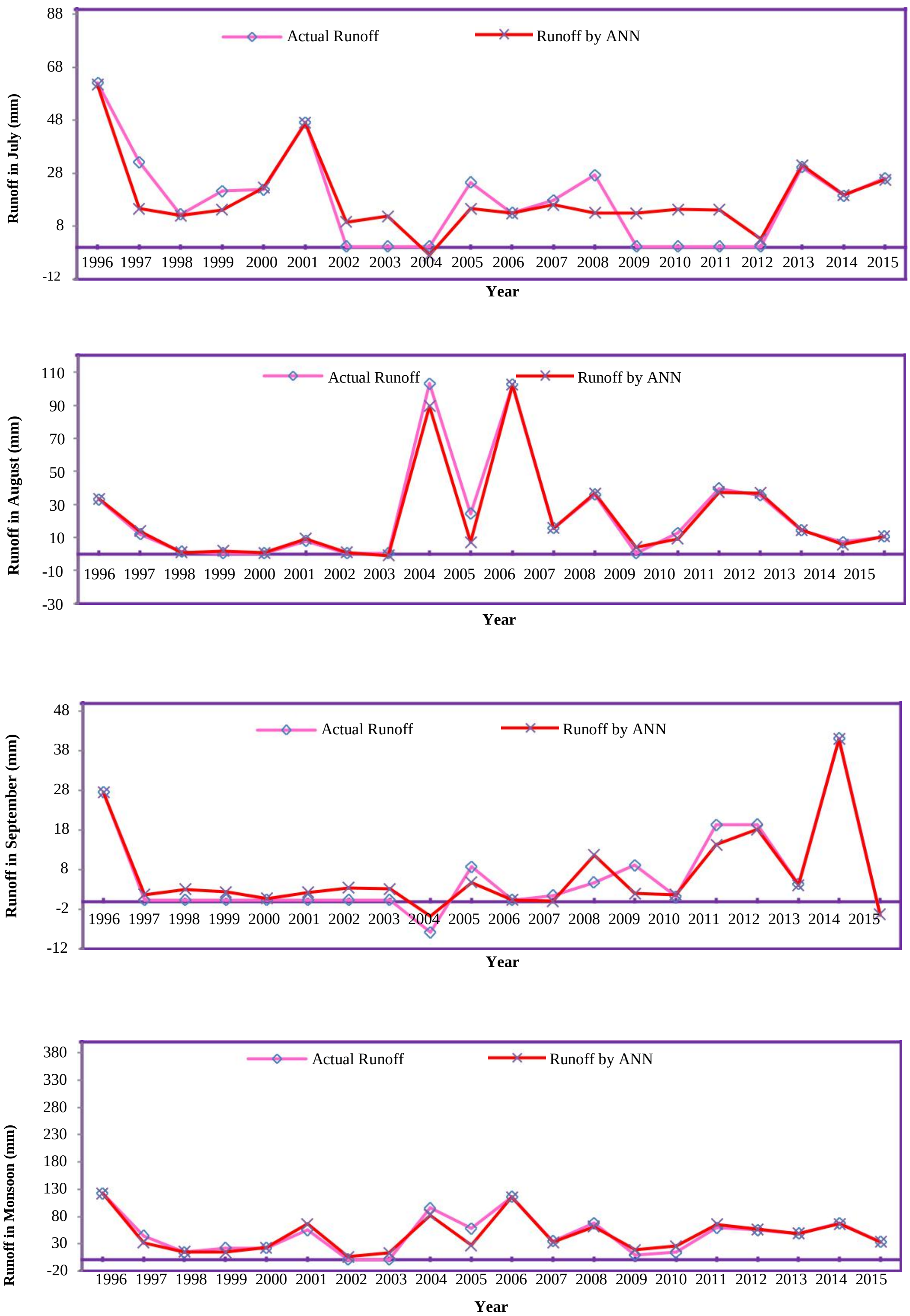


Fig. 5.19: Comparison of actual runoff and runoff predicted by ANN model for Wagan Dam Catchment

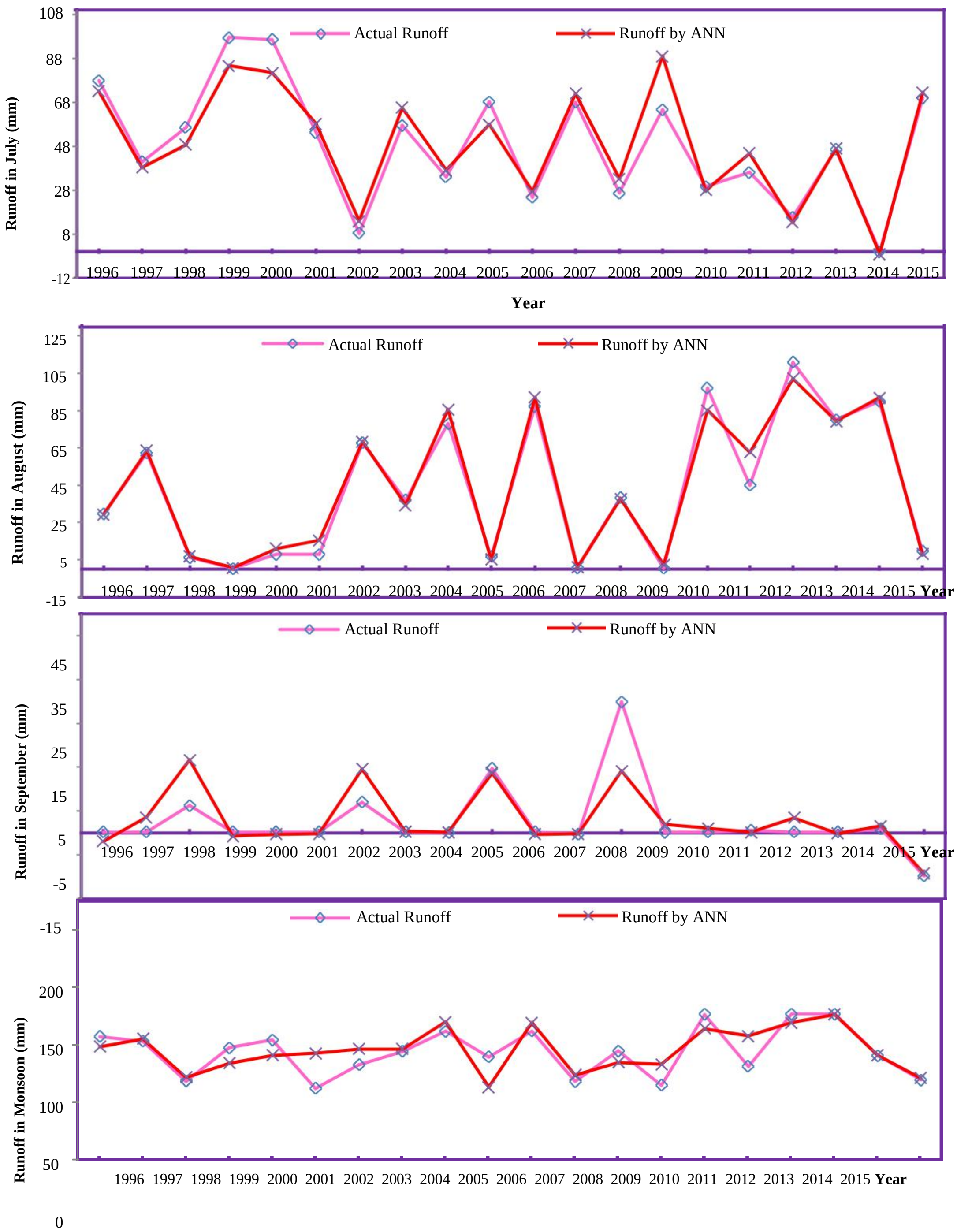


Fig. 5.20: Comparison of actual runoff and runoff predicted by ANN model for Jetpura Dam Catchment

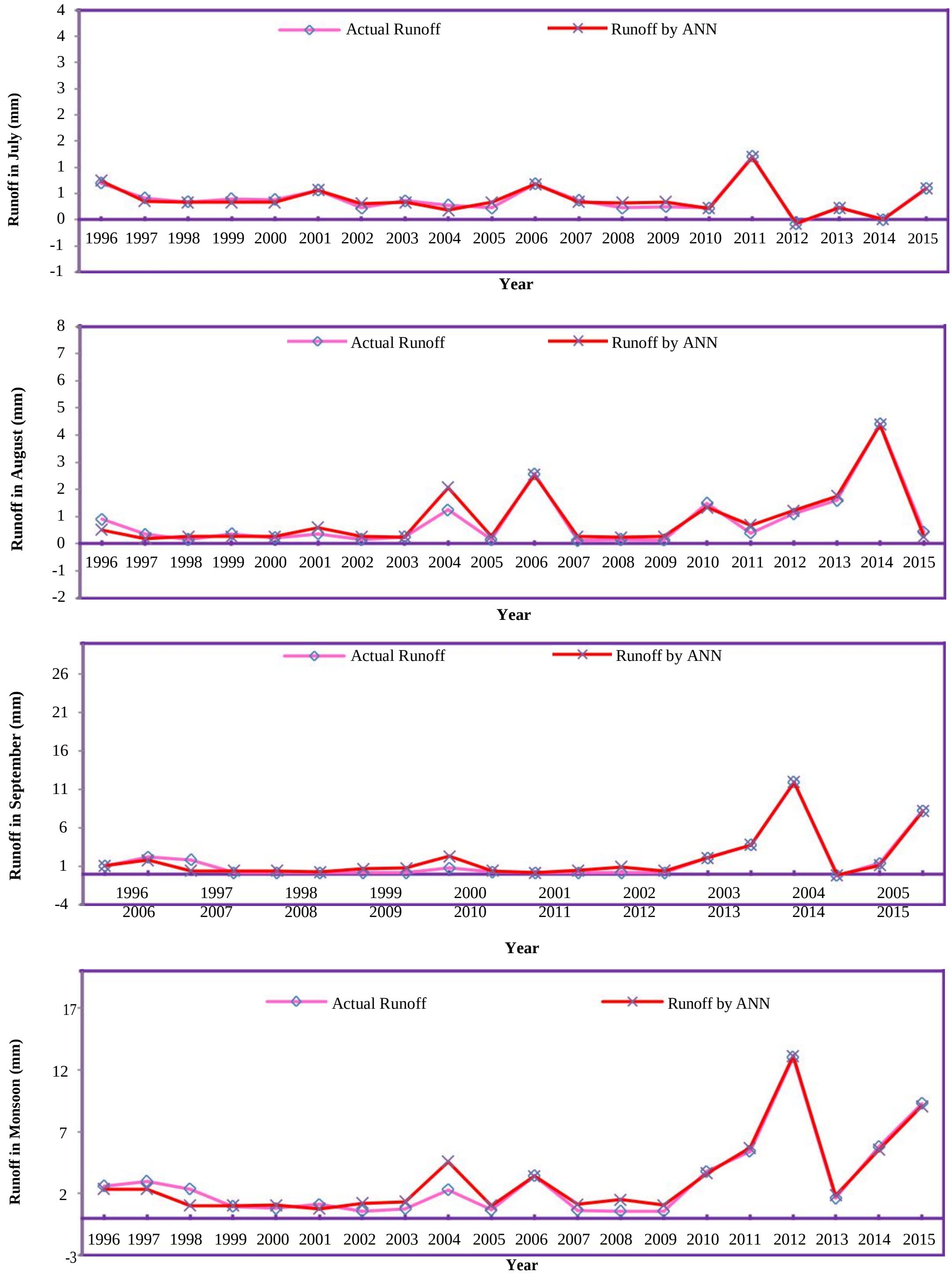


Fig. 5.21: Comparison of actual runoff and runoff predicted by ANN model for Meja Dam Catchment

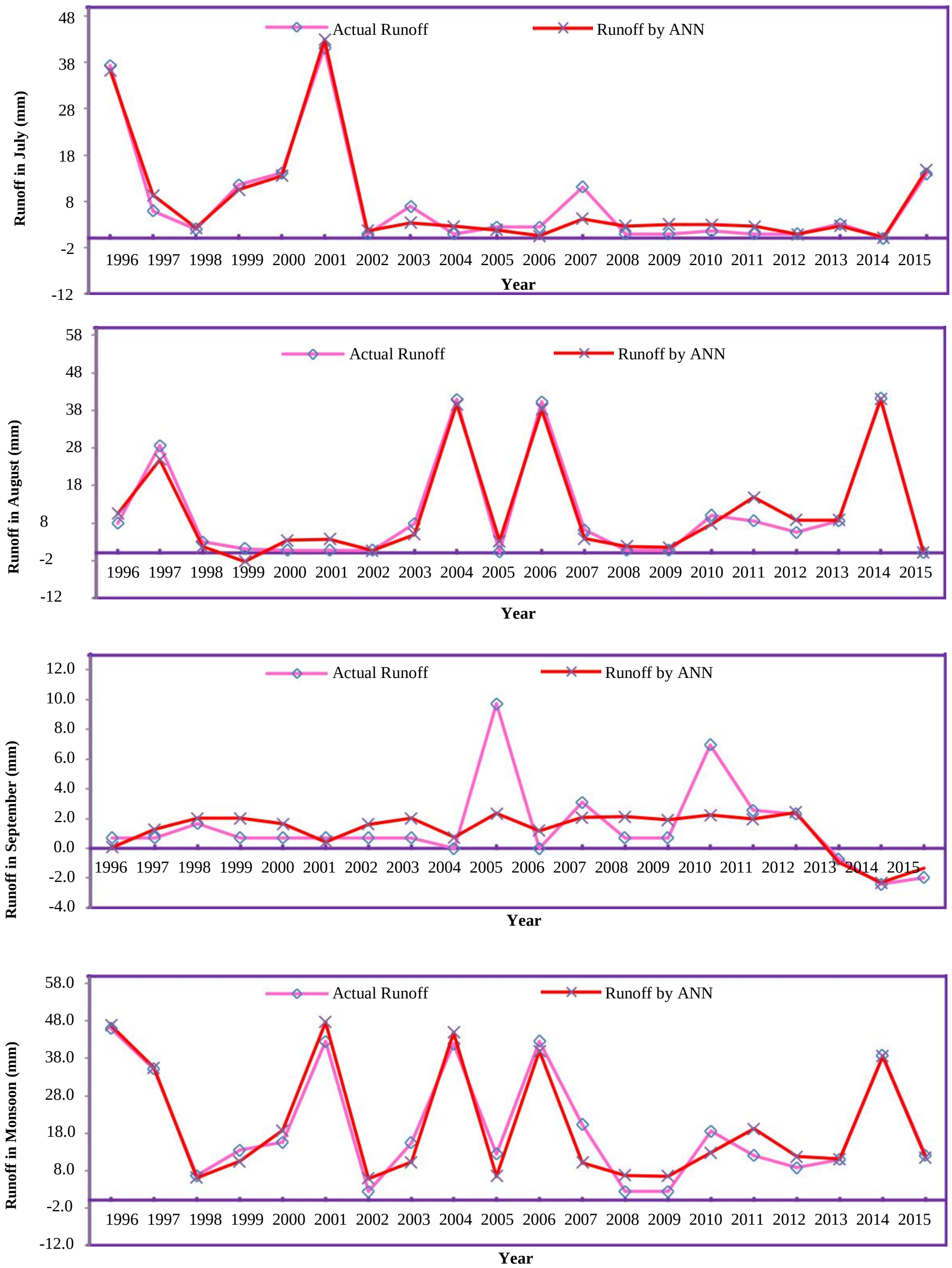


Fig. 5.22: Comparison of actual runoff and runoff predicted by ANN model for Nahar Sagar Dam Catchment

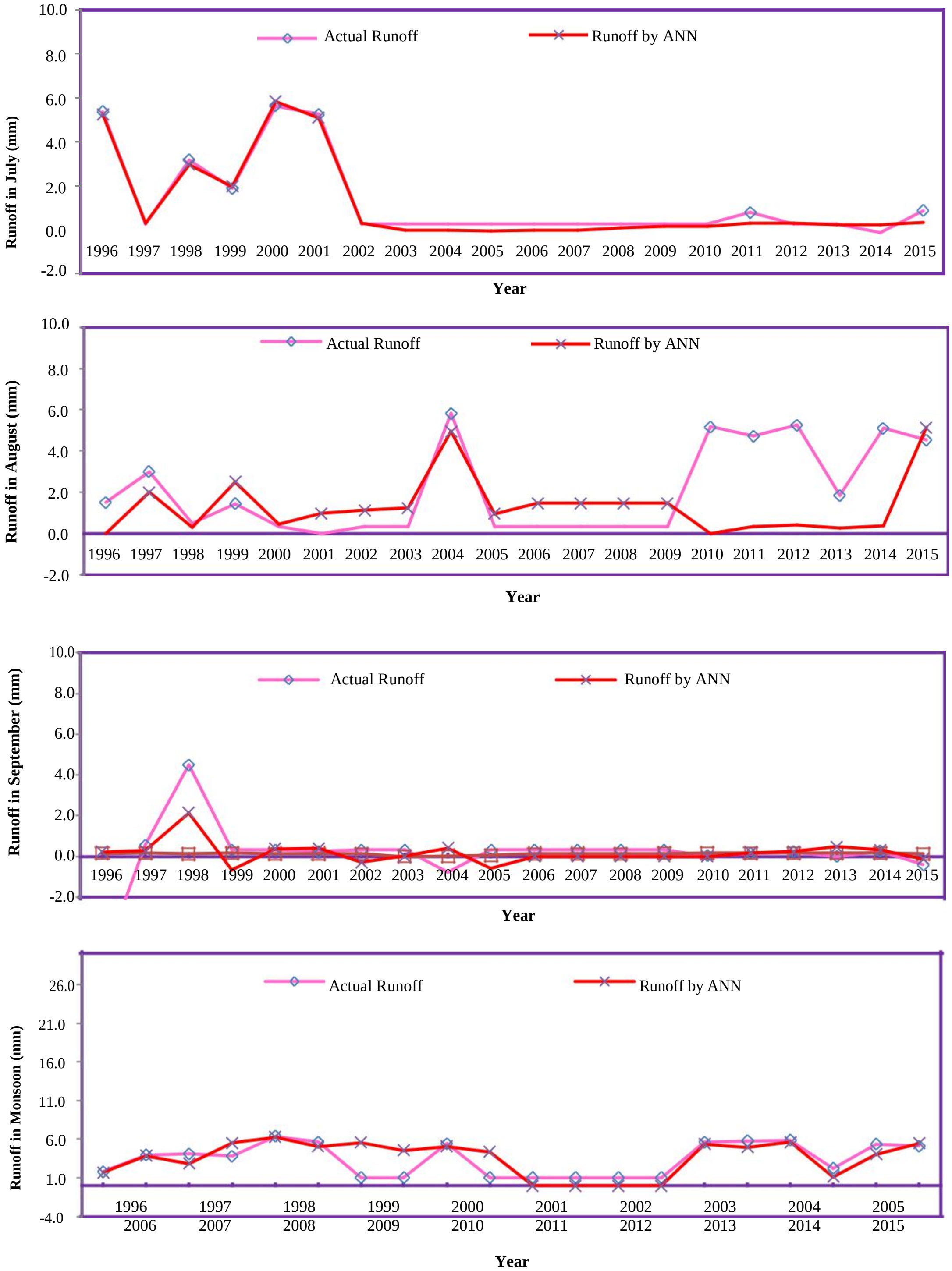


Fig. 5.23: Comparison of actual runoff and runoff predicted by ANN model for Lassaria Dam Catchment

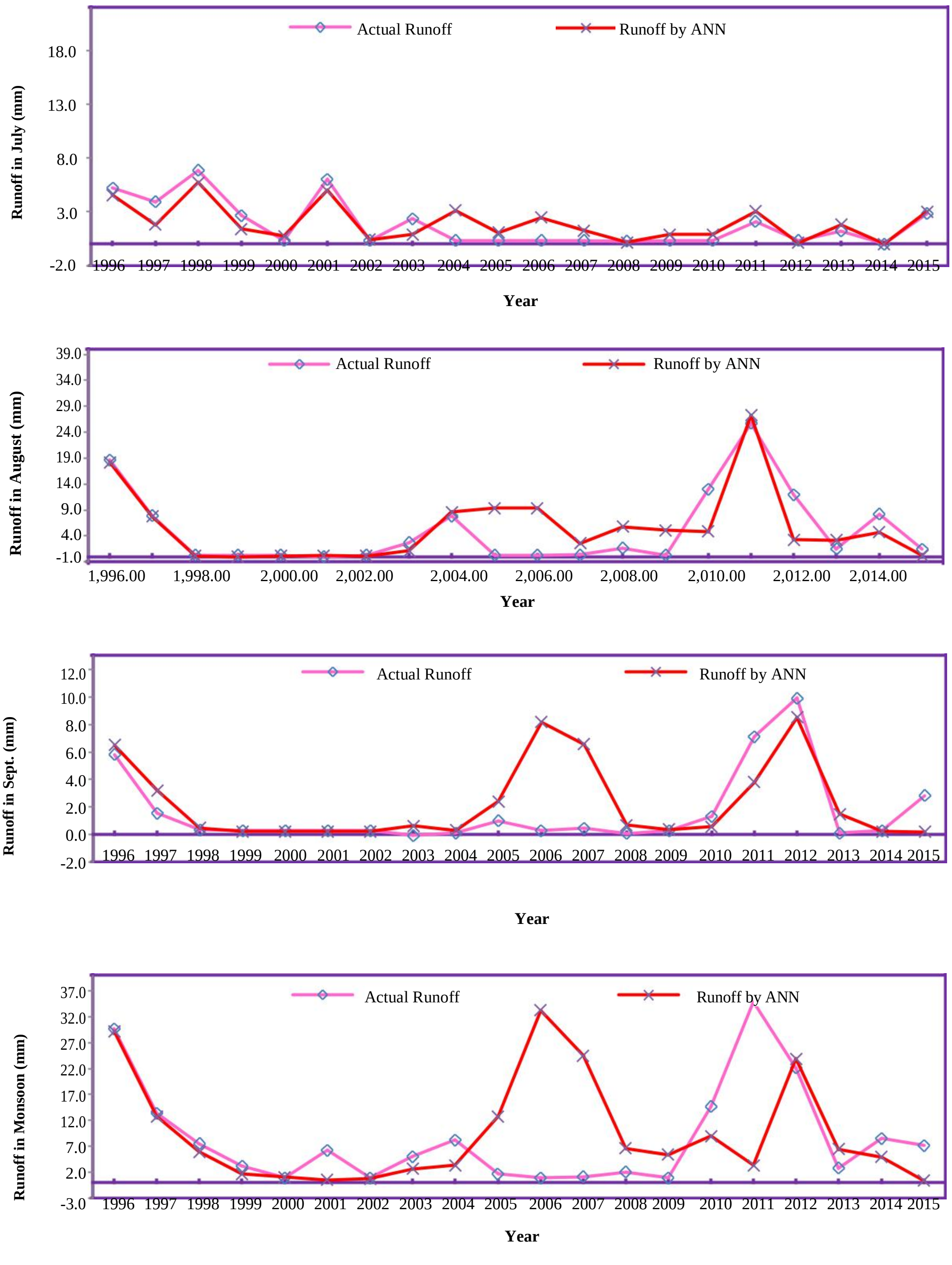


Fig. 5.24: Comparison of actual runoff and runoff predicted by ANN model for Chhapawara Dam Catchment

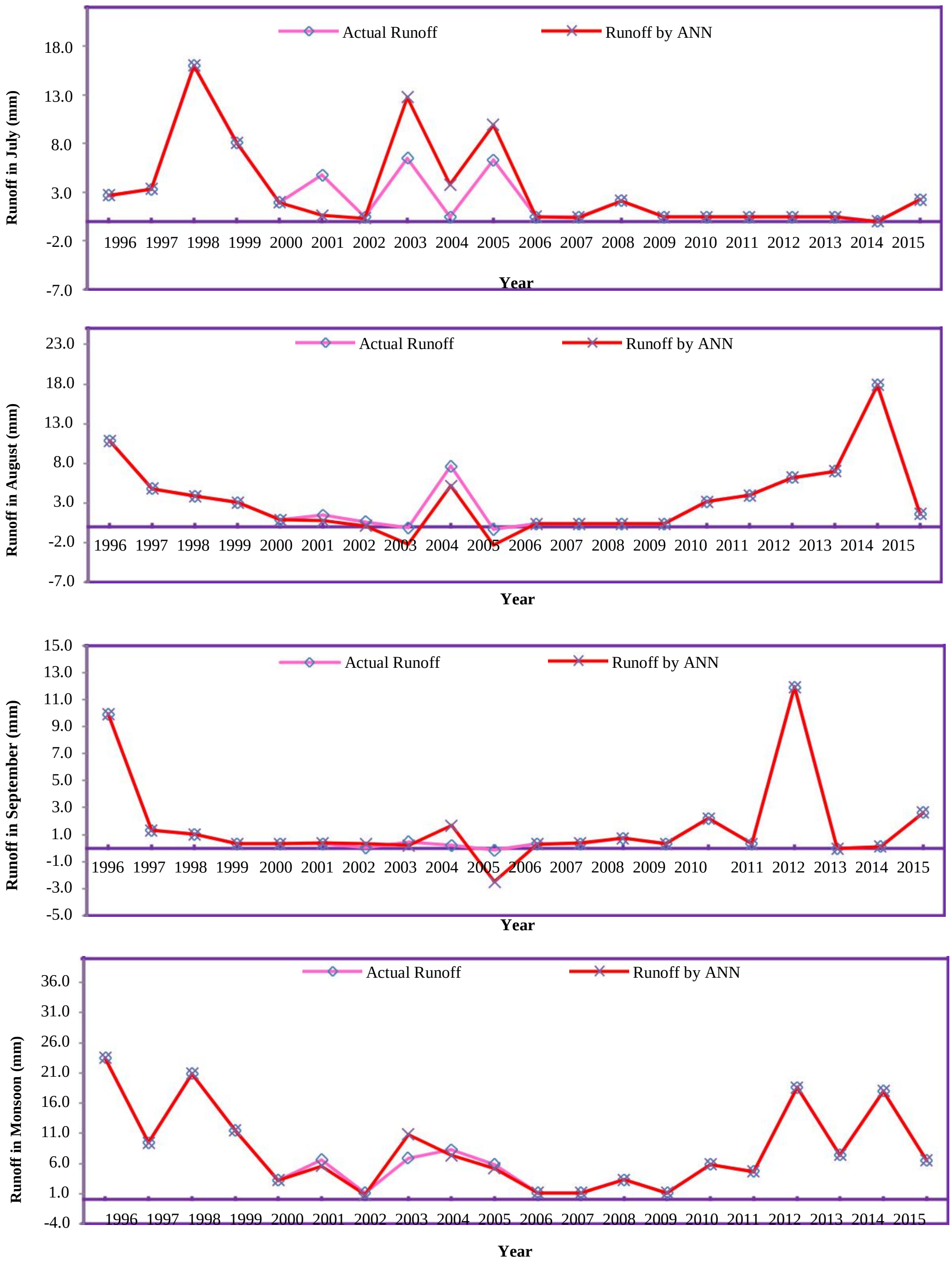


Fig. 5.25: Comparison of actual runoff and runoff predicted by ANN model for Morel Dam Catchment

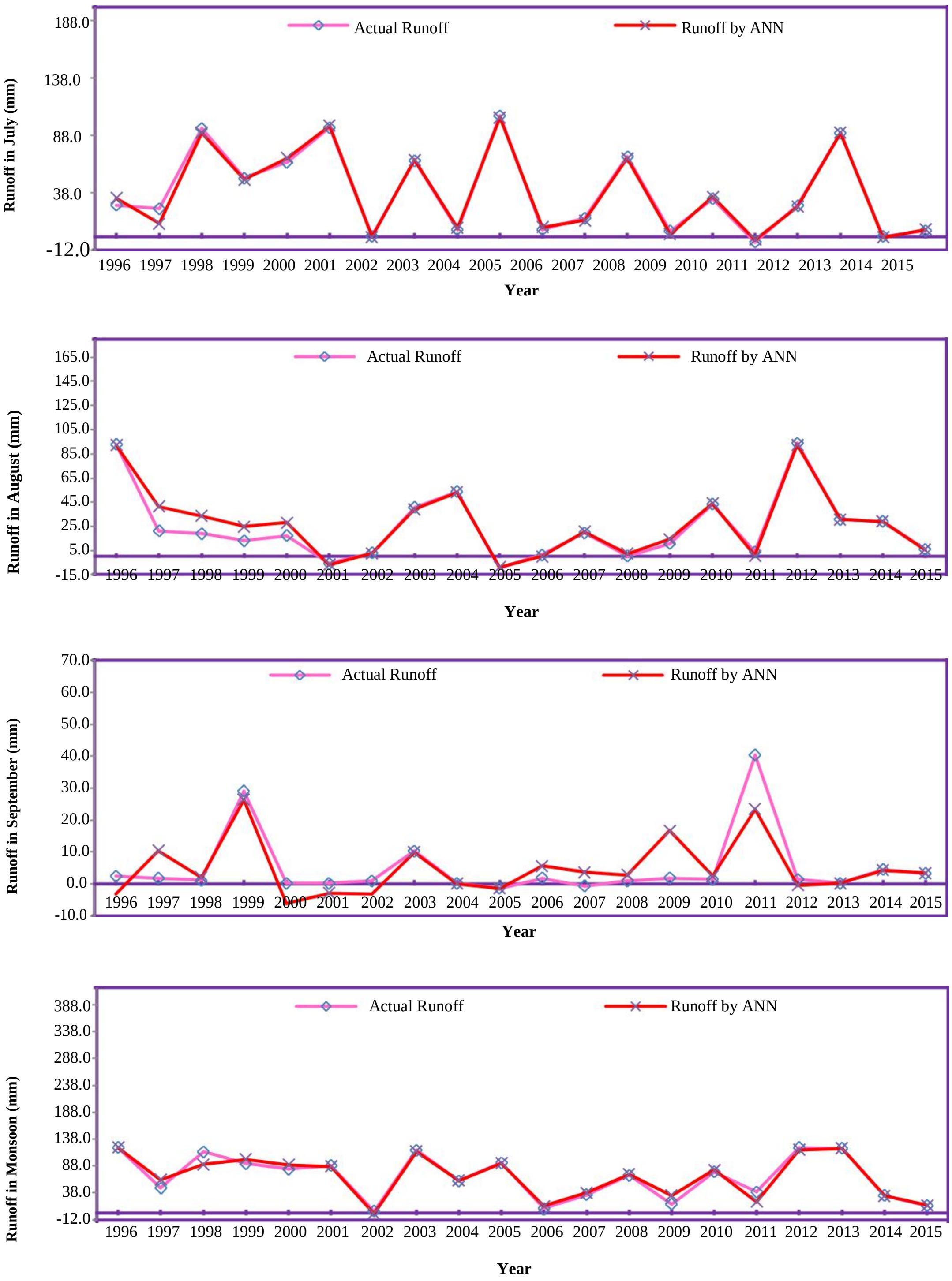


Fig. 5.26: Comparison of actual runoff and runoff predicted by ANN model for Kalisil Dam Catchment

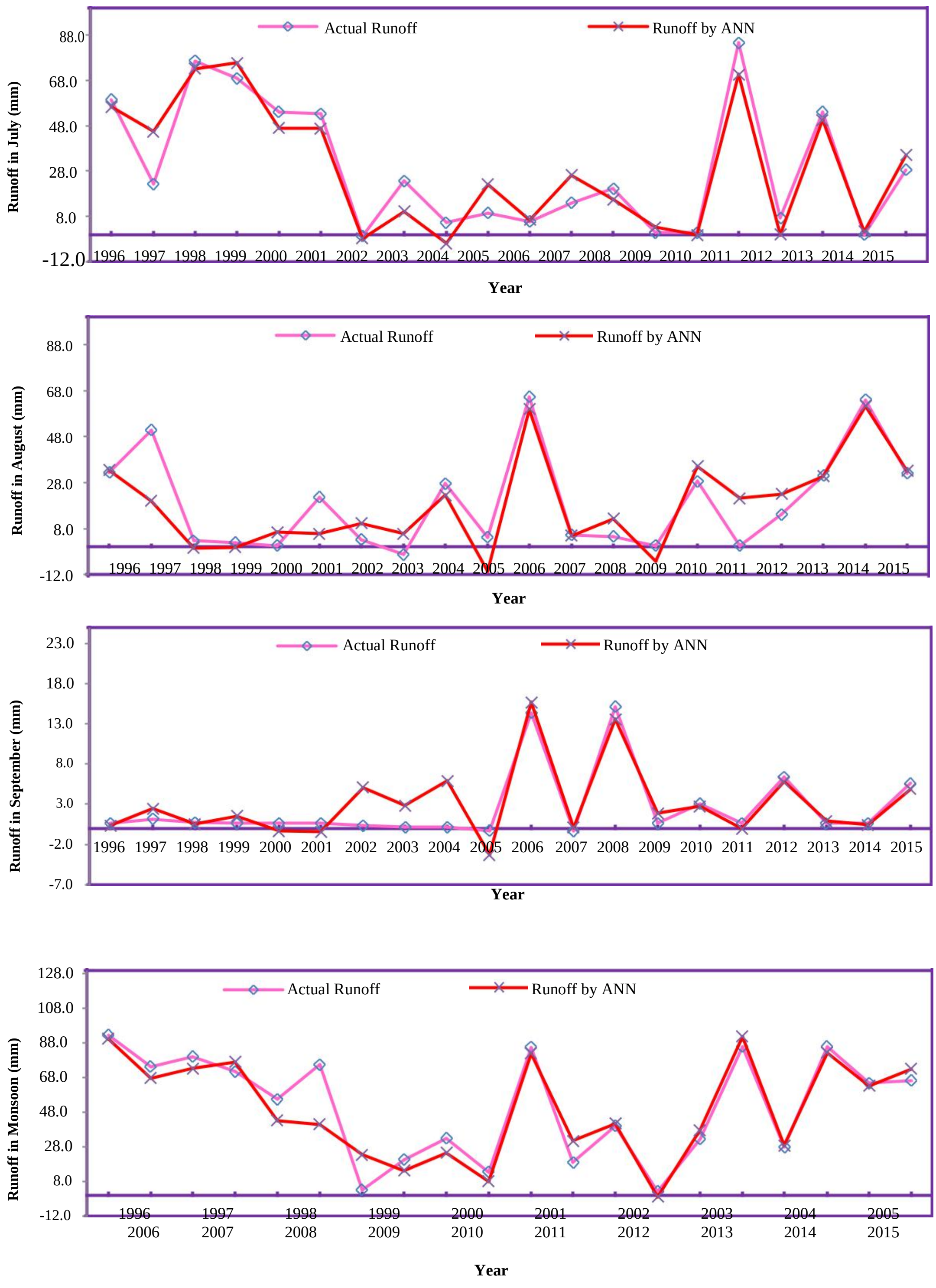


Fig. 5.27: Comparison of actual runoff and runoff predicted by ANN model for Motisagar Dam Catchment

Table 5.4-A: Performance metrics of ANFIS models for the dam catchments fromdifferent sub-basins

S. No.	Name of Sub-basin	Name of selected dam	Month	Training			Validation		
				R^2	RMSE	MAE	R^2	RMSE	MAE
1	Berach	Wagan	July	1.00	0.00	0.00	0.94	11.23	7.76
			August	1.00	0.00	0.00	0.75	44.68	27.13
			September	0.86	4.45	3.38	0.20	10.68	6.44
			Monsoon	1.00	0.01	0.00	1.00	0.01	0.00
2	Banas I	Jetpura	July	0.98	3.71	1.17	1.00	0.00	0.00
			August	1.00	0.01	0.00	1.00	0.00	0.00
			September	1.00	0.08	0.05	1.00	0.09	0.06
			Monsoon	1.00	0.01	0.01	1.00	0.00	0.00
3	Kothari	Meja	July	1.00	0.00	0.00	0.21	0.49	0.35
			August	1.00	0.00	0.00	0.92	0.41	0.28
			September	0.99	0.11	0.06	0.29	8.83	4.77
			Monsoon	1.00	0.00	0.00	0.30	1.98	1.61
4	Khari	Nahar Sagar	July	1.00	0.16	0.08	0.98	2.78	1.71
			August	1.00	0.00	0.00	0.12	14.93	10.43
			September	1.00	0.03	0.02	0.29	2.18	1.82
			Monsoon	1.00	0.00	0.00	0.43	13.50	9.75
5	Dai	Lassaria	July	1.00	0.00	0.00	1.00	0.00	0.00
			August	1.00	0.00	0.00	1.00	0.00	0.00
			September	0.99	0.04	0.01	0.99	0.05	0.02
			Monsoon	1.00	0.01	0.01	1.00	0.01	0.01

Table 5.4-B: Performance metrics of ANFIS models for the dam catchments from different sub-basins

S. No.	Name of Sub-basin	Name of selected dam	Month	Training			Validation		
				R^2	RMSE	MAE	R^2	RMSE	MAE
6	Mashi	Chhaparwara	July	1.00	0.00	0.00	0.86	1.71	1.29
			August	1.00	0.00	0.00	0.43	3.56	2.28
			September	1.00	0.00	0.00	0.15	3.20	2.09
			Monsoon	1.00	0.05	0.02	0.88	4.48	3.33
7	Morel	Morel	July	1.00	0.00	0.00	1.00	0.00	0.00
			August	1.00	0.09	0.04	1.00	0.07	0.03
			September	0.99	0.16	0.07	0.83	0.09	0.06
			Monsoon	1.00	0.00	0.00	1.00	0.00	0.00
8	Kalisil	Kalisil	July	1.00	0.00	0.00	1.00	0.00	0.00
			August	1.00	0.00	0.00	1.00	0.00	0.00
			September	0.99	0.47	0.26	0.86	0.39	0.25
			Monsoon	1.00	0.03	0.01	1.00	0.00	0.00
9	Banas II	Moti Sagar	July	1.00	0.00	0.00	1.00	0.00	0.00
			August	1.00	0.03	0.01	1.00	0.00	0.00
			September	0.99	0.17	0.08	0.95	0.07	0.05
			Monsoon	1.00	0.00	0.00	1.00	0.00	0.00

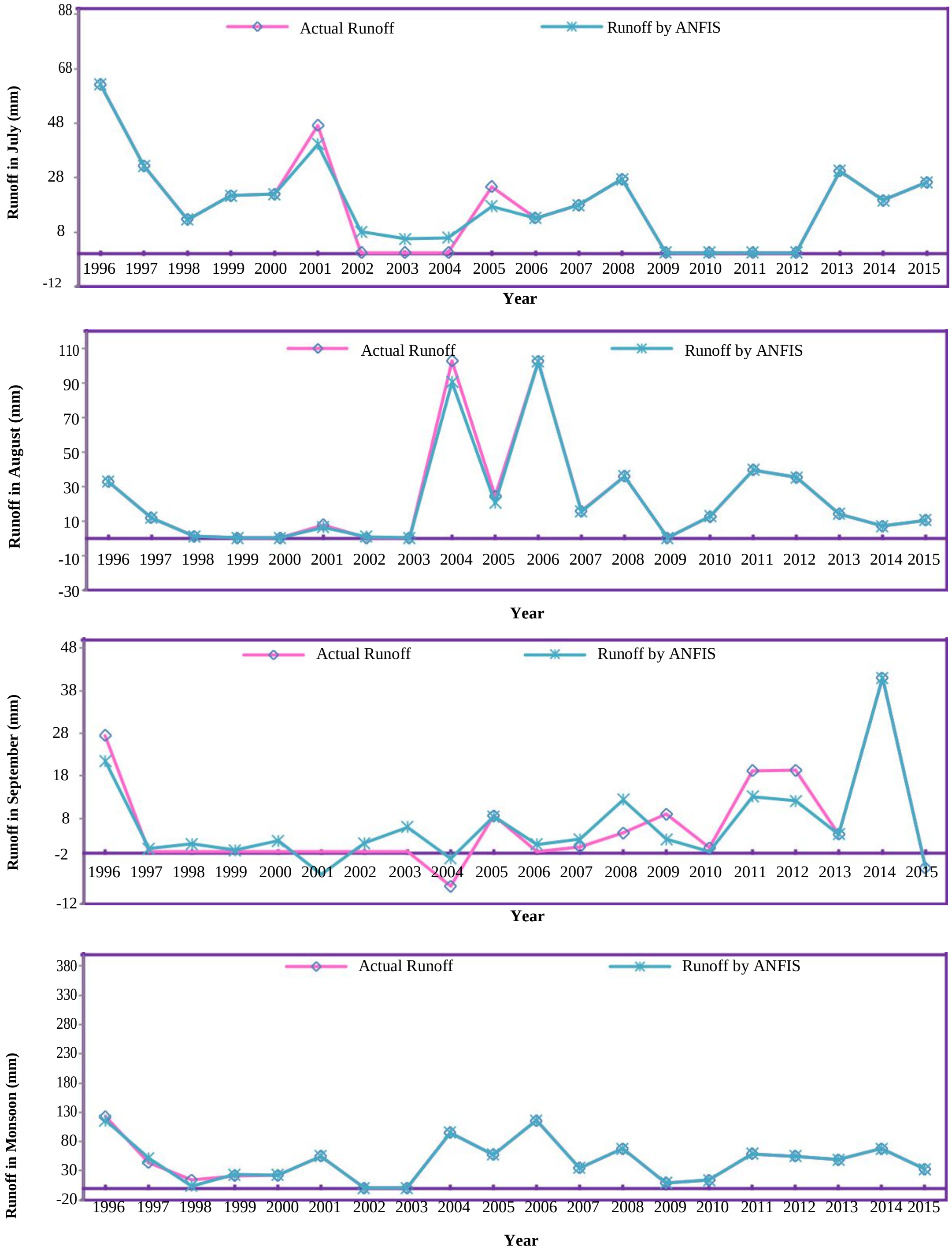


Fig. 5.28: Comparison of actual runoff and runoff predicted by ANFIS model for Wagan Dam Catchment

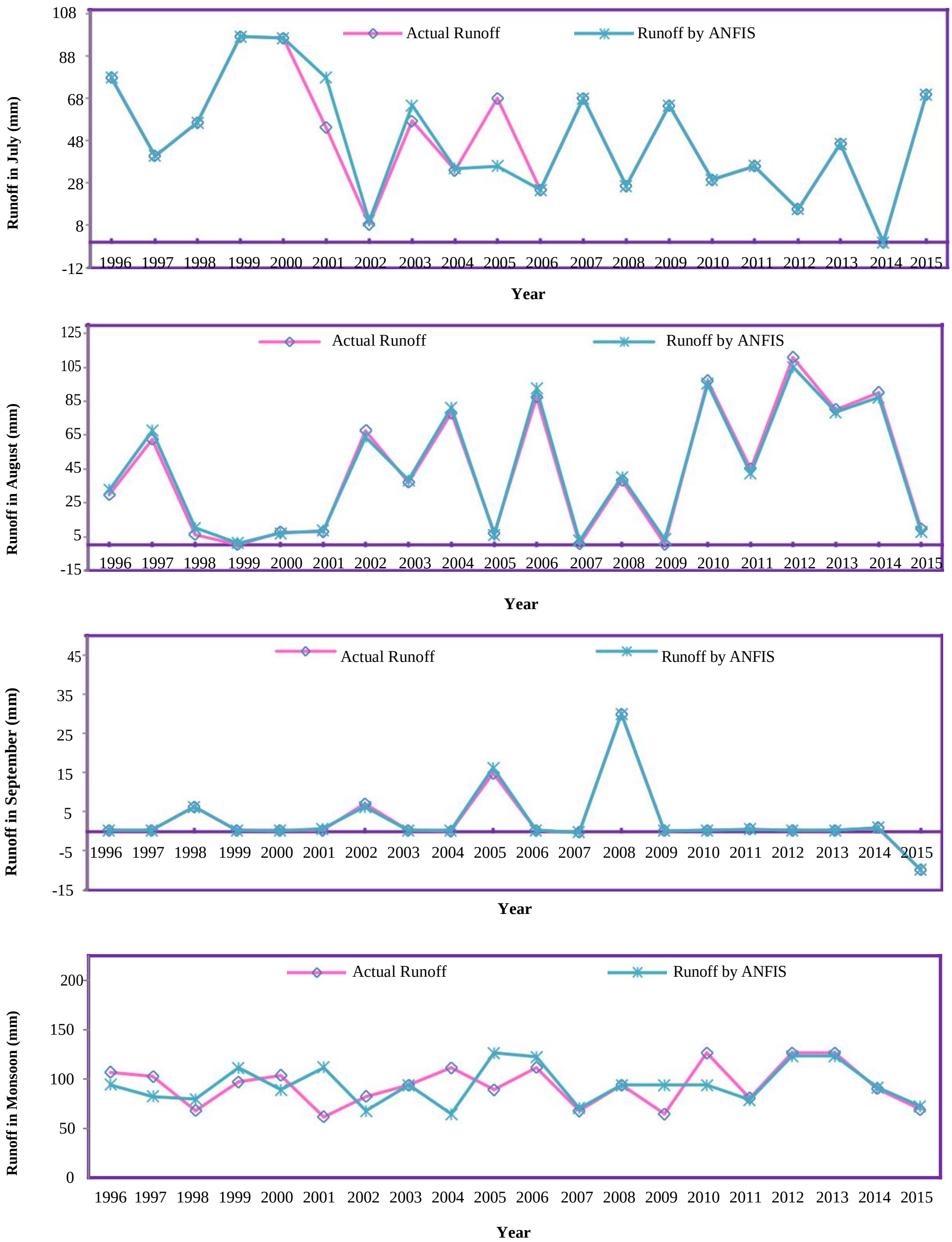


Fig. 5.29: Comparison of actual runoff and runoff predicted by ANFIS model for Jetpura Dam Catchment

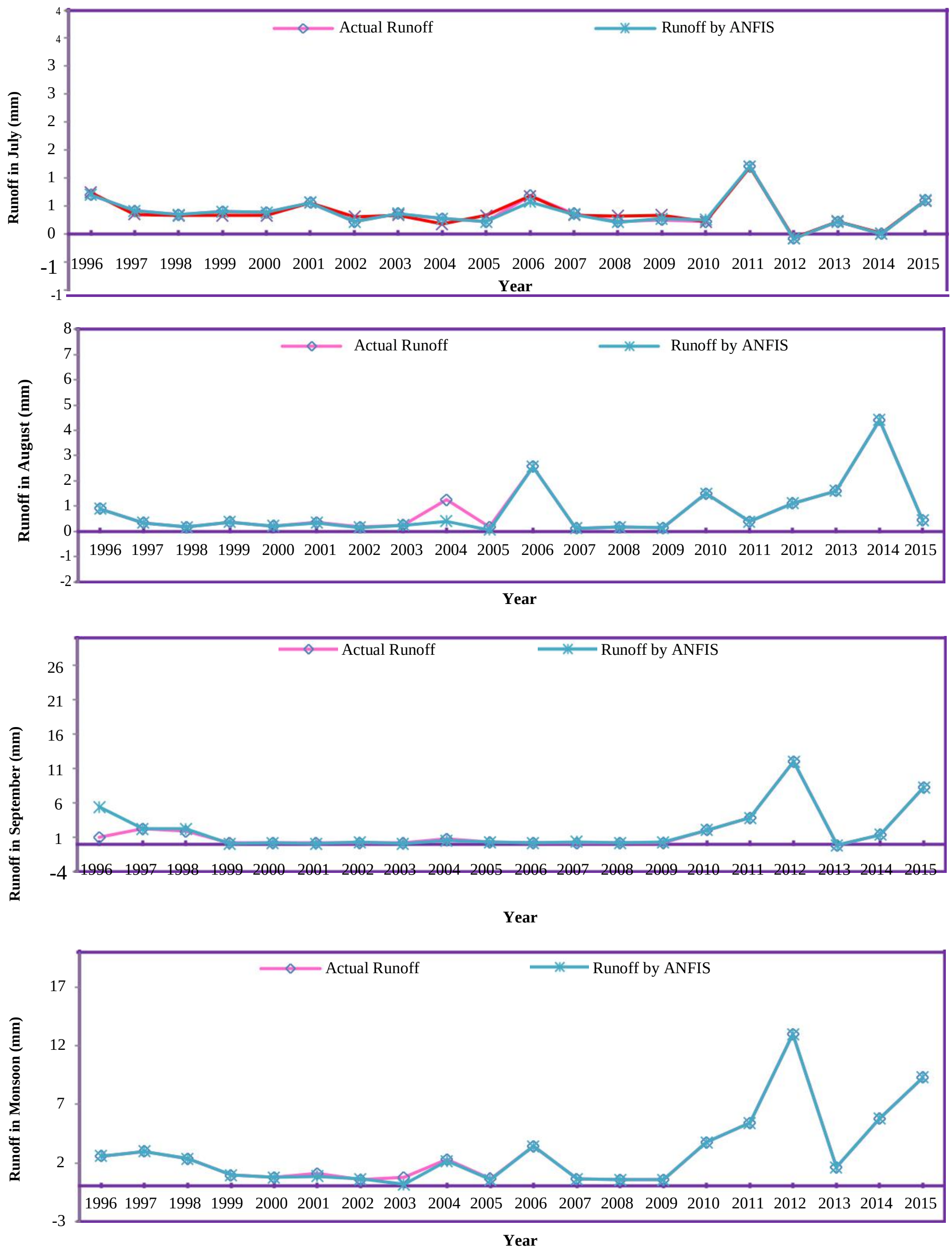


Fig. 5.30: Comparison of actual runoff and runoff predicted by ANFIS model for Meja Dam Catchment

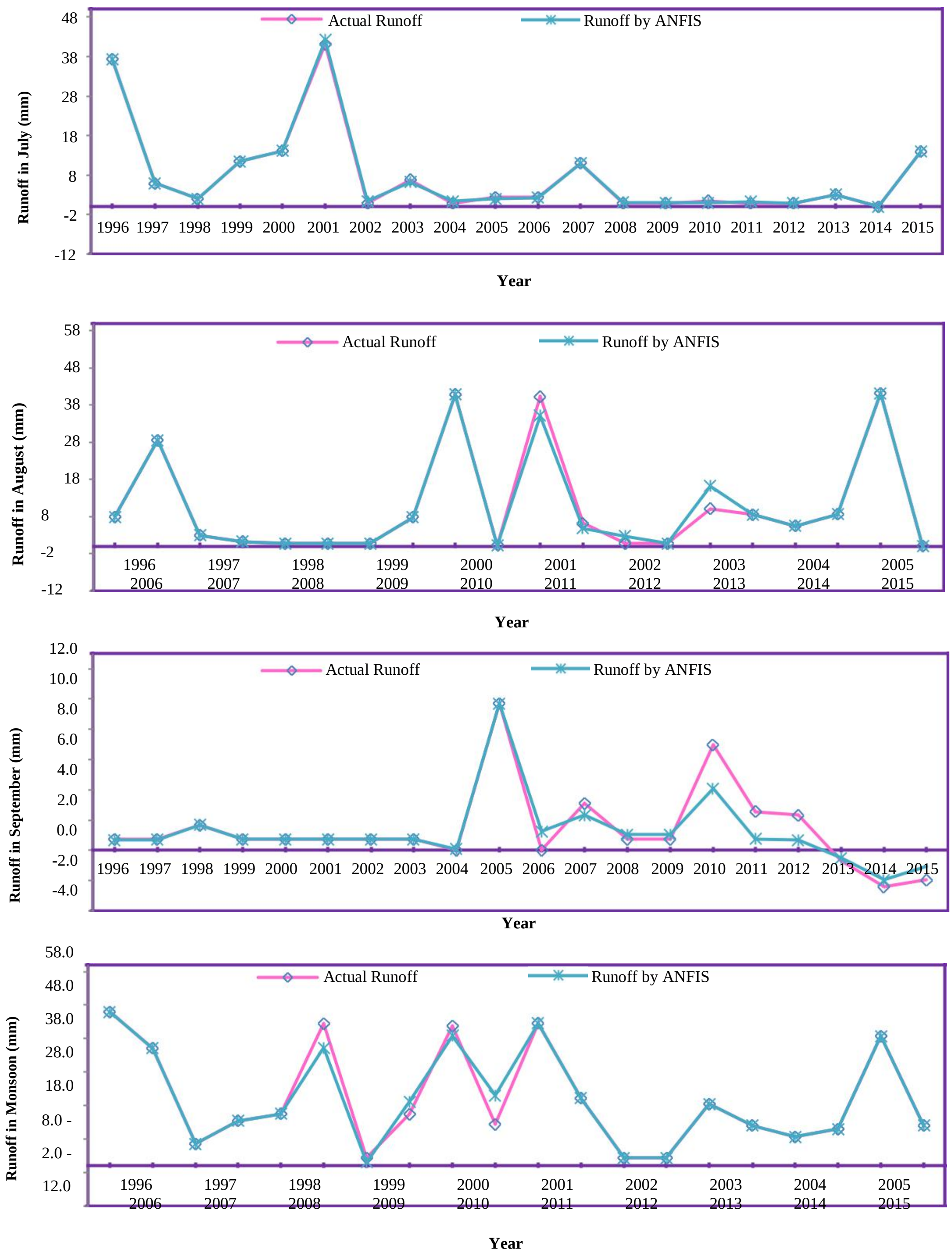


Fig. 5.31: Comparison of actual runoff and runoff predicted by ANFIS model for Nahar Sagar Dam Catchment

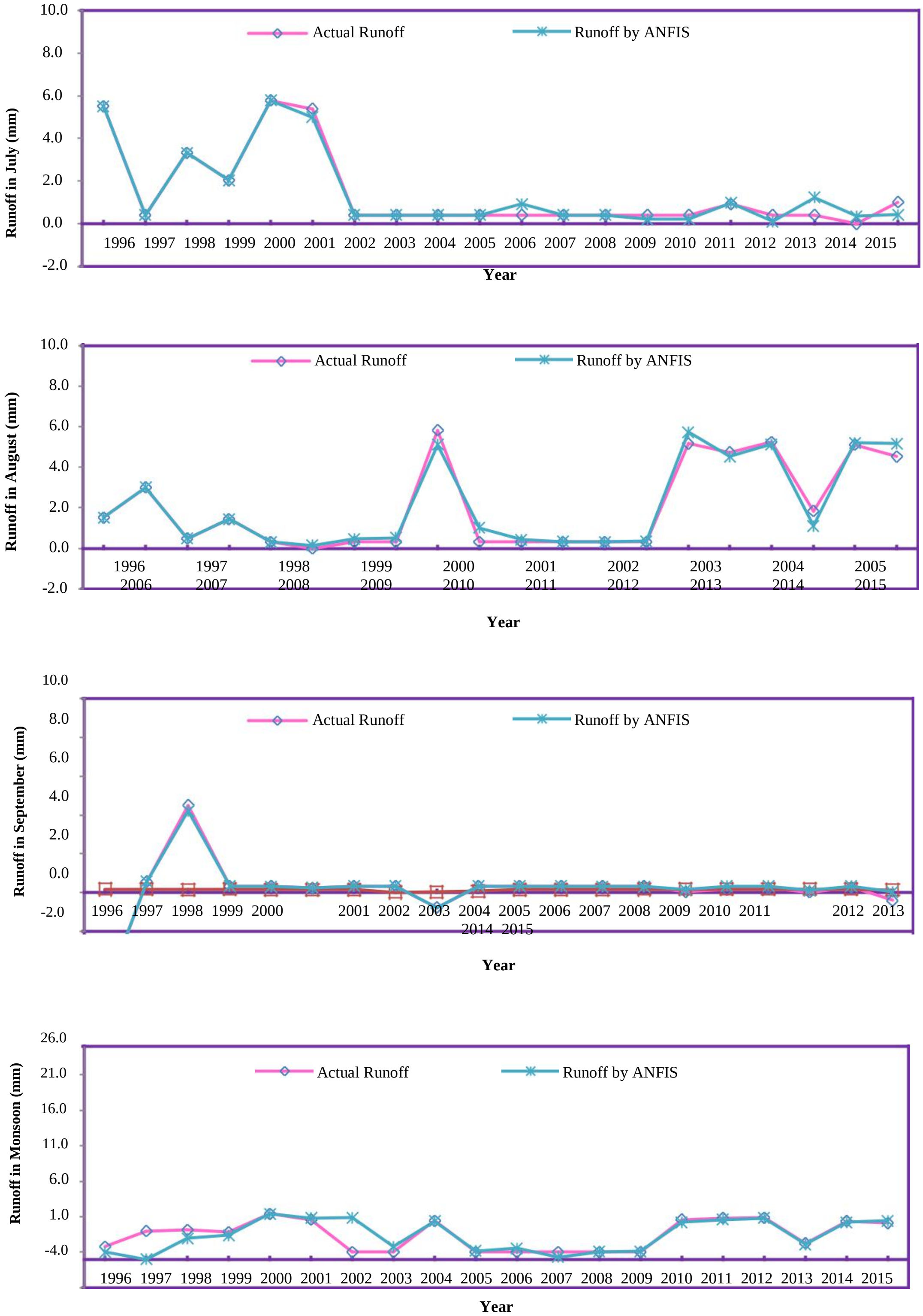


Fig. 5.32: Comparison of actual runoff and runoff predicted by ANFIS model for Lassaria Dam Catchment

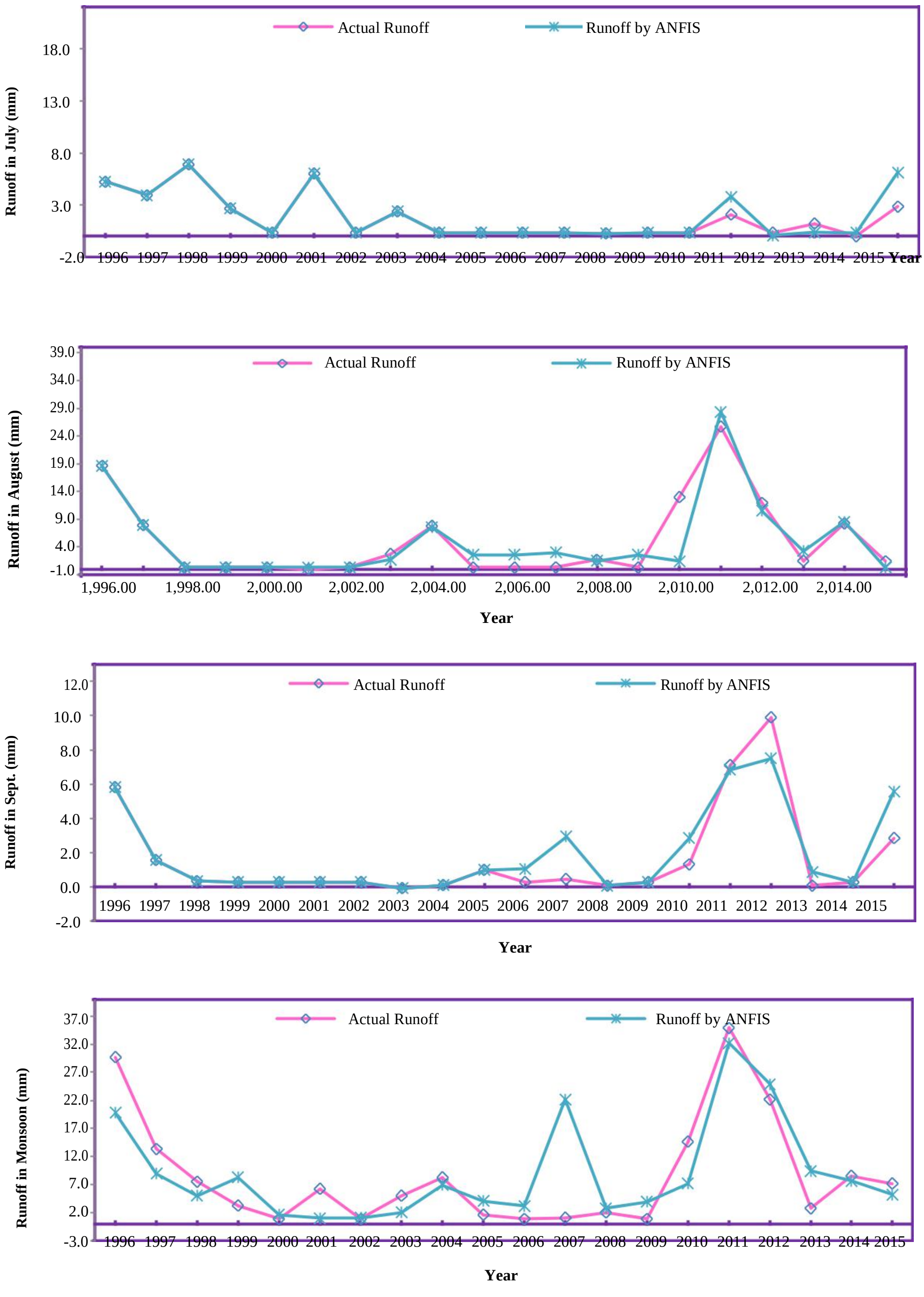


Fig. 5.33: Comparison of actual runoff and runoff predicted by ANFIS model for Chhaparwara Dam Catchment

Fig. 5.34: Comparison of actual runoff and runoff predicted by ANFIS model for Morel Dam Catchment

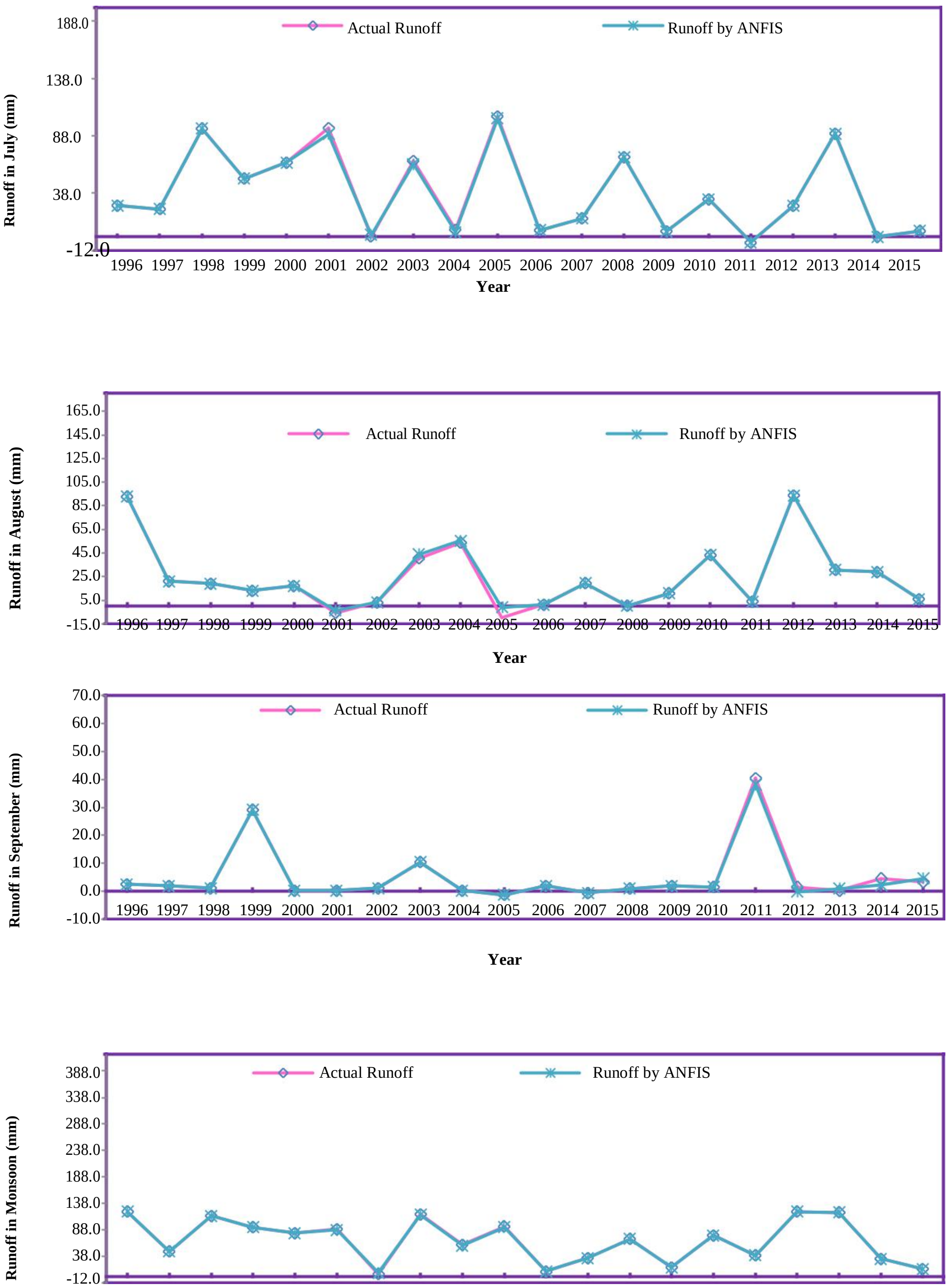


Fig. 5.35: Comparison of actual runoff and runoff predicted by ANFIS model for Kalisil Dam Catchment

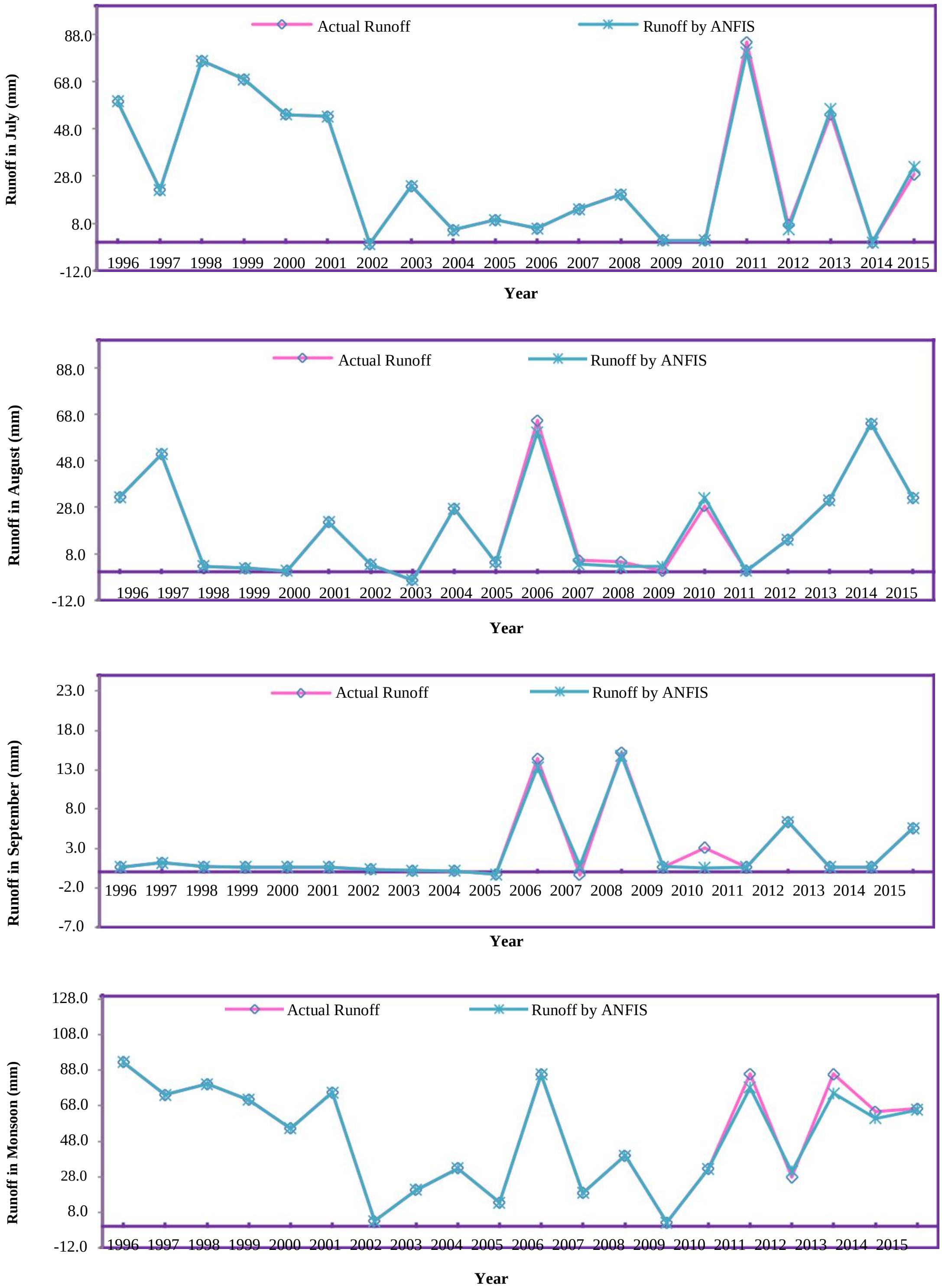


Fig. 5.36: Comparison of actual runoff and runoff predicted by ANFIS model for Moti Sagar Dam Catchment

5.3.3 Significance of the developed models

As the available testing datasets were less than 30 so Student's t distribution test, was applied for testing the hypothesis and checking the significance of the developed rainfall-runoff empirical models. Fifteen number of rainfall-runoff pairs were used as training data at a time for the training of the model and then comparing the computed co-relation coefficients of the developed models with Student's critical t distribution values and corresponding correlation coefficient values for 13 degree of freedom are shown in **Table 4.3**. It has been found that the developed relation or model is significant at different % of confidence levels i.e., if R is more than 0.35 then at 80%, if R is more than 0.44 then at 90%, if R is more than 0.51 then at 95%, if R is more than 0.59 then at 98% and if R is more than 0.64 then at 99% confidence level.

5.4 Comparison of different modelling techniques adopted

Simple ranking technique was applied for comparing the first order rainfall-runoff regression model, second order rainfall-runoff regression model, rainfall-runoff ANN model and rainfall-runoff ANFIS model. The sub-basin wise computed values of the performance metrics namely R^2, RMSE and MAE in training and validation process with final ranks for the developed first and second order polynomial models using conventional regression technique, ANN and ANFIS models using soft computing techniques for the individual dam catchment are shown in **Tables- 5.5, 5.7, 5.9, 5.11, 5.13, 5.15, 5.17, 5.19 and 5.21**.

The sub-basin wise comparison plots between the actual runoff and the computed runoffs in different time period i.e. July, August, September and Monsoon period from 1996 to 2015, using different developed model, in individual dam catchments situated in the differential sub-basins are shown in the **Figures-5.37 to 5.45.** The sub-basin wise statistical parameters i.e. mean, standard deviation and skewness of the predicted runoff as well as the actual runoff were also calculated and are shown in the **Tables- 5.6, 5.8, 5.10, 5.12, 5.14, 5.16, 5.18, 5.20, and 5.22**.

5.4.1 Berach sub-basin

Table 5.5: Performance metrics and ranking sum in different models

<table>
<tr><th rowspan="2">Sub-basin No.</th><th rowspan="2">Name of Sub-basin</th><th rowspan="2">Name of selected dam</th><th rowspan="2">Time period</th><th rowspan="2">Type of model</th><th colspan="3">Training</th><th colspan="3">Validation</th><th rowspan="2">Final Rank</th></tr>
<tr><th>R^2</th><th>RMSE</th><th>MAE</th><th>R^2</th><th>RMSE</th><th>MAE</th></tr>
<tr><td rowspan="16">1</td><td rowspan="16">Berach</td><td rowspan="16">Wagan</td><td rowspan="4">July</td><td>I order</td><td>0.62</td><td>11.01</td><td>8.98</td><td>0.53</td><td>24.03</td><td>22.44</td><td>4</td></tr>
<tr><td>II order</td><td>0.68</td><td>10.15</td><td>8.28</td><td>0.6</td><td>32.87</td><td>28.9</td><td>3</td></tr>
<tr><td>ANN</td><td>0.70</td><td>0.44</td><td>5.82</td><td>0.82</td><td>3.265.</td><td>6.77</td><td>2</td></tr>
<tr><td>ANFIS</td><td>1.00</td><td>0.00</td><td>0.00</td><td>0.94</td><td>11.23</td><td>7.76</td><td>1</td></tr>
<tr><td rowspan="4">August</td><td>I order</td><td>0.25</td><td>22.14</td><td>15.71</td><td>0.26</td><td>32.77</td><td>20.88</td><td>4</td></tr>
<tr><td>II order</td><td>0.33</td><td>26.17</td><td>18.2</td><td>0.56</td><td>17.12</td><td>15.99</td><td>3</td></tr>
<tr><td>ANN</td><td>0.99</td><td>0.22</td><td>1.23</td><td>0.89</td><td>7.79</td><td>11.58</td><td>1</td></tr>
<tr><td>ANFIS</td><td>1.00</td><td>0.00</td><td>0.00</td><td>0.75</td><td>44.68</td><td>27.13</td><td>2</td></tr>
<tr><td rowspan="4">September</td><td>I order</td><td>0.23</td><td>6.64</td><td>4.45</td><td>0.01</td><td>25.98</td><td>20.99</td><td>4</td></tr>
<tr><td>II order</td><td>0.23</td><td>6.64</td><td>4.49</td><td>0.01</td><td>18.94</td><td>18.19</td><td>3</td></tr>
<tr><td>ANN</td><td>0.94</td><td>0.31</td><td>1.95</td><td>0.29</td><td>1.33</td><td>4.52</td><td>1</td></tr>
<tr><td>ANFIS</td><td>0.86</td><td>4.45</td><td>3.38</td><td>0.2</td><td>10.68</td><td>6.44</td><td>2</td></tr>
<tr><td rowspan="4">Monsoon</td><td>I order</td><td>0.92</td><td>10.98</td><td>9.31</td><td>0.06</td><td>179.63</td><td>145.84</td><td>3.5</td></tr>
<tr><td>II order</td><td>0.62</td><td>19.82</td><td>15.42</td><td>0.74</td><td>19.09</td><td>14.8</td><td>3.5</td></tr>
<tr><td>ANN</td><td>0.97</td><td>0.07</td><td>4.06</td><td>0.8</td><td>7.13</td><td>14.32</td><td>2</td></tr>
<tr><td>ANFIS</td><td>1.00</td><td>0.01</td><td>0.00</td><td>1</td><td>0.01</td><td>0.00</td><td>1</td></tr>
</table>

Table 5.6: Statistical parameters for the actual and predicted runoffs

<table>
<tr><th rowspan="2">Sub-basin No.</th><th rowspan="2">Name of sub-basin</th><th rowspan="2">Name of dam</th><th rowspan="2">Time Period</th><th rowspan="2">Statistical Parameter</th><th colspan="5">Runoff(mm)</th></tr>
<tr><th>Actual</th><th>First Order Regression Model</th><th>Second Order Regression Model</th><th>ANN Model</th><th>ANFIS Model</th></tr>
<tr><td rowspan="12">1</td><td rowspan="12">Berach</td><td rowspan="12">Wagan</td><td rowspan="3">July</td><td>Average</td><td>18.02</td><td>22.81</td><td>24.25</td><td>18.46</td><td>18.22</td></tr>
<tr><td>St. Dev.</td><td>17.18</td><td>17.47</td><td>21.95</td><td>14.37</td><td>15.68</td></tr>
<tr><td>Skewness</td><td>0.92</td><td>0.61</td><td>1.51</td><td>1.78</td><td>1.12</td></tr>
<tr><td rowspan="3">August</td><td>Average</td><td>22.81</td><td>15.68</td><td>22.24</td><td>21.41</td><td>21.97</td></tr>
<tr><td>St. Dev.</td><td>30.28</td><td>24.91</td><td>23.15</td><td>28.55</td><td>28.65</td></tr>
<tr><td>Skewness</td><td>2.00</td><td>2.43</td><td>-0.50</td><td>1.99</td><td>1.95</td></tr>
<tr><td rowspan="3">September</td><td>Average</td><td>6.40</td><td>8.90</td><td>6.67</td><td>6.73</td><td>6.36</td></tr>
<tr><td>St. Dev.</td><td>11.81</td><td>13.79</td><td>8.44</td><td>11.02</td><td>10.34</td></tr>
<tr><td>Skewness</td><td>1.76</td><td>1.95</td><td>1.48</td><td>2.06</td><td>2.24</td></tr>
<tr><td rowspan="3">Monsoon</td><td>Average</td><td>47.23</td><td>83.69</td><td>47.48</td><td>46.42</td><td>46.88</td></tr>
<tr><td>St. Dev.</td><td>35.08</td><td>91.28</td><td>25.22</td><td>33.09</td><td>34.93</td></tr>
<tr><td>Skewness</td><td>0.72</td><td>1.66</td><td>-0.21</td><td>1.00</td><td>0.57</td></tr>
</table>

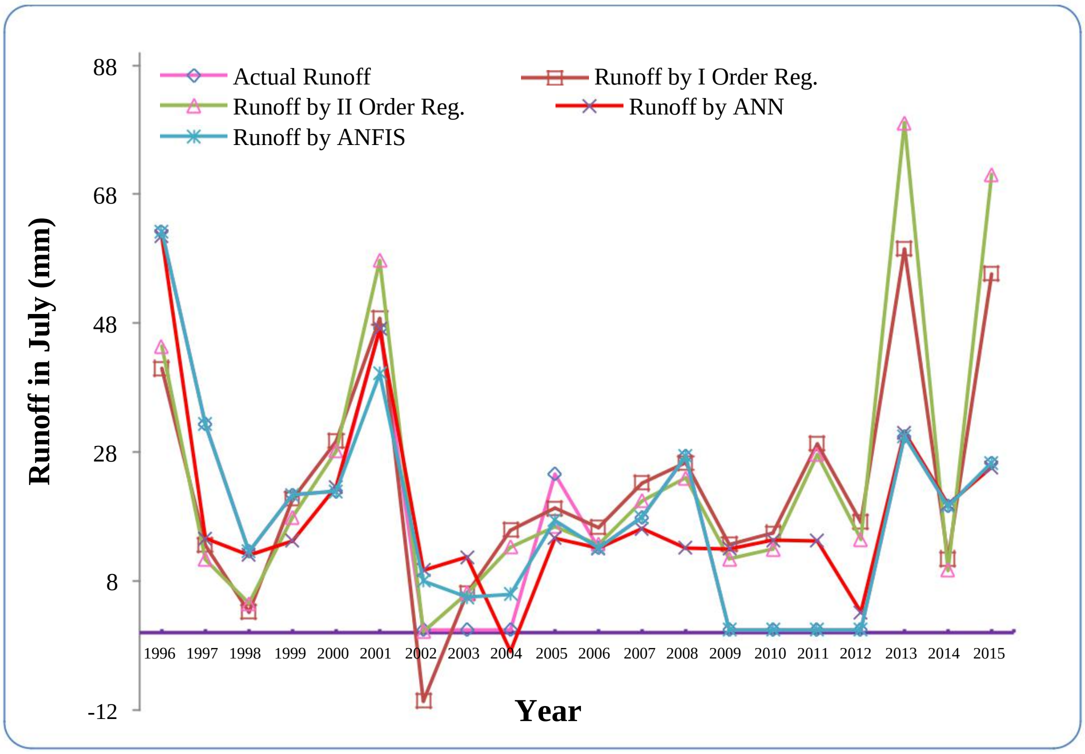


Fig. 5.37 A: Comparison of Actual and Predicted Runoff in July for Wagan Dam Catchment

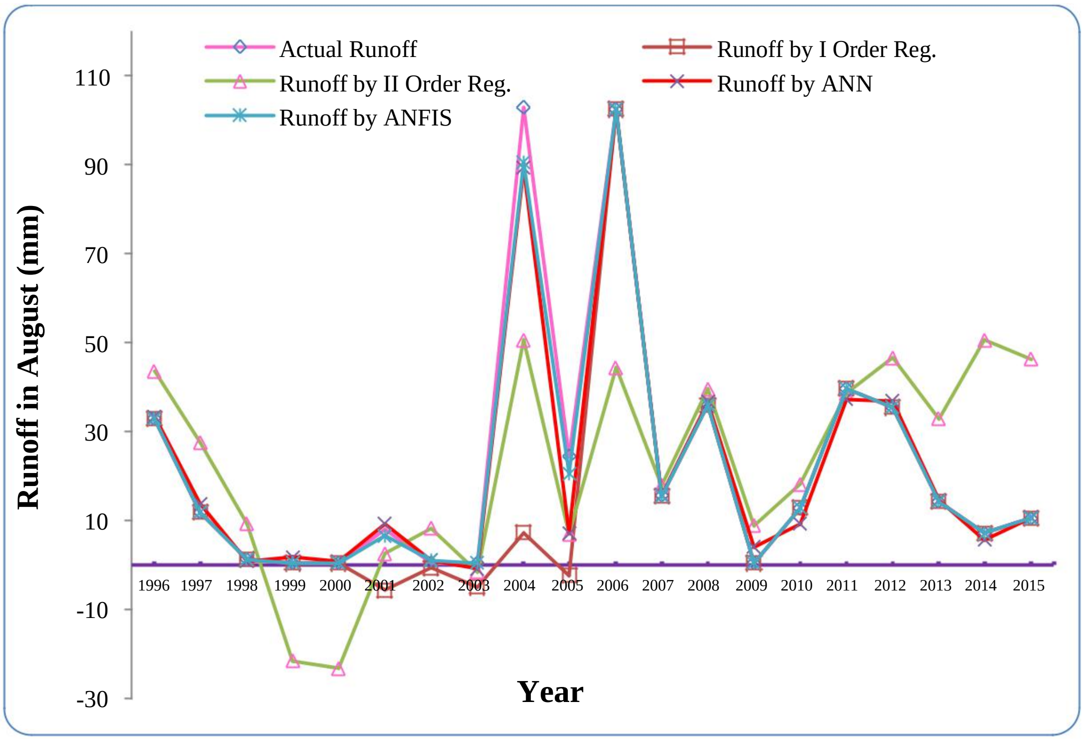


Fig. 5.37 B: Comparison of Actual and Predicted Runoff in August for Wagan Dam Catchment

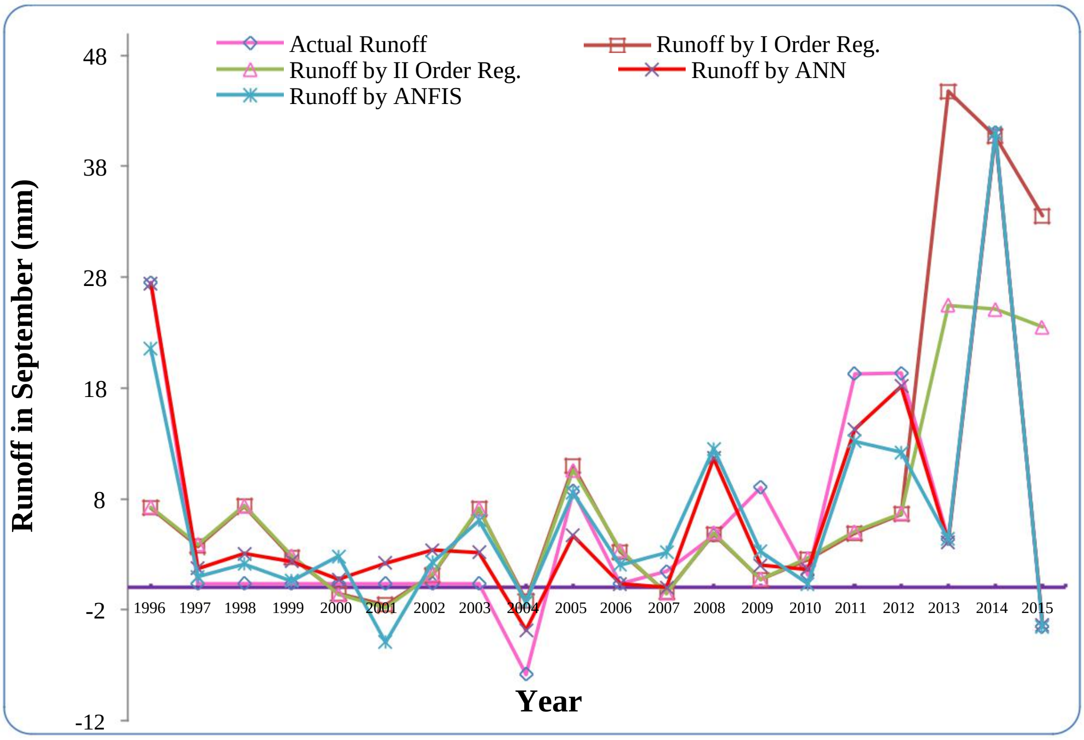


Fig. 5.37C: Comparison of Actual and Predicted Runoff in Sept. for Wagan Dam Catchment

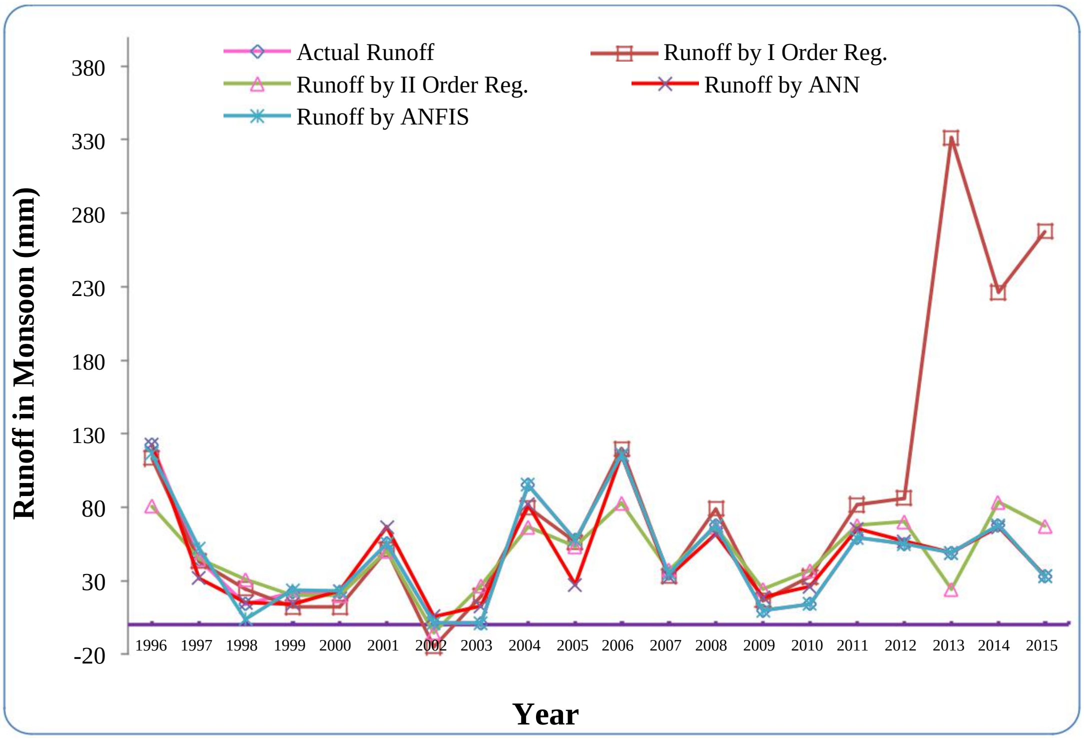


Fig. 5.37D: Comparison of Actual and Predicted Runoff in Monsoon for Wagan DamCatchment

5.4.2 Banas I sub-basin

Table 5.7: Performance metrics and ranking sum in different models

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
Zsaq02	Banas I	Jetpura	July	I order	0.46	16.27	11.75	0.63	32.60	29.65	4
				II order	0.69	14.04	11.46	0.31	32.80	25.71	3
				ANN	0.90	0.19	5.46	0.98	16.48	8.56	2
				ANFIS	0.98	3.71	1.17	1.00	0.00	0.00	1
			August	I order	0.58	22.78	16.62	0.43	28.00	24.62	4
				II order	0.63	21.62	14.14	0.44	22.92	19.56	3
				ANN	0.98	0.91	3.51	0.96	3.07	7.13	2
				ANFIS	1.00	0.01	0.00	1.00	0.00	0.00	1
			September	I order	0.01	4.95	3.23	0.06	12.75	6.98	3
				II order	0.20	7.18	4.29	0.03	50.96	38.94	4
				ANN	0.96	0.09	0.78	0.96	10.63	5.11	2
				ANFIS	1.00	0.08	0.05	1.00	0.09	0.06	1
			Monsoon	I order	0.30	15.88	13	0.00	58.46	52.24	4
				II order	0.06	20.58	18.26	0.00	15.66	11.55	3
				ANN	0.72	0.76	7.13	0.65	1.85	14.49	2
				ANFIS	1.00	0.01	0.01	1.00	0.00	0.00	1

Table 5.8: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
2	Banas I	Jetpura	July	Average	48.68	30.23	55.11	49.23	48.75
				St. Dev.	27.20	22.36	20.87	25.57	27.79
				Skewness	0.08	0.06	-0.8	-0.22	0.14
			August	Average	43.23	40.31	44.26	44.15	43.58
				St. Dev.	37.86	25.97	31.25	36.92	37.03
				Skewness	0.34	0.85	-0.37	0.2	0.29
			September	Average	2.62	1.09	1.09	2.93	2.69
				St. Dev.	7.83	0.82	0.83	6.61	7.92
				Skewness	2.47	-0.51	-0.47	0.94	2.43
			Monsoon	Average	94.53	104.48	71.31	95.86	95.03
				St. Dev.	20.92	30.4	42.54	18.29	19.66
				Skewness	0.05	2.08	-1.2	0.04	0.28

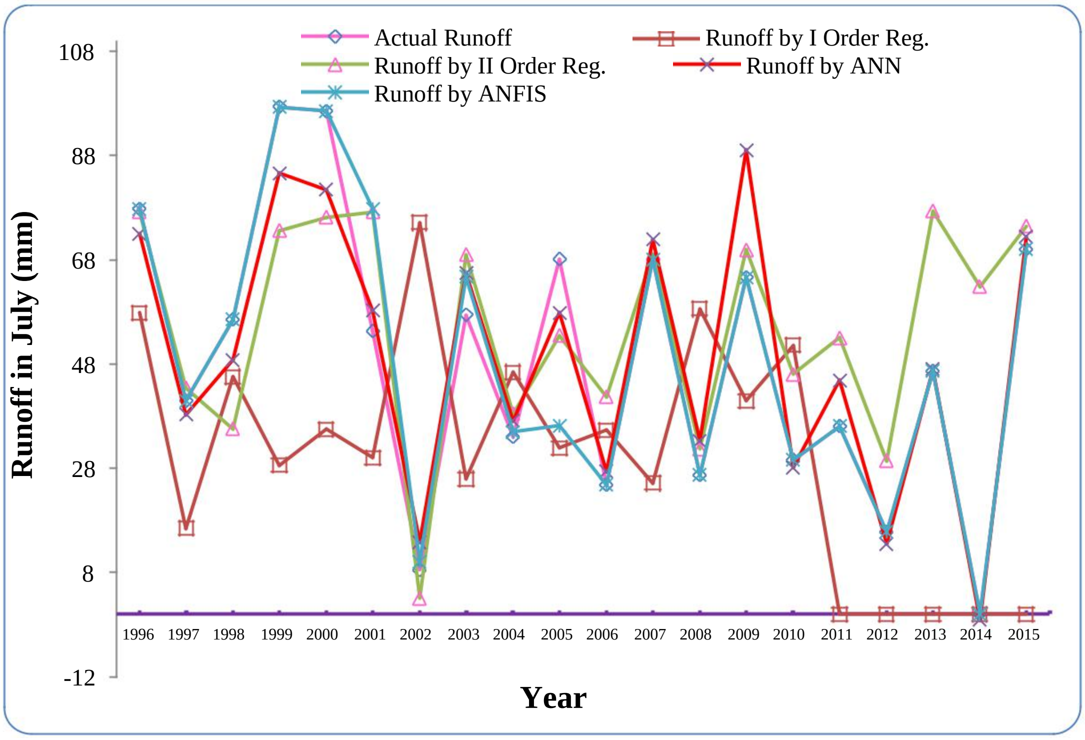


Fig. 5.38 A: Comparison of Actual and Predicted Runoff in July for Jetpura Dam Catchment

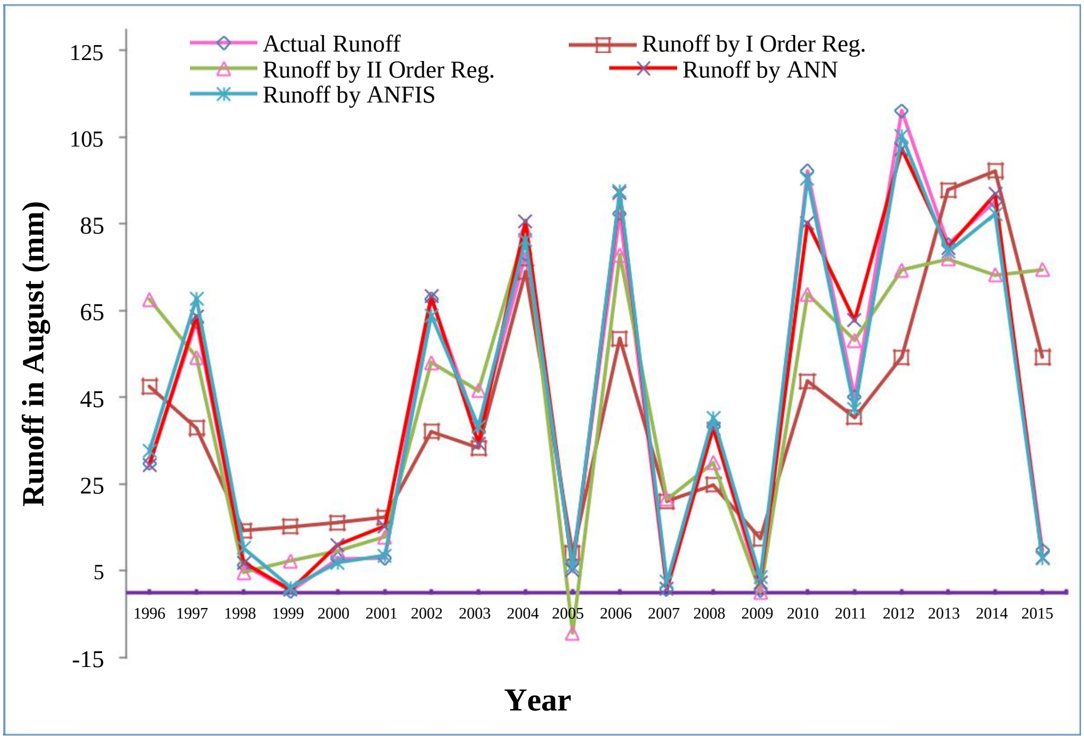


Fig. 5.38 B: Comparison of Actual and Predicted Runoff in August for Jetpura Dam Catchment

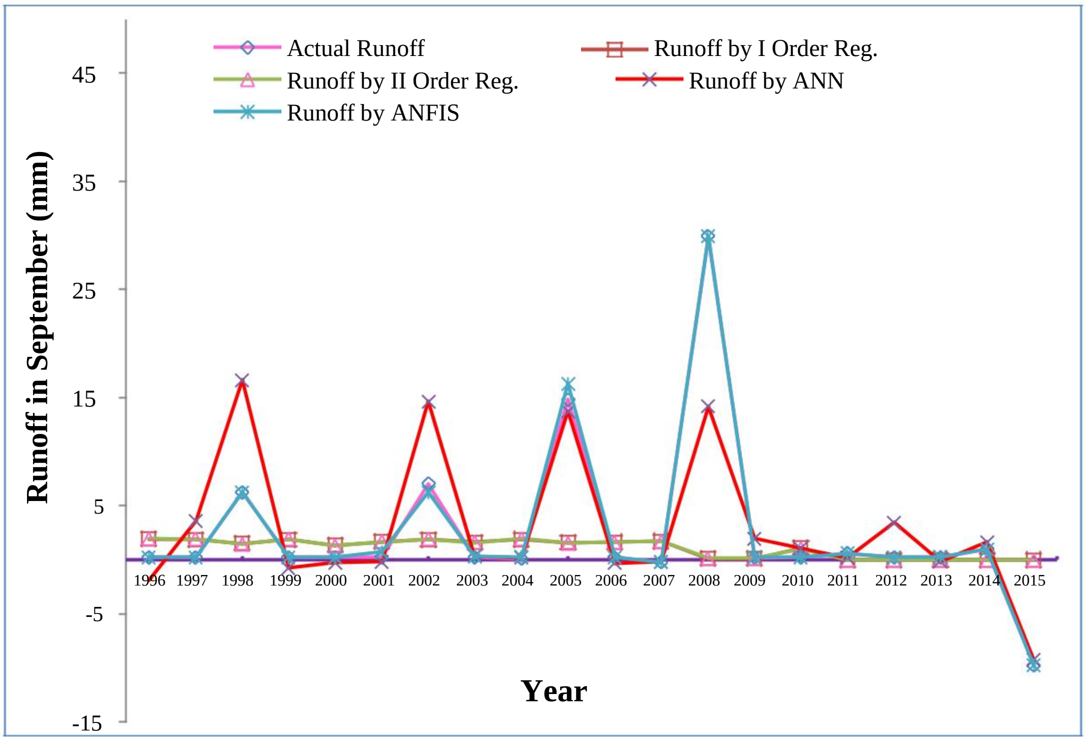


Fig. 5.38 C: Comparison of Actual and Predicted Runoff in Sept. for Jetpura Dam Catchment

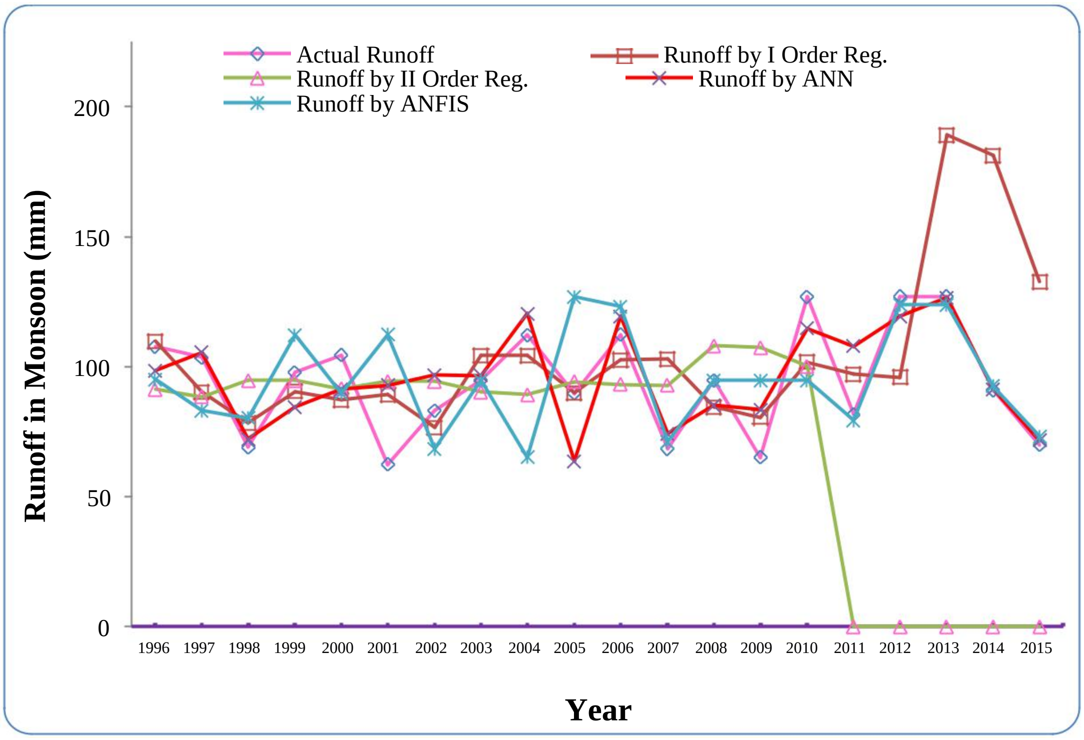


Fig. 5.38 D: Comparison of Actual and Predicted Runoff in Monsoon for Jetpura Dam Catchment

5.4.3 Kothari sub-basin

Table 5.9: Performance metrics and ranking sum in different models

S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
3	Kothari	Meja	July	I order	0.03	0.30	0.2	0.53	0.14	0.09	3
				II order	0.39	0.12	0.09	0.01	0.54	0.50	4
				ANN	0.99	0.00	0.02	0.93	0.19	0.13	1
				ANFIS	1.00	0.00	0.00	0.21	0.49	0.35	2
			August	I order	0.48	0.83	0.52	0.14	0.30	0.26	3
				II order	0.49	0.83	0.53	0.18	0.40	0.34	4
				ANN	0.99	0.00	0.06	0.87	0.46	0.38	2
				ANFIS	1.00	0.00	0.00	0.92	0.41	0.28	1
			September	I order	0.04	3.36	2.38	0.96	0.92	0.80	3.5
				II order	0.33	2.75	1.66	0.78	1.14	1.10	3.5
				ANN	0.98	0.01	0.24	0.56	0.43	0.59	1
				ANFIS	1.00	0.11	0.06	0.29	8.83	4.77	2
			Monsoon	I order	0.18	3.25	2.21	0.94	0.81	0.73	3
				II order	0.42	2.72	1.97	0.63	1.42	1.05	4
				ANN	0.99	0.01	0.25	0.99	0.15	0.74	1
				ANFIS	1.00	0.00	0.00	0.30	1.98	1.61	2

Table 5.10: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
3	Kothari	Meja	July	Average	0.38	0.35	0.42	0.38	0.37
				St. Dev.	0.28	0.05	0.16	0.27	0.27
				Skewness	1.28	0.39	1.36	1.32	1.37
			August	Average	0.83	0.79	0.78	0.9	0.78
				St. Dev.	1.06	0.8	0.83	1.08	1.07
				Skewness	2.38	0.84	0.51	2.16	2.49
			September	Average	1.74	1.87	1.86	1.86	1.97
				St. Dev.	3.09	0.60	1.84	3.02	3.20
				Skewness	2.59	1.86	0.58	2.66	2.19
			Monsoon	Average	2.95	3.06	2.94	3.11	2.90
				St. Dev.	3.27	1.43	2.37	3.20	3.30
				Skewness	2.01	1.66	-0.47	2.07	1.98

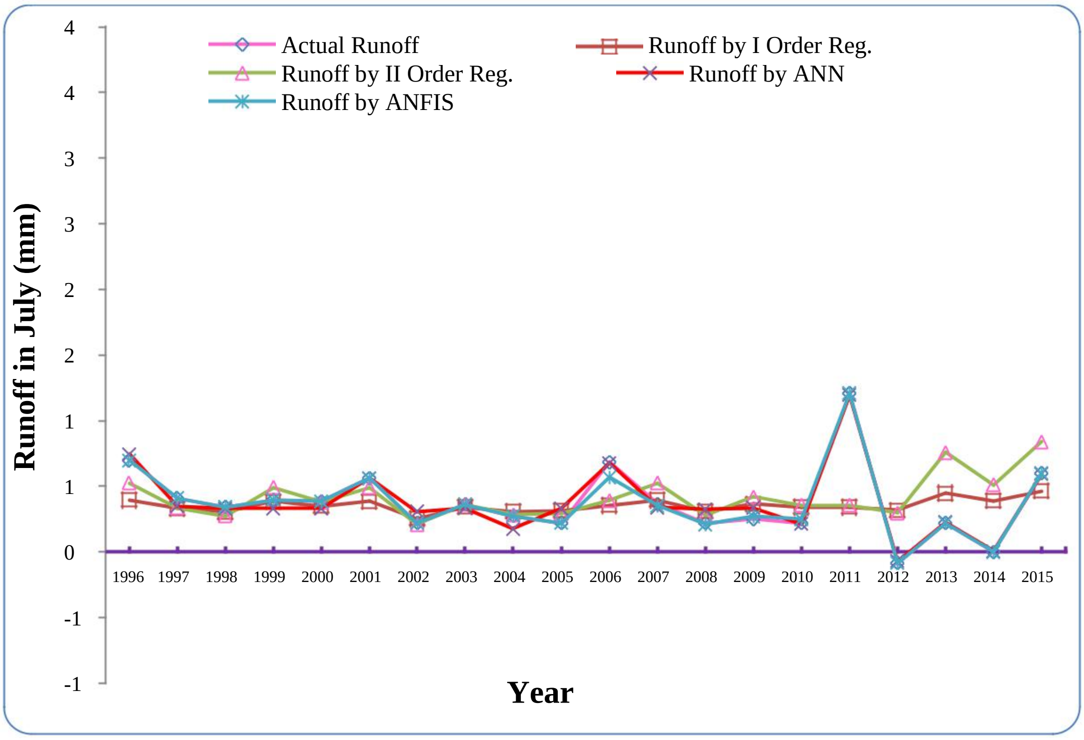


Fig. 5.39 A: Comparison of Actual and Predicted Runoff in July for Meja Dam Catchment

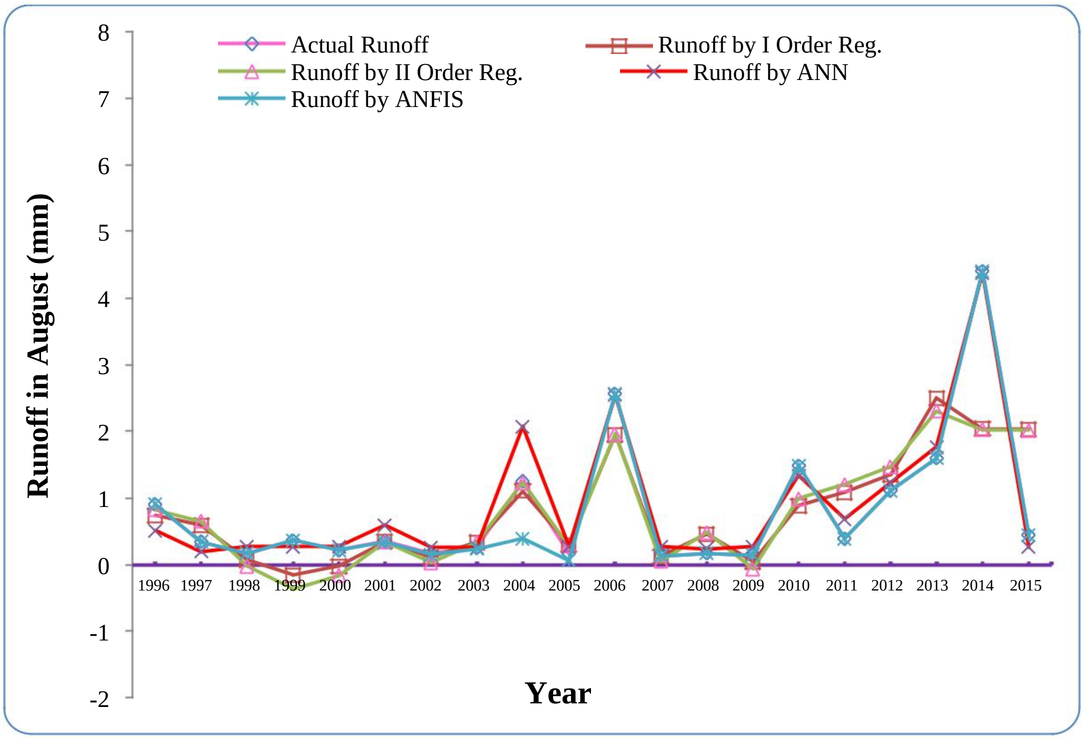


Fig. 5.39 B: Comparison of Actual and Predicted Runoff in August for Meja Dam Catchment

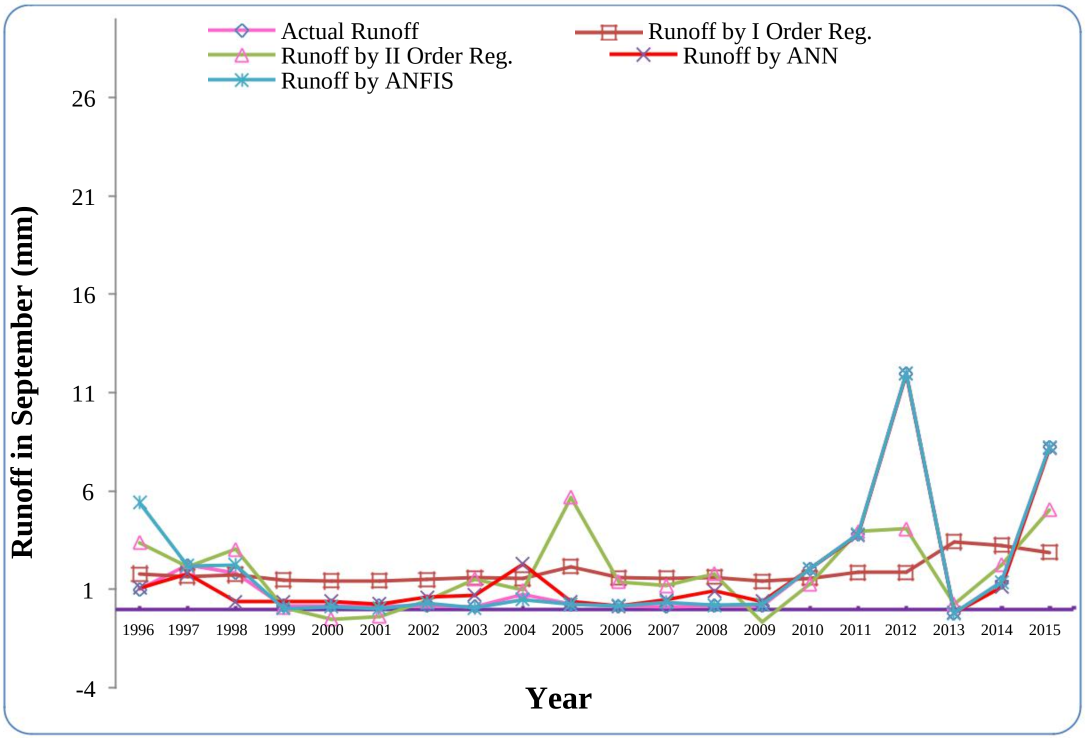


Fig. 5.39 C: Comparison of Actual and Predicted Runoff in Sept. for Meja Dam Catchment

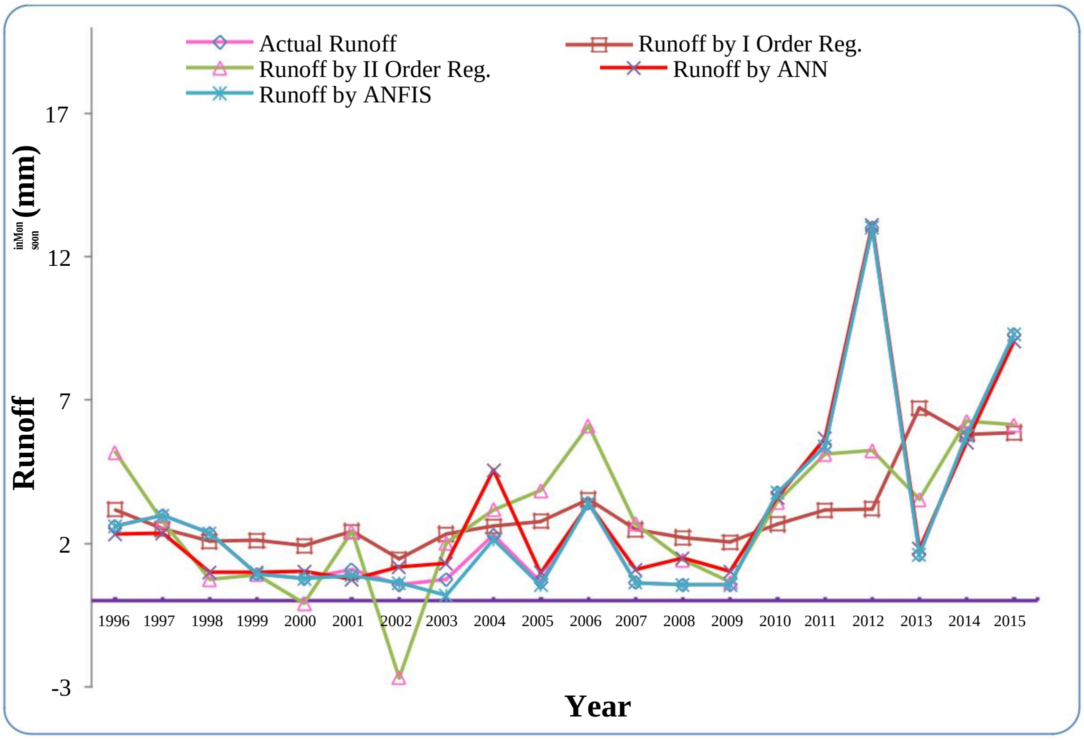


Fig. 5.39 D: Comparison of Actual and Predicted Runoff in Monsoon for Meja Dam Catchment

5.4.4 Khari sub-basin

Table 5.11: Performance metrics and ranking sum in different models

S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
4	Khari	NaharSagar	July	I order	0.52	8.7	7.02	0.82	4.65	4.19	4
				II order	0.73	4.97	3.7	0.94	3.79	3.29	3
				ANN	1.00	0.01	0.09	0.38	1.59	3.16	2
				ANFIS	1.00	0.16	0.08	0.98	2.78	1.71	1
			August	I order	0.77	6.62	4.67	0.12	17.45	16.23	3
				II order	0.78	6.46	4.72	0.11	18.62	17.32	4
				ANN	1.00	0.01	0.04	0.97	2.82	4.74	1.5
				ANFIS	1.00	0.00	0.00	0.12	14.93	10.43	1.5
			September	I order	0.07	2.96	2.15	0.8	1.19	1.1	2.5
				II order	0.35	1.74	1.27	0.34	3.71	2.31	4
				ANN	1.00	0.01	0.01	0.47	0.57	1.73	1
				ANFIS	1.00	0.03	0.02	0.29	2.18	1.82	2.5
			Monsoon	I order	0.12	13.63	11.42	0.06	13.99	10.33	4
				II order	0.48	10.52	8.64	0.53	9.01	7.98	3
				ANN	1.00	0.03	0.07	0.97	1.80	6.14	1
				ANFIS	1.00	0.00	0.00	0.43	13.50	9.75	2

Table 5.12: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
4	Khari	NaharSagar	July	Average	7.92	8.89	7.61	7.89	7.97
				St. Dev.	11.67	8.18	10.01	11.68	11.81
				Skewness	2.17	-0.44	1.52	2.33	2.21
			August	Average	10.68	13.49	13.91	10.84	10.77
				St. Dev.	14.46	12.84	13.26	13.8	13.98
				Skewness	1.52	0.96	0.57	1.47	1.44
			September	Average	1.38	1.66	1.16	1.18	1.2
				St. Dev.	2.75	0.76	1.15	1.35	2.34
				Skewness	1.83	-1.84	-2.58	-1.45	2.71
			Monsoon	Average	19.98	18.33	20.46	20.02	20.03
				St. Dev.	15.12	4.79	9.77	15.56	14.36
				Skewness	0.65	1.16	-0.99	0.87	0.50

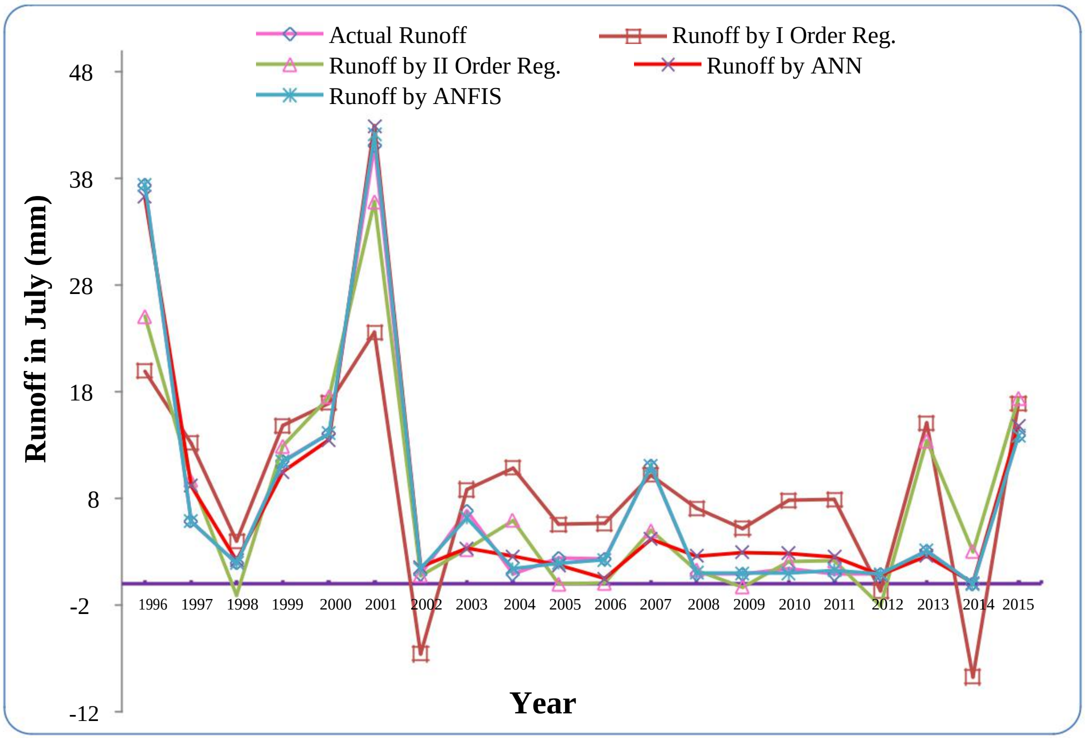


Fig. 5.40 A: Comparison of Actual and Predicted Runoff in July for Nahar Sagar Dam Catchment

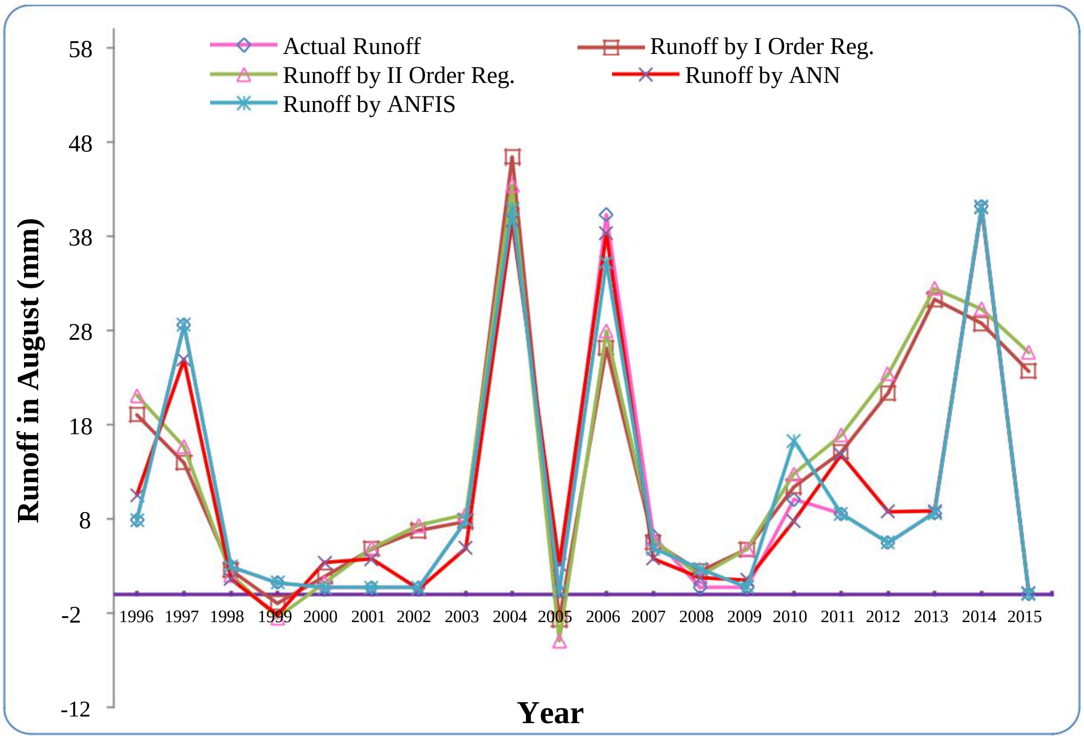


Fig. 5.40 B: Comparison of Actual and Predicted Runoff in August for Nahar Sagar Dam Catchment

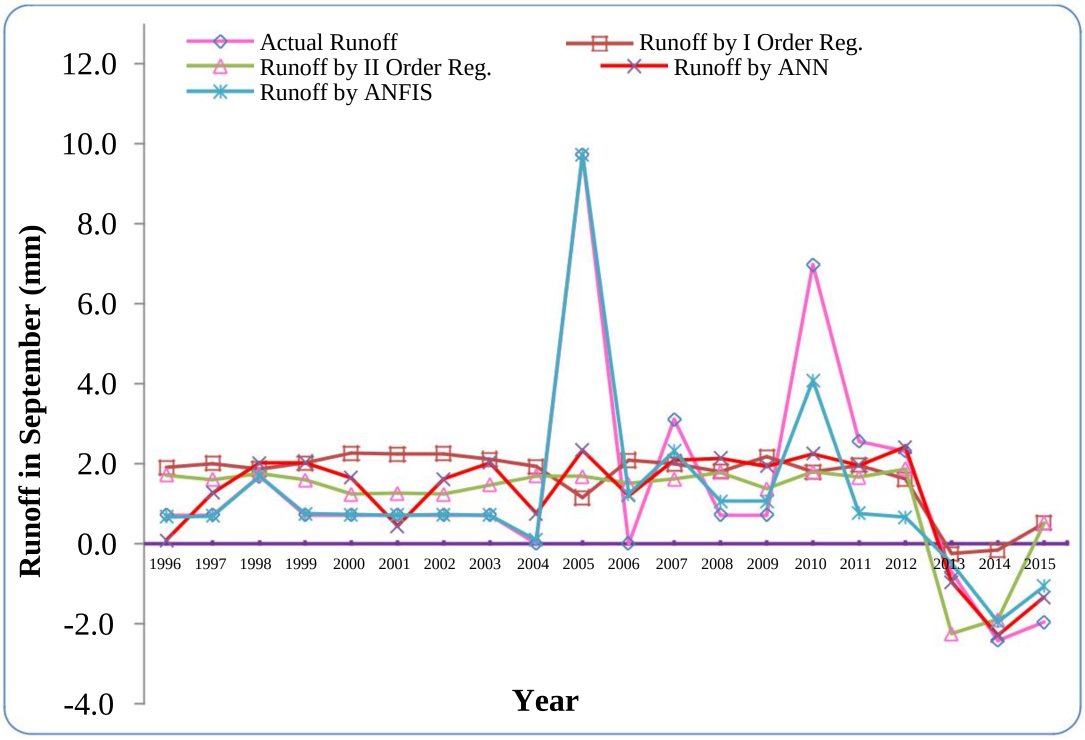


Fig. 5.40 C: Comparison of Actual and Predicted Runoff in Sept. for Nahar Sagar Dam Catchment

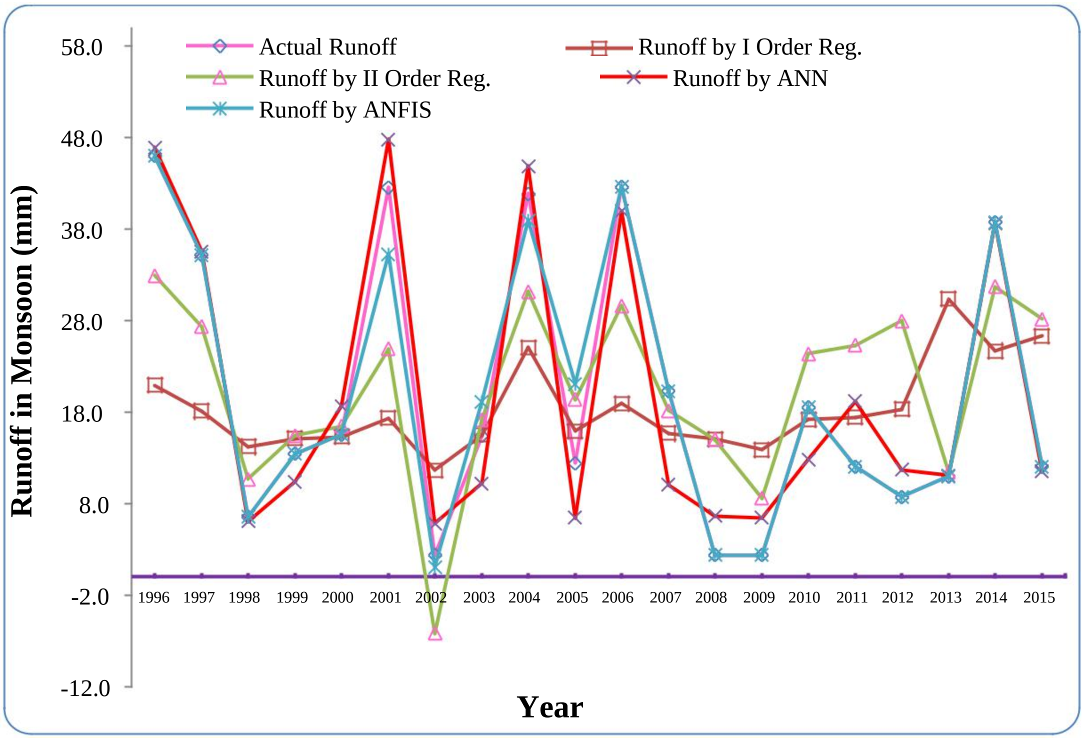


Fig. 5.40 D: Comparison of Actual and Predicted Runoff in Monsoon for Nahar Sagar Dam Catchment

5.4.5 Dai sub-basin

Table 5.13: Performance metrics and ranking sum in different models

S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training R^2	Training RMSE	Training MAE	Validation R^2	Validation RMSE	Validation MAE	Final Rank
5	Dai	Lassaria	July	I order	0.21	1.82	1.46	0.73	1	0.92	4
				II order	0.21	1.82	1.44	0.75	0.96	0.88	3
				ANN	0.86	0.00	0.41	0.9	0.03	0.64	2
				ANFIS	1.00	0.06	00.05	1.00	0.01	0.05	1
			August	I order	0.57	1.53	1.22	0.83	0.84	0.58	3
				II order	0.6	1.48	1.26	0.7	1.24	0.97	4
				ANN	0.96	0.06	0.23	0.99	0.26	0.30	2
				ANFIS	1.00	0.05	0.03	1.00	0.07	0.07	1
			September	I order	0.03	0.31	0.21	0.01	2.41	1.25	4
				II order	0.03	1.35	0.71	0.01	0.59	0.44	3
				ANN	0.98	0.02	0.1	0.99	0.13	0.06	2
				ANFIS	1.00	0.04	0.01	0.99	0.05	0.02	1
			Monsoon	I order	0.03	1.96	1.78	0.24	2.22	2.21	4
				II order	0.09	1.90	1.68	0.25	2.05	1.92	3
				ANN	0.98	0.00	0.18	0.94	0.16	0.43	2
				ANFIS	1.00	0.01	0.01	1.00	0.01	0.01	1

Table 5.14: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm) Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
5	Dai	Lassaria	July	Average	1.44	1.67	1.66	1.31	1.45
				St. Dev.	1.92	0.88	0.89	1.97	1.88
				Skewness	1.65	-0.02	0.22	1.69	1.62
			August	Average	2.07	2.01	2	1.34	2.11
				St. Dev.	2.16	1.76	1.89	1.43	2.14
				Skewness	0.69	0.33	-0.21	1.85	0.73
			September	Average	0.12	0.13	-0.1	0.18	0.15
				St. Dev.	1.61	0.05	0.28	0.56	1.57
				Skewness	-0.96	-1.94	-0.08	2.22	-1.35
			Monsoon	Average	3.43	3.56	3.49	3.58	3.54
				St. Dev.	2.12	0.31	0.68	2.24	2.16
				Skewness	-0.02	1.47	-1.05	-0.71	-0.11

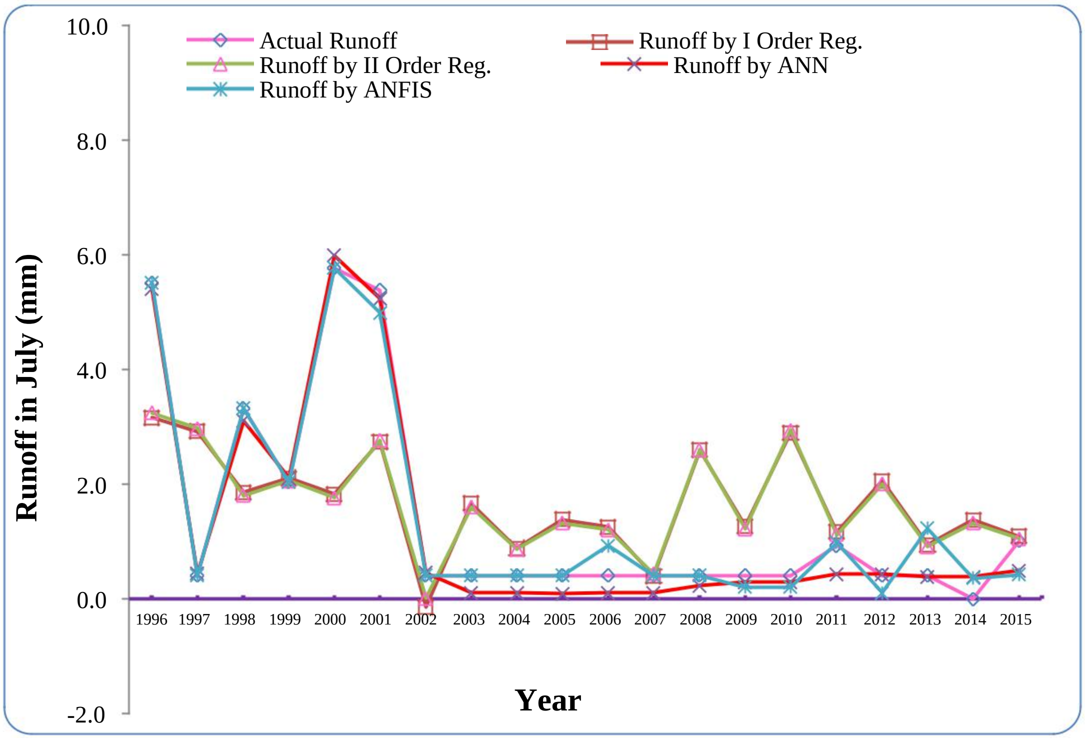


Fig. 5.41 A: Comparison of Actual and Predicted Runoff in July for Lassaria Dam Catchment

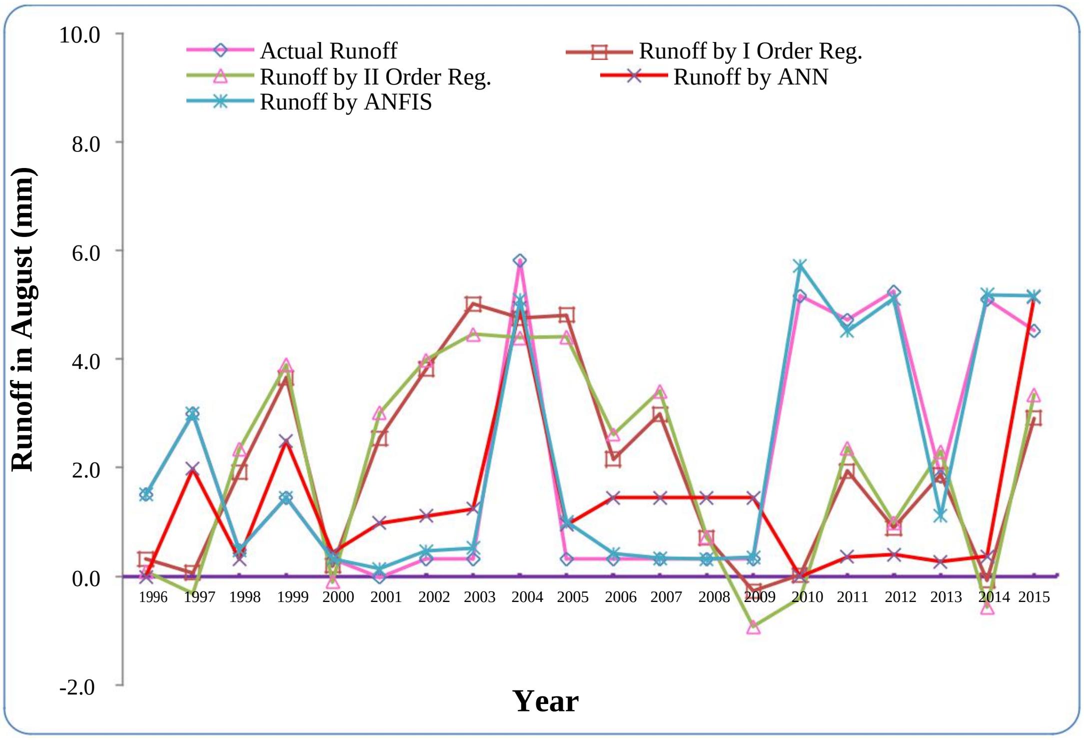


Fig. 5.41 B: Comparison of Actual and Predicted Runoff in August for Lassaria Dam Catchment

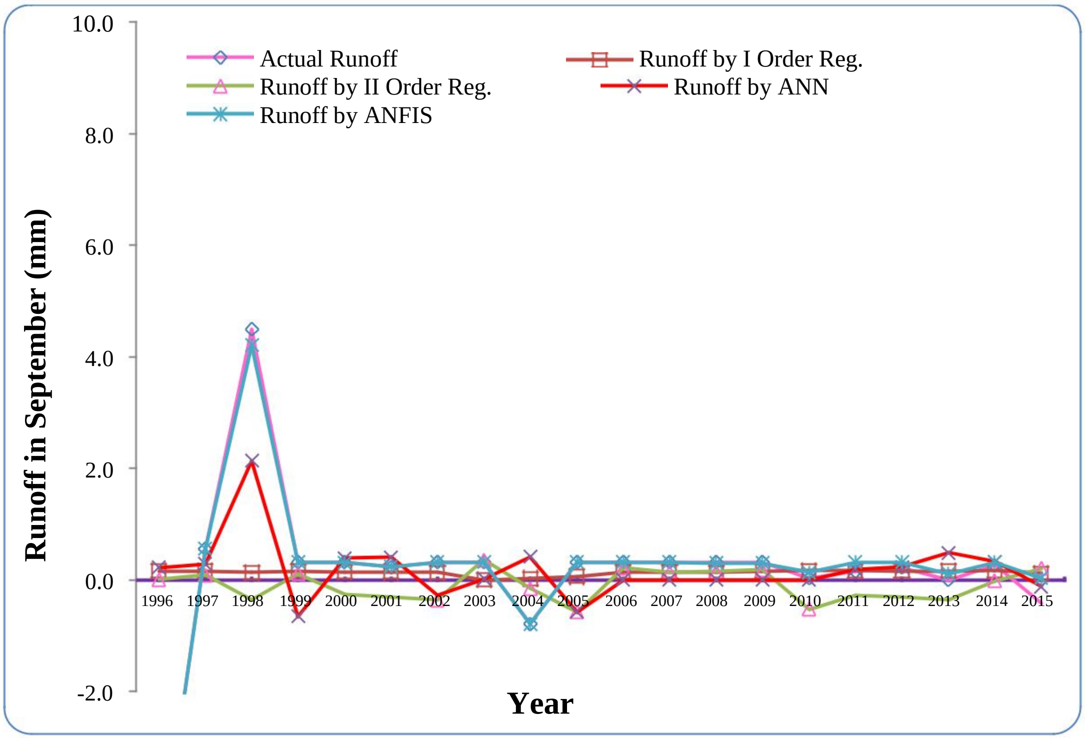


Fig. 5.41 C: Comparison of Actual and Predicted Runoff in Sept. for Lassaria Dam Catchment

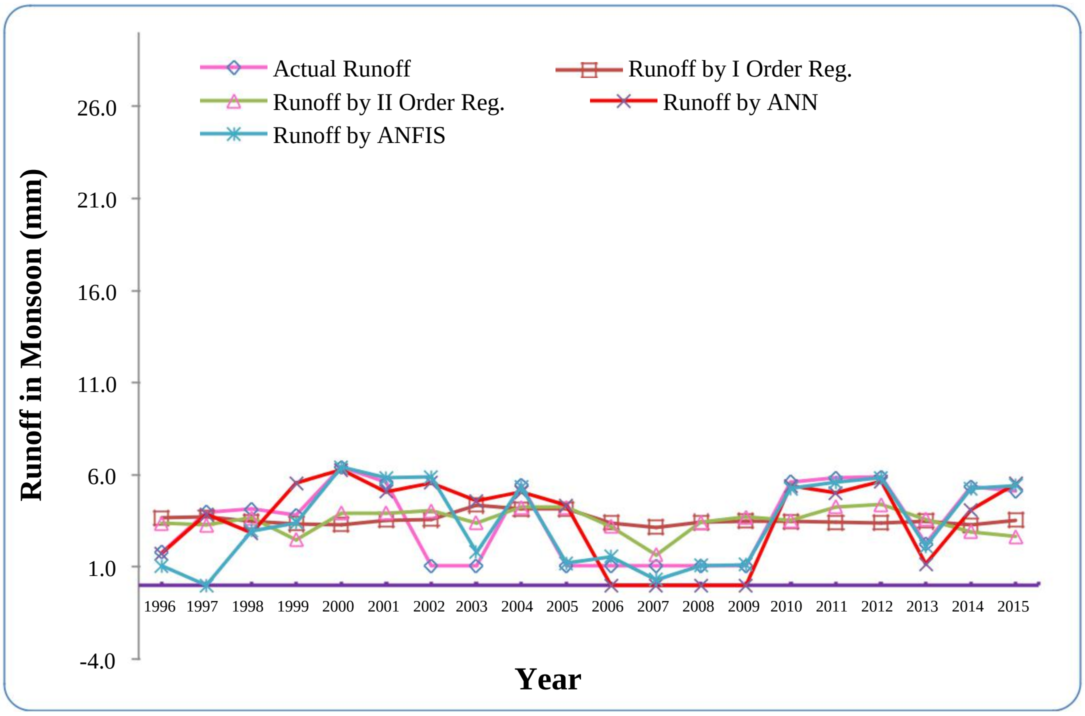


Fig. 5.41 D: Comparison of Actual and Predicted Runoff in Monsoon for Lassaria Dam Catchment

5.4.6 Mashi sub-basin

Table 5.15: Performance metrics and ranking sum in different models

S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
6	Mashi	Chhaparwara	July	I order	0.41	1.68	1.30	0.9	1.85	1.79	3
				II order	0.66	1.34	0.98	0.61	6.90	3.51	4
				ANN	1.00	0.01	0.05	0.89	1.27	0.88	1.5
				ANFIS	1.00	0.01	0.04	0.86	1.71	1.29	1.5
			August	I order	0.12	7.27	5.78	0.46	3.24	3.18	4
				II order	0.20	6.91	5.28	0.48	3.62	2.70	3
				ANN	1.00	0.01	0.15	0.87	1.49	2.72	1.5
				ANFIS	1.00	0.01	0.13	0.43	3.56	2.28	1.5
			September	I order	0.29	2.39	1.45	0.13	2.15	1.09	4
				II order	0.35	2.30	1.64	0.25	1.93	1.24	3
				ANN	1.00	0.08	0.03	0.90	1.33	0.64	1
				ANFIS	1.00	0.08	0.01	0.15	3.20	2.09	2
			Monsoon	I order	0.13	9.91	8.11	0.32	3.48	2.81	3
				II order	0.28	7.84	5.84	0.88	6.96	4.21	4
				ANN	1.00	0.01	0.13	0.93	4.02	3.04	1
				ANFIS	1.00	0.05	0.02	0.88	4.48	3.33	2

Table 5.16: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
6	Mashi	Chhaparwara	July	Average	1.83	2.28	2.64	1.93	2.05
				St. Dev.	2.14	1.28	4.07	1.67	2.39
				Skewness	1.27	0.67	3.30	1.00	0.97
			August	Average	5.13	5.92	5.68	5.58	5.08
				St. Dev.	7.25	2.73	3.86	6.84	7.19
				Skewness	1.66	0.70	-0.28	2.04	2.27
			September	Average	1.62	1.40	1.47	2.24	1.91
				St. Dev.	2.75	1.43	1.57	2.88	2.50
				Skewness	2.16	1.12	0.27	1.30	1.34
			Monsoon	Average	8.58	9.28	7.92	9.41	8.86
				St. Dev.	9.87	3.76	4.89	10.18	8.80
				Skewness	1.65	1.30	-0.38	1.31	1.55

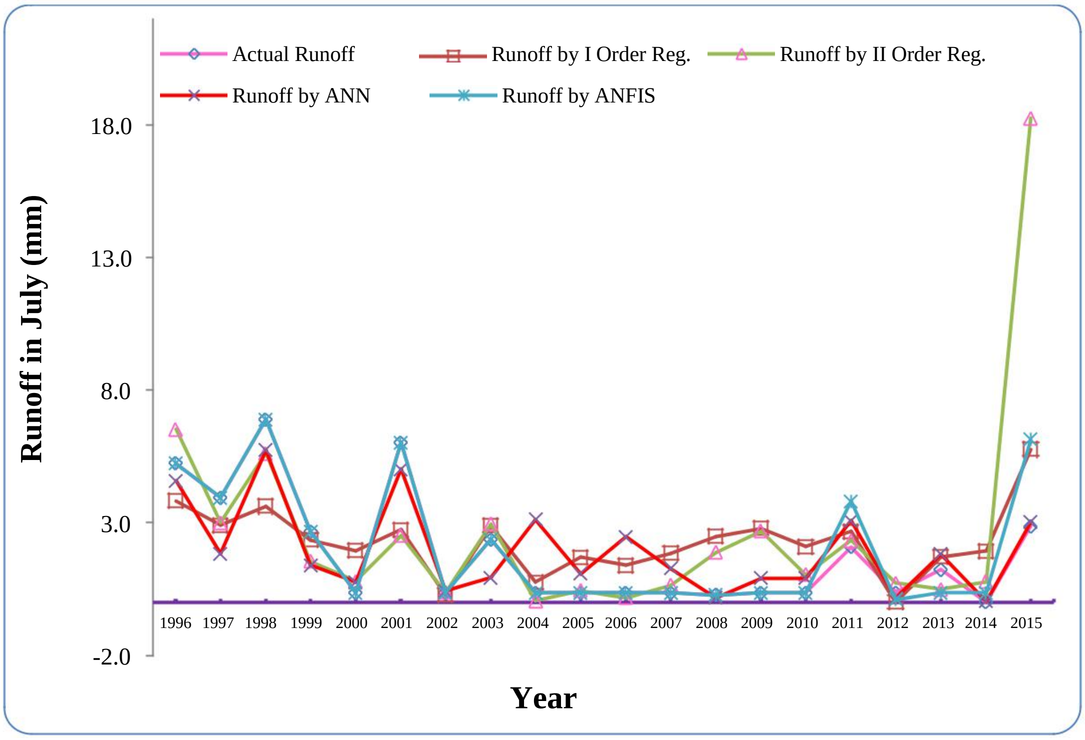


Fig. 5.42 A: Comparison of Actual and Predicted Runoff in July for Chhaparwara Dam Catchment]

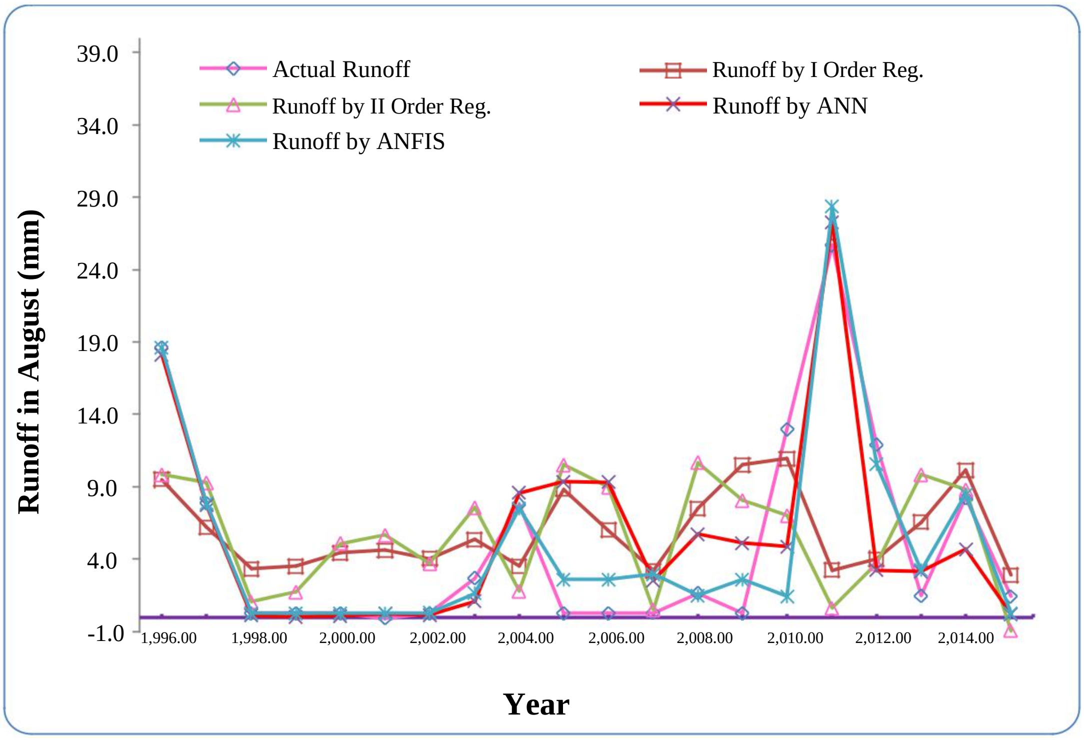


Fig. 5.42 B: Comparison of Actual and Predicted Runoff in August for Chhaparwara Dam Catchment

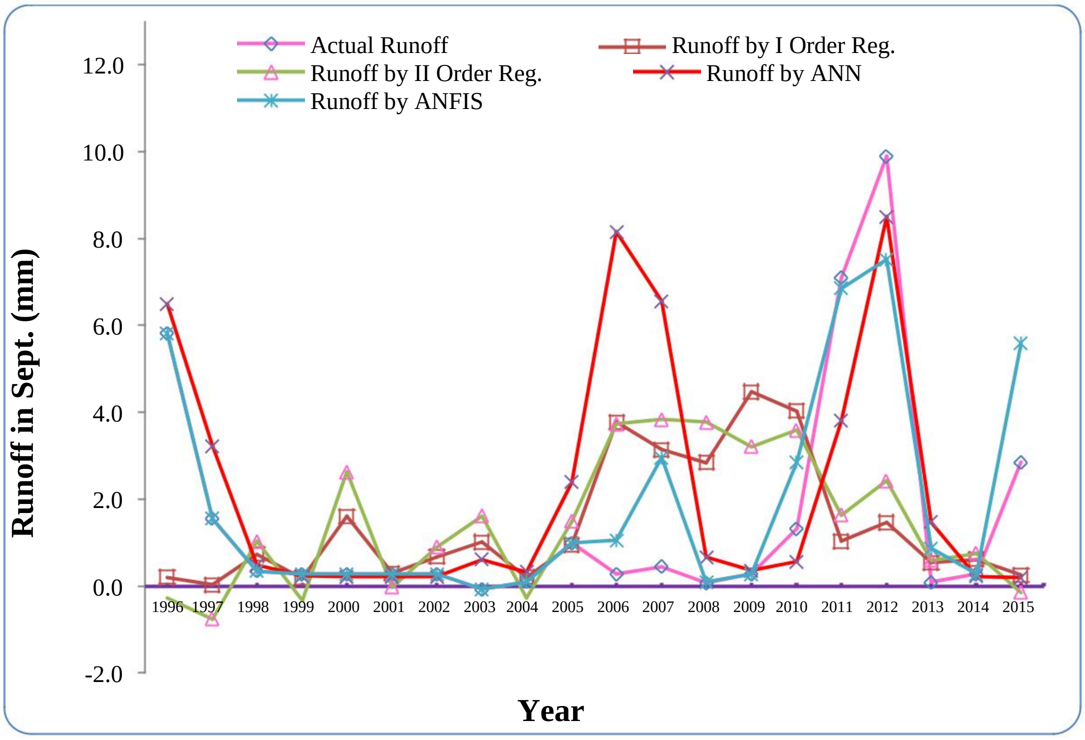


Fig. 5.42 C: Comparison of Actual and Predicted Runoff in Sept. for Chhaparwara Dam Catchment

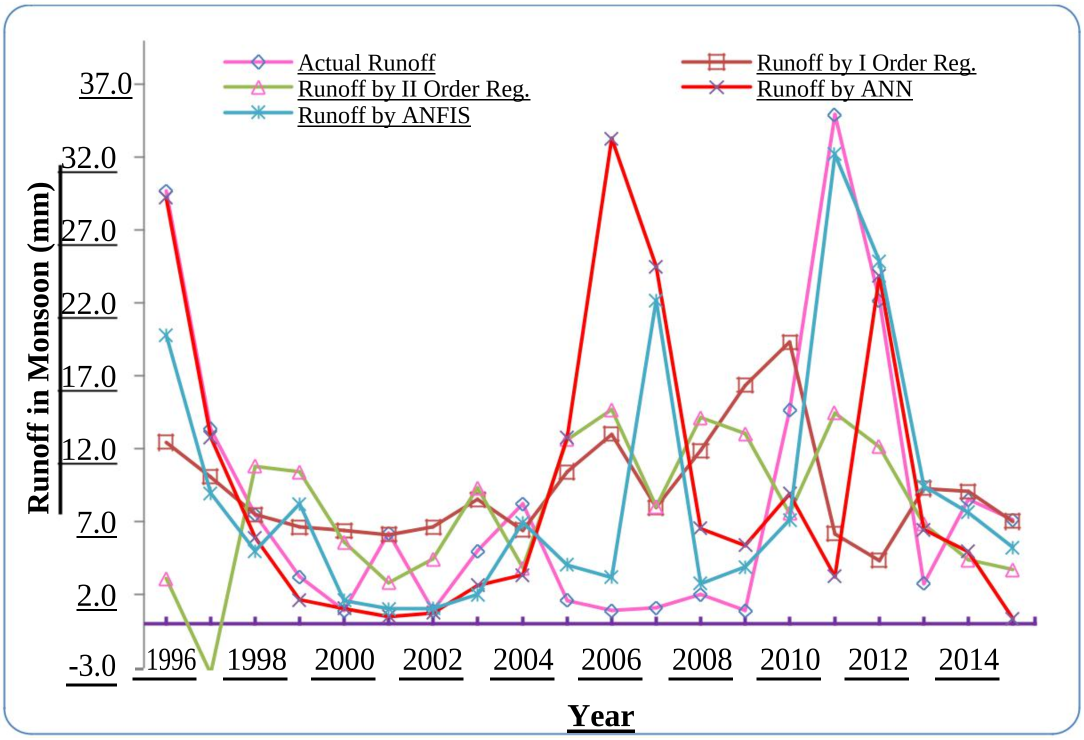


Fig. 5.42 D: Comparison of Actual and Predicted Runoff in Mons.for Chhaparwara Dam Catchment

5.4.7 Morel sub-basin

Table 5.17: Performance metrics and ranking sum in different models

S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
7	Morel	Morel	July	I order	0.18	3.71	2.41	0.68	1.93	1.75	2
				II order	0.23	3.58	2.55	0.62	2.67	2.18	4
				ANN	1.00	0.09	0.01	0.52	4.02	3.50	3
				ANFIS	1.00	0.08	0.01	1.00	0.09	0.08	1
			August	I order	0.64	1.87	1.51	0.24	5.76	4.83	4
				II order	0.6	2.97	2.02	0.63	3.08	2.70	3
				ANN	1.00	0.04	0.01	0.93	3.46	1.55	2
				ANFIS	1.00	0.09	0.04	1.00	0.07	0.03	1
			September	I order	0.01	3.59	2.44	0.69	1.13	1.08	3.5
				II order	0.36	2.84	2.09	0.53	1.79	1.65	3.5
				ANN	1.00	0.09	0.01	0.41	0.36	0.87	2
				ANFIS	1.00	0.16	0.07	0.83	0.09	0.06	1
			Monsoon	I order	0.21	4.67	3.48	0.17	10.34	8.61	4
				II order	0.43	3.95	3.14	0.20	9.00	7.63	3
				ANN	1.00	0.09	0.07	0.52	0.20	2.42	2
				ANFIS	1.00	0.08	0.06	1.00	0.09	0.08	1

Table 5.18: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
7	Morel	Morel	July	Average	2.88	2.47	2.34	3.33	2.5
				St. Dev.	3.92	1.87	2.59	4.63	2.06
				Skewness	2.26	0.38	-1.44	1.76	0.73
			August	Average	3.69	3.94	4.37	3.30	3.55
				St. Dev.	4.52	4.37	3.47	4.70	4.40
				Skewness	1.88	1.71	0.17	1.74	2.02
			September	Average	1.63	1.86	1.65	1.59	1.62
				St. Dev.	3.27	0.39	2.25	3.36	3.28
				Skewness	2.70	1.99	0.16	2.44	2.7
			Monsoon	Average	8.21	6.25	6.43	8.26	8.41
				St. Dev.	6.85	2.20	3.31	6.92	6.65
				Skewness	1.06	2.31	-0.19	1.01	1.15

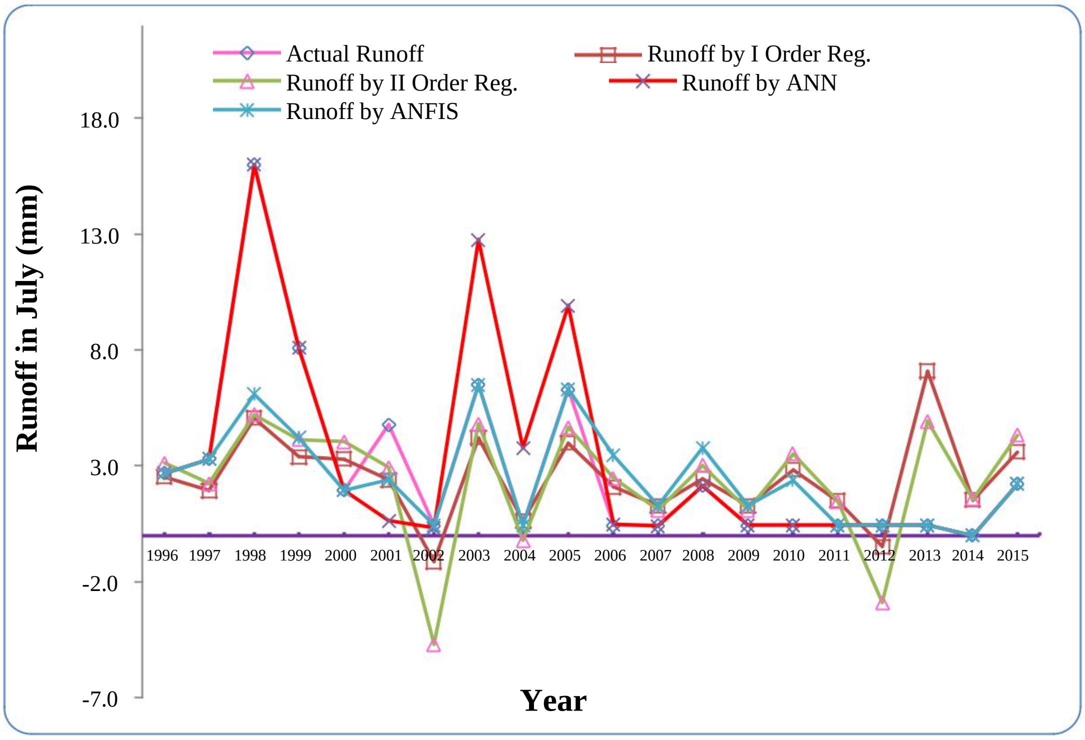


Fig. 5.43 A: Comparison of Actual and Predicted Runoff in July for Morel Dam Catchment

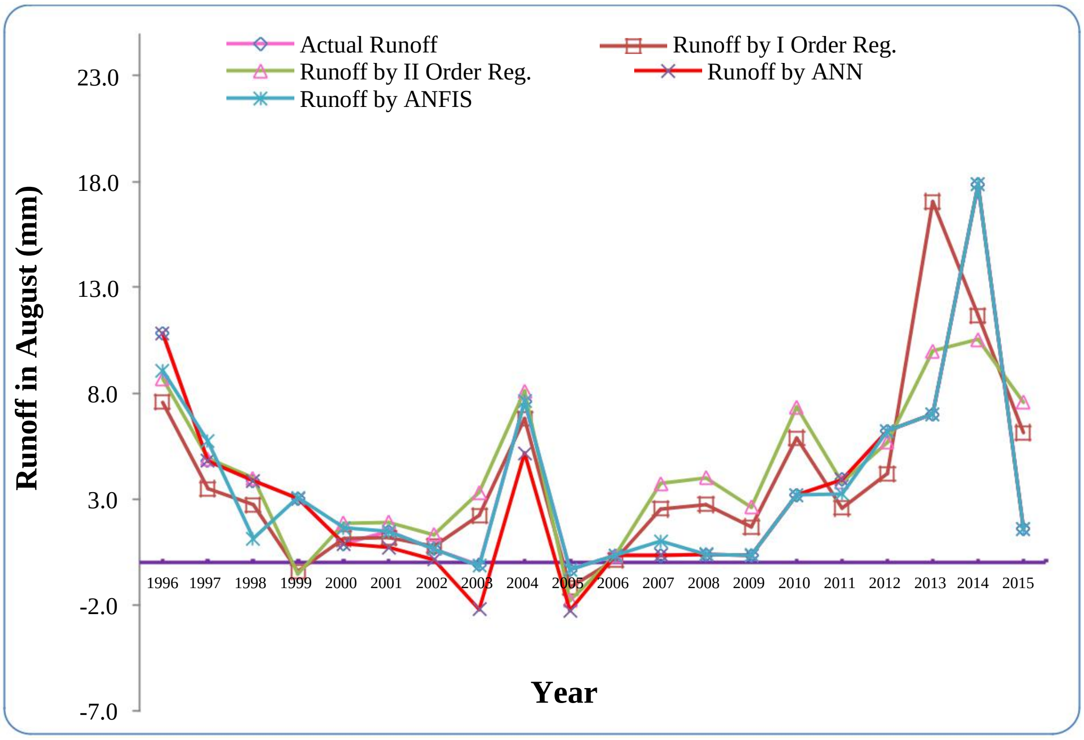


Fig. 5.43 B: Comparison of Actual and Predicted Runoff in August for Morel Dam Catchment

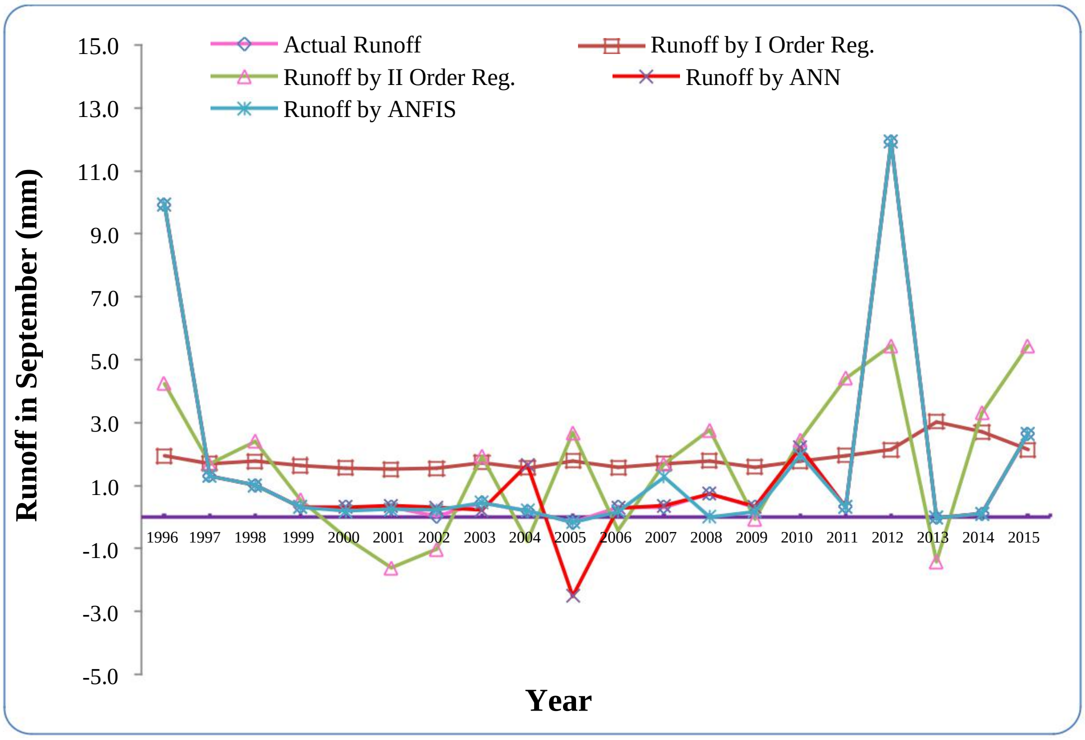


Fig. 5.43 C: Comparison of Actual and Predicted Runoff in Sept. for Morel Dam Catchment

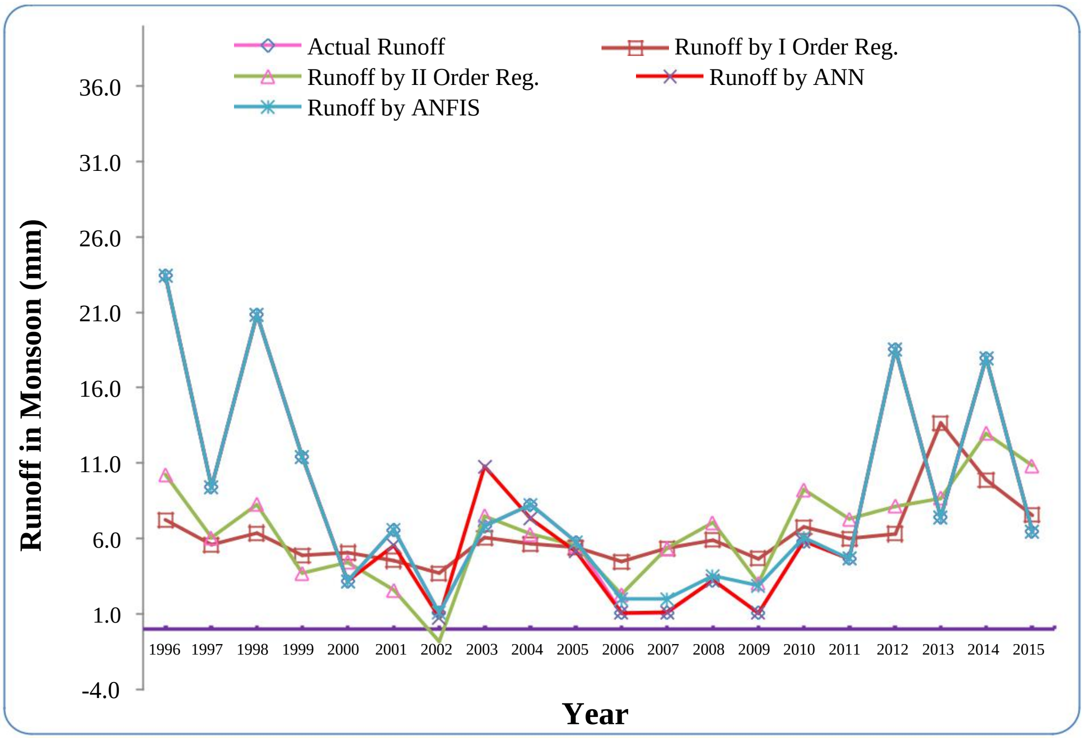


Fig. 5.43 D: Comparison of Actual and Predicted Runoff in Monsoon for Morel Dam Catchment

5.4.8 Kalisil sub-basin

Table 5.19: Performance metrics and ranking sum in different models

S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
8	Kalisil	Kalisil	July	I order	0.88	13.3	11.53	0.82	19.23	14.1	3
				II order	0.87	12.45	9.92	0.93	27.34	21.13	4
				ANN	0.98	0.02	3.04	0.96	23.22	14.53	2
				ANFIS	1.00	0.06	0.05	1.00	0.09	0.01	1
			August	I order	0.26	23.1	17.65	0.17	28.63	15.22	4
				II order	0.47	19.55	13.89	0.16	25.06	18.73	3
				ANN	0.98	0.04	3.46	0.76	13.89	13.99	2
				ANFIS	1.00	0.01	0.00	1.00	0.01	0.01	1
			September	I order	0.25	6.34	3.97	0.1	31.65	26.69	4
				II order	0.09	11.09	7.65	0.31	5.47	5.29	3
				ANN	0.99	0.03	1.02	0.14	3.22	3.14	2
				ANFIS	1.00	0.47	0.26	0.86	0.39	0.25	1
			Monsoon	I order	0.66	21.92	18.37	0.14	143.3	300	4
				II order	0.66	21.89	18.43	0.09	106.24	90.4	3
				ANN	1.00	0.06	1.7	0.97	12.56	18.99	2
				ANFIS	1.00	0.03	0.01	1.00	0.01	0.09	1

Table 5.20: Statistical parameters for the actual and predicted runoffs

Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
8	Kalisil	Kalisil	July	Average	38.91	36.92	44.12	38.51	38.42
				St. Dev.	37.09	32.38	38.7	37.21	36.46
				Skewness	0.53	0.45	1.08	0.51	0.52
			August	Average	24.14	20.6	21.36	26.92	24.93
				St. Dev.	28.88	12.85	18.23	28.68	28.47
				Skewness	1.4	1.58	-0.56	1.05	1.46
			September	Average	5.02	8.04	6.34	4.71	4.82
				St. Dev.	10.61	13.17	3.16	8.73	10.27
				Skewness	2.8	2.55	-1.00	1.38	2.74
			Monsoon	Average	68.07	93.08	87.2	68.42	67.93
				St. Dev.	40.97	77.22	57.54	39.75	40.66
				Skewness	-0.12	2.78	1.81	-0.25	-0.1

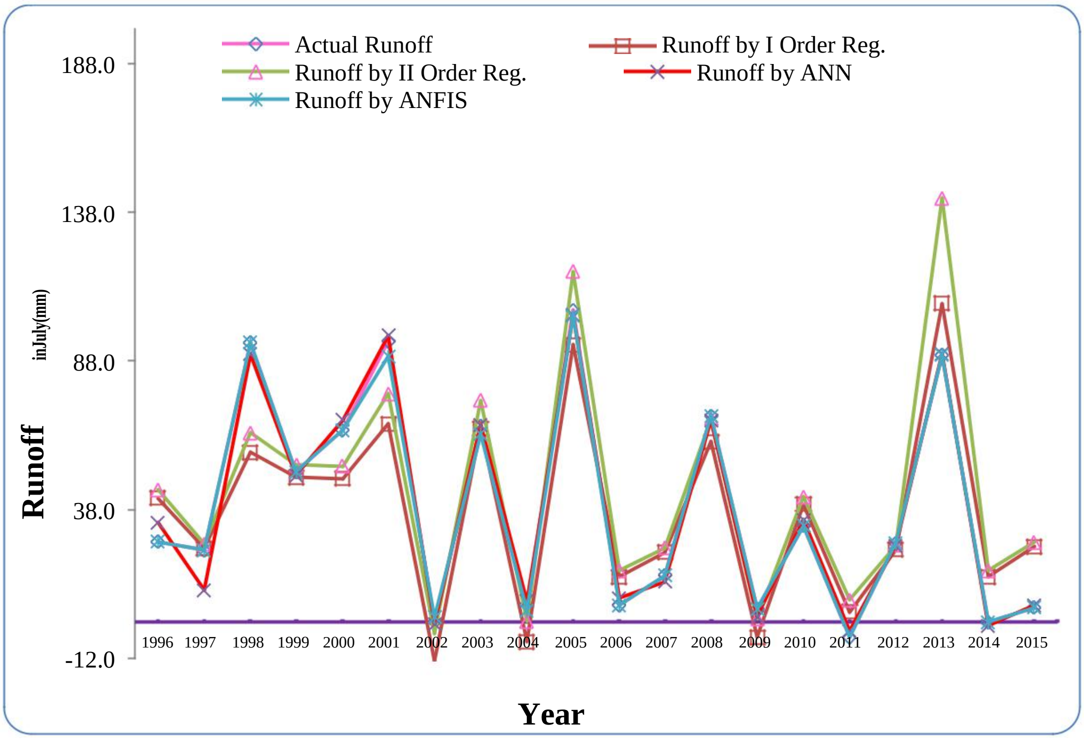


Fig. 5.44 A: Comparison of Actual and Predicted Runoff in July for Kalisil Dam Catchment

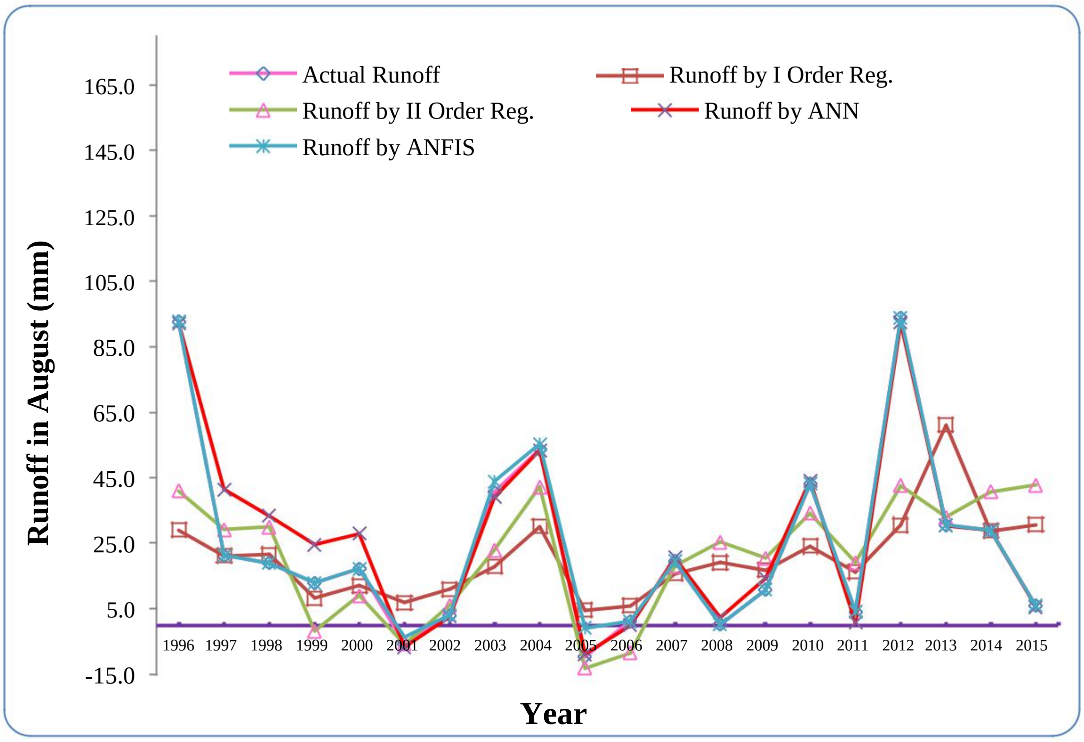


Fig. 5.44 B: Comparison of Actual and Predicted Runoff in August for Kalisil Dam Catchment

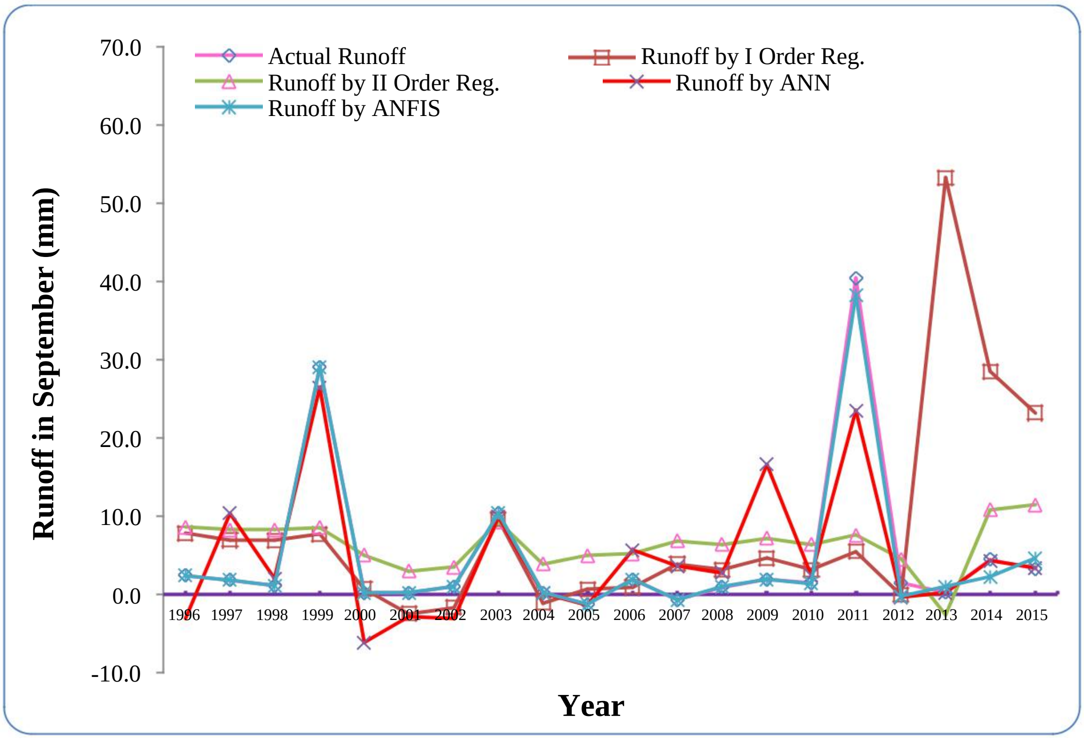


Fig. 5.44 C: Comparison of Actual and Predicted Runoff in Sept. for Kalisil Dam Catchment

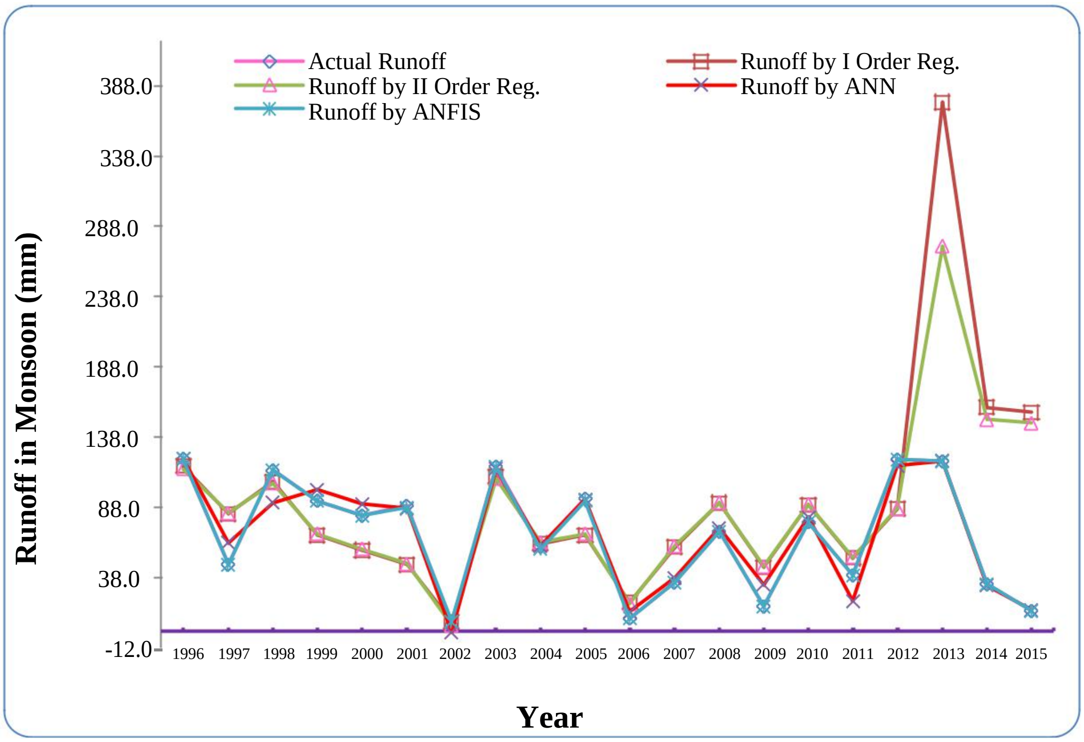


Fig. 5.44 D: Comparison of Actual and Predicted Runoff in Monsoon for Kalisil Dam Catchment

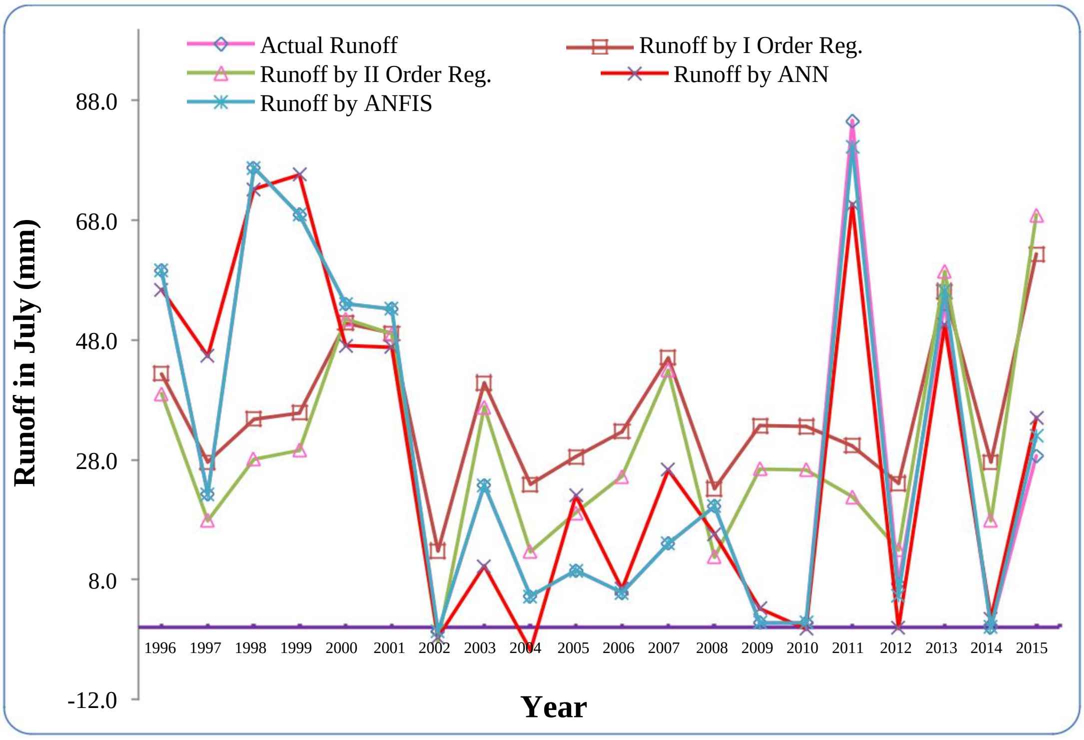
5.4.9 Banas II sub-basin

Table 5.21: Performance metrics and ranking sum in different models

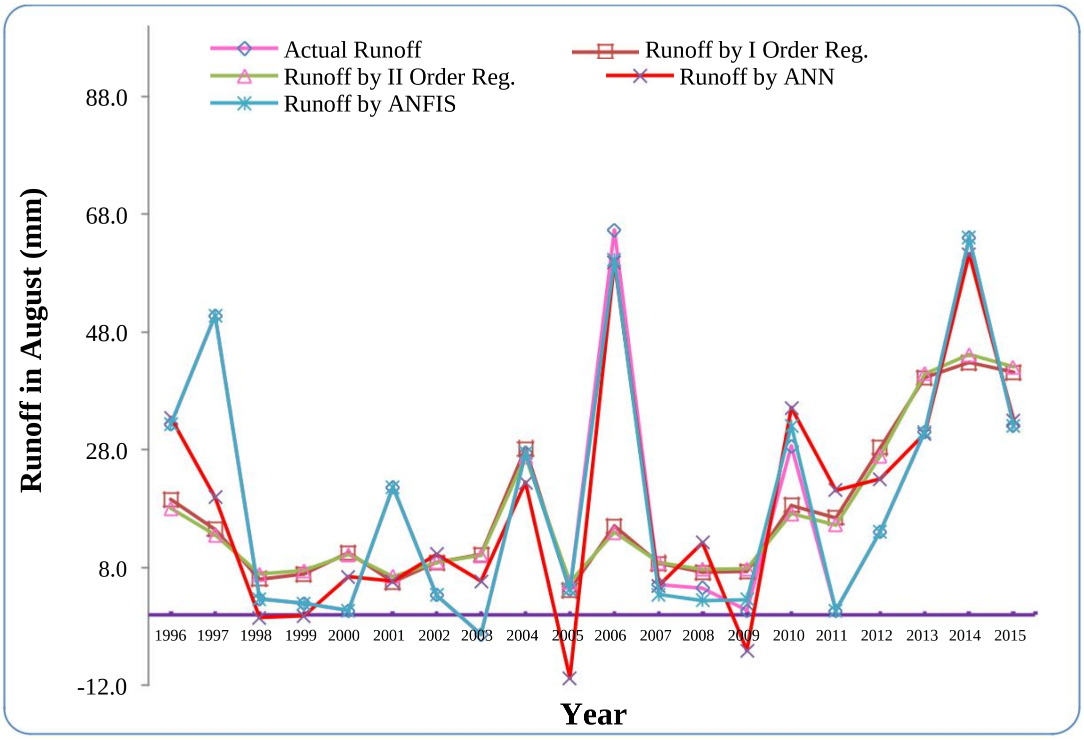
S. No.	Name of sub-basin	Name of selected dam	Time Period	Type of model	Training			Validation			Final Rank
					R^2	RMSE	MAE	R^2	RMSE	MAE	
9	Banas II	Moti Sagar	July	I order	0.22	25.16	20.48	0.31	27.74	25.3	3
				II order	0.30	22.04	17.3	0.07	34.47	26.4	4
				ANN	0.98	0.03	2.42	0.65	29.81	18.93	2
				ANFIS	1.00	0.01	0.05	1.00	0.08	0.07	1
			August	I order	0.46	14.51	11.52	0.18	23.23	14.64	3.5
				II order	0.46	14.51	11.52	0.18	23.23	14.64	3.5
				ANN	0.92	0.07	4.40	0.07	13.32	18.93	2
				ANFIS	1.00	0.03	0.01	1.00	0.09	0.09	1
			September	I order	0.09	1.81	1.17	0.08	8.76	6.19	4
				II order	0.15	4.47	3.24	0.13	3.21	2.29	3
				ANN	0.97	0.15	0.51	0.08	4.23	2.28	2
				ANFIS	1.00	0.17	0.08	0.95	0.07	0.05	1
			Monsoon	I order	0.11	26.68	24.02	0.2	31.91	29.29	4
				II order	0.17	25.81	23.52	0.22	31.85	28.86	3
				ANN	1.00	0.03	1.77	0.73	20.71	13.27	2
				ANFIS	1.00	0.01	0.03	1.00	0.08	0.09	1

Table 5.22: Statistical parameters for the actual and predicted runoffs

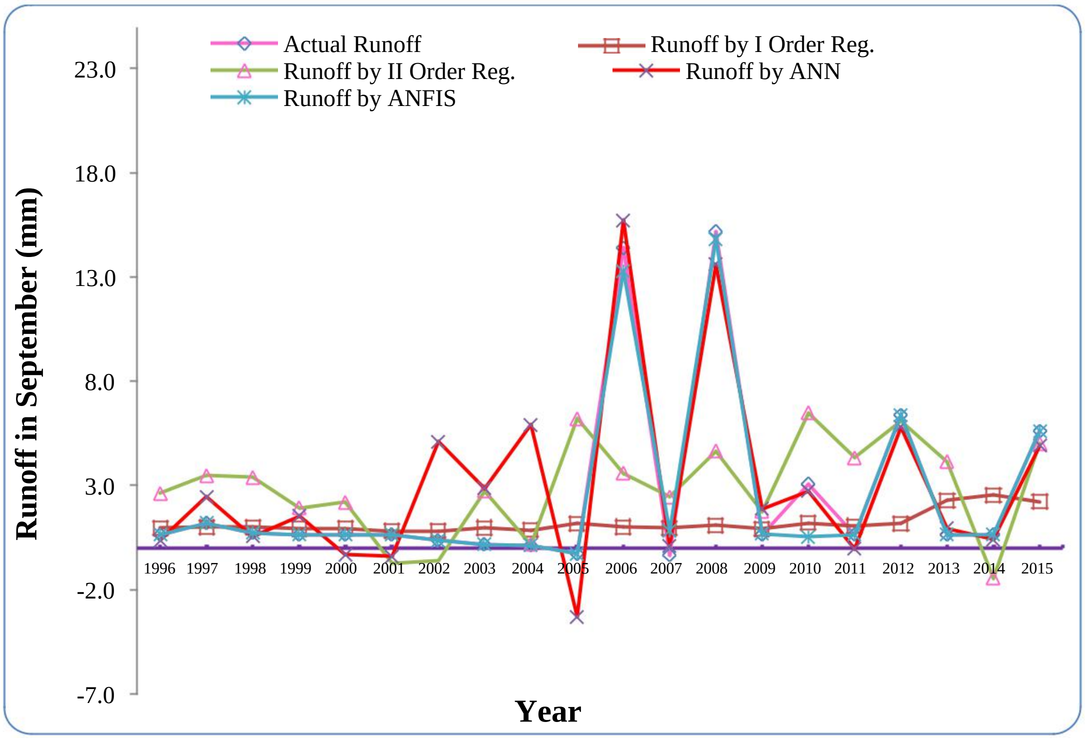
Sub-basin No.	Name of sub-basin	Name of selected dam	Time Period	Statistical Parameter	Runoff (mm)				
					Actual	First Order Regression Model	Second Order Regression Model	ANN Model	ANFIS Model
9	Banas II	Moti Sagar	July	Average	29.44	35.77	29.77	29.01	29.41
				St. Dev.	28.44	12.32	17.77	27.39	28.21
				Skewness	0.65	0.47	0.55	0.38	0.58
			August	Average	19.37	17.00	16.93	18.37	19.19
				St. Dev.	21.53	12.55	12.55	19.71	21.15
				Skewness	0.99	1.09	1.30	0.78	0.89
			September	Average	2.58	1.19	2.92	3.04	2.44
				St. Dev.	4.54	0.51	2.31	4.62	4.32
				Skewness	2.24	1.98	-0.33	1.67	2.27
			Monsoon	Average	51.4	55.44	55.68	49.61	50.41
				St. Dev.	30.42	8.77	11.18	28.91	29.23
				Skewness	-0.26	1.77	-0.41	-0.08	-0.29



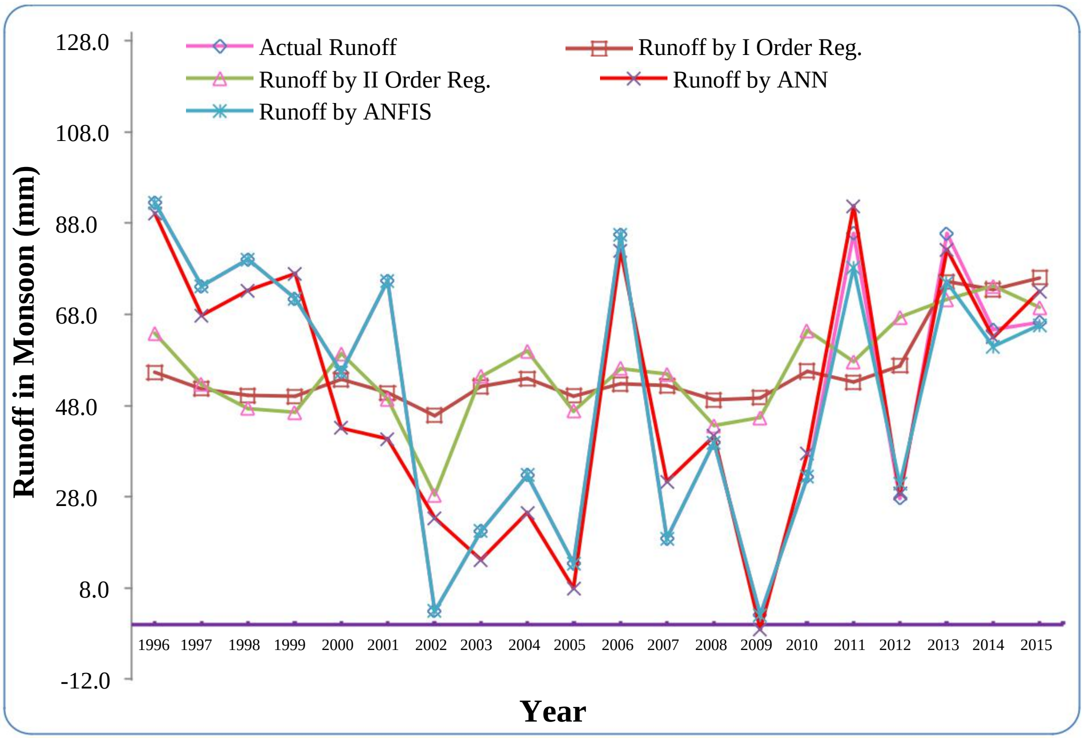
5.45 A: Comparison of Actual and Predicted Runoff in July for Moti Sagar Dam Catchment



5.45 B: Comparison of Actual and Predicted Runoff in August for Moti Sagar Dam Catchment



5.45 C: Comparison of Actual and Predicted Runoff in Sept. for Moti Sagar Dam Catchment



5.45 D: Comparison of Actual and Predicted Runoff in Monsoon for Moti Sagar Dam Catchment

5.5 Discussions

In this study, the entire catchment was divided in 9 sub-basins and each sub-basin is assumed to behave as a small unit having unique micro-climate. The dam catchment selected for analysis is situated in the particular sub-basin, the general physical and hydrological characteristics of the dam catchment resembles the sub-basin, so the developed models can be generalized for the individual sub-basin and may be further used for any hydrological purpose.

The developed first and second order rainfall-runoff regression equations which are tabulated in **Table 5.1 and Table 5.2** for the particular time period or the ANN and ANFIS models can be used for predicting the monthly or seasonal runoff at a particular site, in Banas river basin, if the location of the catchment and the rainfall is known.

The developed model should have maximum value of R^2 near to 1 with minimum value of RMSE and MAE near to 0 for getting the better model. In some models it was found that the model has good R^2 value but does not have the low values of RMSE and MAE. It indicates that there is a discrepancy in the actual and the predicted values of runoff, so the model is not perfect. Thus a single performance metric cannot provide an unbiased model prediction. For giving equal importance to the training as well as the validation performance parameters, ranking technique was adopted. The model which was having best final ranked value would be the best model.

Observing and comparing the results of performing metrics in different time periods and final ranks obtained by the developed model, using different techniques in the selected different dam catchments are shown in **Tables- 5.5, 5.7, 5.9, 5.11, 5.13, 5.15, 5.17, 5.19 and 5.21** it can be interpreted that R^2 for training and validation increases from first order regression models, second order regression models, ANN models, ANFIS models while the RMSE and MAE decreases in the same order. In case of ANN and ANFIS the R^2 value is nearly unity but not one; while RMSE and MAE are close to zero in most of the catchments. The standard deviation for R^2, RMSE and MAE is minimum for the model for which the final rank is minimum.

From the results shown in **Tables 5.5, 5.7, 5.9, 5.11, 5.13, 5.15, 5.17, 5.19 and 5.21**, it can be concluded that compared to the first order regression model, a significant improvement in the performance of the second order regression model is noticed. This indicates that, as the order of the regression model or its complexity is increased, there is an improvement in the prediction accuracy during training and validation in 19 out of 36 cases. Comparing the performance metrics and final ranks obtained by the developed model which are shown in **Tables- 5.5, 5.7, 5.9, 5.11, 5.13, 5.15, 5.17,5.19 and 5.21,** it can also be interpreted that the ANN and ANFIS models are far superior to the regression models. The results thus demonstrate the effectiveness and applicability of the soft computing techniques namely ANN and ANFIS for modeling highly complex rainfall-runoff phenomenon.

R^2 represents the degree of determination between the effective rainfall and effective runoff. As per the hypothesis a value of R and R^2 is not 0, so there is association between rainfall and runoff in the catchment. Seeing the value of computed R, it had been found out that all the developed linear models in the different dam catchments are fit at 80% confidence level while the second order polynomial model fit at 90% confidence level in most of the sub-basins. The soft computing models namely ANN and ANFIS models are fit at 99 % confidence level in most of the sub-basins.

It was also found that, for five sub-basins namely Banas I, Dai, Morel, Kalisil and Banas II, the ANFIS was giving least standard deviation in the performance metrics which infers more consistency and give good prediction accuracy. Whereas for the remaining four sub-basins namely, Berach, Kothari, Khari and Mashi, the ANN model provided more consistency and good prediction. The minimum final ranks for ANN and ANFIS were also showing the same prediction.

As seen in the comparison plots between the actual and the runoff predicted and shown in **Figures- 5.37 to 5.45** by the different developed models, the value of runoff predicted by ANN and ANFIS are very closer to the actual runoff as compared to the first and second order regression models for most of the time periods. For checking the consistency of the predicted runoff, the value of the statistical parameters i.e., mean, standard deviation and skewness were also computed and shown in **Tables- 5.6, 5.8, 5.10, 5.12, 5.14, 5.16, 5.18, 5.20, and 5.22.** It was found that, the parameters computed, for the runoffs predicted by ANFIS and ANN is closer to the parameters of the actual runoff which also shows their more consistency and gives good prediction accuracy.

It was, also found that the models developed using the soft computing technique viz., ANN and ANFIS, give better performance parameters and closer runoff prediction than the conventional regression analysis, so the models using soft computing techniques can be better substitutes of the conventional rainfall runoff models, in all the sub-basins of the study area.

5.6 Decision support tool to estimate runoff using rainfall and different modeling techniques

The results obtained from the conventional regression analysis for first and second order polynomial, the computed weights and biases for ANN and the radius of cluster for ANFIS were used in the preparation of a decision support tool. A typical decision support tool prepared for Chhaparwara catchment situated in Mashi sub-basin to estimate runoff using rainfall is shown in the **Figure- 5.46**. The tool is developed using the functionalities of MS Excel and MATLAB software. MS Excel is used as front end software, and MATLAB is used as back-hand software. The developed decision support tool requires only the occurred rainfall in the area and the corresponding runoff in mm can directly be computed selecting the particular model. A graphical user interface (GUI) for Mashi Sub-basin has also been prepared for predicting runoff using rainfall data and selecting model as shown in **Figure- 5.46.** This GUI can be easily accessed by any computer literate person.

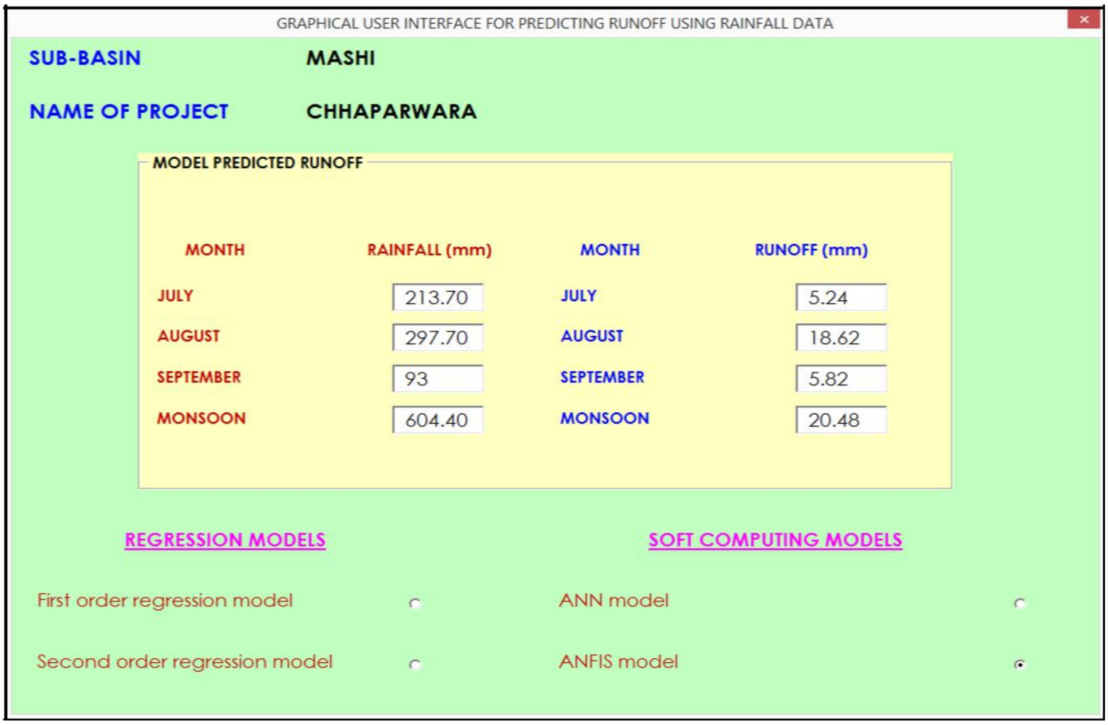


Fig.: 5.46: Decision support tool to estimate runoff using rainfall

5.7 Practical applicability

Rainfall-runoff empirical models are important and necessary tools for water resources management. Demands from society on the predictive capabilities of such models are becoming higher and higher, leading to the need of enhancing existing models. The approximation inherent in today’s models suggests that it should be possible to do better.

The developed polynomial regression equations or the soft computing models for the particular month or the monsoon period, in different sub-basins can be used for estimating or predicting the runoff or volume of water coming at a particular site, situated in the particular sub-basin, which is mainly needed at the project planning and preparation. Developed models are also helpful to extend the river flow data with the help of rainfall data and to study the influences of variability of flow regime. These may also be useful for the determination of low flow duration curves and reservoir design with its operations.

5.8 Summary

Finally it is summarized that the soft computing models namely ANN and ANFIS rainfall-runoff empirical models are providing a better fit than the conventional regression first and second order empirical models in all the sub-basins of the Banas river basin. Soft computing models yielded less skewness and a smaller range of errors than the regression models.

Summary and Conclusions

6.1 Introduction

The results and discussions on the development of rainfall-runoff empirical models, has been included in the previous chapter. The main aim of this research was to develop the rainfall runoff empirical models and then prepare a decision support system in the Banas river basin that can be directly employed for yield computation at different locations in the basin. The conclusions and further recommendations regarding this work have been presented in this chapter.

6.2 Research Summary

The empirical relation between the rainfall occurred and the corresponding runoff received at the outlet of a catchment is very much required for the preparation of new developmental project proposals for regulation and efficient management of water resources in the basin. The transformation of occurred rainfall into runoff within a catchment is a complex natural phenomenon that passes through various inter-related processes and influenced by many local topographic, geographic, geologic, and sociologic factors.

The rainfall runoff models can be divided into two broad groups namely, conceptual and empirical models. Empirical models are easy to apply and more economical when compared to conceptual models. Empirical models can be developed using the conventional regression and soft computing techniques. Due to complexity of affecting factors, underlying the rainfall-runoff interactions, soft computing models outperform the regression models.

The study area was divided in 9 sub-basins for getting the influence of localised areal factors and one dam from each sub-basin was selected for rainfall-runoff analysis and model development. Thiessen Polygon weighting technique was used for computing the total effective rainfall over the dam catchment. The corresponding total effective runoff received from the dam catchment was computed with the help of dam inflow data including the evaporation from the catchment in that period.

Four-fold hold out technique was applied on the available 20 years data for giving equal opportunity to each data for the participation in training as well as in the validation process of the modeling. Three performance metrics namely, coefficient of determination, root mean square error, mean absolute error were used for checking the training as well as validation performance of the developed models. Simple ranking technique was applied for providing equal importance to each training and validation performance metrics and the best model was selected based on minimum value of final ranks obtained by the various models.

Using conventional regression and soft computing techniques four types of rainfall–runoff empirical models namely first order polynomial regression equation model, second order polynomial regression equation model, ANN and ANFIS models were employed. These models were further compared with each other with the help of computed training and validation performance metrics along with a simple ranking technique. A decision support tool based on the developed models was prepared for predicting runoff from the easily available rainfall data only.

The results showed that as the order of the polynomial regression equation model is increased, there is an improvement in the runoff prediction accuracy during training as well as validation process of the modelling along with R^2 value. ANN and ANFIS rainfall-runoff empirical models are far superior to the first and second order polynomial regression models and these soft computing models might be the best substitute for the conventional regression models.

6.3 Conclusions

The following broad conclusions were derived from the study:-

1. The empirical models for establishing rainfall-runoff interactions are easy to formulate and provide stable relationship.
2. First order polynomial regression model shows unsatisfactory results. Second order polynomial regression model marginally fits better on the rainfall-runoff data than the first order polynomial regression model. They fail to account for the inherent nonlinearity present in the process of transformation of rainfall into runoff.

3. Conventional regression models are easy to formulate and can be used for predicting runoff. However in comparison to regression models, the soft computing technique based models using ANN and ANFIS techniques, presented in the study, give better prediction of runoff, based on the available rainfall data.
4. As the transformation of rainfall into runoff depends on many local factors, the model should be physically distributed for getting more actuality and accuracy. For smaller river system, it would be better to use a conceptual model while the physically distributed model is more suitable for medium and large sized catchments and the model developing methodology for this type of catchment has been followed in this study.
5. ANN methodology is inspired by the capabilities of human brain; providing a simple approach for dealing with real life phenomena. ANN and ANFIS models are superior in capturing the nonlinear dynamics and in the generalization of the natural phenomenon.
6. A single ANN model can be effectively used for modeling problems associated with multiple inputs and multiple outputs. In contrast the ANFIS model can deal with problems having multiple inputs but single output; this is the limitation of ANFIS.
7. The combination of ANN model with Fuzzy Logic enhances its performance and computational effort. Hence it can be concluded that the hybrid of two soft computing techniques as used in ANFIS gives better result than the simple soft computing technique i.e. ANN, Fuzzy Logic or Genetic Algorithm.
8. The methodology presented can be harnessed, to develop a decision support tool, for quickly computing runoff for a particular area, based on the readily available rainfall data. The tool can be used for planning of water resources projects, without performing cumbersome hydrological calculations required for runoff estimation.

…

6.4 Recommendations

Based on the study following recommendations are made:-

1. The combination of artificial neural networks and fuzzy logics, can significantly improve the prediction accuracy and speed of the model. The adaptive neuro fuzzy inference system (ANFIS), caninterpret accurate modeling for problems that are unstructured and highly complex in nature.
2. The ANN and ANFIS models have provided insight into the behaviour of the complex rainfall- runoff phenomenon. The methodology can also be used to analyze and compare the behaviour of the other natural complex phenomenon.
3. Model development is totally dependent on the available data. Remote sensing and GIS techniques can provide more data availability for water resources studies, in addition to the traditional ground observations of hydrometeorological variables.

6.5 Future scope of study

In the present study, the rainfall-runoff empirical models have been developed using the available rainfall and corresponding runoff data on monthly basis. If 10-daily data are available then these models can also be developed on 10-daily data basis for the better results and efficient management of the basin area.

Similar decision support system can also be developed for the other river basins in Rajasthan or anywhere using their relative rainfall runoff data.

Additional inputs i.e., temperature, relative humidity, transpiration and antecedent soil moisture may be included to increase accuracy. A combination of transformations of the data may also be tried, to better preserve the statistical structure of historical data that are non-linear inherent and thereby improve the performance of the model.

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Appendix-I

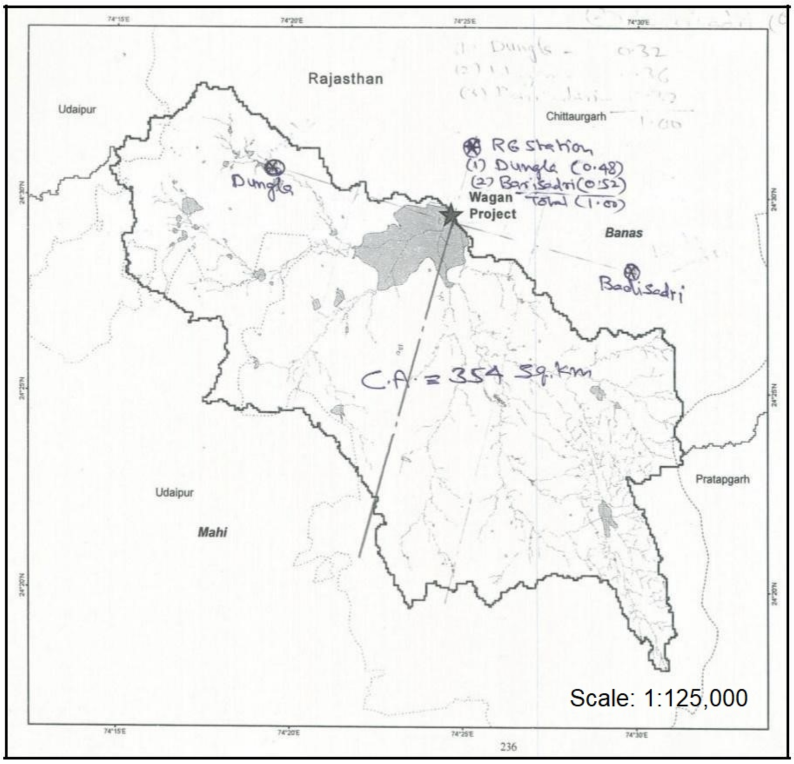


Fig. 7.1: Catchment area and Thiessen polygon for Wagon Dam in Berach Sub-Basin

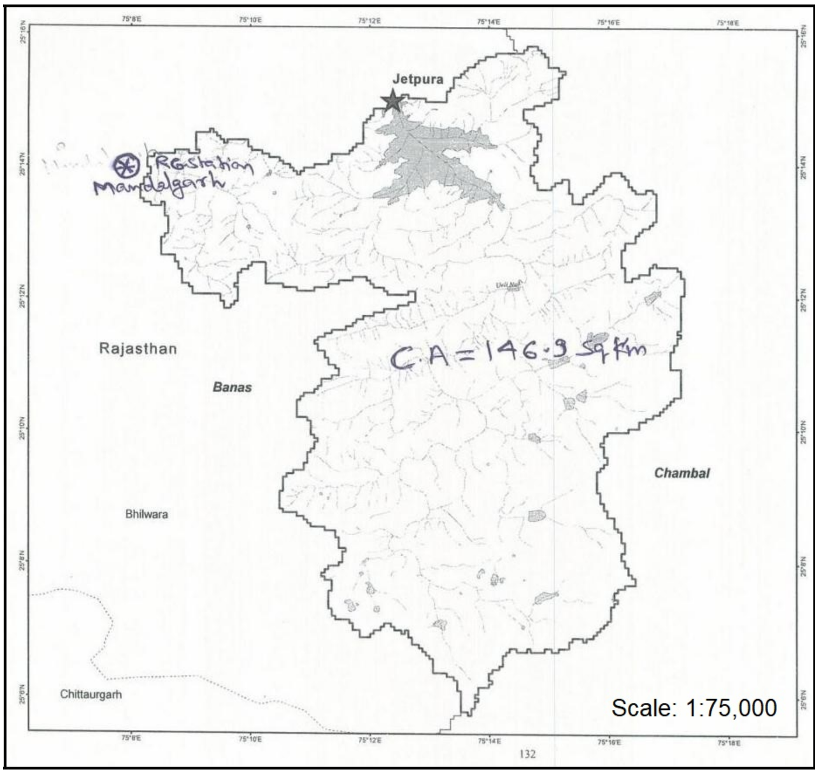


Fig. 7.2: Catchment area and Thiessen polygon for Jetpura Dam in Banas-I Sub-Basin

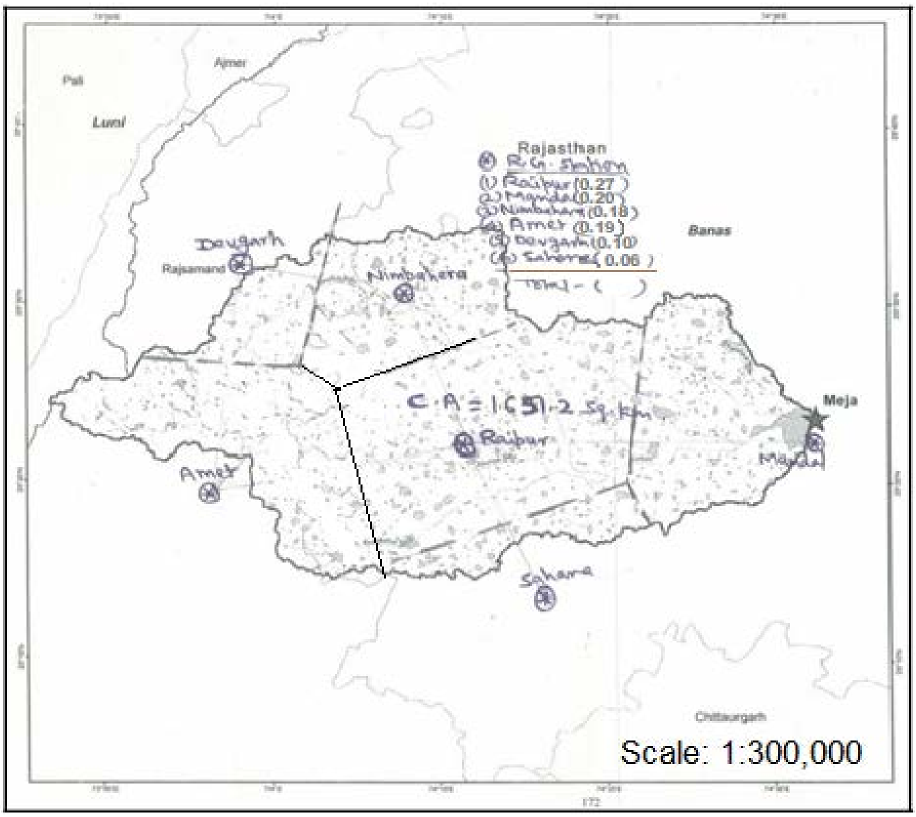


Fig. 7.3: Catchment area and Thiessen polygon for Meja Dam in Kothari Sub-Basin

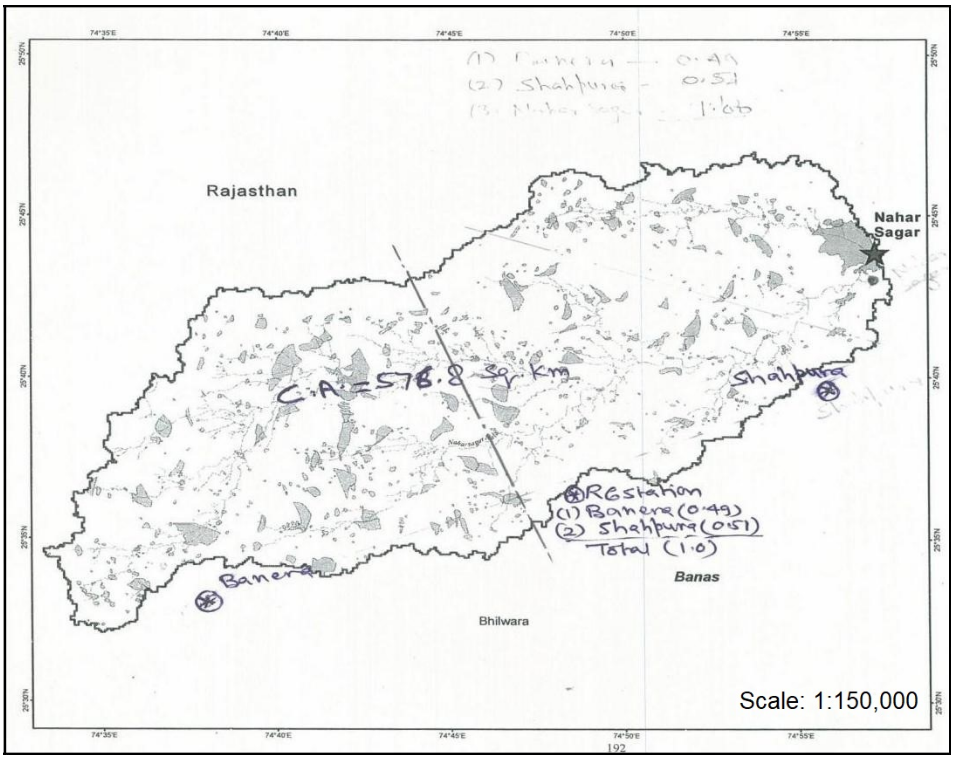


Fig. 7.4: Catchment area and Thiessen polygon for Nahar Sagar Dam in Khari Sub-Basin

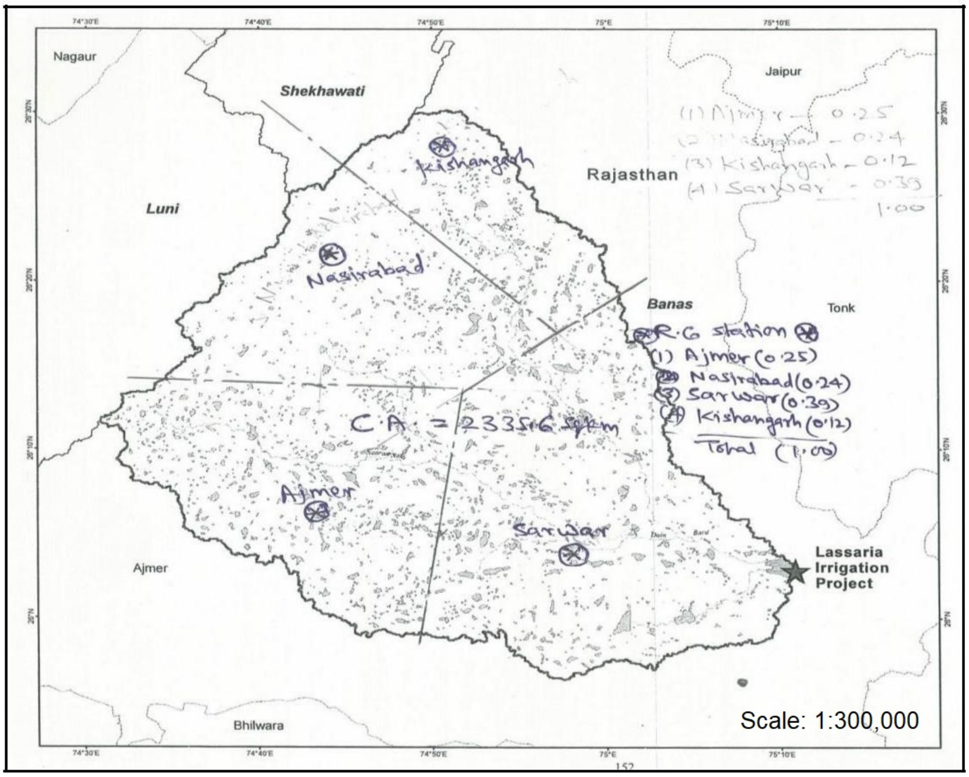


Fig. 7.5: Catchment area and Thiessen polygon for Lassaria Dam in Dai Sub-Basin

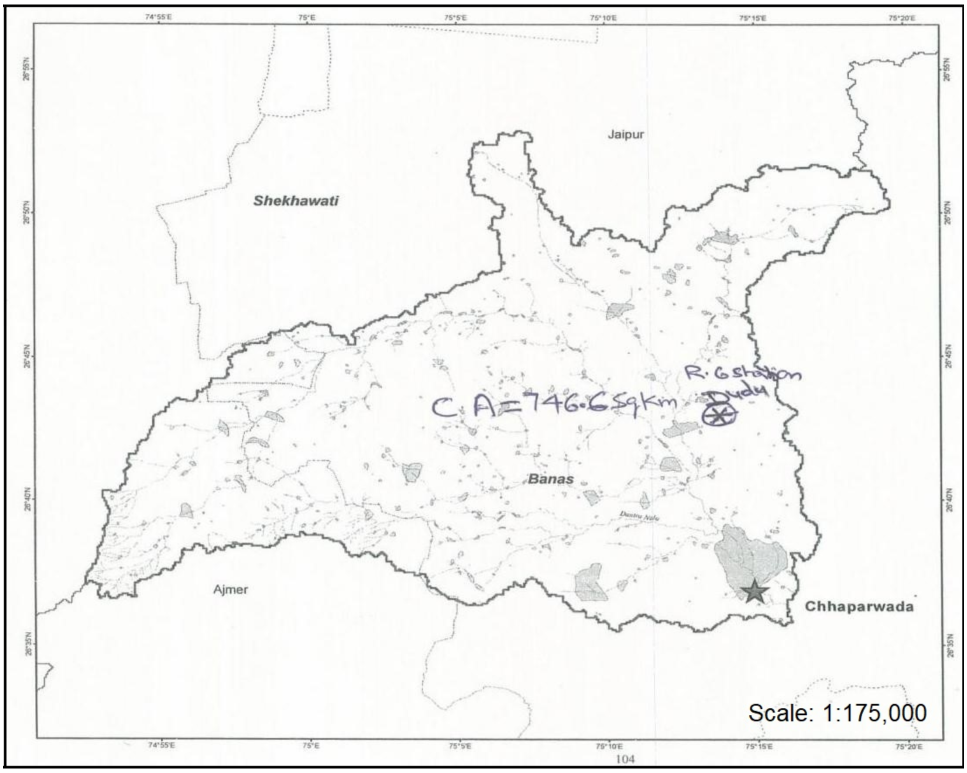


Fig. 7.6: Catchment area and Thiessen polygon for Chhaparwada Dam in Mashi Sub-Basin

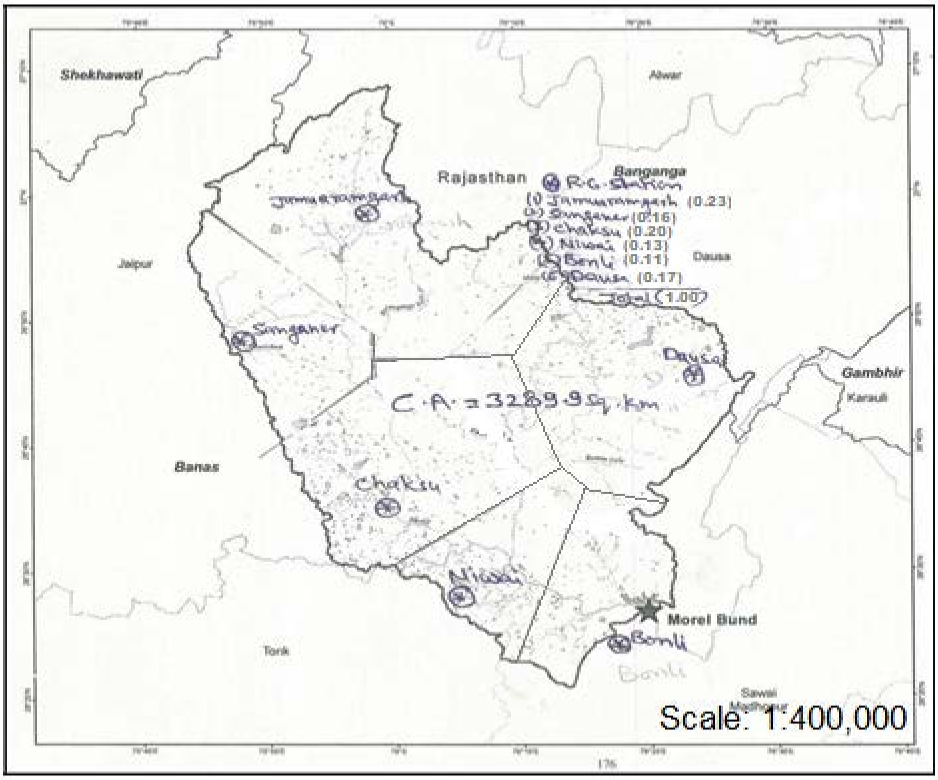


Fig. 7.7: Catchment area and Thiessen polygon for Morel Dam in Morel Sub-Basin

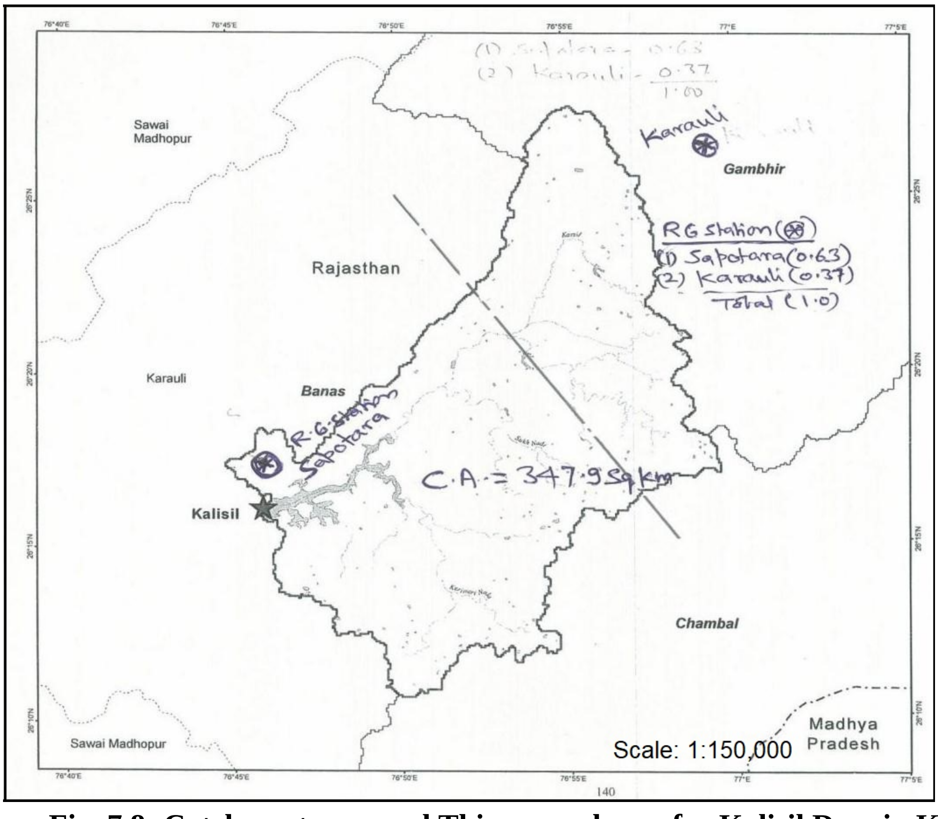


Fig. 7.8: Catchment area and Thiessen polygon for Kalisil Dam in Kalisil Sub-Basin

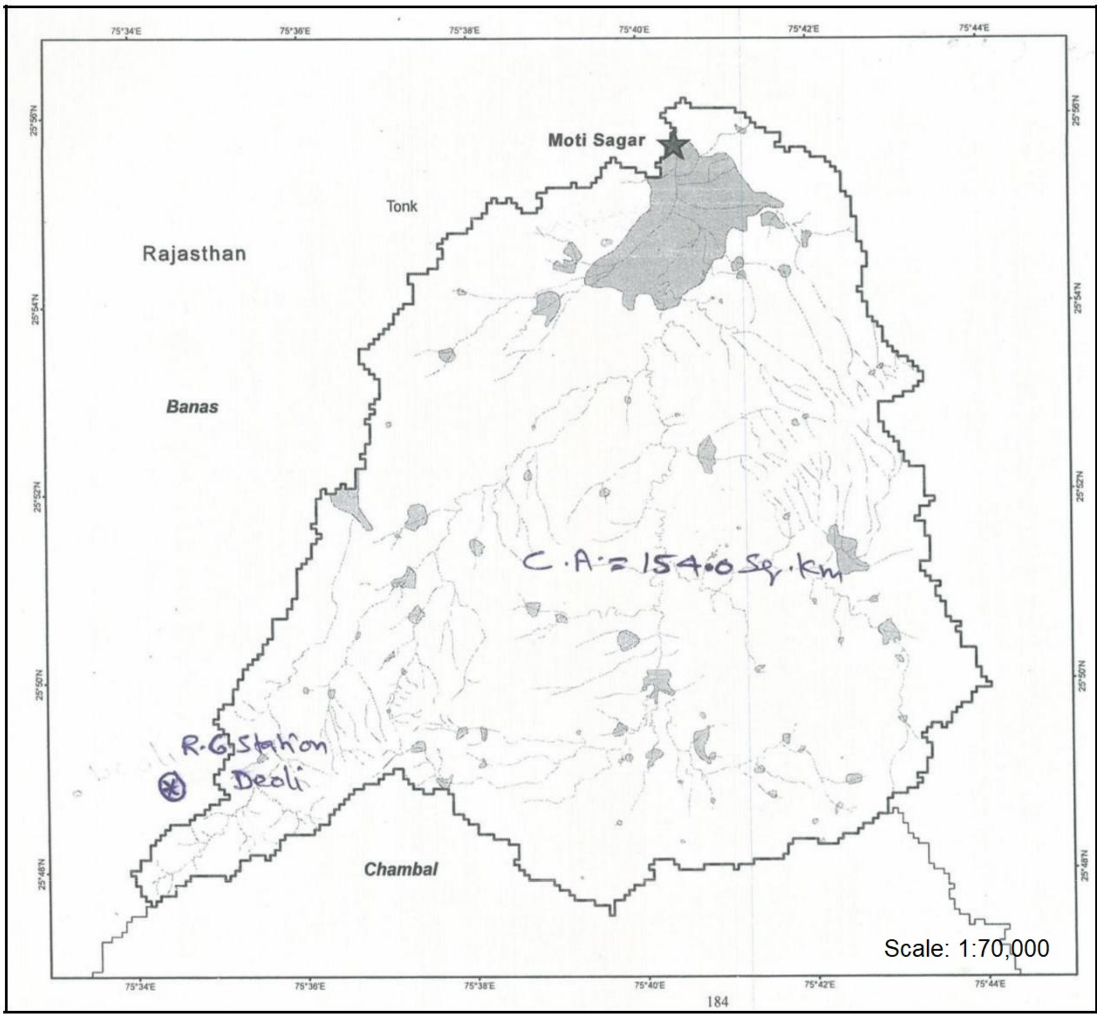


Fig. 7.9: Catchment area and Thiessen polygon for Moti Sagar Dam in Banas II Sub-Basin

Appendix-II

Table 7.1: Total effective rainfall and total effective runoff for Wagan dam Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	390.08	373.56	171.04	934.68	62.20	32.89	27.52	122.62
1997	187.64	252.04	107.96	547.64	32.34	11.79	1.26	45.39
1998	111.12	159.96	173.28	444.36	12.65	1.28	1.24	15.17
1999	240.74	42.80	90.20	373.74	21.38	0.35	0.35	22.08
2000	306.84	37.44	30.80	375.08	21.92	0.35	0.35	22.62
2001	447.40	131.20	12.04	590.64	47.20	7.87	0.35	55.41
2002	9.40	155.32	60.88	225.60	0.45	0.35	0.35	1.15
2003	132.52	115.00	169.04	416.56	0.45	0.35	0.35	1.15
2004	205.04	524.60	18.68	748.32	0.45	102.84	0.12	103.41
2005	229.80	149.52	238.96	618.28	24.66	24.42	8.71	57.79
2006	208.28	664.00	98.52	970.80	13.16	102.44	0.35	115.95
2007	258.72	200.00	32.76	491.48	17.88	15.63	1.45	34.96
2008	281.76	335.68	127.44	744.88	27.37	35.92	4.70	67.99
2009	188.52	158.12	53.72	400.36	0.45	0.35	9.05	9.85
2010	201.52	201.48	86.28	489.28	0.45	12.67	1.33	14.44
2011	303.72	327.28	129.36	760.36	0.45	39.62	19.27	59.34
2012	214.08	410.48	160.52	785.08	0.45	35.38	5.54	41.36
2013	526.84	761.60	851.84	2140.28	30.45	14.19	4.36	49.00
2014	172.00	529.32	778.40	1559.72	0.00	7.05	41.08	48.13
2015	498.60	641.24	648.12	1787.96	26.32	10.44	4.99	41.75

Table 7.2: Total effective rainfall and total effective runoff for Jetpura dam Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	445.00	363.00	67.00	875.00	77.79	29.79	0.25	107.83
1997	188.00	279.00	97.00	564.00	40.96	62.40	1.13	104.49
1998	157.00	72.00	143.00	372.00	56.55	6.24	1.02	63.81
1999	375.00	81.00	110.00	566.00	97.32	0.25	0.25	97.82
2000	414.00	89.00	13.00	516.00	96.51	7.81	0.25	104.56
2001	445.00	100.00	0.00	545.00	54.30	7.94	0.25	62.49
2002	53.00	272.00	18.00	343.00	8.49	67.71	7.05	83.25
2003	329.00	239.00	217.00	785.00	57.43	37.15	0.25	94.83
2004	168.00	593.00	25.00	786.00	34.01	78.06	0.17	112.24
2005	233.00	27.00	298.00	558.00	68.12	6.92	14.81	89.86
2006	181.00	459.00	121.00	761.00	24.83	87.32	0.25	112.39
2007	609.00	132.00	25.00	766.00	68.05	0.73	0.23	68.55
2008	143.00	165.00	161.00	469.00	26.66	38.30	29.93	94.89
2009	337.00	57.00	13.00	407.00	64.65	0.45	0.18	65.28
2010	199.00	373.00	175.00	747.00	29.59	97.19	2.69	129.47
2011	231.00	301.00	140.00	672.00	36.06	45.11	0.59	81.75
2012	135.00	421.00	98.00	654.00	15.77	111.07	3.38	130.22
2013	452.00	758.00	929.00	2139.00	46.61	80.24	0.25	127.09
2014	285.00	796.00	934.00	2015.00	0.00	90.11	1.00	91.10
2015	386.00	422.00	431.00	1239.00	69.96	9.78	3.32	83.05

Table 7.3: Total effective rainfall and total effective runoff for Meja dam Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	578.44	497.94	284.77	1361.15	0.70	0.90	1.00	2.60
1997	330.93	434.13	190.78	955.84	0.41	0.34	0.17	0.92
1998	219.44	213.63	257.81	690.88	0.34	0.17	0.17	0.69
1999	537.98	111.43	62.22	711.62	0.40	0.37	0.17	0.94
2000	396.16	170.18	28.47	594.82	0.38	0.22	0.17	0.78
2001	539.08	329.45	35.68	904.21	0.56	0.36	0.17	1.09
2002	14.18	228.89	81.09	324.16	0.22	0.17	0.17	0.56
2003	373.03	325.64	150.20	848.87	0.36	0.25	0.13	0.75
2004	243.08	656.64	114.12	1013.84	0.28	1.25	0.06	1.59
2005	256.56	307.32	555.18	1119.06	0.22	0.17	0.26	0.65
2006	416.64	1020.60	140.64	1577.88	0.68	2.57	0.16	3.42
2007	578.15	235.37	127.92	941.44	0.37	0.13	0.13	0.63
2008	231.24	376.40	166.64	774.28	0.22	0.17	0.17	0.56
2009	456.48	200.60	21.60	678.68	0.25	0.14	0.17	0.56
2010	362.64	559.90	133.34	1055.88	0.22	1.49	2.04	3.74
2011	363.68	648.56	335.48	1347.72	1.21	0.39	3.80	5.40
2012	263.88	764.04	347.16	1375.08	0.08	1.11	1.57	2.59
2013	790.80	1255.68	1454.80	3501.28	0.22	1.60	0.21	1.61
2014	562.40	1058.36	1328.00	2948.76	0.00	4.41	1.36	5.77
2015	853.48	1055.60	1071.40	2980.48	0.60	0.45	0.17	0.87

Table 7.4: Total effective rainfall and total effective runoff for Nahar Sagar Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	361.96	326.51	89.36	777.83	37.35	7.89	0.72	45.96
1997	276.49	257.00	66.81	600.30	5.87	28.55	0.72	35.14
1998	160.35	100.32	97.22	357.89	1.95	2.95	1.67	6.57
1999	297.21	52.76	63.92	413.89	11.49	1.21	0.72	13.42
2000	324.24	91.39	11.39	427.02	14.09	0.73	0.72	15.53
2001	407.64	131.17	14.47	553.28	41.08	0.73	0.72	42.53
2002	27.24	158.08	11.86	197.18	0.93	0.73	0.72	2.38
2003	221.74	171.08	43.73	436.55	6.82	7.84	0.72	15.38
2004	247.28	700.94	84.32	1032.54	0.93	40.88	0.00	41.81
2005	180.28	27.74	257.67	465.69	2.40	0.28	9.72	12.40
2006	181.72	423.45	48.67	653.84	2.33	40.26	0.00	42.59
2007	238.96	141.01	68.78	448.75	11.04	6.14	3.09	20.27
2008	199.16	99.17	110.11	408.44	0.93	0.73	0.72	2.38
2009	175.52	130.45	29.58	335.55	0.93	0.73	0.72	2.38
2010	209.00	221.50	113.83	544.33	1.47	10.06	6.96	18.48
2011	209.86	272.14	78.19	560.19	0.93	8.53	2.56	12.02
2012	101.80	358.12	154.05	613.97	0.93	5.46	2.31	8.70
2013	300.39	494.04	571.53	1365.96	3.10	8.60	0.72	10.97
2014	0.00	459.15	553.60	1012.75	0.00	41.18	2.42	38.76
2015	323.20	389.64	400.70	1113.54	13.93	0.05	1.97	12.02

Table 7.5: Total effective rainfall and total effective runoff for Lassaria Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	177.71	137.83	67.63	383.17	5.51	1.51	5.22	1.80
1997	166.44	175.77	71.78	413.99	0.41	3.00	0.56	3.97
1998	114.28	71.31	79.36	264.94	3.33	0.48	0.32	4.13
1999	126.47	26.00	31.11	183.58	2.04	1.45	0.32	3.80
2000	112.51	39.83	4.80	157.13	5.78	0.32	0.32	6.42
2001	157.56	53.08	4.40	215.03	5.38	0.02	0.24	5.60
2002	16.30	41.83	13.19	71.32	0.41	0.32	0.32	1.05
2003	104.69	126.67	11.29	242.65	0.41	0.32	0.32	1.05
2004	66.52	206.80	7.58	280.90	0.41	5.82	0.79	5.44
2005	90.90	47.70	116.32	254.92	0.41	0.32	0.32	1.05
2006	80.43	127.59	28.18	236.20	0.41	0.32	0.32	1.05
2007	124.00	79.57	18.69	222.26	0.41	0.32	0.32	1.05
2008	69.35	124.74	79.66	273.75	0.41	0.32	0.32	1.05
2009	90.64	35.42	15.99	142.05	0.41	0.32	0.32	1.05
2010	76.68	172.59	64.92	314.18	0.41	5.16	0.03	5.61
2011	84.65	155.74	72.59	312.98	0.93	4.72	0.15	5.81
2012	42.64	213.90	80.21	336.75	0.41	5.24	0.23	5.88
2013	150.29	269.28	402.22	821.79	0.41	1.83	0.00	2.25
2014	85.50	257.13	343.29	685.92	0.00	5.10	0.26	5.36
2015	164.90	259.78	262.20	686.88	1.01	4.52	0.41	5.12

Table 7.6: Total effective rainfall and total effective runoff for Chhaparwara Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	213.70	297.70	93.00	604.40	5.24	18.62	5.82	29.68
1997	162.00	154.20	133.50	449.70	3.94	7.88	3.35	15.17
1998	202.00	29.90	48.50	280.40	6.88	0.27	0.27	7.43
1999	131.00	37.20	54.80	223.00	2.67	0.27	0.27	3.21
2000	108.70	77.70	21.80	208.20	0.35	0.27	0.27	0.89
2001	152.70	25.50	17.00	195.20	6.01	0.06	0.27	6.22
2002	15.20	59.70	1.00	75.90	0.35	0.27	0.27	0.89
2003	161.00	170.00	66.00	397.00	2.37	2.68	0.08	4.98
2004	42.00	326.00	15.00	383.00	0.35	7.79	1.04	7.09
2005	94.00	10.00	146.00	250.00	0.35	0.27	0.99	1.62
2006	78.00	86.00	26.00	190.00	0.35	0.27	0.27	0.89
2007	103.00	60.00	61.00	224.00	0.35	0.30	0.44	1.09
2008	139.00	117.00	92.00	348.00	0.28	1.65	0.07	2.00
2009	156.00	38.00	17.00	211.00	0.35	0.27	0.27	0.89
2010	117.00	269.00	86.00	472.00	0.35	12.98	12.63	25.97
2011	149.00	146.00	345.00	640.00	2.09	25.70	7.10	34.89
2012	0.00	24.00	287.00	311.00	0.35	11.91	4.70	16.97
2013	96.00	211.00	260.00	567.00	1.22	1.47	0.08	2.77
2014	108.00	342.00	410.00	860.00	0.35	8.23	0.27	8.85
2015	322.00	361.00	370.00	1053.00	2.85	1.44	0.72	3.57

Table 7.7 : Total effective rainfall and total effective runoff for Morel Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	194.78	395.10	235.20	757.03	2.67	10.84	9.93	23.44
1997	165.59	223.03	112.51	471.93	3.30	4.80	1.31	9.42
1998	319.43	190.82	141.70	607.48	15.99	3.86	1.01	20.86
1999	237.04	57.40	71.44	349.85	8.08	3.02	0.33	11.43
2000	232.50	124.42	32.56	385.71	1.94	0.88	0.33	3.15
2001	187.92	125.54	4.71	296.47	4.77	1.47	0.33	6.57
2002	13.96	108.42	21.78	152.13	0.42	0.64	0.02	1.08
2003	277.48	168.84	121.91	556.32	6.49	0.11	0.46	6.84
2004	101.32	362.31	29.48	485.39	0.42	7.62	0.20	8.24
2005	267.17	26.30	153.28	442.49	6.29	0.35	0.17	5.77
2006	172.78	81.23	40.03	283.57	0.42	0.33	0.33	1.08
2007	133.14	182.76	112.70	433.15	0.42	0.33	0.33	1.08
2008	190.89	191.48	156.58	529.21	2.13	0.36	0.74	3.24
2009	132.79	147.10	51.24	317.98	0.42	0.33	0.33	1.08
2010	209.75	323.82	143.37	674.58	0.42	3.18	2.21	5.81
2011	143.39	184.42	246.29	542.19	0.42	3.92	0.33	4.67
2012	46.04	252.45	345.76	598.72	0.42	6.22	11.92	18.56
2013	419.50	794.00	826.81	1857.41	0.42	7.00	0.02	7.40
2014	145.54	566.91	653.59	1212.13	0.00	17.86	0.11	17.97
2015	248.07	334.39	344.91	812.18	2.22	1.60	2.65	6.47

Table 7.8 : Total effective rainfall and total effective runoff for Kalisil Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	261.59	391.46	170.66	823.71	27.21	92.61	2.44	122.25
1997	197.64	277.06	156.98	631.68	24.22	21.21	1.83	47.25
1998	319.74	283.76	156.33	759.83	94.18	18.97	1.12	114.27
1999	287.84	88.75	169.64	546.22	50.67	12.90	29.08	92.65
2000	286.45	145.30	55.00	486.74	64.75	17.21	0.19	82.16
2001	356.08	69.33	2.89	428.30	94.64	5.81	0.19	89.03
2002	54.66	129.20	15.96	199.83	0.25	2.90	1.00	4.15
2003	350.09	230.12	199.98	780.19	66.10	40.64	10.34	117.08
2004	78.85	408.02	25.90	512.77	6.03	53.69	0.17	59.89
2005	456.64	35.93	54.07	546.64	105.05	9.58	1.30	94.17
2006	161.54	56.89	58.38	276.80	5.80	1.14	1.89	8.83
2007	192.78	198.29	107.52	498.59	15.91	19.45	0.70	34.67
2008	333.06	248.12	94.76	675.94	69.55	0.20	0.94	70.69
2009	84.57	214.26	118.90	417.73	4.59	10.80	1.89	17.28
2010	253.65	319.56	94.44	667.65	32.56	43.20	1.45	77.21
2011	117.18	204.91	132.94	455.03	5.04	4.08	40.43	39.47
2012	195.94	414.13	41.95	652.03	26.72	93.87	1.45	122.04
2013	509.45	858.79	915.04	2283.28	89.99	30.49	0.25	120.73
2014	161.50	388.00	509.56	1059.06	0.00	28.82	4.48	33.30
2015	200.06	416.52	422.85	1039.44	5.05	5.94	3.25	14.25

Table 7.9 : Total effective rainfall and total effective runoff for Moti Sagar Catchment

YEAR	RAINFALL (mm)				RUNOFF (mm)			
	JULY	AUG.	SEPT.	TOTAL	JULY	AUG.	SEPT.	TOTAL
1996	298.20	315.60	79.00	692.80	59.58	32.32	0.63	92.53
1997	149.80	221.10	102.30	473.20	22.24	50.77	1.19	74.19
1998	222.80	63.00	100.00	385.80	76.72	2.65	0.71	80.08
1999	233.00	77.60	61.40	372.00	68.93	1.87	0.63	71.43
2000	383.00	146.00	68.00	597.00	54.06	0.64	0.63	55.32
2001	366.00	54.00	0.00	420.00	53.21	21.61	0.63	75.45
2002	2.00	114.80	3.00	119.80	0.68	3.30	0.37	2.98
2003	283.00	140.00	82.00	505.00	23.73	3.39	0.17	20.52
2004	113.00	477.00	20.00	610.00	5.23	27.45	0.13	32.81
2005	159.00	28.00	190.00	377.00	9.51	4.21	0.28	13.44
2006	202.00	230.00	105.00	537.00	5.81	65.31	14.39	85.52
2007	325.00	113.00	75.00	513.00	14.06	5.18	0.35	18.89
2008	106.00	84.00	137.00	327.00	20.23	4.53	15.17	39.93
2009	211.00	87.00	57.00	355.00	0.81	0.64	0.63	2.07
2010	210.00	297.00	200.00	707.00	0.81	28.56	3.08	32.45
2011	178.00	258.00	127.00	563.00	84.58	0.64	0.63	85.84
2012	115.00	480.00	185.00	780.00	7.30	14.08	6.38	27.76
2013	436.00	702.00	755.00	1893.00	54.06	31.03	0.63	85.72
2014	150.00	749.00	891.00	1790.00	0.00	64.01	0.63	64.64
2015	498.00	719.00	728.00	1945.00	28.67	32.06	5.60	66.33

Table 7.10 : Month wise percentage distribution of evaporation in Rajasthan

S. No.	Month	Mean monthly evaporation in Rajasthan (in cm)	% Evaporation
1.	January	8.5	3.87
2.	February	10.8	4.92
3.	March	18.7	8.52
4.	April	26.6	12.12
5.	May	34.6	15.76
6.	June	30.4	13.85
7.	July	21.4	9.75
8.	August	16.8	7.65
9.	September	16.6	7.56
10.	October	15.7	7.15
11.	November	11	5.01
12.	December	8.4	3.83
	Total	219.5	100

Source: IMD, 1990 to 2009

Appendix-III

General Characteristics of adopted Artificial Neural Network (ANN) Model

A neural network is characterized by its three fundamental entities namely, the architecture, learning algorithm and the transfer function.

(1) **Architecture**

ANN architecture is the arrangement of interconnected neurons with connection links in different layers. The most commonly used neural network architecture is a feed forward back propagation neural network. As the name suggests, a feed forward neural network contains neurons arranged in inter-layers that are connected in the forward direction only, i.e. no intra-layer connections or feedback loops are permitted. This arrangement compels the information to flow in the forward direction through a single or multilayer sandwiched hidden layer; therefore the output is dependent entirely on the inputs provided. In this study three layer architecture composed of one input layer having four neurons, one hidden layer having 2 to 11 neurons and one output layer having four neurons as shown in the Fig.- 7.10 are used. Selection of hidden layer neurons is a trial and error process for getting the best performance parameters. Increase in the hidden layer neurons provide complexity of the neural network and indirectly control the learning and generalization ability of the ANN.

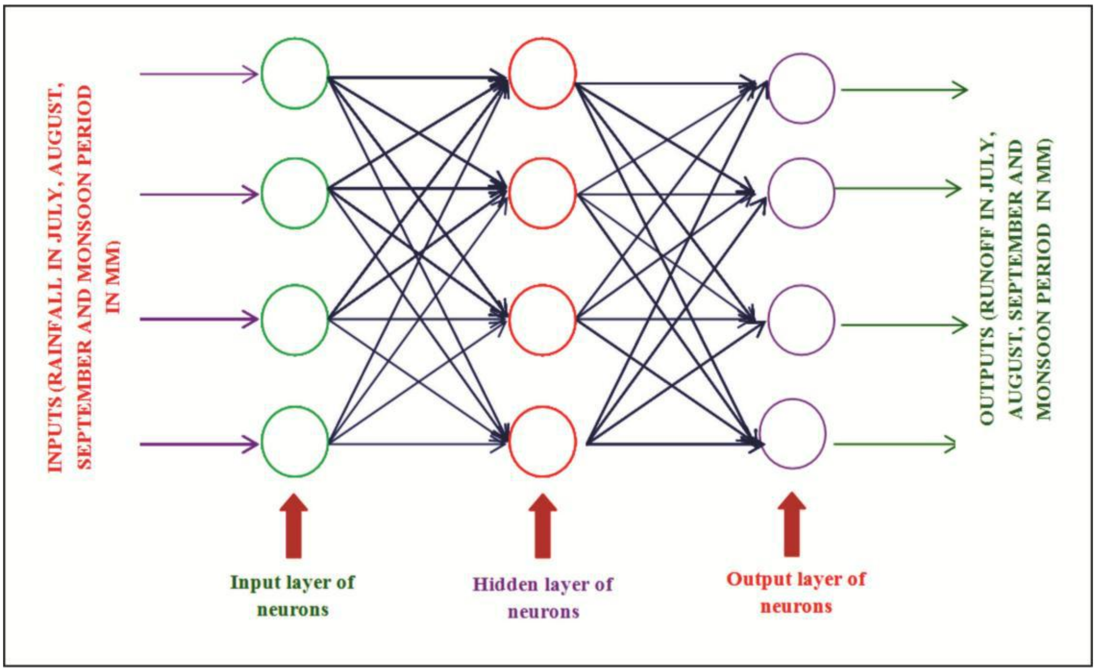


Fig. 7.10 : Feed Forward Neural Network with single hidden layer of neurons

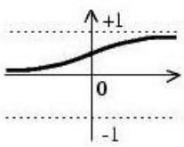
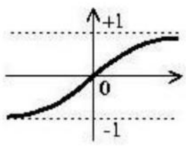
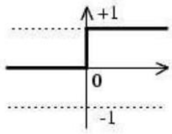
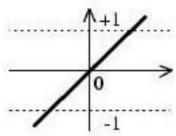
(2) Learning Algorithm

A learning algorithm is the procedural path for systematic updating and adjustment of synaptic weights with biases between the different layer neurons with an activation function to forecast the predicted value near to the actual observed value. **Haykin, S. (2009)** suggested that in the learning process the information is presented to the neural network in the form of input-output data pairs with each input associated with the corresponding output. The learning rule is then applied for adjustment of weights and biases to render network error between actual or target values and neural network predicted outputs as minimum. In this study 10 neural network sub-models for each model having different complexities were trained using Levenberg-Marquardt training algorithm with MATLAB-2011 software. Error correction learning (ECL) rule was used here for the supervised learning of ANN which modifies the weights and biases during each training cycle to reduce the arithmetic difference between the actual or target values and network predicted values to a threshold minimum.

(3) Activation or transfer functions

The typical activation or transfer function generally used in neural networks is non-linear function (log-sigmoid and hyperbolic tangent sigmoid), step functions (hard limit) and linear functions as presented in **Table 7.11** and are introduced to imitate the nonlinear characteristics of the biological neurons.

Table 7.11: Activation or transfer functions used in artificial neurons

Transfer Functions			
Log-sigmoid	Hyperbolic tangent sigmoid	Hard limit	Linear
$f(x) = \frac{1}{1+e^{-x}}$	$f(x) = \frac{2}{1+e^{-2x}} - 1$	$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$	$f(x) = x$
$f(x) \in [0,+1]$	$f(x) \in [-1,+1]$	$f(x) \in [0,1]$	$f(x) \in [-\infty,+\infty]$
			

In the analysis of this study the actual data were normalized between -1 to 1 and after analysis obtained results were again de-normalized for getting the actual value of the runoff. A hyperbolic tangent sigmoid transfer function (tansig) has been used in the hidden layer for providing complexity in the relation and linear transfer function (purelin) in the output layer for facilitating the comparison of the observed and predicted runoff.

(4) Back propagation neural networks :

Back-propagation neural network (BPNN) is a gradient descent algorithm consists of three basic layers called the input layer, output layer and a number of sandwiched hidden layers. It adjusts the weights and biases of the neural network by calculating the network error commonly in terms of squared error namely, mean square error (MSE) or the sum of squared error (SSE) and back-propagating this error to the move of the weights and biases along the negative of the gradient of computed error.

The entire ANN process can be narrated in the following steps:

Step 1: The ANN architecture represents the pattern of the input neurons, hidden layer neurons, and output neurons with information in the form of input-output pairs. The independent variables present in the architecture are represented as input neurons and the dependent variables as output neurons.

Step 2: Initialization of Back-propagation algorithm with random values of weights and biases.

Step 3: Forward propagation of the information through the hidden layer neurons and computing of output of hidden layer neuron using transfer functions for each training pattern.

Step 4: Forward propagation of information computed in Step 3 to the output layer and evaluating the output at the output layer of neurons.

Step 5: Compute the error between the target value and the predicted output

Step 6: Apply the steepest descent algorithm to adjust the weights by back propagation of the error computed in Step 5. High learning rate leads to faster convergence, but may result in overshooting of optimal values of the weights. The problem is counteracted by introducing a momentum factor which provides a smoothing effect to weight oscillations rendered by using a higher learning rate into the weight updating algorithm.

A simplified weight updating relation given by **Erb (1993)** shows the effect of both learning rate and the momentum factor as:

Current change in weight = learning rate × (error) + momentum factor × (previous change in weight)

The steepest gradient descent principle utilized by a standard back-propagation procedure is a local optimization algorithm that exhibits good convergence when the weights are located in the proximity of a minimum point, but slower convergence when the weights are located far away from the desired minimum. To address this problem **Hagan and Menhaj (1994)** presented the *Levenberg-Marquardt algorithm* for training the BPNN. The Levenberg-Marquardt back propagation algorithm can be regarded as a trade-off between the conventional gradient descent and Gauss-Newton method as it utilizes the advantage of fast convergence through non-linear least square optimization rendered by Newton method and the stability provided by gradient descent through maximum neighborhood principle. Although the weight updating using the LM algorithm increases the convergence rate of the back-propagation algorithm, it still carries the drawback of getting trapped at the local minima.

Since the gradient descent algorithm possesses inherent drawback of slow convergence, the LM algorithm attempts to shift to Gauss-Newton method as quickly as possible near the vicinity of an error minimum to enable accurate and faster convergence **(Samani *et al.*,2007)**.

Factors affecting rainfall-runoff Modeling

The general factors affecting rainfall-runoff as described by *Mc Mahon and Arenas* (UNESCO, 1982) are -

1. Natural factors

The first category of factors is directly related to the generation of flow and it determines directly the minimum discharge. The major factor for the flow generation is precipitation. This is the principal source of surface flows and groundwater. Groundwater of course depends upon the surface flows and determines the runoff in the absence of precipitation over a prolonged period. The second category of factors affects the regime and discharge of river through temporal and spatial reduction or distribution of precipitation. These factors are called indirect factors and include all those that do not directly contribute to the formation of the rainfall and runoff but it affects the variation of its rate. This category includes evaporation losses, type of soil, plant cover and relief, number of lakes and swamps and hydro-geological characteristics of the basin. The third category is composed of factors that determine the relationship between river discharges and the subsequent of the direct and indirect factors described above. This category includes factors that are most frequently used for practical computation purposes and comprises the zonal characteristics of flow such as annual runoff, annual groundwater flow of river, self regulation of streamflow etc. The various important factors are briefly described here under :-

1.1 Climatic factors

(1) Precipitation

Precipitation forms the major source of all water occurring as river flow. During less rainfall rivers are fed essentially from water contained below the ground surface. This storage is depleted by precipitation that occurred prior to the period in which the surface flow has substantially diminished or ceased altogether.

The effect of precipitation on streamflow can be directly observed in the basin's discharge characteristics. Natural characteristics of the basin such as topography, soil vegetation characteristics, hydrogeology etc. determine the time it takes for saturated flow. There is a short time in case of a small karst basin to a month or considerably longer in other types of rainfall. Precipitation as snow contributes directly in the formation of runoff only at the time of summer in case of snow fed basins. This process begins in spring which continues throughout summer and sometimes extends to the following autumn or winter.

(2) Evaporation

Evaporation is an extremely important factor in the hydrological cycle, since it largely determines the river discharge and reduces the flow during rainfall-runoff periods. The effect of evaporation is the most significant at the beginning of summer, when a large mass of water returns from the surface soil and from open water bodies to the atmosphere. In regions where the rate of evaporation cannot be compensated by a higher rate of rainfall, an appreciable reduction in river discharge occurs. However during rainfall-runoff periods, when rivers are fed almost exclusively by groundwater, evaporation is practically insignificant. The amount of evaporation depends mainly on solar radiation, temperature of air and water, surface soil water, humidity, vapour pressure, wind velocity and quality of water etc.

(3) Air and soil temperature

Local air and soil temperature affect the total runoff by influencing other climatic factors, especially evaporation and rainfall. Air temperature also affects the flow distribution through freezing. Thus it is one of the principal regulatory elements in temperate and cold countries through temporary retention of water within the soil in the form of snow and ice. The influence of air temperature upon the minimum discharge in the river is the largest during the winter season.

(4) Humidity and wind

Humidity and wind affect the total runoff of streams and influence other climatic factors, particularly evaporation. Evaporation is closely related to air moisture deficit. Slight increase in it causes an increase in evaporation, which in turn reduces soil moisture and possible ground recharge. Air moisture deficit plays an important role in dry regions. In some countries, the persistence of particular winds significantly affects rainfall and hence rainfall-runoff period. Wind also affects the distribution of river flows fed by large lakes. The quantity of water flowing into a river from a lake will vary with wind speed and direction.

1.2 Hydro-geological factors

(1) Geology of the catchment

Geology of any catchment is one of the major factor influencing rainfall and runoff. In the areas where surface geology includes unconsolidated sands and gravels produce a sustained flow during periods of drought which contrasts to these streams in which surface formations consists of un-fractured igneous rocks, clays and shales. In crystallized rocks where little fissuring has occurred, there is little ground flow. For two adjacent basins with the same meteorological conditions, the basin underlain by the more impervious formations will have higher discharges during rainfall-runoff periods. The influence of karast on runoff is very significant in small basins.

(2) Hydro-geological regime

The type of soil and its composition largely determine the basin absorption capacity. For soils with large effective porosity, soil reiteration is low water yield and permeability is high. This explains the great dissimilarly in the behavior of river in sandy or loam areas compared with those that are located in clay regions. With greater infiltration capacity, the water is able to penetrate further into the sandy soils. Consequently, there is a very clear dependence of rainfall-runoff on infiltration. Basins with friable, porous or fissured rock are most favorably placed for groundwater storage, which subsequently contribute base flow to the river during rainfall-runoff periods.

(3) Groundwater

Groundwater is the main source of runoff, available in the form of contribution as artesian groundwater and as phreatic water. The volume of groundwater depends basically on the climate of the region, geological structure and hydro-geological conditions of the basins. Infiltration which is the property of local soil is the process by which water on the ground surface percolates into the different layers of the soil and finds its way either into the groundwater or through the intermediate layers into a stream.

This groundwater after flowing some natural earthen strata feeds the effluent stream in the form of re-generation . During the rainfall-runoff period the groundwater regime is characterized by a gradual reduction of seasonal reserves. The inner geological structure affects the velocity of ground flow and hence the groundwater storage. The transmissivity of an aquifer also affects groundwater discharge and hence river flow.

(4) Phreatic water

Phreatic water is found in the active zone of groundwater storage, that is in the shallower sub soil layers. It seeps to the river system and constitutes the main source of river replenishment during the rainfall-runoff period. This may involve one or more water bearing sediments. The regime of deep phreatic aquifers is steadier since they are fed by deep percolation. Where phreatic water is in direct contact with surface water bodies of the basin, such as lakes and reservoirs, it has a marked influence on the discharge and the runoff regime during the rainfall-runoff period.

(5) Water in unsoldered sediment

From the point of view of river flow, alluvial groundwater is very important. The water occurring in permeable formations is generally discharged over large areas or in some places it may take the form of concentrated outflows. This type of groundwater is generally found in large river valleys.

(6) Crack or fissure water

Crack or fissure water is formed in massive igneous rocks and in highly metamorphosed sedimentary rocks where water accumulates and circulates in fissures. It is of great importance in small and Mountain Rivers as well as in the middle reaches of Valley Rivers. In karastic regions concentrated outflow of groundwater is predominate.

(7) Artesian water

Artesian water is a subject of sudden changes in discharge with time and represents an important supply source for base water flow. This water is confined under pressure between impervious layers or in fissures in the earth's crust. It is found in horizons under pressure that are deeper than those where phreatic water is located. In small sectors of a basin, it can rise as a spring yielding with considerable amount of water, during times of minimum flow of the majority of rivers. The contribution artesian water is very small.

(8) Permafrost groundwater

In cold regions river flow may also be affected by formation of ice in permafrost zones. In such a case undergroundwater flow is transformed into ice which ultimately on melting during the warm season, flows into the stream.

1.3 Morphological factors

Morphological factors such as the relief of basin, presence of lake swamps and plant cover also influence the water flows during rainfall-runoff period. Variations in precipitation in lakes and other water bodies modify the river flow and have stabilizing effect on discharge. Lakes that are located close to the outlet yield greater discharge than those situated farther away.

The vegetation of a basin affects river flow mainly through transpiration of water stored in the ground. This effect reduces the runoff. Further the local vegetation increase soil storage and permeability by its roots breaking up the soil. A surface layer of dead leaves and humus has high infiltration capacity and retards overland flow and also promotes infiltration. Crops with shallow roots rapidly exhaust water in upper soil layers. Some plants also extract moisture from deeper zones. In both cases water is transpired that would otherwise contribute to runoff. Interception of water by vegetation is closely associated with the transpiration phenomena and both reduce the generated runoff from the catchment.

1.4 Morphometrical factors

Morphometrical factors such as basin area, altitude, slope, orientation, drainage density and channel embedment also affect the rainfall and runoff. Studies have shown that for most of rivers there is a direct relation between basin area and the minimum discharge in the river during rainfall-runoff periods. The surface of the basin constitutes the catchment area for precipitation. Generally rainfall increases with altitude, thus creating more favorable conditions for runoff in the river. In some areas, where altitude exceeds a certain limit the precipitation occurs as snow, basin slopes are steeper, rocks are more impervious and therefore sub-surface runoff is much lower than in basin lying at lower altitudes. Slope of the basin affects mainly the quantity of infiltration and the rate of overland flow. Basins with steeper slopes allow less time for infiltration and the supply of groundwater is therefore reduced. The drainage system is directly related to the efficiency of water removal. The greater the basin area and more highly developed its channel system the greater will be probability that surface water derived from rainfall will contribute to flow during rainfall-runoff periods. Increased embedment of the channel throughout a river course taps deeper water bearing horizons and thereby the yield of groundwater basin to streamflow increases.

2. Factors due to human activity

The influence of man's activity on the regime and discharge of a river varies in nature. The intensity of man-made factors varies according to the level of development, type of economic activity involved such as urbanization, irrigation, hydraulic works, water transfer schemes, hydro-electric stations, mining, navigation, treatment of urban and industrial effluents, drainage works and land use changes etc. which directly influence the flows during lean season.

Large cities and industries exert a significant influence on runoff in the downstream of water intakes or effluent out falls. With urbanization and increase in population densities, residential and commercial building etc. impervious area increases and hydro-logical regime get significantly changed. Irrigation water is supplied from rivers, reservoirs and wells. Whatever be the method, it results in a substantial increase in both evapo-transpiration from fields and evaporation from the distribution system, hence reducing the out flow from a basin. The hydraulic works for controlling urban water supply also results in reduction of surface and sub-surface runoff, but their effect varies according to the purpose of works and degree of regulation. The use of hydraulic works for controlling urban water supply also results in reduction of surface and sub-surface runoff. The use of dams for purpose of power generation generally causes an increase in runoff in the down-stream in the form of regenerated water.

River navigation requires the regulation of flows so that an adequate depth of water is available to allow the navigation. When natural flows are inadequate, water stored upstream is released. In this way, flows during lean season get increased. A significant change in land use pattern also alters the regime and discharge of the river draining the basin. In various tropical regions deforestation has led to a reduction of sub-surface runoff with increase in surface runoff and in some cases to the cessation of flow altogether. In respect of the pattern of land use changes the runoff depends on a balance between infiltrations which is affected by plant cover and water losses through soil.

Publication List

List of Paper Publications:

A. International Journals

1. Sharma, G., Mathur, Y.P., Vyas, S.K. (2014) 'Rainfall Runoff Regression Model for Meja Catchment', *International Journal of Innovative Research inEngineering Science and Technology*, Vol.1, No.1, April 2014.
2. Vyas, S.K., Sharma, G., Mathur, Y.P., (2015) 'Rainfall Runoff Regression Model for Galwa Catchment in Banas River Basin', *International Journal ofAdvanced Technology in Engineering and Science,* Vol.3, Special IssueNo.2, February 2015.
3. Chandwani, V., Vyas, S.K., Agrawal, V., and Sharma G. (2015) 'Soft computing approach for Rainfall Runoff Modelling: A review', ELSEVIER, Science Direct, Aquatic Procedia 2015, Volume 4C, pp. 1054-1061.
4. Vyas, S.K., Sharma, G., Mathur, Y.P. and Chandwani, V. (2015) 'Interlinking Feasibility of Five River Basins of Rajasthan in India' *ELSEVIER, Perspectives in Science 2016* ,Volume 8C, pp. 83-86.

B. International Conference

1. Vyas, S.K., Sharma, G., Mathur, Y.P., (2014) 'Rainfall Runoff Regression Model for Morel Catchment in Banas River Basin',*3rd International Conference on Advance Trends in Engineering Technology and Science(ICATETR-2014)* December 24, 2014, Kota.
2. Vyas, S.K., Sharma, G., Mathur, Y.P., (2014) and Chandwani, V. 'Rainfall Runoff Modelling: Conventional Regression and Artificial Neural Networks approach', accepted for *2ndIEEE International Conference on Recent Advances and Innovations in Engineering and Science (ICRAIE-2016)*, 23-25 December, Jaipur.

Author's Bio-data

The author has been felicitated with State as well as National level Govt. scholarships from School education namely- ‘Gramin Pratibha Khoj Examination’ held after class eighth and ‘National Merit Scholarship’ through class tenth board examination. He obtained his Bachelor’s degree in Civil Engineering from Engineering College, Kota (Presently Technical University of Rajasthan) in 1990 and enrolled for Master’s degree in Water Resources Engineering from Malaviya Regional Engineering College, Jaipur (Presently Malaviya National Institute of Technology, Jaipur) through GATE in the year 1992. The author has joined Govt. of Rajasthan as a Forest Officer and served from 1995 to 1998 with two years training course in Forest and Environment held by the Ministry of Forest & Environment, Govt. of India. In the year 1998, he joined as Assistant Engineer in Water Resources Department, Government of Rajasthan, and is presently holding the post of Executive Engineer. He was actively engaged in the design of irrigation structures like dams, anicuts, canals etc., during his posting at the Investigation Design and Research (ID&R) unit of Water Resources Department. He is in the expert panel of Engineering Staff Training Institute, Jaipur (Govt. of Rajasthan) which imparts training to the Engineers of various Govt. Departments. He has worked in a panel on ‘Guidelines to prepare Manual of Operation and Maintenance of Irrigation Structures’. The author has served as a team leader in the alignment and preparation of pre-feasibility report of ‘Interlinking of Parwati and Kalisindh Rivers of Chambal Basin with Banas, Gambhir and Parbati River Basins up to Dholpur’, presently known as ‘Eastern Rajasthan Canal Project’ which is the dream project of Rajasthan. He worked on the all India fame *Mukhyamantri Jal Swavlamban Abhiyan* (MJSA), going on the water conservation theme in the urban areas of Rajasthan, serving as Executive Engineer in Rajasthan River Basin and Water Resources Planning Authority. Now he is serving as Executive Engineer in Investigation Design and Research (ID&R) unit of Water Resources Department, Rajasthan.