RAINFALL-RUNOFF MODELING USING ARTIFICIAL NEURAL NET WORKS

A DISSERTATION

submitted in partial fulfilment of the
requirements for the award of the degree
of
MASTER OF ENGINEERING
in
WATER RESOURCES DEVELOPMENT

By
K. S. NAIDU

WATER RESOURCES DEVELOPMENT TRAINING CENTRE
UNIVERSITY OF ROORKEE
ROORKEE-247 667 (INDIA)
JANUARY, 2001

CANDIDATE'S DECLARATION

I hereby declare that the work which is being presented in this dissertation entitled, **"RAINFALL – RUNOFF MODELING USING ARTIFICIAL NEURAL NETWORKS"**, in partial fulfilment of the requirement for the award of the degree of Master of Engineering in Water Resources Development, submitted in Water Resources Development Training Centre, University of Roorkee, is an authentic record of my own work carried out from 16th July, 2000 to 29th January, 2001 under the supervision of **Dr. U.C.Chaube,** Professor, WRDTC and **Dr S.K.Jain,** Scientist 'F', NIH, Roorkee.

The matter embodied in this dissertation has not been submitted for the award of any other degree.

Kochalamvardu

Dated: **(K. S. NAIDU)**

CERTIFICATE

This is to certify that the above statement made by the candidate is true to the best of our knowledge.

(Dr. S.K.Jain)
Scientist 'F'
NIH
Roorkee-247667
Roorkee-247667 (INDIA)

(Dr U.C.Chaube)
Professor, WRDTC
University of Roorkee
Roorkee-247667
(INDIA)

ACKNOWLEDGEMENTS

I am previleged to record profound sense of gratitude and sincere thanks to **Dr.U.C.Chaube**, Professor, WRDTC, University Of Roorkee, Roorkee and **Dr S.K.Jain,** Scientist, 'F' , NIH, Roorkee for their valuable guidance, supervision, inspiring encouragement at every stage, while completing this dissertation.

I am thankful to Prof. Devadutta Das, Director WRDTC for extending necessary facilities and support that were required while completing this dissertation.

I owe special thanks to Professor G.C.Mishra, and Professor Gopal Chauhan , research scholars S.Balaprasad and M.P.Rajurkar and fellow ME students U.S.Vidyarthi and T.R.Patnaik for their help while completing this dissertation

I extend my thanks to staff of library, staff of computer lab, office staff and all those directly or indirectly helped in bringing up this dissertation work.

It is my duty to express my sincere thanks to the Director General, Chief Engineer, Director(Tech), Superintending Engineer, Director (Admn) and Deputy Director (Hydrology) of my organisation ,NWDA, New Delhi for sponsoring me to study the ME in this prestigious institute, University of Roorkee.

I wish to mention the sacrifices made by my parents, wife **Gourishree** and children **Siddhartha** and **Nagaruna** who are staying away from Roorkee and praying always for success and improvement in my academic career.

(K.S.NAIDU)

Dated: January ,2001

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF PLATES

SYNOPSIS

The quest for understanding the human brain and emulating its functions unfolded new versions in system analysis. The complexity and non-linearity of the neural networks in brain is best utilised in evolving the analogical Artificial Neural Networks (ANNs). In the last decade the ANNs have found in many hydrologic applications. The rainfall-runoff modeling is one such field where ANNs can be applied extensively. Runoff is the response of a catchment for a particular rainfall pattern under various hydrometeorological factors and the exact prediction of which is rather difficult but essential for planning of a water resources project for irrigation and water supply, hydropower, floodcontrol and navigation etc.

This thesis deals with the application of ANNs for rainfall-runoff modeling of Paleru sub-basin (2928 sqkm) and Musi sub basin of Krishna basin in AP and Samakoi sub basin (787 sqkm) of Brahmani basin in Orissa with an available rainfall and runoff data of 18 years (monthly), 15 years (monthly) and 11 monsoon years (10 daily) respectively. In addition the Panevapotranspiration (PET) data is available in case of Samakoi sub basin for the above mentioned period.

The Linear Least Square SIMplex (LLSSIM) and Back Propagation algorithms are used for training the network. The results are compared with those obtained using Multiple Linear Regression (MLR) and analysed with the help of coefficient of correlation, sum of least squared errors and coefficient of efficiency.

The Artificial Neural Networks are capable of capturing the peaks and gives better performance if the analysis is made monthly rather than ten-daily. It is found that PET has bearing on yield of the catchment. Further, the ANNs are adaptable for hydro-meteorologically-similar regions. The LLSSIM imparts speedy training though the Back Propagation shows consistently better performance with the increase in size of the input vector.

CHAPTER 1

INTRODUCTION

1.1 GENERAL

The response of the catchment for a particular rainfall event is runoff. Estimation of runoff from a particular rainfall event is of vital significance in planning for irrigation, hydropower, flood control, water supply and navigation. Runoff is geneally influenced by the climatological factors like sunshine, temperature and humidity; catchment characteristics like soil and vegetation cover; and the land use and agricultural practices. Except for the hill regions where the headwater basins are small with steeper slopes, most Indian river basins are big enough and planning needs attention towards such big catchments with complex features.

1.2 RAINFALL–RUNOFF PROCESS

The response of a catchment varies with space and time. This response is the outcome of certain physical processes that occur in the catchment. The rainfall that is prime input in the process that yields runoff, too varies with space and time. The atmospheric, lithographic and hydrographic conditions over the catchment under consideration are the other inputs that are contributing in the process.

A watershed is a complex system. The rainfall is subjected to the physical processes which depends on climatalogical factors like temperature, humidity, wind velocity, cloud cover, evaporation and evapotranspiration; topographical features like depressions, slope of the catchment, vegetation and land use pattern. The soil characteristics like permeability, antecedent moisture content and irrigability characteristics and the hydro-geological conditions like rock formations, elevation of water table and sub surface channels too affect this process considerably. Under these influencing parameters, it is utmost difficult task to estimate the likely runoff from a particular storm. Further, the data that is supplied by different field authorities is not always consistent, neither the record is long enough and continuous.

1.3 RAINFALL-RUNOFF MODELING

A mathematical model is an assembly of concepts in the form of mathematical equation (s) that approximate the behavior of a natural system or phenomena. It represents the actual systems to certain degree of accuracy. It is difficult to analyse each and every system for the purpose of meeting the needs of planning and development. Moreover it needs voluminous data, procurement of which is difficult and expensive. The model will replace several prototypes and the basic purpose of a model is to simulate and predict the operation of the system that is unduly complex and the effect of changes on this operation.

Rosenblueth and Wiener (1945) perhaps best expressed the rationale for model building

" *No substantial part of the universe is so simple that it can be grasped and controlled without abstraction. Abstraction consists in replacing the parts of the universe under consideration by a model of similar but simpler structure. Models, formal or intellectual on the one hand, or material on the other, are thus a central necessity of scientific procedure*".

The modeling of rainfall-runoff process that is a part of hydrological system is more complex with various factors as described. However it is essential part of planning and development of a water resources project to have such model to save time and money. The essential data like rainfall, discharge, evapo-transpiration, permeability of the soil, infiltration and the land use are collected, the influencing parameters are calibrated and tested under similar conditions and the mathematical formulation is done accordingly which is used as a model equation. These models after proper testing are suited to simulate any other system of similar characteristics thus saving time in evaluating another model. The models are broadly classified as narrated below.

1.3.1 Empirical Models

Empirical model treat hydrologic systems such as watershed as a black box and try to find a relationship between historical inputs and outputs. Lumped catchment models fall under this category (Blackie and Eles 1985). These models need long historic records and have no physical basis and as such are not applicable for ungauged watersheds.

1.3.2 Conceptual Models

These models represent the watershed structure and the stream network well, but various assumptions concerning the linearity of response of individual watershed units (streams and overland sections) need to be made.

1.3.3 Physically Based Models

Physically based models involve solution of a system of partial differential equations that represent our best understanding of the flow processes within the watershed. For most of the problems, a numerical solution is sought by discretizing time - space dimensions in to a discrete set of nodes. This implies that such models work best when data on the physical characteristics of the watershed are available at the model grid scale. This kind of data is rarely available even in heavily instrumented research watersheds. These models suffer from problems such as identification, estimiability and uniqueness of parameter estimation. Even with the current computing capabilities, physical representation of the watershed in the model is at best, an approximation.

1.4 NEW APPROACHES

Keeping in view the limitations of the currently available models, researchers look towards new concepts. Artificial Neural Networks (ANNs) are one such emerging new techniques in the field of hydrologic modeling.

The ANN structure (model) is developed from the training (calibration) process that stores the overall relationship between rainfall and runoff resulting from influencing physical parameters. This is because the training is given by inducing the rainfall and runoff data into the network which is allowed to recognize the patterns among input data and store the related weights (response functions) between the nodes (processing units) of the structure. The number of nodes and inter connections and respective weights (parameters) associated with these interconnections are system dependent. The weights and the input data are used along with the number of nodes to find out the output runoff, the coefficient of correlation and the sum of least square errors between observed and computed runoff. The ANN model that is trained from the experience of passing through various patterns of input data is capable of producing the same level of accuracy when applied to the similar system. This is analogous to the human brain that perceives every thing in patterns.

Briefly, due to the following advantages, ANNs have become an attractive computational tool nowadays.

1. They are able to recognise the relation between the input and output variables without explicit physical consideration.
2. They work well even when the training (calibration) sets contain noise and measurement errors.
3. They are able to adapt to solutions over time to compensate for changing circumstances.
4. They posses other inherent information-processing characteristics and once trained are easy to use.
5. The non-linear nature of activation function, enhances the generalizing capabilities of ANNs and make them desirable for large class of problems in hydrology.

1.5 OBJECTIVES & SCOPE OF STUDY

The objectives of the current study are

1. To apply ANNs to model the rainfall - runoff relationship in Paleru sub basin of drainage area of 2928 sq.km in the lower reaches of Krishna basin in Andhra Pradesh, using the monthly training data set for the period from 1965-66 to 1976-77 and validation data set from 1977-78 to 1982-83 and to compare the results with that of multiple regression analysis
2. To apply ANNs to model the rainfall - runoff relationship in Musi sub basin of larger drainage area of 11050 sq.km in the lower reaches of Krishna basin in AndhraPradesh, using the monthly training data set for the period from 1968-69 to 1976-77 and validation data set from 1977-78 to 1982-83 and to compare the results with that of the multiple regression analysis.

3. To apply the ANN model as obtained for Paleru sub basin, in the study of Musi sub basin and vice versa, and to analyse the performance, as these two catchments are adjacent and with similar characteristics.
4. To apply ANNs to model rainfall - runoff relationship in Samakoi sub basin of Brahmani basin having drainage area of 787 sq.km, using monthly training data set for the monsoon period from 1985 to 1992 and validation data set from 1993 to 1995 and ten daily training data set for the monsoon period from 1985 to 1992 and validation data set from 1993 to 1995 and to compare the results with those of multiple regression analysis.
5. To apply ANNs to model rainfall - runoff relationship in Samakoi sub basin of Brahmani basin, having drainage area of 787 sq.km, using panevapotranspiration (PET) as one of the cause variables, using training data set for the monsoon period from 1985 to 1992 and validation data set from 1993 to 1995 on monthly and ten daily basis and to compare with the results those are obtained from the study without PET.

1.6 ORGANISATION OF THE THESIS

This dissertation work has been arranged in six chapters as detailed below

Chapter 2:

The conceptualization of ANNs, various training algorithms emphasising on Linear Least Square Simplex and Back Propagation, Applications of ANN as modeling tool, its applicability in rainfall runoff modeling, its strengths and limitations etc. are discussed.

Chapter 3:

Review of recent applications of ANNs and various models in Hydrology, emphasising on the rainfall runoff modeling is presented.

Chapter 4:

The details of study area, availability and processing of data is presented.

Chapter 5:

The results obtained in this study using LLSSIM algorithm are discussed, analysed and compared with those of Multiple Regression Analysis. The results obtained from the LLSSIM are compared with Back Propagation in one case.

Chapter 6:

The conclusions and recommendations are presented.

CHAPTER 2

ARTIFICIAL NEURAL NETWORKS

2.1 INTRODUCTION

Artificial Neural Networks (ANNs) are massively parallel distributed information processing systems that have certain performance characteristics resembling biological neural networks of the human brain. ANNs have been developed as a generalization of mathematical models of neural biology and are based on the following rules.

1. Information processing occurs at many single elements called nodes, also referred to as units or neurons
2. Signals are passed between nodes through connection links.
3. Each connection link has an associated weight that represents its connection strength.
4. Each node typically applies a nonlinear transformation called activation function to its net input to determine its output signal.

2.2 CONTEXT

Inspired by a desire to understand the human brain and emulate its functioning, Mc Culloch and Pitts (1943) have paved the way for development of artificial neural networks. In the last decade, it has experienced a huge resurgence due to the phenomenal growth of sophisticated algorithms and powerful computational tools. The effort in iterative auto associative neural networks by Hopfield (1982) set the pace of development in the last decade. A tremendous growth in the interest of this computational mechanism has occurred since Rumalhart et al (1986) rediscovered a mathematically rigorous theoretical framework for training neural networks, viz. back propagation algorithm. Extensive research has been devoted to investigate the potential of ANNs that acquire, represent and compute a mapping from one multivariate input space to another (Wasserman 1989).The development of Linear Least Square Simplex algorithm (Hsu et al, 1995) helped in the faster process of training.

2.3 BIOLOGICAL BASIS OF ANNs

The fundamental unit of a network is neuron, that consists of nucleus in its cell body or soma.Tree like nerve fibers called dendrites are associated with cell body which receives signals from other neurons. The long fiber, axon, extending from the cell body eventually branches into strands and sub-strands connecting to many other neurons at the synaptic junctions, or synapses. The receiving ends of these junctions on other cells can be found both on the dendrites and on the cell bodies. The axon of a typical neuron leads to a few thousand synapses associated with other neurons.

The transmission of a signal from one cell to another at a synapse is a complex chemical process in which specific transmitter substances are released from the sending side of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If this potential reaches a threshold, an electrical activity in the form of short pulses is generated. When this happens, the cell is said to have fired. These electrical signals of fixed strength and duration are sent down the axon. Generally the electrical activity is confined to the interior of a neuron, as the chemical mechanism operates at the synapses.

The dendrites serve as receptors for signals from other neurons, where as the purpose of axon is transmission of the generated neural activity to other cells (inter-neuron) or to muscle fibers (motor neuron). A third type of neuron, which receives information from muscles or sensory organs, such as the eye or ear, is called a receptor neuron. Figure 2.1 shows the sketch of a typical biological neuron.

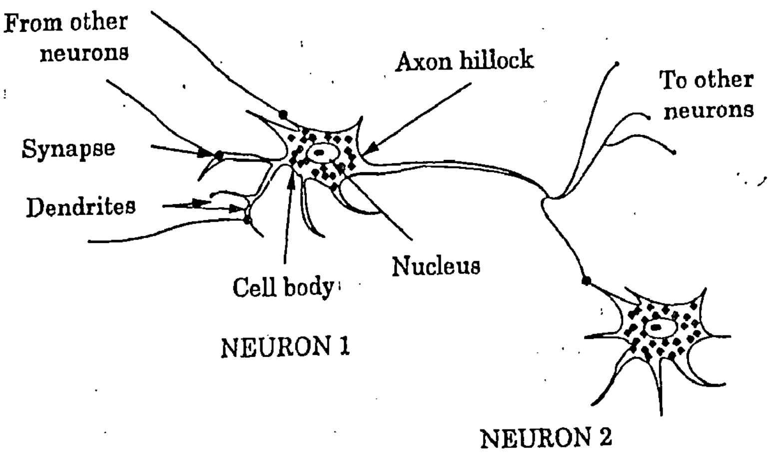


Fig. 2.1 Schematic diagram of a typical biological neuron

2.3.1 Attractive Features of Biological Neural Networks

The attractive features of the biological neural network that make it superior to even the most sophisticated Artificial Intelligence computer system for pattern recognition tasks are:

a) *Robustness /fault tolerance:* The decay of cells does not seem to affect the performance significantly.

b) *Flexibility:* The network automatically adjusts to a new environment without using any pre programmed instructions.

c) *Ability to deal with a variety of data situations:* The network can deal with data that is fuzzy, probabilistic, noisy and inconsistent information.

d) *Collective computation:* The network performs routinely many operations in parallel and a given task in a distributed manner.

2.4 THE ANN STRUCTURE

The artificial neural network resembles the brain in two respects.

1. Knowledge is acquired by the network through a learning process.
2. Inter neuron connection strengths known as synaptic weights are used to store the knowledge.

The evolution of ANN structure is described in the following articles.

2.4.1 The Network Topology

The arrangement of the processing units, connections and pattern input/output in an ANN is referred to as topology. The processing units are arranged in three layers that are input, hidden and output. The units of a layer are similar in the sense that they all have the same activation dynamics and output function. The number of inputs and the number of outputs are problem specific. There are no fixed rules as to how many units should be included in the hidden layer. If there are too less units in the hidden layer the network may have difficulty in generalizing the problem. On the other hand, if there are too many units in the hidden layer, the network may take an unacceptably long time to learn. On the basis of direction of information flow and processing the ANNs are classified as

Feed forward network

The nodes are arranged in layers starting from first input layer and ending with final output layer and each of the hidden layers having one or more nodes.The nodes in one layer are connected to those in the next but not to those in the same layer. Thus the output of a node in one layer is only a dependent on the inputs it receive from previous layers and the corresponding weights.

Recurrent network

Information flows through the nodes in both directions from the input to the output side and vice versa. This is generally achieved by recycling previous network outputs as current inputs, thus allowing for feed back.

Lateral network

In lateral connections the nodes are also connected within a layer of a network.

On the basis of number of layers the ANNs are classified as

1. Single layer (Hopfield nets)
2. Bilayer (Carpenter/Grossberg adaptive resonance networks)
3. Multi layer (most of the back propagation networks)

A typical three layer feed forward neural network that is used in the present study, with LLSSIM algorithm is shown in Figure 2.2. Where, X_{t-2}, X_{t-1} and X_t are the nodes in input layer and Y_t is the output node. The interconnections between the nodes of different layers carries the weights that are the strengths. Five hidden nodes and one bias node each in input and hidden layer are shown in the network.

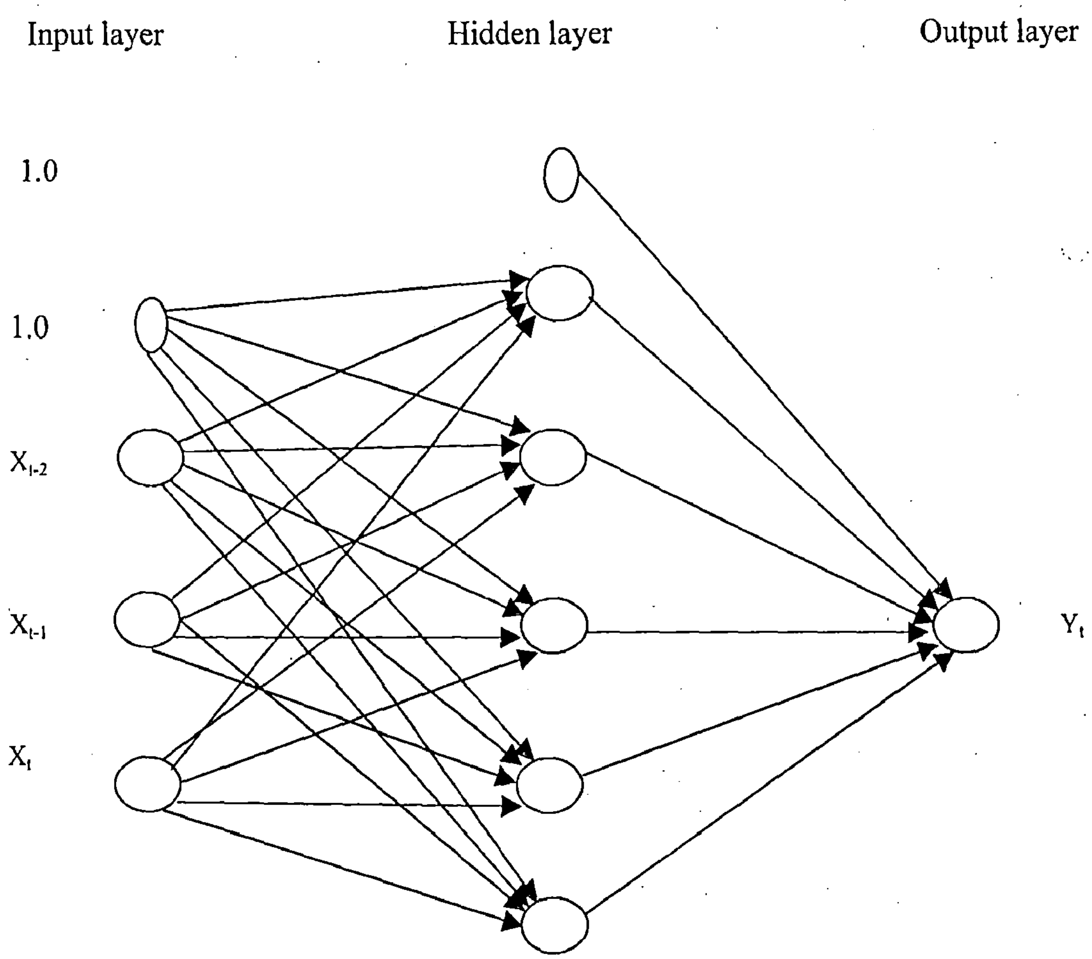


Fig.2.2 : Typical three layer feed forward neural network with 3-5-1 structure and with one bias node each input layer and hidden layer.

2.4.2 Activation Function

The inputs to node j come from the system cause variables or outputs of other nodes and input vector X. The sequence of weights leading to the node form a weight vector W_j and represents the connection weight from a particular node in preceding layer to the node j. The output of node j, y_j is obtained by computing the value of function f with respect to the inner product of vector X_j and W_j minus b_j, where b_j is the threshold value, called bias, associated with this node. In ANN parlance, the bias of the node must be exceeded before it can be activated. The following equation defines the operation

$$y_j = f(X^*W_j - b_j) \tag{2.1}$$

The function f is called activation function and determines the response of a node to the input signal it receives. The most commonly used form of f(.) in above equation is the sigmoid logistic function, given as

$$f(t) = 1/(1+e^{-t}) \tag{2.2}$$

Sigmoid function is used for activation as it is bounded, monotonic, non decreasing, differentiable at every point and provides a graded, non linear response. The Fig 2.3 shows the schematic diagram of a node j and Fig.2.4 shows the sigmoid function

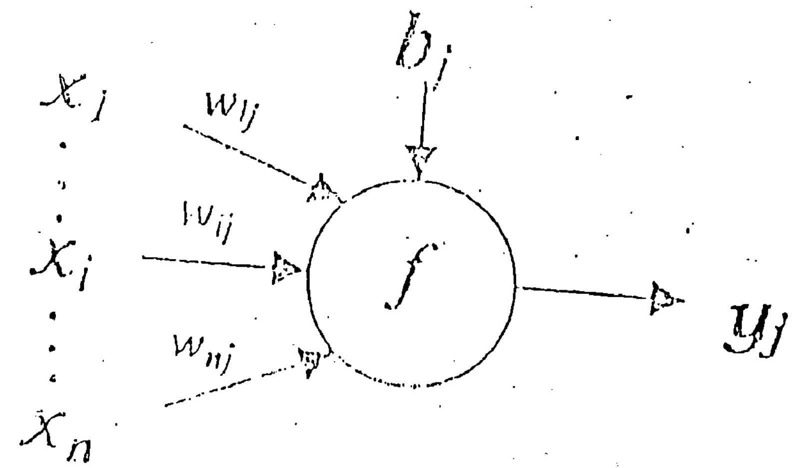


Fig. 2.3 : Schematic diagram of a node j

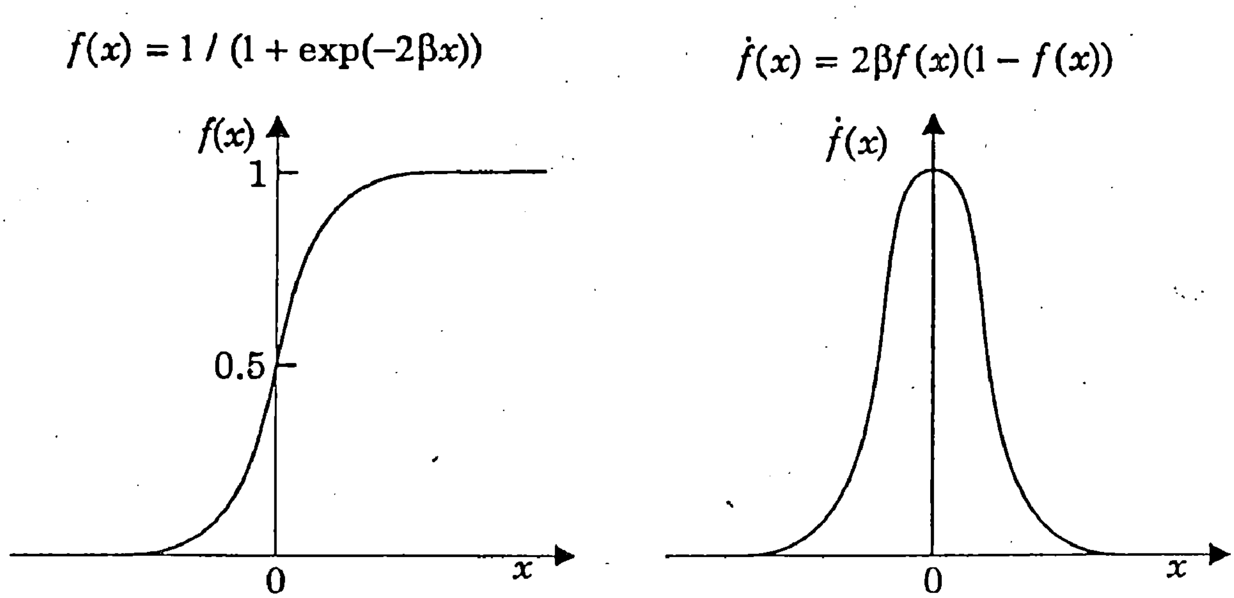


Fig.2.4 : Sigmoid (Logistic) Function and its derivative

Normalization

Due to the nature of sigmoid function used in activation in neural networks, it is necessary to normalize (i.e to convert to the range {0,1}) all input values before passing them into a neural network. Without this normalization, large input values into ANN would require extremely small weighting factors to be applied. This can cause following problems.

i) Inaccurate results due to floating point calculations on microcomputer
ii) Sluggish and time consuming training as the changes made by the learning algorithm would significantly be very small.

Due to output range of the sigmoid function, all values leaving an ANN are in a normalized format. These output values must be 'denormalized' to provide meaningful results. This can be achieved by simply reversing the normalization algorithm used on the input units.

There are two ways for data normalization:

i). The values are normalized with respect to the range of all values i.e.

$$N = (R_i - Min_i) / (Max_i - Min_i) \tag{2.3}$$

ii) The values are normalized with respect to the sum of squares of all values.

$$N = Ri / \sqrt{SSi} \tag{2.4}$$

Where,

Ri	is the actual value applied to unit i
N	is the subsequent normalized value calculated for unit i
Min_i	is the minimum value of all values applied to unit i
Max_i	is the maximum value of all values applied to unit i
SSi	is the sum of squares of all values applied to unit i

There are no fixed rules as to which should be used in a particular circumstance and there has been very little research on the subject.

2.4.3 Network Training/Learning

Training is a process by which the connection weights of an ANN are adapted through a continuous process of simulation by the environment in which the network is embedded. In order for an ANN to generate an output vector Y that is as close as possible to the target vector T, the training process (also called learning process) employed. From this training process optimal weight matrices W and bias vectors V, if any, is obtained. This weight matrix is optimal because it is obtained at the minimum of the predetermined error function that usually has the form

$$E = \Sigma_P \Sigma_p (y_i - t_i)^2 \tag{2.5}$$

where,

- t_i is a component of the desired output T
- y_i is corresponding ANN output
- p is number of nodes
- P is number of training patterns

The training algorithms that are generally used for the network training are explained below. The selection of a particular training process depends on the time available for training, accuracy, number of input data available etc.

Back propagation

Each input pattern of the training data set is passed through the network from the input layer to the output layer. The network output is compared with desired target output and error is computed and is propagated backward through the network to each node, and correspondingly the connection weights are readjusted using the equation

$$\Delta w_{ij}(n) = - \varepsilon^* (\partial E/ \partial w_{ij}) + \propto^* \Delta w_{ij} (n-1) \tag{2.6}$$

Where, Δw_{ij} (n) and Δw_{ij} (n-1) are weight increments between node I and j during the nth and (n-1)th pass or epoch. ε and $\propto$ are called learning rate and momentum respectively. The momentum factor can speed up training in flat regions of error surface and help prevent oscillations in the weights. A learning rate is used to increase the chance of avoiding the training process being trapped in a local minimum instead of global minima. The solution often follows a zigzag path while trying to reach a minimum error position, which may lead to slower training process. It is also possible for the process to be trapped in the local minimum despite the use of learning rate (Wasserman,1989and Fausettl,1994).

Conjugate Gradient Algorithms

This method does not proceed along the direction of the error gradient, but in a direction orthogonal to the one in the previous step. This prevents future steps from influencing the minimization achieved during the current step. The minimization in this case is quadratically convergent and if it is used in the case of the non-quadratic iteration problem, a convergence criterion is required (Fletcher and Reeves,1964).

Radial Basis Function

Radial Basis Function (RBF) is a three layer network in which the hidden layer performs a fixed non linear transformation with no adjustable parameters. This layer consists of a number of nodes and a parameter vector called a "center" which can be considered the weight vector of the hidden layer. The major task of RBF network design is to determine center **c**. The simplest and easiest way is, to choose the centers randomly from the training set. The non linearity in back propagation is implemented by a constant function such as sigmoid. The RBF ,on the other hand, bases its non linearities on the data in the training set. Once all the bases functions in the hidden layer have been found, the network only needs to learn at the output layer in a linear summation fashion (Leonard et al.1992).

Cascade Correlation Algorithm

It starts with a minimal network without any hidden units and grows during the training by adding hidden units one by one, maximizing the impact of the new node on the network error, creating a multi layer structure. The addition of new hidden nodes is continued until maximum correlation between the hidden nodes and output error is attained. This is a unique algorithm as the architecture is determined as part of the training process (Fahlman and Lebiere,1990).

Linear Least Square SIMplex Algorithm

The efficiency of the back propagation and other gradient search training strategies is sensitive to the initial starting point. Further they are easily trapped by local optima and are often ineffective when searching weight spaces (parameter spaces) of high dimension. These findings prompted Hsu et al. (1995) to develop an algorithm for training three layer feed forward ANNs that appears to be more effective. The new algorithm, Linear Least Square SIMplex algorithm (LLSSIM) is a training process in which the weight space is divided in to two parts to implement two training strategies. The hidden output layer weights are estimated using optimal linear least squares estimation (LLS) [Scalero and Tepedelenlioglu, 1992], while the input hidden layer weights are estimated using a multi start version of the simplex nonlinear optimization algorithm [Nelder and Mead, 1965].

The LLSSIM is used to identify the architecture and weights of an ANN, assuming that the number of hidden nodes is known initially. In this algorithm two bias nodes one each in input layer and hidden layer are assigned. The algorithm takes advantage of the weight space partition to conduct the nonlinear portion of the search in a reduced dimensional space, resulting in an acceleration of the training process. The simplex search algorithm provides improved global search characteristics owing to the use of multiple starts initiated randomly in the search space and its ability to not be trapped by minor local optima. Identification of ANN structure is done using a strategy of progressively adding nodes to the hidden layer until a structure appropriate to the complexity of the problem is achieved.

2.4.4 Architecture of ANN

The optimal architecture is one which yields the best performance in terms of error minimization, while retaining simple and compact structure. No unified theory exists for deciding such an optimal structure.The number of input and output nodes are problem dependent. The flexibility lies in selecting number of hidden layers and in assigning the number of nodes to each of these layers. A trial and error procedure is applied to decide the optimal architecture. The LLSSIM is an efficient method for finding the architecture and training the network and the same is used in the present study.

2.5 APPLICATIONS

ANNs have found applications in diverse fields such as neuro-physiology, physics, biomedical engg., electrical engg., computer science, acoustics, cybernetics, robotics, image processing, financing. They have been successfully used in hydrology related areas such as rainfall – runoff modeling, stream flow forecasting, ground water modeling, water quality, water management policy, precipitation forecasting, and reservoir operations.

2.5.1 Rainfall- Runoff Modeling using ANNs

The water shed is a complex system that may be poorly described or less understood. The rain that falls on ground is influenced by certain physical processes which depends on antecedent moisture content, depression storages, infiltration to the subsurface flow, slope of the catchment, vegetation, soil characteristics and land use pattern.Under these physical parameters it is utmost difficult to estimate the likely runoff from a particular storm. Further, the data that is supplied by different field authorities is not always consistent, neither the record is long and continuous.

The ANN architecture that is developed from the training process captures the influencing physical parameters. This is because the training is given by inducing the rainfall and runoff into the network and allowed it to recognize the patterns among input data and store the related connection weights between the nodes of the structure. The number of nodes and inter connections and respective weights or parameters associated with these interconnections are system dependent. The weights and the input data are used along with the number of nodes to find out the output runoff, the coefficient of correlation and the sum of least square errors between observed and computed runoff.

The validity of the ANN structure is established by supplying different data set of the same watershed into the ANN along with the weights stored in training process and finding the coefficient of correlation and sum of least square errors between the observed and computed runoff. If these values are comparable with those obtained in training process, the structure is said to be able to recognize the new patterns from the watershed and can be used as a model, i.e. ANN model. The schematic diagram of rainfall-runoff process through ANN structure is shown in Fig.2.5.

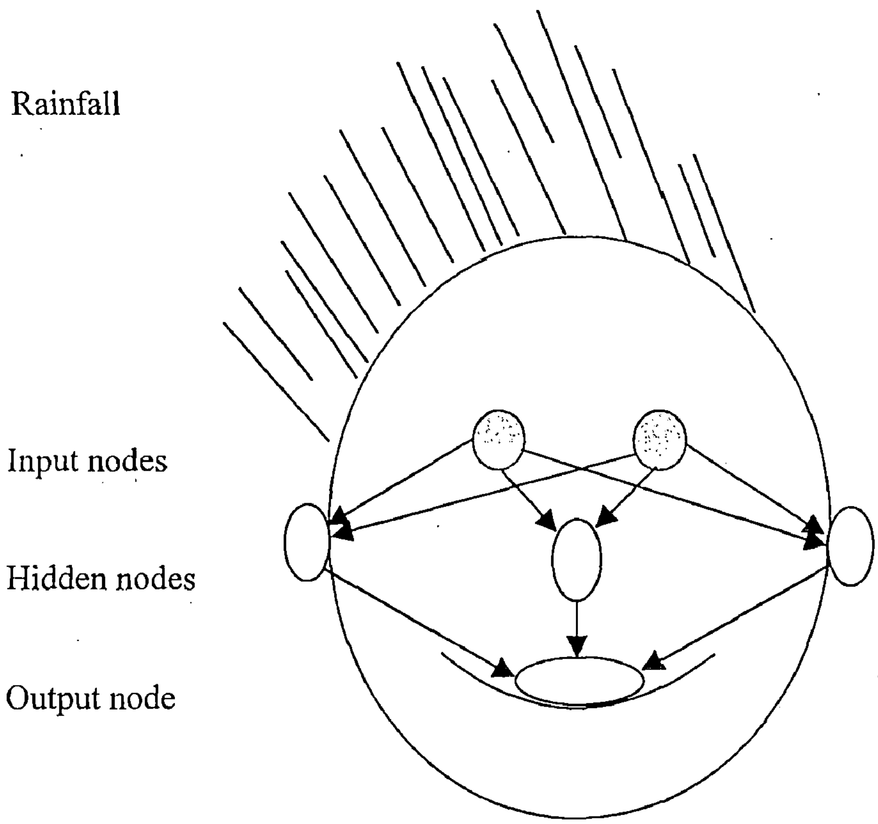


Fig.2.5: Schematic diagram of rainfall – runoff process through ANN structure

The rainfall that is received by peripheral brain that is the catchment surface is seen by eyes that are input nodes. The patterns are recognised by sensitive organs ears and nose which are hidden nodes and output is obtained from mouth that is output node.

CHAPTER 3

A PEEP INTO THE PAST

3.1 HYDROLOGICAL MODELS

There are many models available in the field of hydrologic modeling. Some of the conceptual, physically based and mathematical models are briefed below.

3.1.1 SAC-SMA Model

The Sacramento soil moisture accounting (SAC-SMA) model is a conceptual rainfall-runoff model that is one of the components of the National Weather Service River Forecast System (NWSRFS) used to convert precipitation inputs into stream flow outputs (Burnash et al.,1973; Peck,1976; Kitanidis and Bras,1980; Brazil and Hudlow,1980). The inputs to the SAC-SMA model are mean precipitation and potential evapotranspiration. The outputs from the model are estimated evapotranspiration and channel inflow the latter is converted into stream flow by means of a unit hydrograph.

3.1.2 SCRR Model

The conceptual rainfall-runoff model, SCRR, that was developed by McCuen and Snyder (1986) has three storage components-surface, ground water and the unsaturated zone.. The objectives are to approximate a combination of total measured runoff, peak discharges, timing of peak discharges, soil moisture state at the beginning of the record, recession of the storm events, and bias in the flow during dry periods.

3.1.3 Watbal Model

The Watbal model is a physically based model used for forecasting water yields in areas where runoff is dominated by snowmelt (leaf and Brink 1973, 1976; Leaf and Alexander 1975; Markus and Baker 1994). It simulates winter snow accumulation, short wave and long wave radiation balance, snow pack conditions, snowmelt, evapotranspiration and subsequent runoff in time and space. Short wave and long wave radiation represents the energy components available for snowmelt. Long wave radiation is computed by the Stefan-Boltzmann equation (Leaf and Brink 1973,1975).

Snowpack reflectivity varies with precipitation form, air temperature and the water balance. Th snow pack will yield snowmelt only when it becomes isothermal at 0^0C,and its free water holdin capacity is reached. Evapotranspiration is derived from the Hamon equation (Leaf and Brink 1973 1975) for potential evapotranspiration reduced in proportion to the radiation actually received.

3.1.4 ARMAX Model

The ARMAX model can be viewed as a simpler version of the ANN model with a linear threshold function as the transfer function and no hidden layer. The ARMAX model might be expected to simulate very well the behaviour of systems whose input–output characteristics are approximately linear. While this is not usually true for rainfall-runoff systems, ARMAX models have been widely used for watershed modeling because of the ease with which they can be developed (O'Connell and Clarke, 1981; Young and Wallis,1985)

3.1.5 Regression Models

This conventional mathematical modeling technique is widely used in hydrological modeling and performs analysis by using the least squares method to fit a line through a set of observations. The inputs to a system are cause variables and outputs from a system are effect variables. The initial selection of cause variables with strong theoretical justification is required to have a good regression model. In regression model the coefficient of correlation (COR) is a measure of linear association. We can analyze how a single variable is affected by the values of one or more cause variables. The general model equation for a single independent variable is

$$Y = ax + b \tag{3.1}$$

Multiple regression is also an effective tool in trend analysis where one or more cause variables are used to account for the temporal and spatial trend in some relationship. In a multiple linear regression model, the general equation will be

$$Y = m_1x_1 + m_2x_2 + m_3x_3 + \text{------} m_nx_n + b \tag{3.2}$$

Where,

x, x_1, x_2, x_3---, x_n are the cause variables / independent variables.

n is the number of variables

m, m_1, m_2, m_3----, m_n are coefficients / slopes obtained for each of the cause variables

3.2 RELEVANT STATISTICS

When neural networks are used to model one step ahead predictions the solution will in most cases produce a high or near perfect level of fit statistic. All such measures therefore give no real indication of what the network is getting right and wrong or where improvements could be made. Indeed, neural networks are designed to minimise global measures, and a more appropriate metric that identifies real problems and between network differences is perhaps long overdue. However, with embedded solutions and the incorporation of accumulated error the situation is quite different and that there still exists an important role for global statistics. The following are the some of the relevant statistics generally used in the evaluation of results of hydrological models.

3.2.1 Greatest Absolute Error (GAE)

The largest positive error (over prediction) and the largest negative error (under prediction) are seldom reported, although such figures are important in terms of their cumulative knock-on influences and potential ramifications with respect to all applied operations and prediction end users.

3.2.2 Sum of the Squared Errors (SSE)

SSE is a global total that provides an overall estimate of modeling performance. No account is made for sample size and a direct comparison of unequal samples will generate misleading information. It is the most common objective criterion used in fitting and testing models and was the error minimisation function used in the training procedure.

$$SSE = \Sigma(\text{observed-estimated})^2 \qquad (3.3)$$

3.2.3 Mean Absolute Error (MAE)

MAE is a global average wherein all deviations from the original data, be the positive or negative, are treated on an equal basis. Variations in sample size are also accounted for and the statistic is not weighted towards high flow events that tend to be amongst the poorest predictions.

$$MAE = [\Sigma |observed\text{-}estimated|]/N. \tag{3.4}$$

Where N is number of samples

3.2.4 Root Mean Squared Error (RMSE)

RMSE is a common statistical measure. It is often used in neural networks and the other hydrological models. Sample size is taken into consideration and the result is adjusted to reduce the impact of significant errors associated with high flow events.

$$RMSE = \sqrt{[\Sigma(observed\text{-}estimated)^2/N]} \tag{3.5}$$

3.2.5 Coefficiency of Efficiency (COE)

This is a standard hydrological statistic based on moments about the mean. The final value is multiplied by 100 to convert it into a percentage.

$$COE = 1\text{- (variance of the residual error/ variance of the original data)} \tag{3.6}$$

$$= [1 - \{\Sigma(Y - Y^*)^2 / \Sigma(Y - Y_{mean})^2\}] * 100$$

Where,

Y = observed runoff

Y^* = computed runoff

Y_{mean} = Mean of the observed runoff

3.3 RECENT ANN APPLICATIONS IN HYDROLOGY

In the recent past, ANNs have been increasingly used in the modeling of hydrological processes. Some of the significant contributions from the scholars who has created interest and scope for further studies, are presented below.

- Gautam et al (1998), put forth that the RMS error tends to increase with the prediction time, and increase is at a higher rate for the model based on data insertion than for the model based on auto regressive neural networks which are introduced for the non-linear analysis and modeling of time series.
- Hall & Minns (1998) while analysing regional flood frequency using artificial neural networks, suggested that the bias in the relationship between ANN computed and observed flood quantiles is associated more with catchment size than with location of the region.
- Khondker et al (1998) revealed that the use of recursive forecasting (in which the current output will become the next input) in ANNs will help in maintaining the accuracy, which otherwise will be diminishing as the forecast horizon is increased.

  Lange (1998) introduced the idea of generating an hydrograph which is similar to a unit hydrograph with the help of a trained network which reduces calculation time and provides utility in the existing hydrological procedure and models.
- Luk et al (1998), while forecasting rainfall through ANNs, indicated that the lower order lag showed better performance, thus revealing the fact that the rainfall time series may not have a long time dependence structure. Further, suggested that the optimal complexity of network is due to a combined effect of the order of lag and number of hidden nodes.
- Marina et al (1999) put forth that ANN can be applied to forecast the river flow rate on the basis of rainfall and water level data.
- Jain et al (1999) revealed that ANNs can be used for reservoir inflow prediction and operation while Nachimuthu et al (1994) evaluated the applicability of ANN with the available linear output unit for river flow prediction.
- Raman and Sunil kumar (1995) used an ANN to synthesize reservoir flow generation. Similarly, there are few climatological ANN applications such as snowfall prediction,

classification of arctic cloud and sea ice, precipitation and more recently climate change impact modeling(Hewitson and Crane,1996)

- Jain and Chalisgaonkar (2000) found that more and more information, if supplied to input layer the performance improved rapidly and for an hypothetical data set of a loop rating curve, ANN could achieve an almost perfect match.
- Hall and Minns (1998) explained the application of ANN in regional flood frequency analysis is more feasible and practically acceptable.
- Markus et al (1995) using ANNs to predict monthly stream flows at the Del Norte gauging station in the Rio Grande basin in Southern Colorada, revealed that the inclusion of temperature as input improved the model performance.
- Muttiah et al (1997) while predicting two year peak discharge from watersheds all over the United States suggested that the drainage area and basin elevations could be used for predicting two year peak discharges.
- The studies of Karunanithi et al (1994) and Thirumalaiah and Deo (1998) directed network training to better replicate low streamflow events, while Poff et al (1996) concentrated on high flow events to generate improved statistics for floods.
- Hsu et al (1997) provided some heuristic functional relationships between input and output variables of ANN by using self organizing feature maps of the input variables.
- Tokar and Johnson (1999) reported that the length of training record had a much smaller impact on network performance than the types of training data.
- Gupta et al.(1997) concluded that the LLSSIM is likely to be a better training algorithm than back propagation or conjugate gradient techniques, especially in the absence of initial guess of weights.
- Carriere (1996) developed a virtual runoff hydrograph system that employed a recurrent back propagation artificial neural network to generate runoff hydrographs.

3.4 CURRENT STATUS

Currently the ANNs are more attractive in the field of research due to their simplicity in model formulation and requirement of limited data. However the following limitations as revealed by the ASCE task committee (2000) are required to be answered so as the utility of these models can be extended to various fields for the speedy process of planning and development.

1. Most ANN applications have been unable to explain in a comprehensibly meaningful way the basic process by which ANNs arrive at a decision. The physics is locked up in the set of optimal weights and threshold values.
2. In absence of fixed rule to identify the optimal data set for training, trial and error procedure is applied. The optimal data set is one that fully represents the modeling domain and has minimum number of data pairs.
3. The weights do not reveal any physical and statistical interpretation and hence the ANN training cannot be handled in an adaptive fashion.
4. The performance of ANN deteriorated rapidly when the input vectors were far from the space of inputs used for training. Hence the ANNs are poor extrapolators.

3.5 LOOKING FORWARD

In connection with adaptation of new technology, Govinda Raju & Rao opined:

"The reactions to any new technology are common. Skepticism accompanies any new method. People who are comfortable with the existing methods have certain amount of inertia to overcome before adopting a new methodology. Not every body is willing to go through a possibly steep learning curve every time something new comes along."

Dowla and Rogers (1995) state that ANN applications in hydrology will go through three stages.

1. To apply ANNs to old problems that have been solved by other existing methods.
2. To apply ANNs to old unsolved problems that are now amenable to solution with this method.
3. To apply ANNs to new problems to further enhance their role in hydrology

According to ANNs to gain a strong foothold in hydrology and establish as a viable tool, the following things must happen.

1. The practicing community must take sufficient interest and adopt this technique for solving the real world problems.
2. Most academicians like to work on problems that are interesting and challenging. After the initial novelty has worn off ,the challenge is to find more elegant methods for solving new hydrological problems. Instead, the technology should reach the practitioners.
3. Funding opportunities play a large role in how a particular area develops. Funding agencies need to give higher priority to encourage research in this area, and thus help in bringing it to maturity.

CHAPTER 4

STUDY AREA , DATA AVAILABILITY AND DATA PROCESSING

4.1 GENERAL

The study areas are selected in such a way that different regions as well as areas with varied size in the same region are covered in the study. Accordingly the Paleru and Musi sub basins of Krishna basin in Andhrapradesh and Samakoi sub basin of Brahmani basin in Orissa are considered for the study

4.1.1 Paleru Sub Basin

Paleru river is one of the tributaries of the river Krishna joining in its tail reaches. It covers a drainage area of 1.27 percent of the total Krishna basin and lies wholly in Andhra Pradesh, covering the part districts of Warangal, Nalgonda, Khammam and Krishna. There are in all 6 tributaries joining the Paleru, four on the right side and two on the left side.There are many tanks intercepting the catchment of the tributaries along the river course. Most of the area in the sub basin is rugged in nature with patches of smooth surface here and there. A very large plateau of the catchment is having an average elevation of about 168.0m. There are some flatter strips of the catchment on the left side of the Paleru river. The catchment is having the shape of a fern leaf. Major portion is covered by Deccan trap rocks, which on disintegration give rise to red soils. The gneisses rock formations are also found. The types of soils generated from the above geological formations are permeable. The surface is covered with murum and as such runoff is moderate in the sub basin. The quantum of non monsoon observed flows make us to believe that the seeping water has outlets in to the streams of the catchment. The studies by CGWB and SGWB reveal that in all the geological formations, viz. Dharwar schists, peninsular gneisses, in alluvial deposits etc. ground water occurs in the sub basin.

The catchment is served by 10 raingauge stations out of which 7 are considered in the study. It is seen that most of the rainfall i.e. up to 90 percent of annual rainfall occurs during the monsoon months of June to November.. In the non monsoon months there is hardly any yield as the rainfall is very low. The monthly discharges measured at Paleru bridge CWC G&D site and the existing utilisations from the irrigation departments are used in the study.

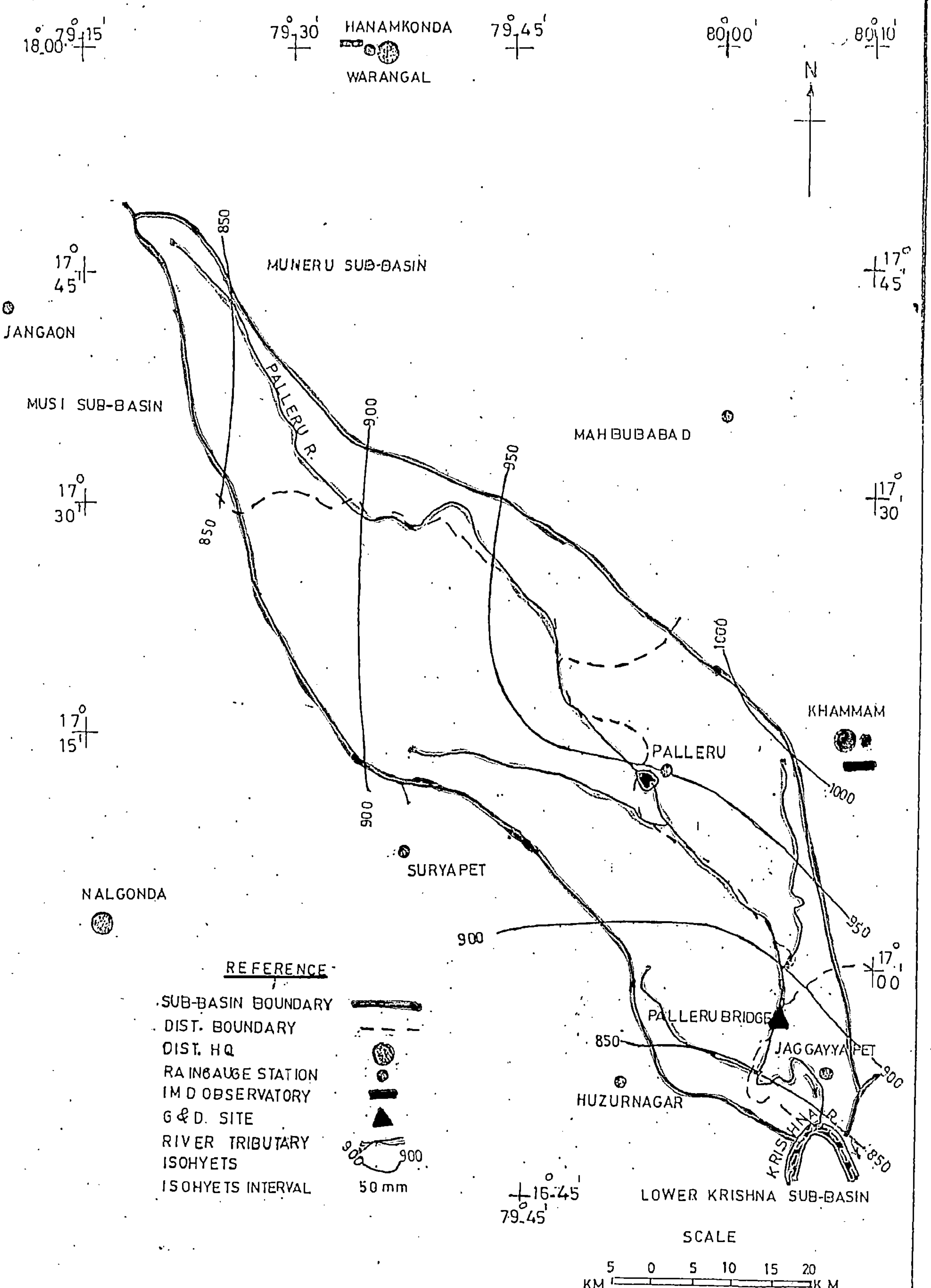
Much heat is experienced during summer and the climate in winter is moderate. The mean annual PET in the catchment is 2540mm. The humidity is as low as 31 percent in dry weather and as high as 81 percent in monsoon as per the records of Khammam observatory. The wind velocity is moderate during entire period but increases during latter part of summer and earlier part of monsoon.

The red soils are the predominant in the sub basin and covers about 96 percent of the catchment area. More friable, light textured and sufficiently permeable and well drained. These soils mostly suited for crops like Jawar, Bazra,Maize, Pulses, Groundnut etc. Based on quality and quantity of irrigation , water, drainage features, land development cost and high benefit cost ratio, the soils of the catchment are placed under Class I of land irrigability classification.The forest area comprises of 6 percent, the culturable area accounts for 82 percent of geographical area and net area sown is 61 percent of culturable area. The index map of the sub basin is shown at Plate 4.1.

4.1.2 Musi Sub Basin

Musi river is one of the tributaries of the river Krishna joining in its tail reaches. It covers a drainage area of 4 percent of the total Krishna basin and lies wholly in AndhraPradesh, covering the part districts of Hyderabad, Rangareddy, Medak, Nalgonda, Warangal and Mahabubnagar. A very large plateau of the catchment is having an elevation of about 640 m at source and 52m at its confluence. The sub basin has a shape of an arc with an average length and width of 225km and 45km respectively. The geological rock formations of the peninsular granites, the Puranas and the Deccan traps. The types of soils generated from these formations are mostly permeable. The hydro-geological studies by CGWB and SGWB reveal that the groundwater occurs in all geological formations viz. peninsular granites, puranas,shales,sand-stones,etc.in the sub basin.

Plate 4.1



Index map of Paleru sub basin

28

The climate of the sub basin is characterised by a hot summer and a mild winter. The sub basin is affected by both the south-west and the north-east monsoons. There are 19 raingauge stations in and around the sub basin of which 15 are considered in the study. The monsoon period has been considered from 1st June to 30th November in the hydrological study of the sub basin. The average annual rainfall of the catchment is 839 mm, most of which occurs in the monsoon months. The monthly discharges measured at Dameracherla CWC G&D site and the existing utilisations from the irrigation departments are used in the study.

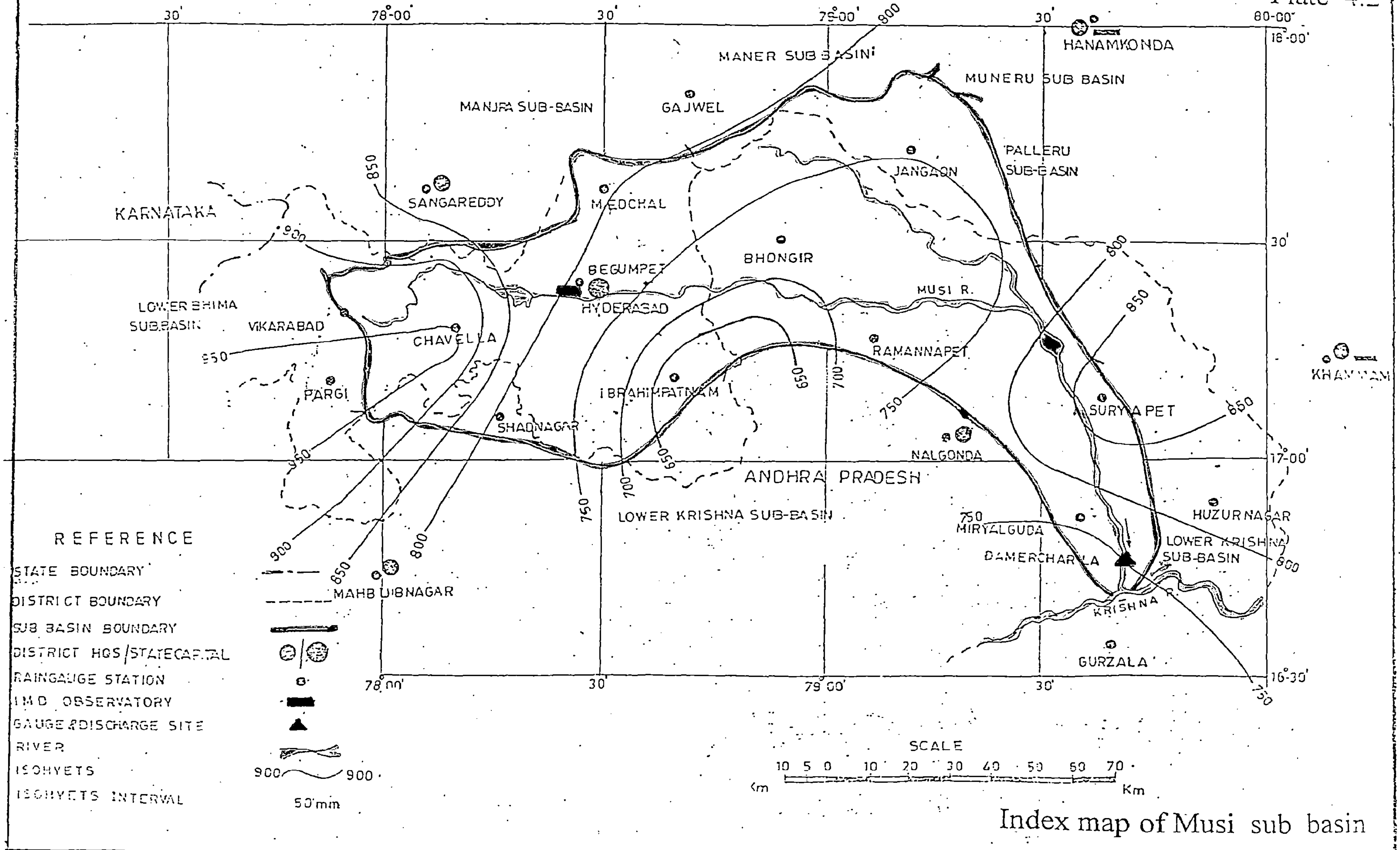
The average annual maximum and minimum temperatures as recorded at the IMD Observatory at Hyderabad are 31.7 °C and 20.0 oC respectively. In the summer the weather is dry and the humidity is low. The sub basin is influenced by winds from south west during monsoon the same are from north-east and south-east in the non-monsoon. The sky is heavily clouded during the south-west monsoon and is clear or lightly clouded in the rest of the period. The sunshine percentage in the catchment varies from 93 to 21. The annual PET in the catchment is 1756.8 mm as recorded at Hyderabad observatory.

The red sandy soils and red earths are the predominant in the sub basin and together covers about 91 percent of the catchment area. More friable, light textured and sufficiently permeable and well drained. These soils developed from granite gneissic complex and are brown in colour, coarse to medium in texture and possess moderate to good drainage characteristics. The forest area comprises of 4 percent, the culturable area accounts for 72 percent of geographical area and net area sown is 43 percent of culturable area. The index map of the sub basin is shown at Plate 4.2.

4.1.3 Samakoi Sub Basin

Samakoi is a small tributary stream originating in Keonjhar district of Orissa and joining the river Brahmani on its left side few kilometers upstream of Samal barrage. The catchment area of the study up to the proposed Samakoi barrage site is 787 sq.km.The whole catchment comes under the free catchment area between Rengali dam and Samal barrage.

Plate 4.2



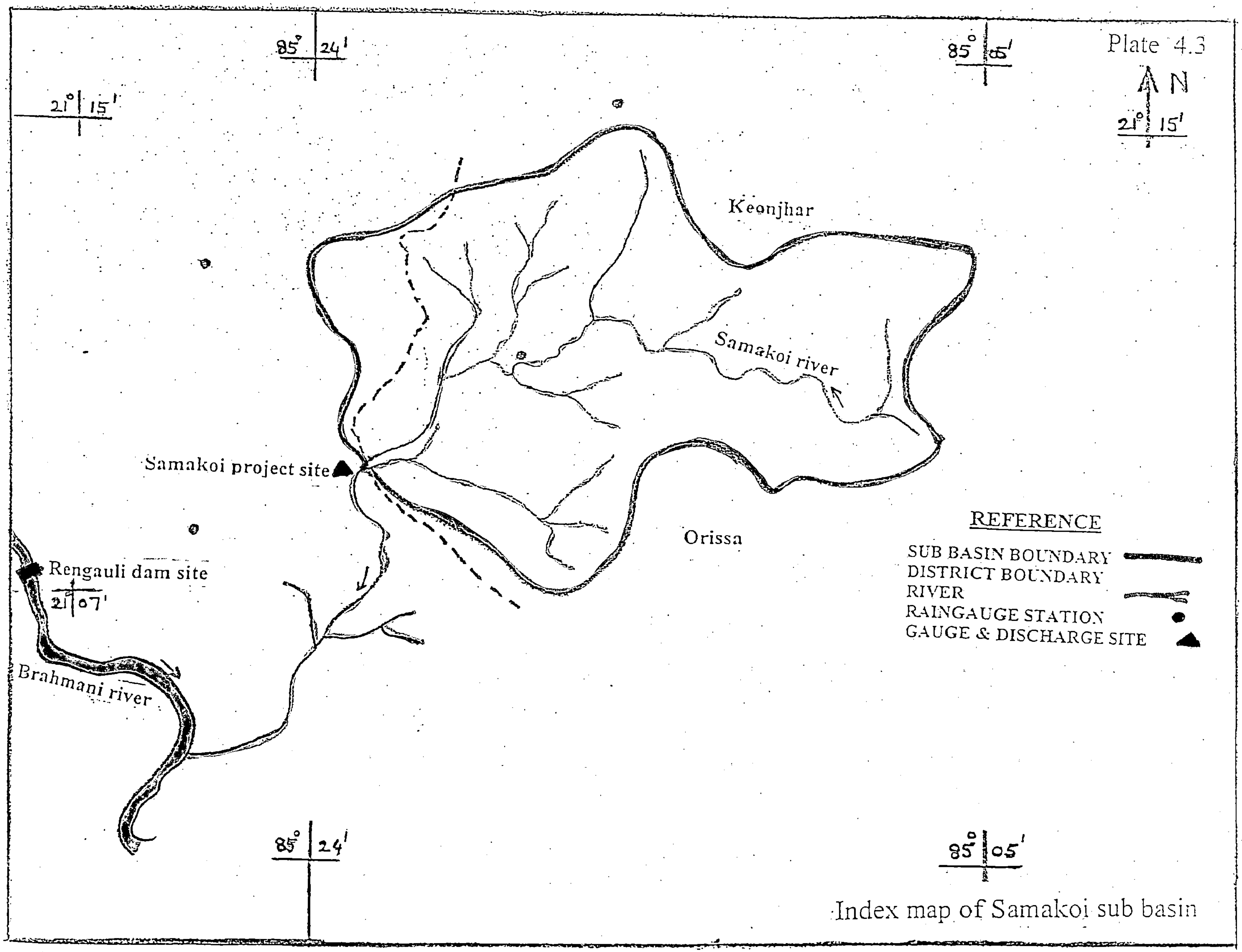
Index map of Musi sub basin

38

The Archean metamorphic and Gondwana sedimentary rocks of Damuda and Talcher series are mainly seen in exposed form in the area. Recent and old Alluvium is also marked in the flood plains and valleys of land form. The area as a whole is gently undulating to gently sloping plain and topographically categorised as the erosional plains with gentle slopes infested with vast extent of agricultural lands and open mixed jungles. The erosional ground constitutes small hills, rock out crops, anticlinal and synclinal ridges and valleys. The depositional grounds are general flood basins of middle reaches of Brahmani basin. The elevation of the catchment at barrage site is about 140m.The river flows in sandy soil. The soil cover generally varies between 45-90 cm and texturally they are mixed with fine, medium and coarse textured soils.

The catchment is served by four rain gauge stations in and around the catchment. The maximum and minimum annual rainfall is 2260mm and 800mm respectively. Nearly 87 percent of the rainfall is received during monsoon months of June to October, the balance being in the non monsoon months. Though the average rainfall is fairly high, it is erratic in nature, entailing late arrival, long dry spells, early withdrawal and considerable variations in quantity both within a year and from year to year. The climate is tropical humid with hot summer and mild winter. The mean annual temperature in the area is about 27°C and the mean maximum and minimum temperature is 32° C and 21.9°C. The mean relative humidity for the project area based on observations made from 1966-67 to 1985-86 at Angul IMD observatory is about 63 percent with maximum of 80 percent in August and minimum of 26 percent in March. The index map of Samakoi sub basin is shown at Plate 4.3. The topographical, climatological and hydrogeological details are given in Table 4.1 for the above three sub basins.

Plate 4.3



Index map of Samakoi sub basin

Table 4.1

Topographical, climatological and hydrogeological details

Sl.no	Parameter	Paleru sub basin Case 1	Musi sub basin Case 2	Samakoi sub basin -Case 3
1	**Location**	Lower reaches of Krishna in AP	Lower reaches of Krishna in AP	Middle reaches of Brahmani, Orissa
	Latitude	16° 39' to 17° 50'(N)	16° 40' to 17° 2' (N)	21°7' to 21° 15' (N)
	Longitude	79°17' to 80°09'(E)	77° 52' to 79° 45' (E)	85° 5' to 85°24' (E)
2	**Area(sqkm)**	2928	11050	787
3	**Elevation**			
	Altitude at source (m)	375	661	
	Altitude at tail end(m)	41.45	61	140
	Wtd. Avg.elevation(m)	63.50		
	Slope %	1 to 3		
4	**Shape of the area**	Fern leaf	Fern leaf	Fan
5	**Length of river (km)**	152	265	52
6	**Geology**	Deccan traps with murum surface	Peninsular granites, Puranas and Deccan traps	Gondwana rocks of Talcher series.
7	**Climate**			
	IMD	Khammam	Hyderabad	
	Annu.avg.Rainfall(mm)	913.7	839	1530
	Monsoon rainfall(%)	91.41	91.66	
	PET(mean annual) mm	1676.6	1756.8	
	Wind speed(mean)km/hr	7.2-9.2	12.6	
	Temperature			
	Max °C	34.2	31.7	
	Min °C	22.9	20.0	
8	**Soils**			
	Depth of soil cover, cm	30-95	5-75	45-90
	Soil type	Red soils (95.67%)	Red soils (90.70%)	Sandy soils
	Permeability, cm/hr	18.5	Good drainage	
	Water table, m	11-20		
9	**Land use (sq,km)**			
	Year	1978-79	1979-80	
	Forest	161	449.27	
	Barren	156	713.67	
	Non-agri. Use	182	1049.13	
	Permanent pastures	324	911.65	
	Land under misc.crops	9	82.17	
	Culturable waste	86	334.63	
	Other follows	114	1064.10	
	Current follows	416	2616.01	
	Net area sown	1480	3829.36	
	Gross area sown	1852	4512.95	
	Geographical area	2928	11050	

2 DATA AVAILABILITY

The required data have been collected from the office of the Chief Engineer, Central 'ater Commission, Hyderabad, and from the library of The Bureau of Economics, yderabad.. The data availability of three of the study areas are shown below.

) Monthly rainfall data for 7 rain gauges located in and around the Paleru sub basin and monthly discharge data of Paleru river at Paleru bridge G&D site for the period from 1965-66 to1982-83. The data available for this sub basin is shown in Appendix-A.

) Monthly rainfall data for 15 rain gauges located in and around the Musi sub basin and monthly discharge data of Musi river at Dameracherla G&D site for the period from 1968-69 to 1982-83. The data available for this sub basin is shown in Appendix-B

) Ten daily rainfall data for the 4 rain gauges located in and around the Samakoi sub basin and the Ten daily discharges of the Samakoi river at barrage site for the period from 1985 to 1995. The monthly and ten daily data available for this sub basin is shown in Appendix–C and Appendix- D respectively.

.3 PROCESSING OF DATA

Before using the rainfall and discharge data as available from the field as input, it is ːquired to check the same for its consistency. Accordingly the rainfall data is checked for s consistency using double mass curve. Further the runoff coefficient (RC) that is defined as ıe ratio of runoff and rainfall in the same units, is also used to check the consistency of ischarge i.e.

$$RC = Q / R \qquad (5.1)$$

/here, R is the rainfall in mm for a specified period

Q is the runoff in mm for the same specified period

The runoff coefficients are calculated monthly, annually and seasonally for all the three sub ısins vi., Paleru, Musi and Samakoi(ten daily and monthly) and are furnished in Table 4.2, Table 3, Table 4.4 and Table 4.5 respectively.

Table 4.2

Monthly, Annual and Seasonal Run off coefficients of Paleru sub basin

Year	Jun	Jul	Aug	Sep	Oct	Nov	Mon	Dec	Jan	Feb	Mar	Apr	May	Non	Ann
1965	0.03	0.17	0.19	0.27	15.83	23.57	**0.24**	31.20	0.02	**0.00**	**0.00**	0.01	1.16	**0.03**	**0.21**
1966	0.04	0.05	0.10	0.11	0.25	0.25	**0.09**	0.02	0.21	**0.00**	0.00	0.01	0.01	**0.01**	**0.08**
1967	0.02	0.17	0.13	0.11	2.09	**0.00**	**0.16**	0.02	0.02	0.01	0.03	0.00	0.01	**0.01**	**0.14**
1968	0.02	0.05	0.06	0.08	0.13	0.15	**0.07**	0.24	0.03	**0.00**	**0.00**	0.05	0.09	**0.09**	**0.08**
1969	0.03	0.02	0.07	0.19	0.25	0.77	**0.19**	0.52	40.37	0.32	0.12	0.04	0.04	**0.18**	**0.19**
1970	0.04	0.04	0.43	0.22	0.31	**0.00**	**0.24**	**0.00**	**0.00**	0.08	0.14	0.41	0.02	**0.10**	**0.23**
1971	0.03	0.01	0.03	0.07	0.10	**0.00**	**0.07**	**0.00**	**0.00**	0.38	**0.00**	0.04	0.02	**0.25**	**0.07**
1972	0.01	0.01	0.03	0.10	0.09	0.15	**0.07**	0.46	**0.00**	**0.00**	0.13	0.09	0.02	**0.19**	**0.07**
1973	0.02	0.01	0.09	0.16	0.22	0.88	**0.12**	**0.00**	**0.00**	**0.00**	**0.00**	0.35	0.01	**0.16**	**0.12**
1974	0.01	0.00	0.04	0.11	0.28	2.66	**0.16**	**0.00**	0.71	1.11	**0.00**	1.95	0.03	**0.46**	**0.18**
1975	0.01	0.05	0.21	0.42	0.56	1.56	**0.28**	**0.00**	41.47	24.2	29.85	1.66	0.05	**0.85**	**0.30**
1976	0.02	0.09	0.52	0.65	0.67	0.40	**0.34**	**0.00**	**0.00**	**0.00**	0.98	0.02	0.04	**0.12**	**0.32**
1977	0.03	0.07	0.19	0.45	0.31	0.22	**0.20**	0.45	0.26	1.19	10.36	2.66	0.25	**0.68**	**0.24**
1978	0.09	0.18	0.45	0.23	0.40	0.41	**0.28**	46.03	**0.00**	0.02	18.33	0.20	0.04	**0.10**	**0.26**
1979	0.01	0.01	0.17	0.18	0.56	0.57	**0.19**	2.63	0.99	**0.00**	2.54	1.09	0.36	**1.80**	**0.32**
1980	0.06	0.21	0.34	0.36	1.45	8.61	**0.29**	0.49	0.49	**0.00**	0.03	0.22	0.04	**0.12**	**0.27**
1981	0.01	0.10	0.32	0.24	0.64	2.06	**0.24**	6.06	**0.00**	**0.00**	0.25	0.13	0.02	**0.14**	**0.23**
1982	0.01	0.02	0.31	0.23	0.38	0.67	**0.18**	**0.00**	**0.00**	5.67	**0.00**	0.82	0.16	**2.53**	**0.22**

0.0 -indicates the RCs obtained against zero rainfall or zero runoff

The monthly runoff coefficients vary between 0.0 and 46.03 in case of Paleru sub basin and the high values up to 46.03 in the post monsoon period are attributed to the bank storage and return flows from canals. The annual values in the range of 0.07 and 0.32 appear to be consistent. The runoff coefficients are calculated on seasonal basis too and lie in the range of 0.07 to 0.34 for the monsoon period of June to November and in the range of 0.01 to 2.53 for the non - monsoon period. Fig.4.1 shows the temporal variations.

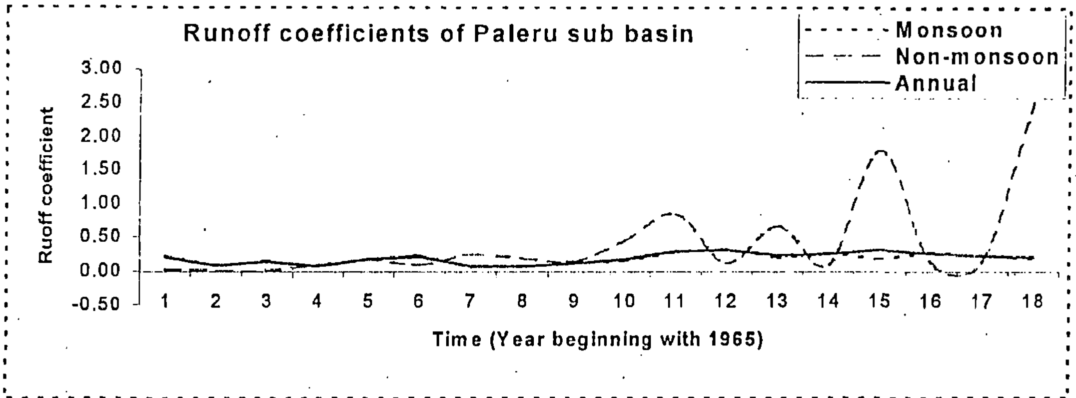


Fig. 4.2: Run off coefficients of Paleru sub basin

Table 4.3

Monthly, Annual and Seasonal Runoff coefficients of Musi sub basin

Year	Jun	July	Aug	Sept	Oct	Nov	Mon	Dec	Jan	Feb	Mar	Apr	May	Non	Ann
1968	0.0	0.0	0.6	0.1	0.4	1.2	0.2	29.7	4.3	0	8.1	0.9	0.1	0.9	0.2
1969	0.0	0.0	0.2	0.2	0.5	0.4	0.2	0.4	20.6	5.5	1.3	0.4	0.0	0.5	0.2
1970	0.0	0.3	0.2	0.2	0.5	0	0.2	0	23.0	1.9	3.2	0.1	0.0	0.5	0.2
1971	0.0	0.1	0.1	0.2	0.2	0	0.1	0	0	4.1	0	0.1	0.1	1.0	0.2
1972	0.0	0.0	0.1	0.1	0.2	0.2	0.1	1.0	0	0	1.2	0.2	0.0	0.6	0.1
1973	0.0	0.0	0.1	0.1	0.2	0.5	0.1	29.1	0	0	5.0	0.7	0.0	0.5	0.1
1974	0.0	0.0	0.1	0.1	0.1	2.4	0.1	0	0.4	0.7	0.3	0.7	0.0	0.3	0.2
1975	0.0	0.0	0.1	0.2	0.5	2.8	0.3	0	0	0	7.7	0.1	0.1	0.9	0.3
1976	0.0	0.0	0.2	0.6	2.1	0.2	0.2	0	0	63.0	0.8	0.1	0.1	0.3	0.2
1977	0.0	0.0	0.1	0.4	0.2	0.2	0.1	0.2	0.1	0.2	4.2	0.2	0.0	0.1	0.1
1978	0.0	0.1	0.3	0.2	0.5	0.3	0.2	0	12.9	0.1	0	0.2	0.0	0.2	0.2
1979	0.0	0.1	0.1	0.1	0.5	0.2	0.1	0.6	1.3	0	1.0	0.2	0.1	0.5	0.1
1980	0.0	0.1	0.1	0.2	1.8	1.2	0.1	0.3	0.1	0	0.0	0.0	0.0	0.0	0.1
1981	0.0	0.0	0.1	0.1	0.4	12.0	0.1	5.3	0	0	0.0	0.0	0.0	0.0	0.1
1982	0.0	0.0	0.1	0.1	0.2	0.4	0.1	0	0	1.0	0.1	0.0	0.0	0.2	0.1

0.00-indicates the RCs obtained against zero rainfall or zero runoff

The monthly runoff coefficients vary between 0.0 and 63.00 in case of Musi sub basin and the high values up to 63.00 in the post monsoon period are attributed to the bank storage and return flows from canals in this sub basin too. The annual value in the range of 0.1 and 0.3 are appears to be consistent. The runoff coefficients are calculated on seasonal basis too and lies in the range of 0.1 to 0.3 for the monsoon period of June to November and in the range of 0.0 to 1.0 for the non - monsoon period.Fig.4.2 shows these details.

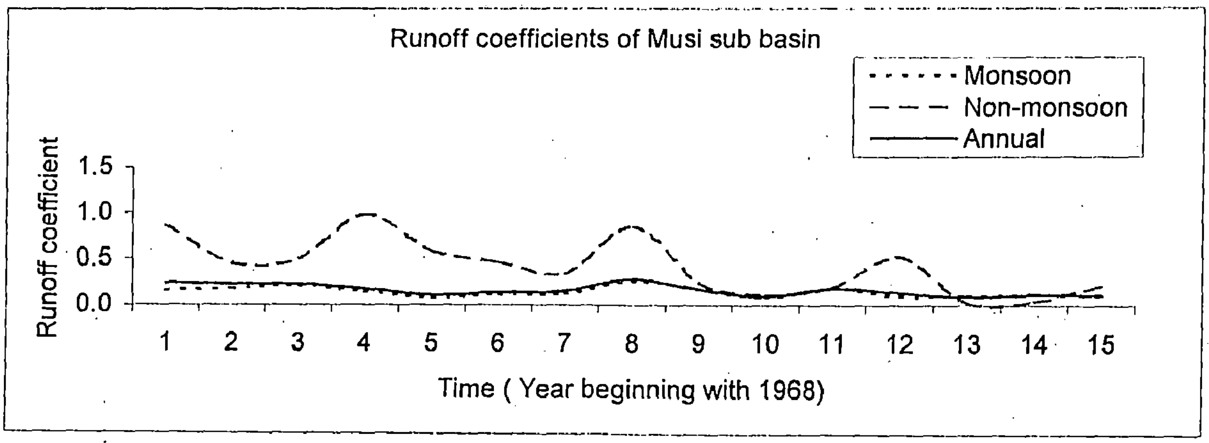


Fig. 4.2: Run off coefficients of Musi sub basin

Table 4.4

Ten daily and Seasonal Runoff coefficients of Samakoi sub basin

Year	Jun -1	June -2	June -3	July-1	July-2	July-3	Augt -1	Aug-2	Aug-3	Sept-1	Sept-2	Sept-3	Oct-1	Oct-2	Oct-3	Mon soon
1985	0.0	0.4	0.0	0.3	0.3	0.1	0.5	0.4	0.5	0.8	0.5	0.3	0.2	0.8	0.4	**0.4**
1986	0.0	0.1	0.2	0.3	0.4	0.7	0.5	0.5	0.8	0.4	0.3	0.2	0.4	1.0	0.5	**0.4**
1987	1.0	0.1	0.0	0.1	0.4	0.6	0.5	0.1	0.6	0.5	0.4	0.7	0.6	0.5	0.6	**0.4**
1988	0.0	0.2	0.3	0.3	1.0	0.2	0.5	1.7	0.7	0.6	0.9	0.9	0.6	1.7	0.4	**0.5**
1989	0.0	2.1	0.8	0.8	0.2	1.3	1.1	1.1	0.6	0.4	3.0	0.7	2.5	0.4	0.5	**0.9**
1990	0.8	0.2	0.1	0.3	0.9	0.6	0.2	0.2	2.0	1.1	0.6	3.3	1.3	1.2	1.7	**0.6**
1991	0.0	0.1	0.1	0.1	0.2	0.9	0.3	1.2	0.9	0.8	0.1	7.5	0.8	3.3	0.5	**0.5**
1992	0.4	0.2	0.1	0.0	0.0	0.8	0.4	1.6	1.4	0.5	0.8	0.2	0.6	0.2	0.4	**0.4**
1993	0.0	0.1	0.3	0.1	0.2	0.1	0.3	0.6	1.6	0.5	0.7	1.4	0.4	0.3	0.9	**0.4**
1994	0.0	0.3	0.3	0.3	0.1	0.4	0.7	0.8	0.1	0.9	1.2	3.6	0.4	2.1	0.3	**0.4**
1995	0.1	0.4	0.2	0.1	0.1	1.0	0.7	1.7	0.8	0.5	0.6	0.4	0.6	0.3	1.1	**0.4**

Table 4.5

Monthly runoff coefficients

Year	June	July	August	Sept	Oct	Mon
1985	0.11	0.26	0.52	0.55	0.56	**0.43**
1986	0.15	0.50	0.58	0.28	0.53	**0.37**
1987	0.12	0.37	0.45	0.50	0.57	**0.41**
1988	0.18	0.44	0.61	0.73	0.70	**0.52**
1989	0.87	0.83	0.97	0.72	0.62	**0.86**
1990	0.18	0.60	0.40	1.06	1.26	**0.62**
1991	0.06	0.38	0.77	0.66	1.11	**0.49**
1992	0.16	0.19	0.82	0.49	0.34	**0.41**
1993	0.16	0.14	0.53	0.69	0.39	**0.40**
1994	0.28	0.23	0.46	1.17	0.43	**0.40**
1995	0.21	0.24	0.80	0.45	0.48	**0.43**

The ten daily and monthly runoff coefficients vary from 0.0 to 3.6 and from 0.37 to 0.86 and the seasonal runoff coefficients for the monsoon period vary between 0.4 to 0.9 in case of Samakoi sub basin. As the area is small and lies in middle reaches of the Brahmani basin, the effect of bank storage and return flows is least in this catchment. The details are shown in Fig.4.3, Fig 4.4 and Fig 4.5 respectively.

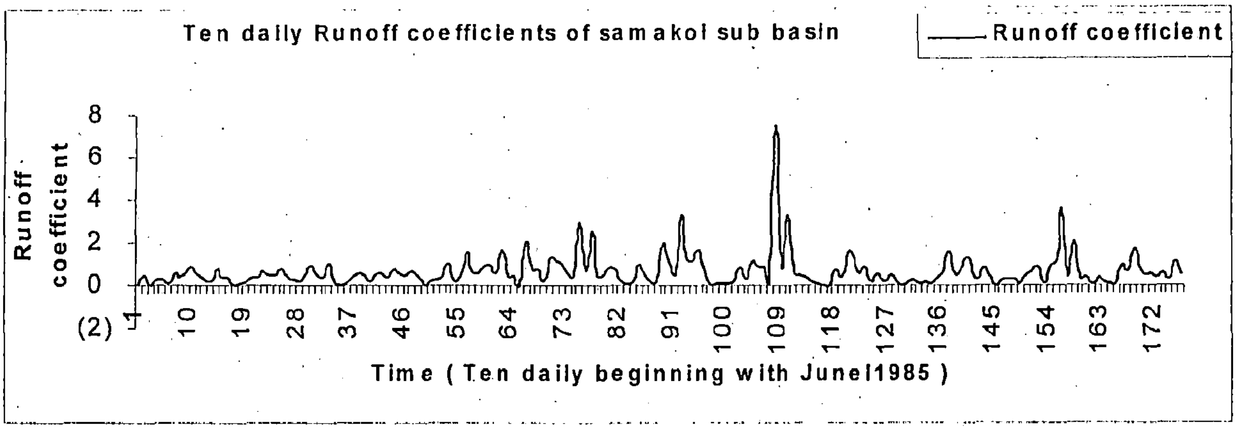


Fig..4.3 Run off coefficients of Samakoi sub basin (Ten daily)

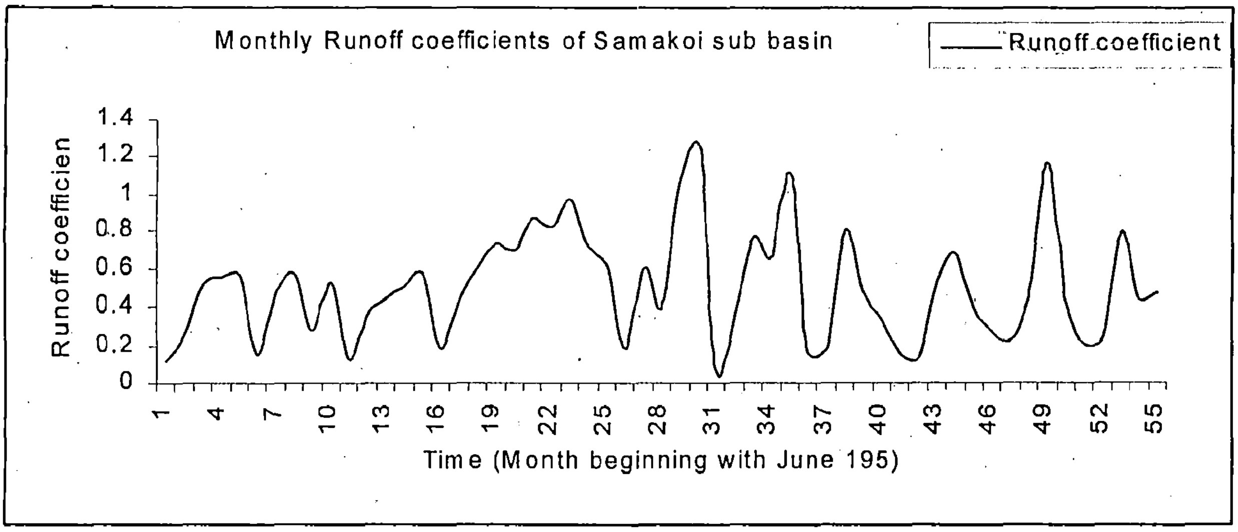


Fig. 4.4 : Runoff coefficients of Samakoi sub basin (Monthly)

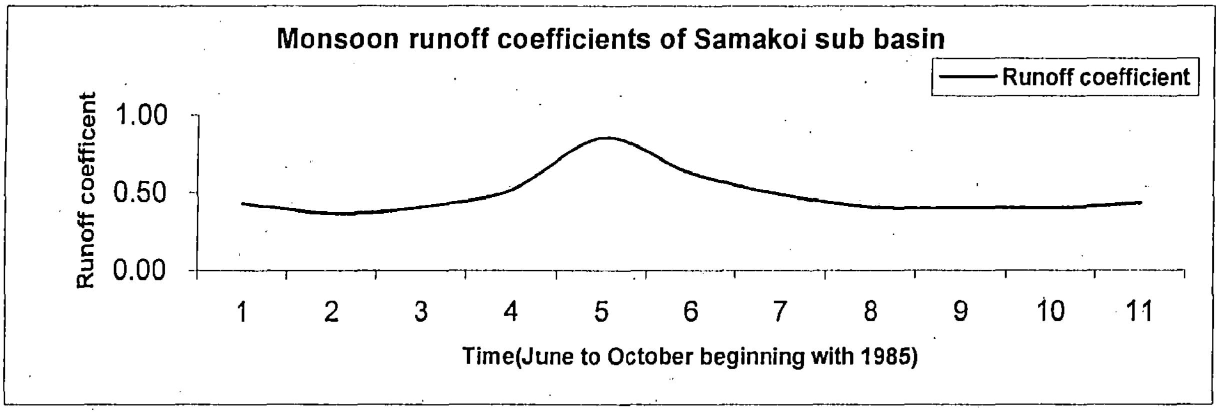


Fig.4.5: Runoff coefficients of Samakoi sub basin (Monsoon)

CHAPTER 5

RESULTS AND ANALYSIS

5.1 PREPARATION OF INPUT DATA

The input data were arranged in a matrix form comprising the cause variables and effect variables in different columns. The number of rows are equal to the number of data used. The following steps are taken to make the data suitable for the application of ANNs.

5.1.1 Normalisation

The processed data has been normalised using the equation (3.3).Due to the nature of sigmoid function, these normalised values varied between 0 and 1. However, to avoid output signal saturation that can sometimes be encountered in ANN applications, the data were normalised to the range of 0 to 0.95

5.1.2 Preparation of Data Sets

The normalised data is partitioned into two sets, one for training and the other for testing , for each of the study area. The details are shown in Table 5.1

Preparation of Data Sets **Table 5.1**

Sl. No.	Sub basin	Total data length	Training data set	Testing data set	Discretization
1	Paleru	18 years	12 years	6 years	monthly
2	Musi	15 years	9 years	6 years	monthly
3	Samakoi				
	a) Monthly	11 years	8 years	3 years	monthly
	b) Ten daily	11 years	8 years	3 years	ten daily

5.2 LINEAR LEAST SQUARE SIMPLEX ALGORITHM (LLSSIM)

The LLSSIM algorithm developed by Hsu, Gupta and Sorooshian (1995) is used in this study. The software for LLSSIM was made available by Prof. H.V.Gupta, Department of Hydrology and Water Resources, University of Arizona, Tucson, USA.

To explain the procedure briefly, the normalised rainfall and runoff records from training data set are arranged in input file in matrix form and initial number of nodes in each layer are assigned. The bias node, one each in input layer and hidden layer are also assigned. The LLSSIM is run and weights are saved in a file. Using these weights and input data the coefficient of correlation (COR) and sum of square errors (SSE) between observed and estimated runoff are computed. Then the rainfall and runoff records from the testing data set are arranged in input file in matrix and using the stored weights that are obtained from training, the COR and SSE are computed.

5.2.1 Network Training using LLSSIM

The input data for LLSSIM was prepared according to guidelines. Each of the training data set is passed into the network for imparting learning to it. While the process of training is on, the hidden nodes are gradually increased automatically in the process of search for minimum error region. When the training process is over, the final structure is displayed and the corresponding weights are saved.

The SSE and COR between observed and estimated runoff are computed for each of the structure obtained from training process of various data sets. Each of the corresponding testing data set is arranged in input file and using the weights that are already acquired in the process of learning , the runoff is estimated and the COR and SSE are computed between the observed and estimated runoff. As an example, the architecture of the network obtained for Musi sub basin is shown in Fig.5.1

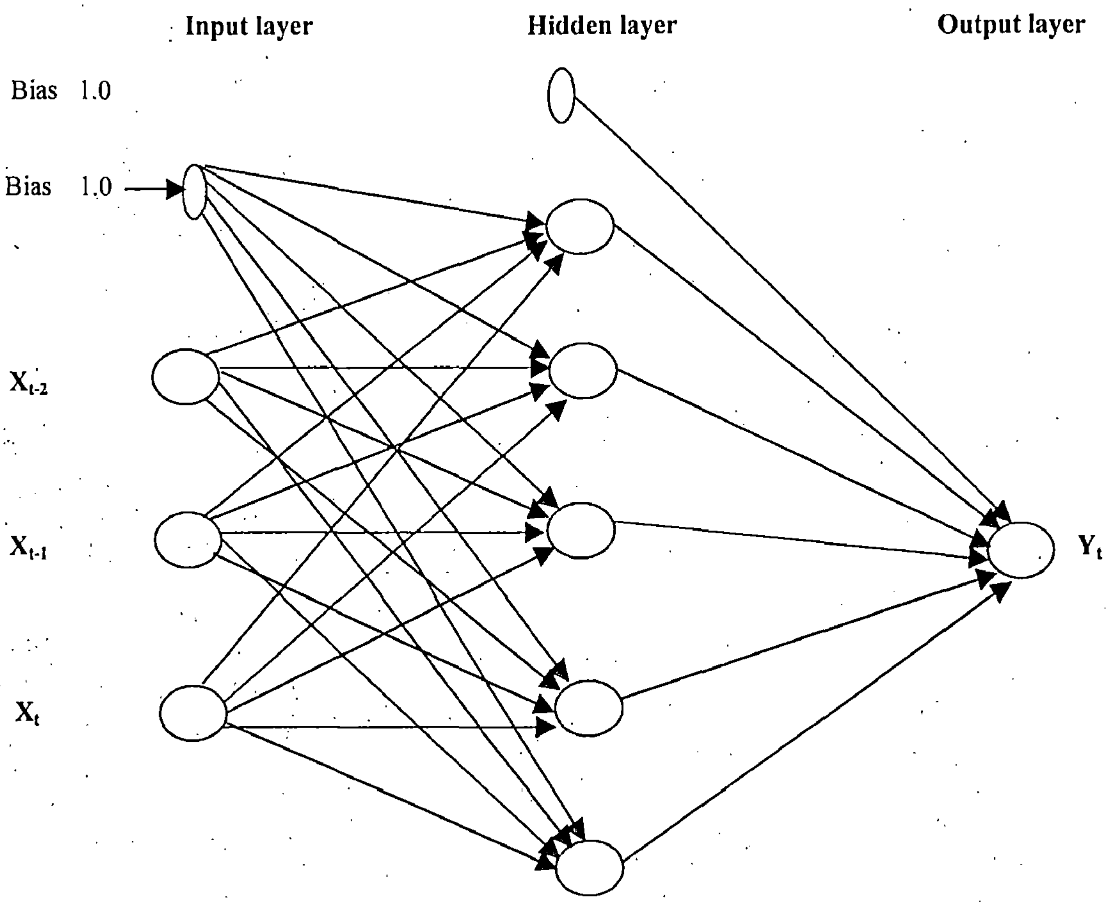


Fig 5.1 : Architecture of neural network incase of Musi sub basin (3-5-1)

5.3 MULTIPLE LINEAR REGRESSION (MLR)

The regression is a general tool for developing rainfall – runoff relationship. The multiple regression analysis is done for each of the cases studied using ANN. The coefficients m_1, m_2, m_3---m_n (where n is the number of variables) obtained for each of the variables x_1, x_2, x_3---x_n in the following equation for MLR using the LINEST function.

$$Ye = m_1 x_1 + m_2 x_2 + m_3 x_3 + \text{------} m_n x_n + b \qquad (5.1)$$

Where Ye is the estimated runoff and b is the constant

The equations are developed and yield is estimated for each of the corresponding best combination of variables of ANN structure. Table 5.2 gives the details of input variables and equations obtained from Multiple Regression Analysis.

Table 5.2

Multiple Regression Equations for various cases of study

Name of study	Input Vector	Equation for Estimated runoff (Ye)
Paleru	$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	$0.11027X_1 - 0.0535X_2 + 0.3740X_3 + 0.3826X_4 - 0.0285$
Musi	X_{t-2}, X_{t-1}, X_t	$0.10\,X_1 + 0.229\,X_2 + 0.22\,X_3 - 0.01$
Samakoi	X_{t-2}, X_{t-1}, X_t	$-0.140\,X_1 + 0.5058\,X_2 + 0.4925\,X_3 + 0.0113$
Samakoi (Ten daily)	Y_{t-1}, X_t	$0.3706\,X_1 + 0.6205\,X_2 + 0.0038$
Samakoi with PET	E_t, X_t	$(-)0.9784\,X_1 + 0.6904\,X_2 + 0.5215$
Samakoi(Tendaily) with PET	E_t, X_t	$(-)0.6478\,X_1 + 0.6426\,X_2 + 0.3607$

Note : X =Rainfall Y = Runoff t = Time period

5.4 ANALYSIS OF RESULTS

The results that are obtained from the application of LLSSIM and Multiple Linear Regression in case of the studies presented in the above pages are analysed. The Table 5.3 to Table 5.8 below gives the detailed information for the both of the approaches.

Paleru sub basin **Table 5.3**

Input Vector	ANN Structure	No.of parameters	Training		Testing	
			COR	SSE	COR	SSE
X_t	1—8—1	25	0.709	4.9830E+04	0.826	1.7640E+04
X_{t-1}, X_t	2—8—1	33	0.824	3.0740E+04	0.764	3.2190E+04
Y_{t-1}, X_t	2—2—1	9	0.835	2.9930E+04	0.776	2.9800E+04
X_{t-1}, Y_{t-1}, X_t	3—3—1	16	0.831	3.1440E+04	0.845	1.8530E+04
X_{t-2}, X_{t-1}, X_t	3—11—1	56	0.890	2.0070E+04	0.680	3.3480E+04
X_{t-2}, X_{t-1}, X_t	3—7—1	36	0.879	2.1790E+04	0.745	3.4640E+04
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	**4—4—1**	**25**	**0.864**	**2.5590E+04**	**0.816**	**2.1240E+04**
$X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t$	5—4—1	29	0.774	4.2270E+04	0.765	2.7320E+04
MLR		4	**0.760**	**0.390e+05**	**0.782**	**0.205e+05**

Note: X = Rainfall
Y = Runoff
t = time period

Musi sub basin **Table 5.4**

Input Vector	ANN Structure	No.of parameters	Training		Testing	
			COR	SSE	COR	SSE
X_t	1—10--1	31	0.767	2.4430E+04	0.771	6.1960E+03
X_{t-1}, X_t	2--8--1	33	0.935	5.8140E+04	0.812	4.5190E+03
Y_{t-1}, X_t	2--10--1	41	0.945	5.5310E+03	0.702	6.4370E+03
X_{t-1}, Y_{t-1}, X_t	3--5--1	26	0.923	7.2370E+03	0.760	5.5090E+03
X_{t-2}, X_{t-1}, X_t	**3--5--1**	**26**	**0.951**	**4.6670E+03**	**0.854**	**3.7330E+03**
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	4--5--1	31	0.880	1.0680E+04	0.816	5.2530E+03
$X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t$	5--4--1	29	0.870	1.1250E+04	0.738	9.3910E+03
MLR		**3**	**0.787**	**1.645e+04**	**0.741**	**8.609e+03**

Samakoi sub basin (monthly) **Table 5.5**

Input Vector	ANN Structure	No.of parameters	Training		Testing	
			COR	SSE	COR	SSE
X_t	1-4-1	13	0.665	0.2778e+06	0.679	0.7577e+05
X_{t-1}, X_t	2-5-1	20	0.773	0.2089e+06	0.862	0.4874e+05
Y_{t-1}, X_t	2-5-1	20	0.680	0.2754e+06	0.590	0.2651e+05
X_{t-1}, Y_{t-1}, X_t	3-3-1	16	0.671	0.2813e+06	0.701	0.6855e+05
X_{t-2}, X_{t-1}, X_t	**3-5-1**	**26**	**0.780**	**0.2042e+06**	**0.876**	**0.5828e+05**
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	4-4-1	25	0.782	0.2034e+06	0.836	0.5523e+05
$X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t$	5-5-1	36	0.439	0.4045e+06	0.418	0.1053e+06
MLR		**3**	**0.774**	**0.199e+06**	**0.860**	**0.453e+05**

Note : X = Rainfall Y = Runoff t = time period

Samakoi sub basin (Ten daily) **Table 5.6**

Input vector	ANN Structure	No.of parameters	Training		Testing	
			COR	SSE	COR	SSE
X_t	1-3-1	10	0.543	0.2245e+05	0.537	0.6702e+05
X_{t-1}, X_t	2-4-1	17	0.590	0.2071e+06	0.576	0.6456e+05
Y_{t-1}, X_t	**2-7-1**	**29**	**0.641**	**0.1892e+06**	**0.653**	**0.5104e+05**
X_{t-1}, Y_{t-1}, X_t	3-4-1	21	0.619	0.1976e+06	0.609	0.5767e+05
X_{t-2}, X_{t-1}, X_t	3-7-1	36	0.597	0.2072e+06	0.628	0.5719e+05
X_{t-2}, X_{t-1}, Y_{t-1}, X_t	4-4-1	25	0.606	0.2020e+06	0.634	0.5652e+05
X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t	5-4-1	29	0.587	0.2086e+06	0.609	0.5763e+05
MLR		**2**	**0.641**	**0.187e+06**	**0.668**	**0.487e+05**

Samakoi sub basin (Monthly) with PET **Table 5.7**

Input Vector	ANN Struc.	No.of para meter	Training		Testing	
			COR	SSE	COR	SSE
E_t, X_t	**2--5--1**	**21**	**0.83**	**1.9340E+05**	**0.748**	**7.1430E+04**
E_{t-1}, E_t, X_t	3--7--1	36	0.67	2.7110E+05	0.761	6.0220E+04
E_{t-1}, Y_{t-1}, E_t, X_t	4--7--1	43	0.71	2.6050E+05	0.326	1.8560E+05
E_{t-1}, X_{t-1}, Y_{t-1}, E_t, X_t	5--6--1	43	0.69	2.7140E+05	0.796	4.5910E+04
E_{t-2}, E_{t-1}, X_{t-1}, X_{t-1}, E_t, X_t	6--7--1	57	0.70	2.5950E+05	0.828	6.4360E+04
E_{t-2}, E_{t-1}, X_{t-2}, X_{t-1}, Y_{t-1}, E_t, X_t	7--5--1	46	0.59	3.2970E+05	0.601	6.0900E+04
E_{t-2}, E_{t-1}, X_{t-2}, X_{t-1}, Y_{t-2} Y_{t-1}, E_t, X_t	8--11--1	111	0.44	4.0270E+05	0.299	1.4820E+05
MLR		**3**	**0.776**	**1.980e+05**	**0.767**	**6.446e+04**

Note: E=PET
X=Rainfall t= time
Y = Runoff period

Samakoi sub basin
(Ten daily) with PET **Table 5.8**

Input Vector	ANN Struc.	No.of parameters	Training		Testing	
			COR	SSE	COR	SSE
E_t, X_t	2--4--1	17	0.62	1.9950E+05	0.627	5.9320E+04
E_{t-1}, E_t, X_t	3--8--1	41	0.53	2.3180E+05	0.496	7.1210E+04
$E_{t-1}, Y_{t-1}, E_t, X_t$	4--8--1	49	0.55	2.2000E+05	0.598	5.6450E+04
$E_{t-1}, X_{t-1}, Y_{t-1}, E_t, X_t$	5--10--1	71	0.58	2.1230E+05	0.587	5.7850E+04
$E_{t-2}, E_{t-1}, X_{t-1}, X_{t-1}, E_t, X_t$	6--12--1	97	0.53	2.3070E+05	0.563	6.2580E+04
$E_{t-2}, E_{t-1}, X_{t-2}, X_{t-1}, Y_{t-1}, E_t, X_t$	7--12--1	109	0.53	2.2980E+05	0.565	5.9140E+04
$E_{t-2}, E_{t-1}, X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, E_t, X_{t-1}$	8--4--1	41	0.51	2.3830E+05	0.558	5.8000E+04
MLR		2	0.597	2.042e+05	0.618	5.666e+04

Note: E=PET X=Rainfall Y=Runoff

5.4.1 Analysis of Results Obtained from LLSSIM and Multiple Linear Regression

The above information illustrates that in all the studies the ANNs gives better results than those of MLR for the training data set whereas it sustains its efficiency while recognising the testing data sets of Paleru and Musi sub basins. However, in case of Samakoi sub basin, the ANN shows slightly lesser efficiency compared to that of MLR. Further, this explains that the ANNs perform better irrespective of location of study area, catchment size. Table 5.9 below gives the comparative statement for the performance of ANN sand MLR in a comprehensive manner. Figure 5.2 to 5.13 shows the graphical representation of the estimated runoff from both the ANN and MLR approaches along with the observed runoff for the training as well as testing in case of Paleru, Musi and Samakoi sub basins. From these graphs it is observed that the ANNs are better in capturing the peak flows. The rainfall pattern too has been shown with the same graph in falling curtain mode. The various statistical parameters are measured for the observed and estimated runoff.

Table 5.9

Comparative Statement showing the performance of ANN and MLR approaches

Sub basin	Input vector	Structure	Training						Testing					
			ANN			MLR			ANN			MLR		
			COE	COR	SSE	COE	COR	SSE	COE	COR	SSE	COE	COR	SSE
Paleru	$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	4-4-1	0.73	0.864	2.56e+04	0.59	0.760	3.90e+04	0.58	0.816	2.12e+04	0.59	0.782	2.05e+04
Musi	X_{t-2}, X_{t-1}, X_{t}	3-5-1	0.90	0.951	4.67E+03	0.63	0.787	1.65E+04	0.70	0.854	3.73E+03	0.30	0.741	8.61E+03
Samakoi	X_{t-2}, X_{t-1}, X_t	3-5-1	0.59	0.780	2.04E+05	0.59	0.774	1.99E+05	0.72	0.876	5.83E+04	0.80	0.860	4.53E+04
Samakoi (10 daily)	Y_{t-1}, X_t	2-7-1	0.40	0.641	1.89E+05	0.40	0.641	1.87E+05	0.39	0.653	5.10E+04	0.42	0.668	4.87E+04
Samakoi with PET	X_t, Y_t	2-5-1	0.61	0.834	1.93E+05	0.60	0.776	1.98E+05	0.65	0.748	7.14E+04	0.69	0.767	6.45E+04
Samakoi 10 daily with PET	X_t, Y_t	2-4-1	0.37	0.615	2.00E+05	0.36	0.597	2.04E+05	0.30	0.627	5.93E+04	0.33	0.618	5.67E+04

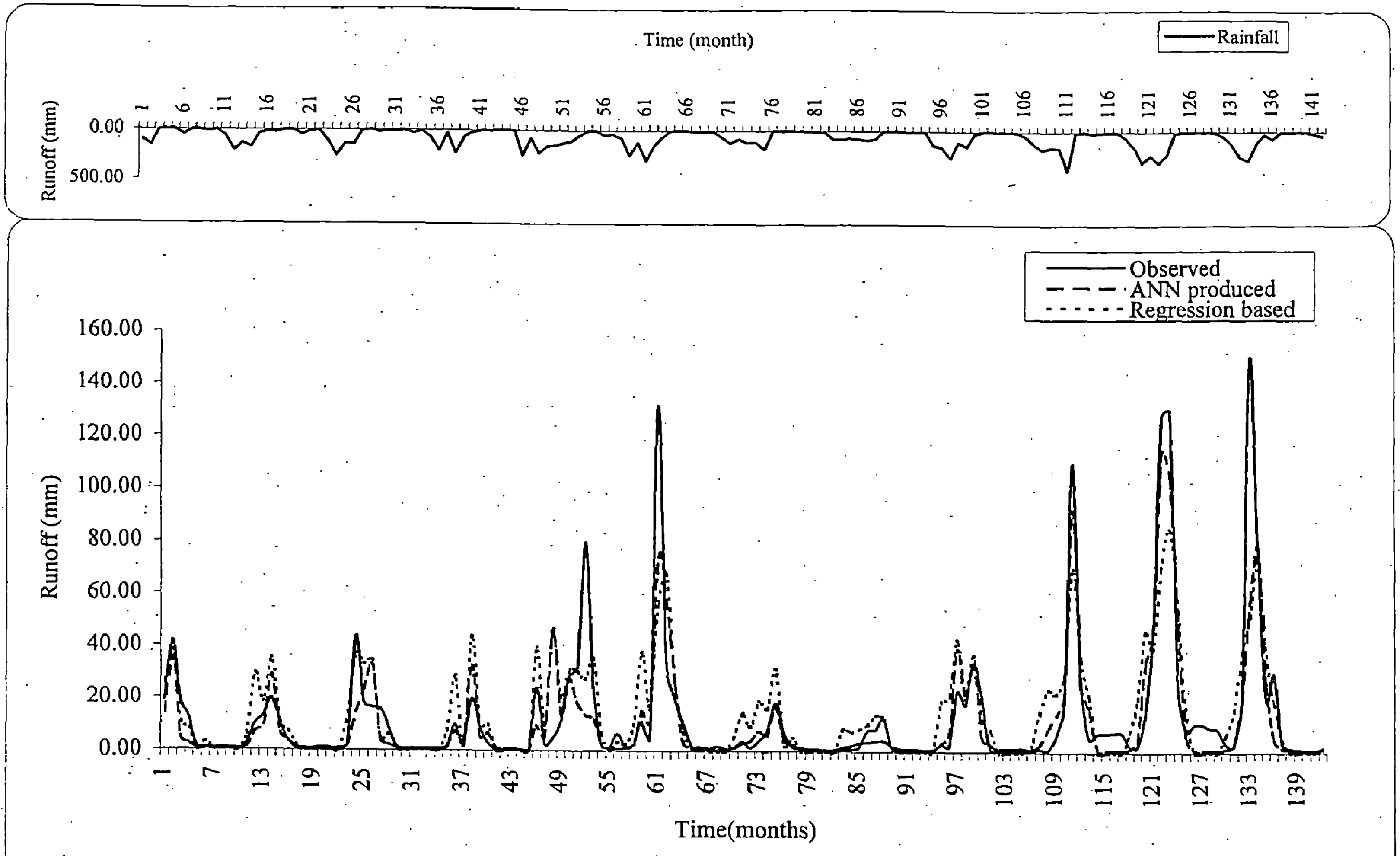


Fig.5.2: Hydrograph of Paleru sub basin-Training

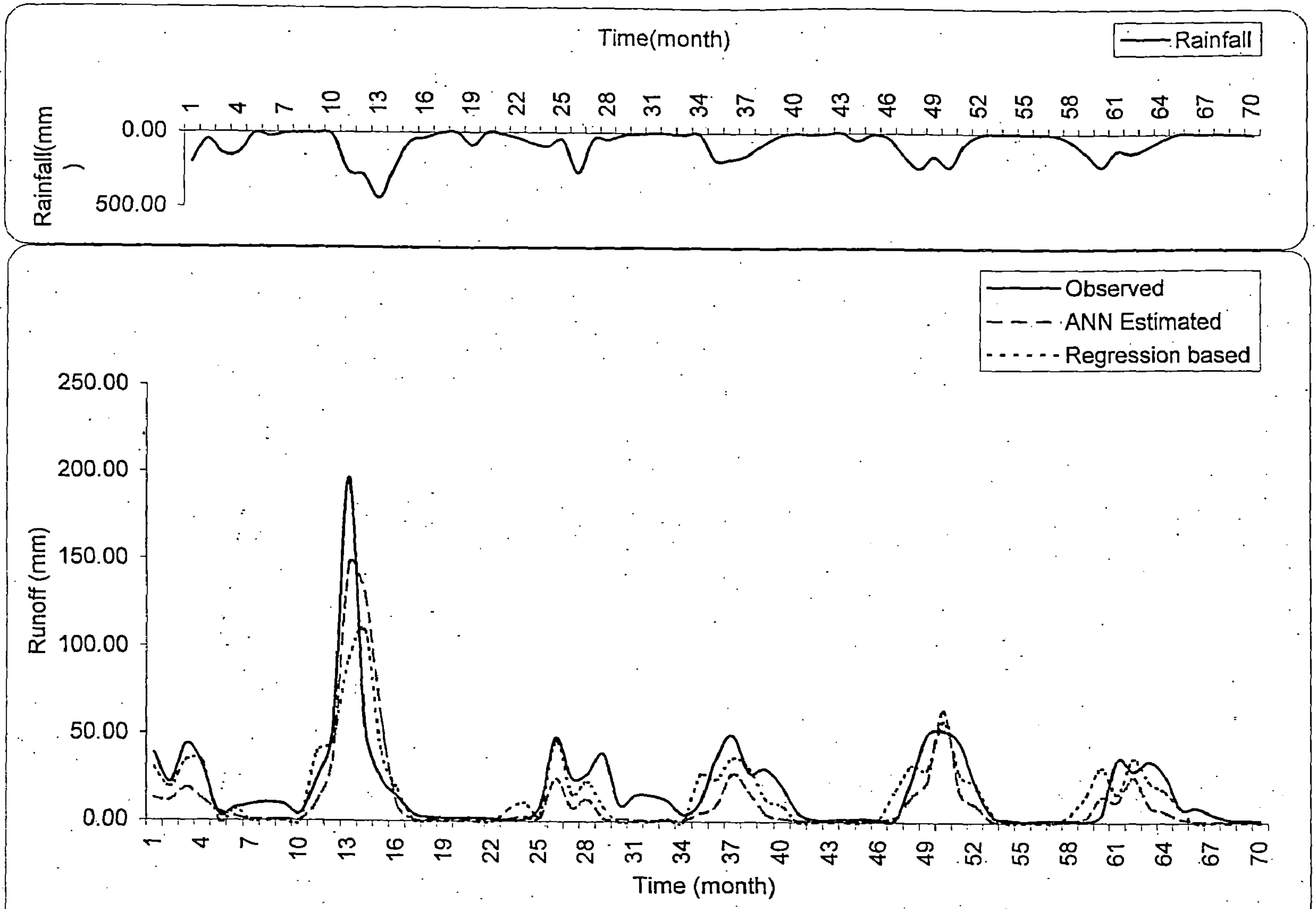


Fig.5.3: Hydrograph of Paleru sub basin-Testing

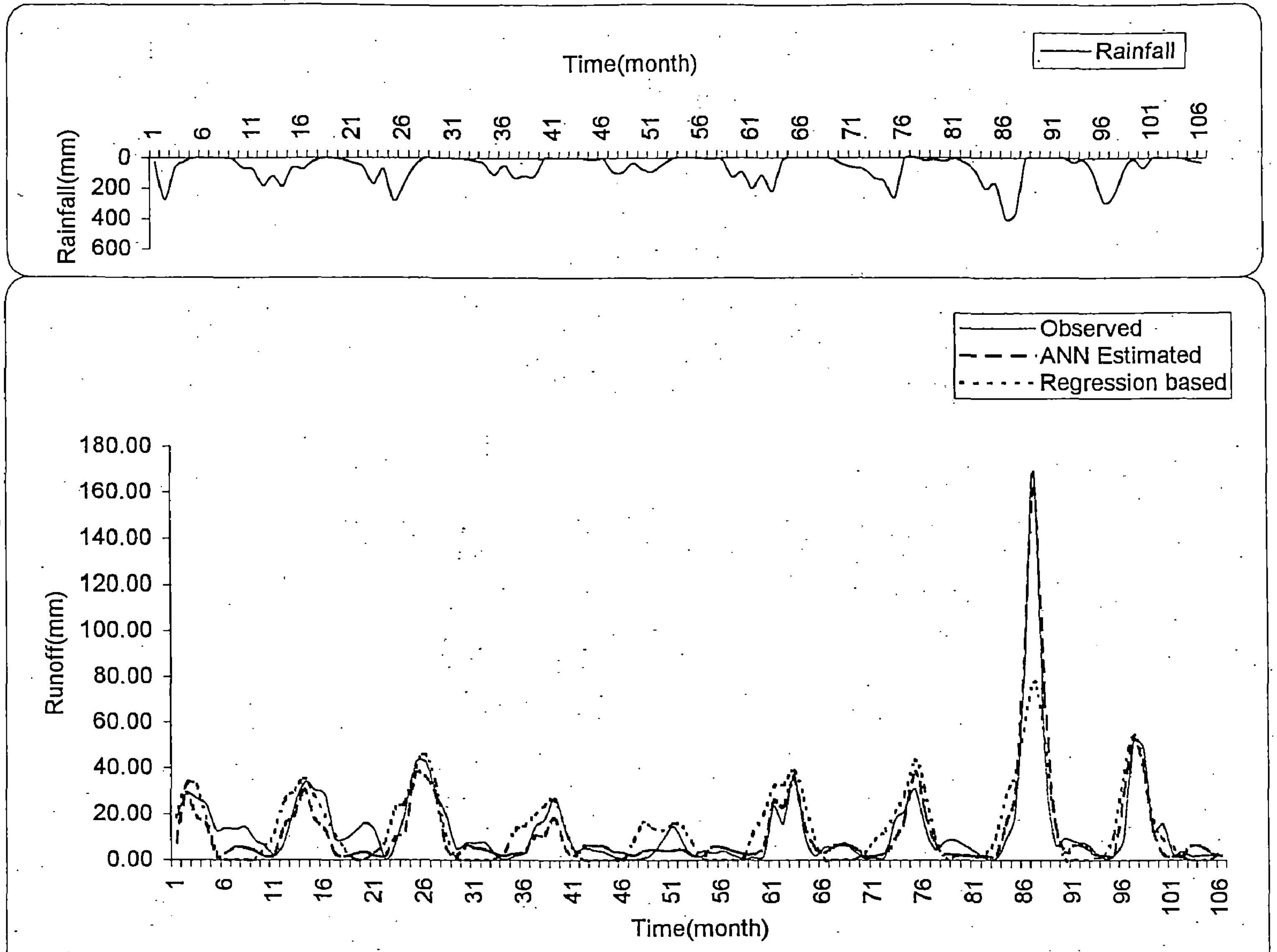


Fig.5.4: Hydrograph of Musi sub basin-Training

G10510.

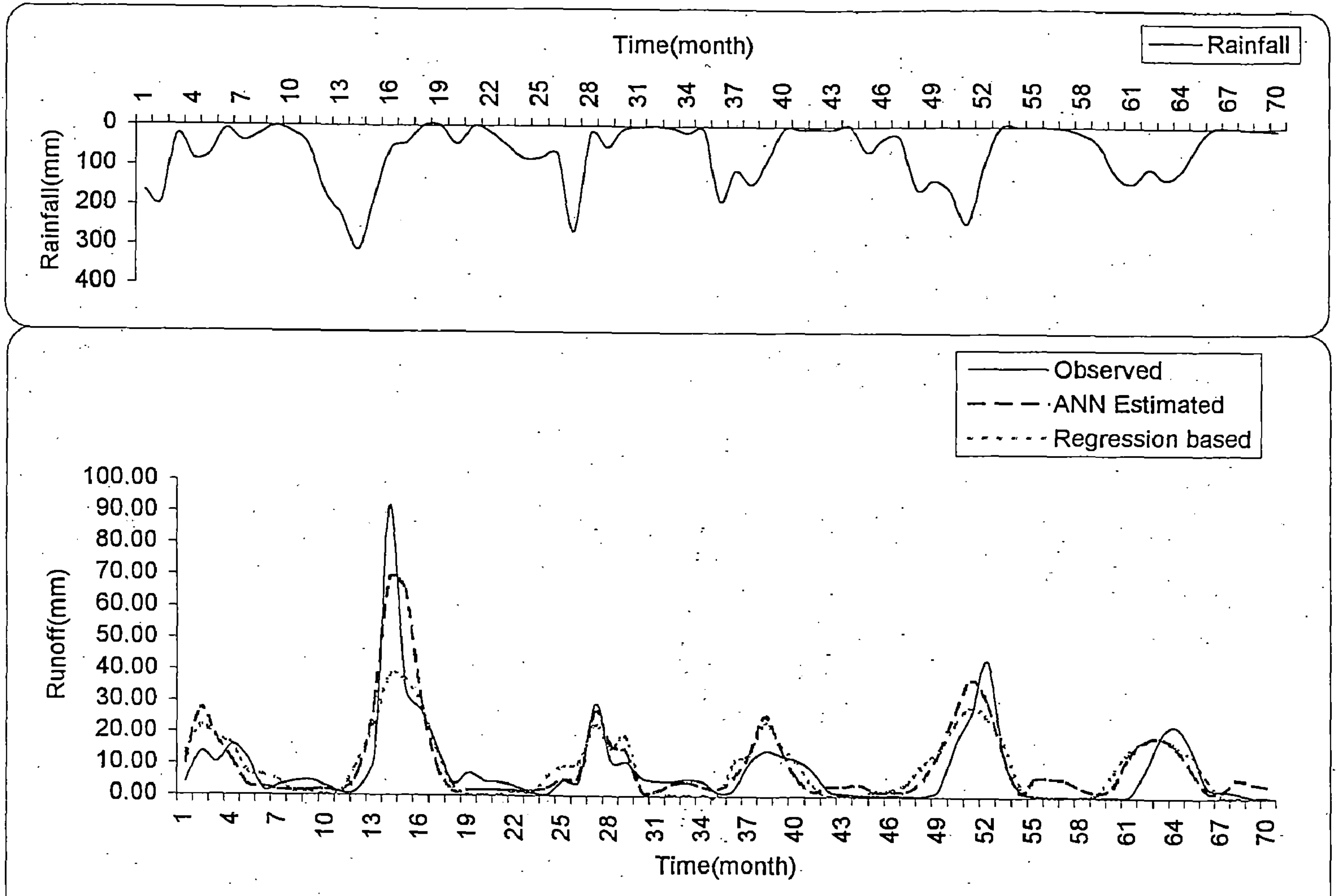


Fig 5.5: Hydrograph of Musi sub basin-Testing

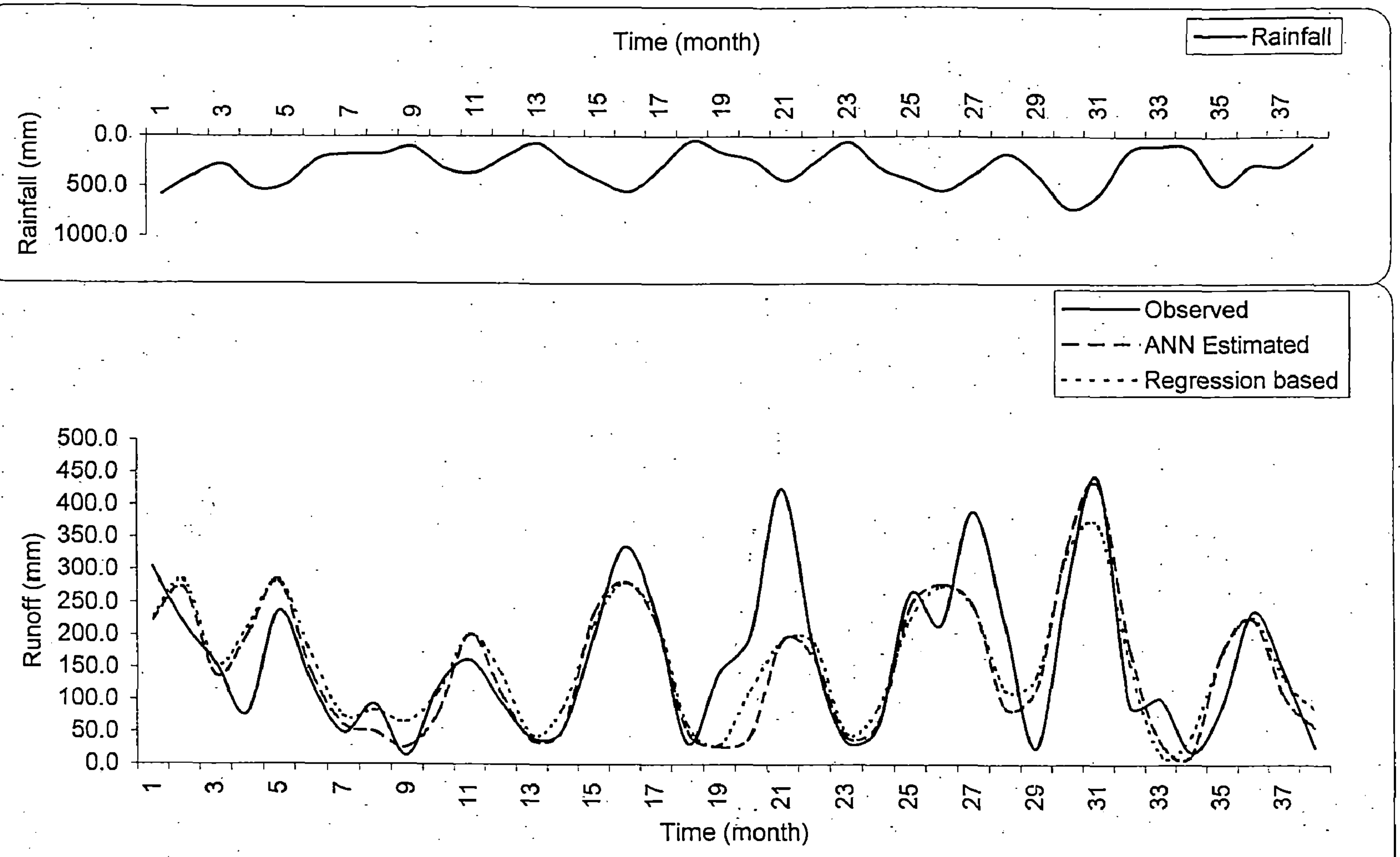


Fig.5.6: Hydrograph of Samakoi sub basin (monthly)-Training

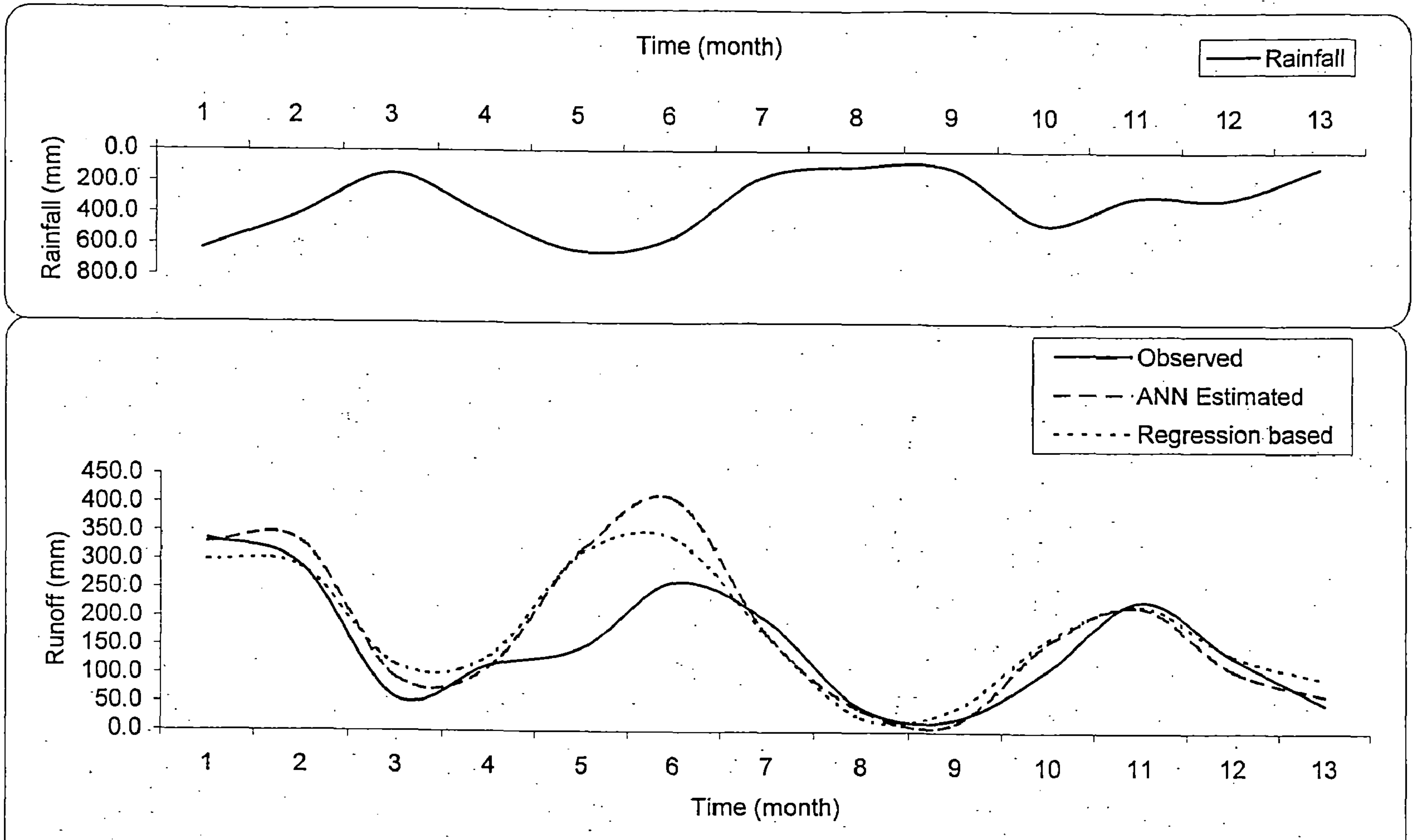


Fig.5.7: Hydrograph of Samakoi sub basin (monthly)-Testing

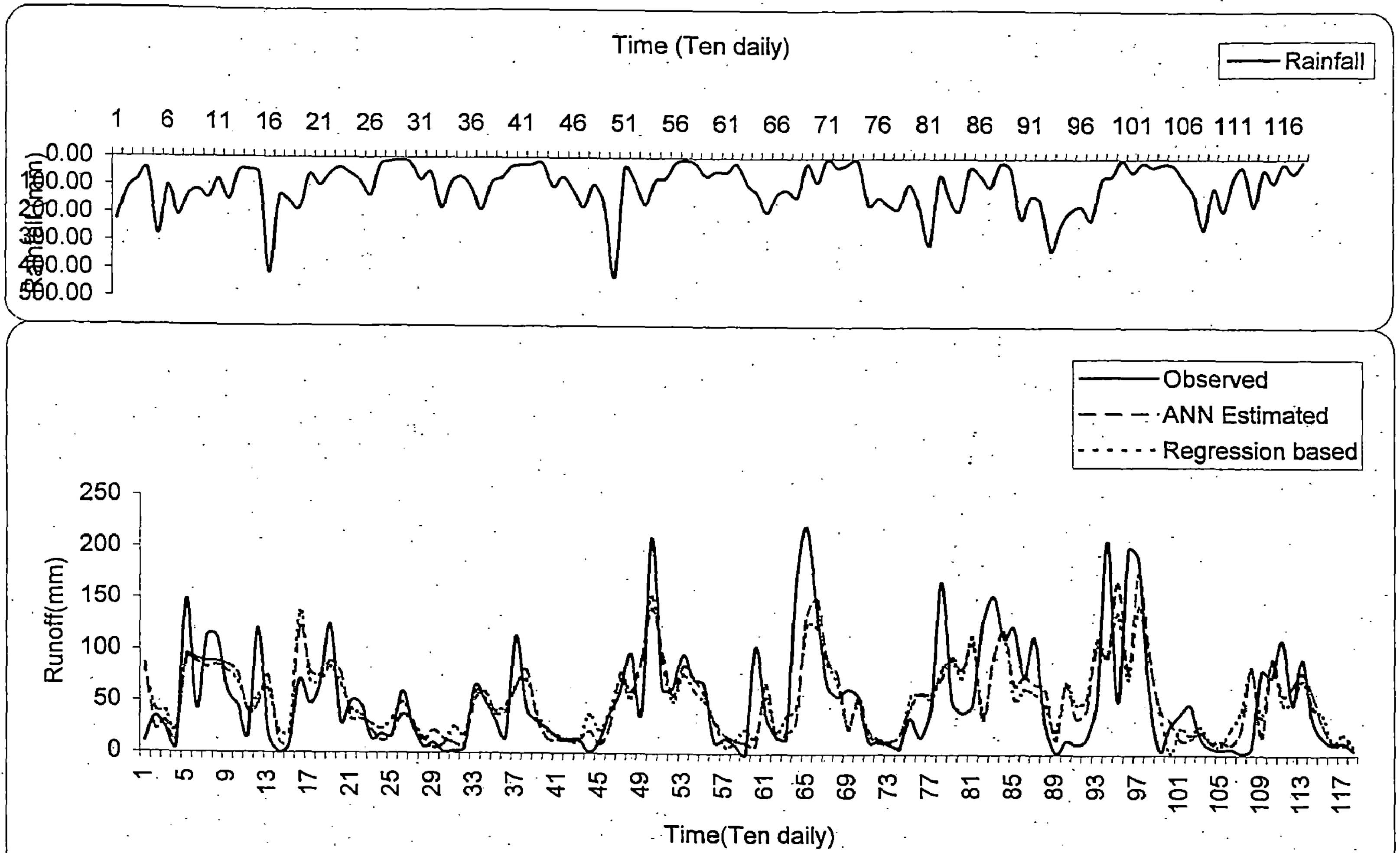


Fig.5.8: Hydrograph of Samakoi sub basin (Ten daily)-Training

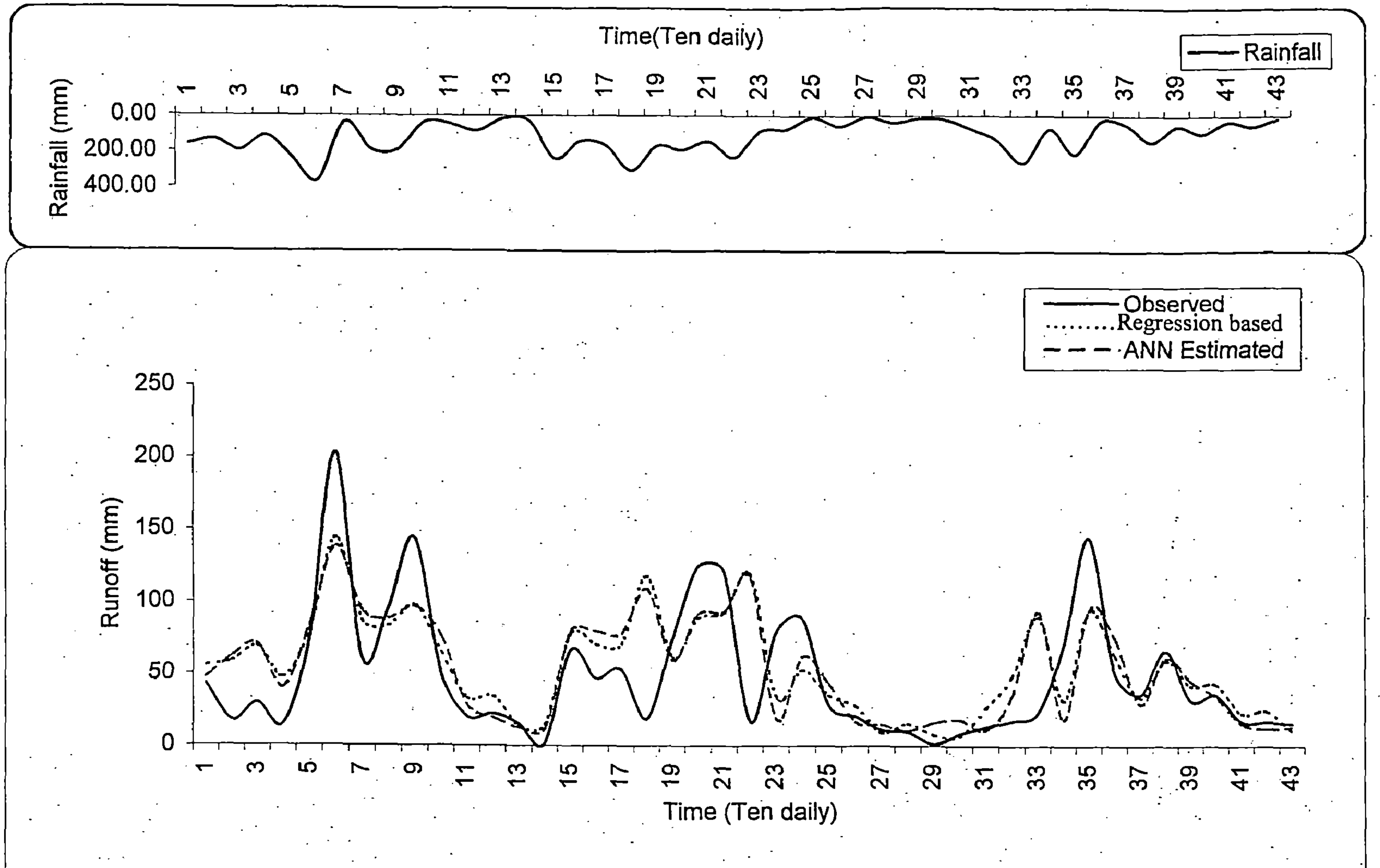


Fig.5.9: Hydrograph of Samakoi sub basin (Ten daily)-Testing

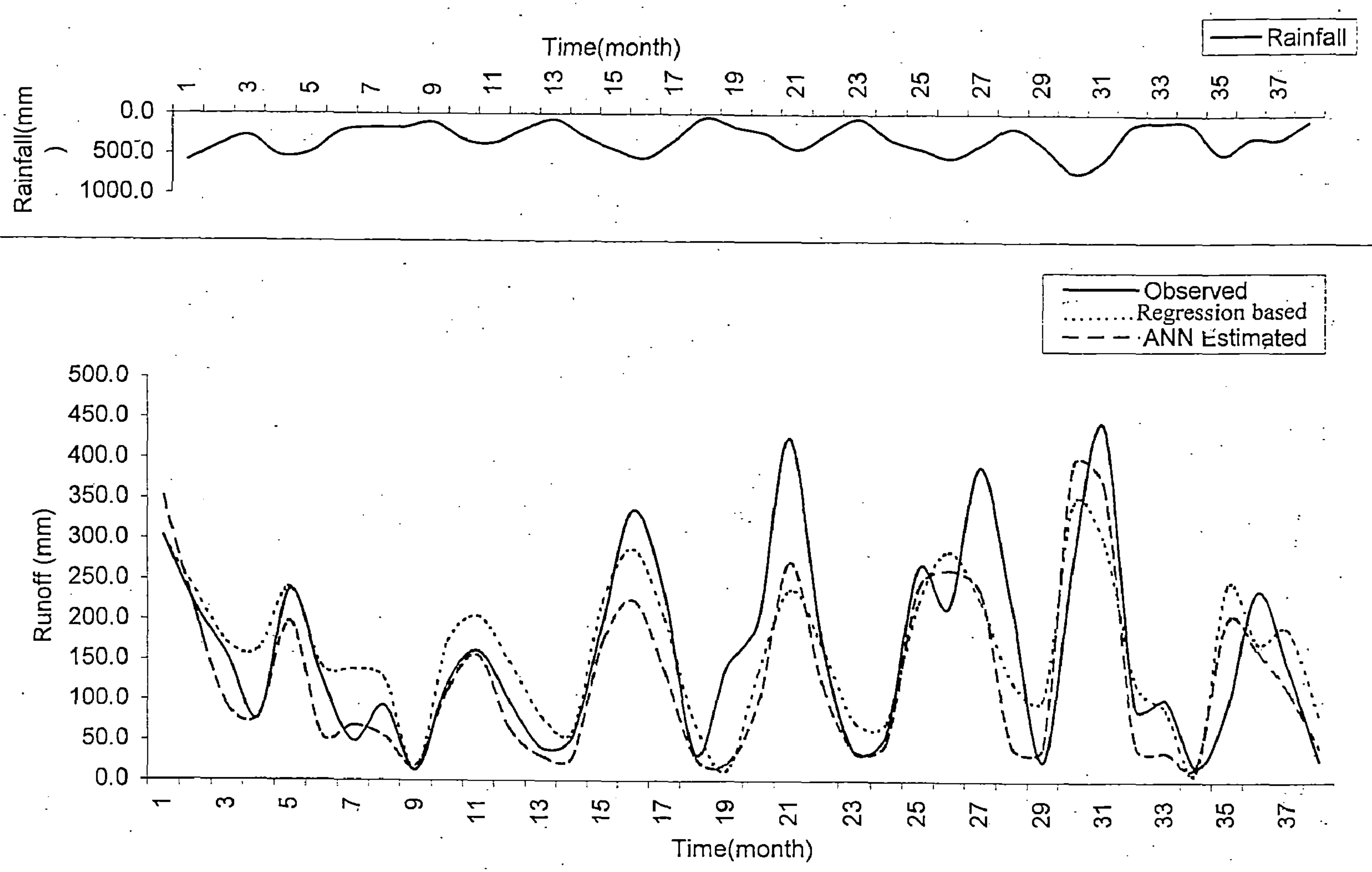


Fig.5.10: Hydrograph of Samakoi sub basin (monthly with PET) - Training

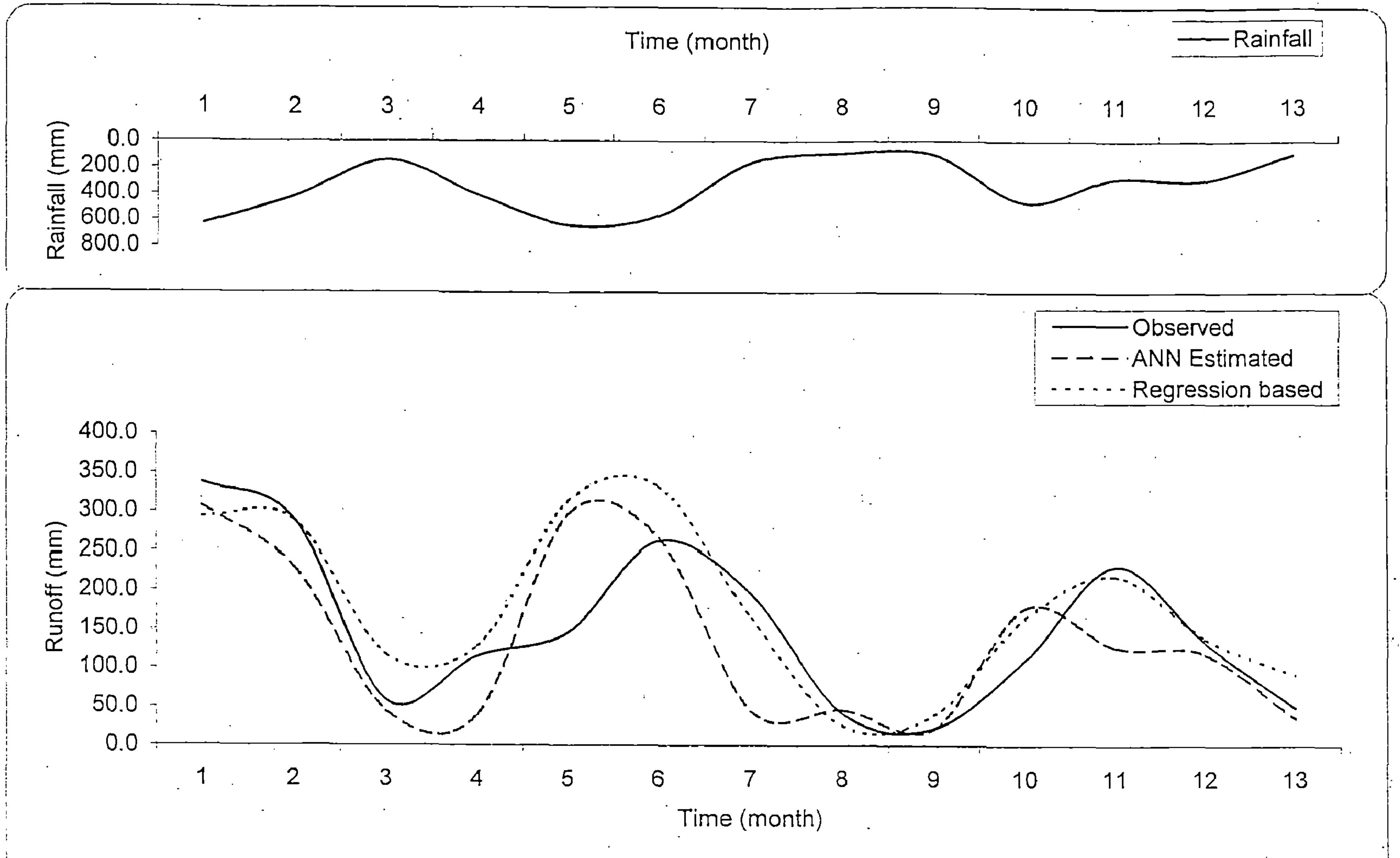


Fig.5.11: Hydrograph of Samakoi sub basin (monthly with PET) - Testing

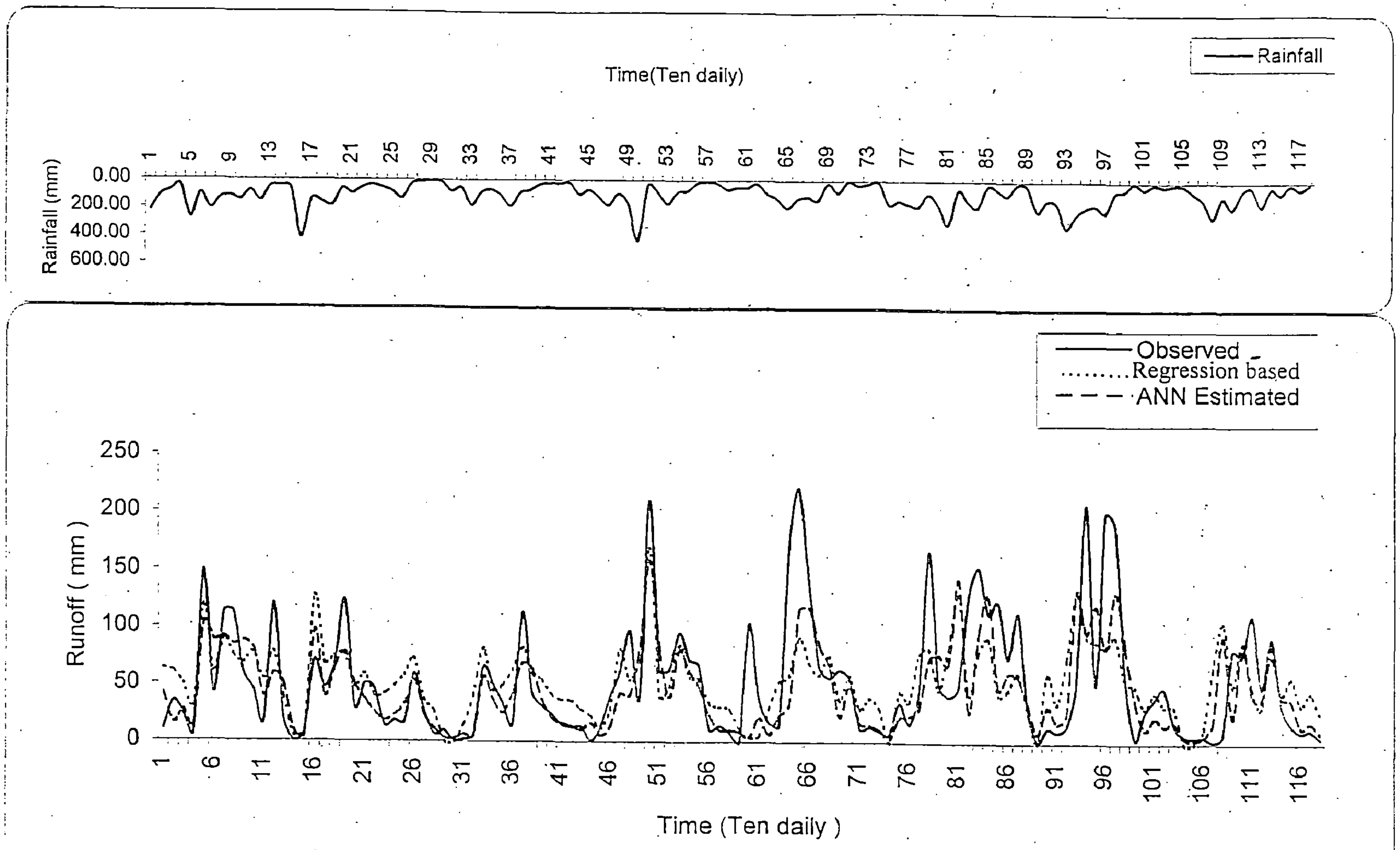


Fig.5.12: Hydrograph of Samakoi sub basin(10daily with PET)-Training

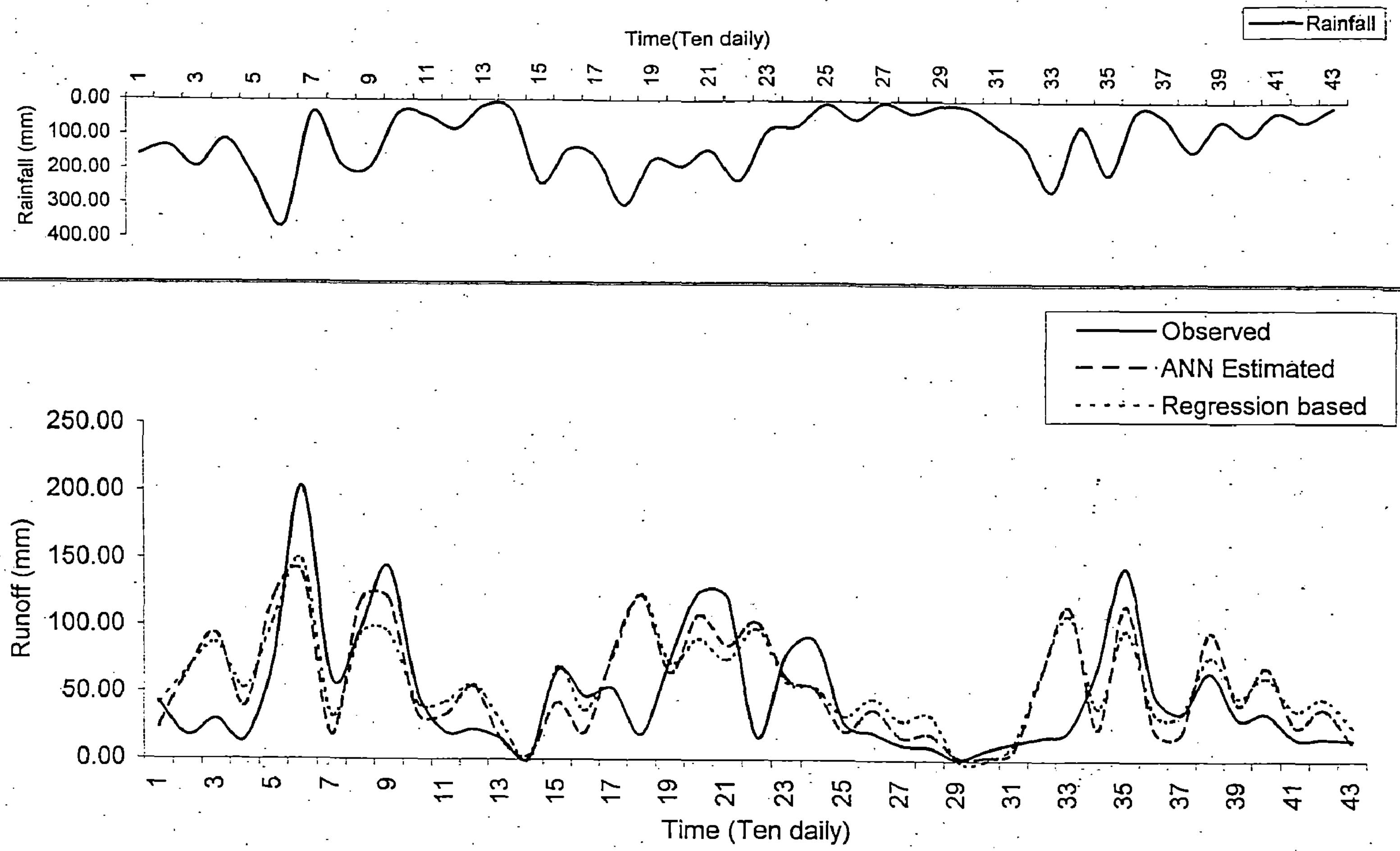


Fig 5.13 :Hydrograph of Samakoi sub basin (Ten daily with PET)- Testing

5.4.2 Analysis of Results Obtained from ANNs Monthly and Ten daily approach

The Samakoi sub basin is selected for studying on Ten daily basis. The Table 5.10 below shows the comparison between the results obtained from Ten daily and monthly approach.

Table 5.10

Results of Samakoi sub basin Monthly and Ten daily

Study	Input Vector	ANN	Training		Testing	
			COR	SSE	COR	SSE
Monthly	X_{t-2}, X_{t-1}, X_t	3-5-1	0.780	0.2042e+06	0.876	0.5828e+05
Ten daily	Y_{t-1}, X_t	2-7-1	0.641	0.1892e+06	0.653	0.5104e+05

From the above information, it is found that the monthly data sets are better in the approximation process of ANNs when compared to ten daily data sets on the basis of COR. In monthly there will be more lumping . The findings of Tokar and Markus (2000) while applying the ANNs to Fraser river(monthly), of Colorado, Big-Thomson river system and Raccoon river(10 daily) near Bayard also report that the ANNs are more accurate with monthly input vector than 10 daily. Generally, the montly flows experiences more lumping when compared to ten daily flows. More over, in ten daily memory in terms of flow plays role in the structure. Further, the time step of ten daily is not having basis as earth revolves round the sun in one year and rotates on its own axis in one day. Even if we consider the Lunar calendar the moon revolves round the earth in one month. All these have significant bearing on the hydro-meteorology. However, the SSE (which appears to be on lower side in the ten daily study) cannot be applied as a scale for measuring the efficiency of the network in this case, as the number of data items are varying.

5.4.3 Analysis of Results Obtained from ANNs with and without PET

The pan evapo-transpiration (PET) has been considered as one of the cause variables and applied along with rainfall and runoff in case of Samakoi sub basin (monthly as well as ten daily) and the results are shown in Table 5.11.

Table 5.11

Results of Samakoi sub basin With and Without PET

Sl. No	Name of the study	Input vector	ANN Struc.	No.of paramete	Training		Testing	
					COR	SSE	COR	SSE
1	Monthly With PET	X_t, Y_t	2-5-1	21	0.83	1.934e+05	0.748	7.143e+04
2	With out PET	X_{t-2}, X_{t-1}, X_t	3-5-1	26	0.78	0.204e+06	0.876	0.583e+05
3	Ten daily With PET	X_t, Y_t	2-4-1	17	0.62	1.995e+05	0.627	5.932e+04
4	Without PET	Y_{t-1}, X_t	2-7-1	29	0.64	0.189e+06	0.653	0.510e+05

The PET as one of the cause variables has improved the performance of the ANN when the study is based on monthly data sets. However the efficiency of the ANN with PET has slightly reduced when the study is made on ten daily data sets. This is perhaps due to the delay in response of high consumption by plant when observed on ten daily basis. Generally, the montly flows experiences more lumping when compared to ten daily flows. More over, in ten daily memory in terms of flow plays role in the structure. Further, the time step of ten daily is not having basis as earth revolves round the sun in one year and rotates on its own axis in one day. Even if we consider in the Lunar calendar the moon revolves round the earth in one month. All these have significant bearing on the hydro-meteorology.

5.5 ADAPTABILITY OF ANN MODELS

A model is said to be adaptable if it can be used for data sets that are different from the training data set from which the model is developed, thus avoiding the repetition of the lengthy training / calibration process. To check for these characteristics, in ANN models the ANN structure and corresponding weights of Paleru sub basin are used to test both the data sets of Musi sub basin located in hydro meteorologically similar region. The Paleru weights are applied on corresponding Musi training as well as testing data sets and the Musi weights are applied on corresponding Paleru training as well as testing data sets. Table 5.12 gives the Musi response to Paleru structure and Table 5.13 gives the Paleru response to Musi structure.

Table 5.12

Paleru structure Vs Musi response

Input Vector	ANN Structur	No. of parameter	Data set From 1977-1982		Data set From 1968-1976	
			COR	SSE	COR	SSE
X_t	1--8--1	25	0.749	0.9542e+04	0.739	2.9490E+04
X_{t-1}, X_t	2--8--1	33	0.830	0.8267e+04	0.865	1.7170E+04
Y_{t-1}, X_t	2--2--1	9	0.776	0.6898e+04	0.847	1.9150E+04
X_{t-1}, Y_{t-1}, X_t	3--3--1	16	0.792	0.5177e+04	0.868	1.7780E+04
X_{t-2}, X_{t-1}, X_t	3--11--1	56	0.830	0.8405e+04	0.785	2.1070E+04
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	4--4--1	25	0.851	0.4012e+04	0.890	1.1150E+04
$X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t$	5--4--1	29	0.826	0.4095e+04	0.837	1.7100E+04

Table 5.13

Musi structure Vs Paleru response

Input Vector	ANN struct	parameter	Data set From 1977-1982		Data set From 1965-1976	
			COR	SSE	COR	SSE
X_t	1-10-1	31	0.858	0.2538e+05	0.686	5.9990E+04
X_{t-1}, X_t	2-8-1	33	0.841	0.1612e+05	0.730	4.9740E+04
Y_{t-1}, X_t	2-10-1	41	0.747	0.3145e+05	0.673	5.2470E+04
X_{t-1}, Y_{t-1}, X_t	3-5-1	26	0.660	0.3615e+05	0.777	3.9900E+04
X_{t-2}, X_{t-1}, X_t	3-5-1	26	0.826	0.1935e+05	0.816	3.5630E+04
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	4-5-1	31	0.743	0.2544e+05	0.799	3.4800E+04

In both the cases the response is very good even better than that obtained from testing with their own structure. *A note worthy thing is found incase of Paleru sub basin with structure 3-11-1, which gives coefficient correlation of 0.680 between observed and estimated runoff for testing data with its own structure where as the same is 0.826 when tested with Musi's structure.*

Further, the response of Samakoi sub basin for various input vectors is found using the corresponding ANN structure of Paleru and Musi sub basins. Table 5.14 gives the details. Obviously both the structures resulted in similar response and the performance is affected to some extent. This is attributed to the fact that both the areas are in different regions and located in different regimes of the respective parent river systems.

Table 5.14

Samakoi response to	**Paleru Structure**		**Musi Structure**	
Input Vector	**Data set From 1985-1995**		**Data set From 1985-1995**	
	COR	**SSE**	**COR**	**SSE**
X_t	0.552	0.6542e+06	0.527	0.9006e+06
X_{t-1}, X_t	0.679	0.5508e+06	0.692	0.5336e+06
Y_{t-1}, X_t	0.689	0.4395e+06	0.460	0.6341e+06
X_{t-1}, Y_{t-1}, X_t	0.676	0.3989e+06	0.693	0.4099e+06
X_{t-2}, X_{t-1}, X_t	0.595	0.5720e+06	0.662	0.5320e+06
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	0.588	0.4887e+06	0.577	0.4866e+06
$X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t$	0.465	0.6221e+06	0.496	0.5639e+06

This shows that the physics behind the rainfall runoff process is someway being captured by ANN. One of the major criticism of ANNs is that they do not have any physical interpretation. However, more work is needed to be done in this direction.

5.6 BACK PROPAGATION FOR COMPARING WITH LLSSIM

The Paleru sub basin is selected for studying the stability of performance of ANNs which basically depends on the training the network. Hence it is essential to check the training process by a different algorithm and accordingly the familiar back propagation is selected. The results that are obtained from the training process incase of Paleru sub basin are presented below in Table 5.15

Table 5.15

Results of Paleru sub basin using Back Propagation

Input Vector	ANN	No.of parameters	Training		Testing	
			COR	SSE	COR	SSE
X_t	1.11.1	22	0.696	4.93E+04	0.821	1.90E+04
X_{t-1}, X_t	2.15.1	45	0.800	3.46E+04	0.826	1.83E+04
Y_{t-1}, X_t	2.8.1	24	0.85	2.65E+04	0.849	1.56E+04
X_{t-1}, Y_{t-1}, X_t	3.5.1	20	0.86	2.51E+04	0.876	1.29E+04
X_{t-2}, X_{t-1}, X_t	3.12.1	48	0.861	2.51E+04	0.833	1.82E+04
$X_{t-2}, X_{t-1}, Y_{t-1}, X_t$	4.7.1	35	0.876	2.24E+04	0.847	1.65E+04
$X_{t-2}, X_{t-1}, Y_{t-2}, Y_{t-1}, X_t$	5.8.1	48	0.880	2.17E+04	0.872	1.39E+04

The above information illustrates that both of the algorithms are in tune with each other except that the Back Propagation gives a continuous improved performance with increase of input variables up to 5 where as the LLSSIM attains the best at the intermittent level. This is in accordance with the observation already made by Jain and Chalisgaonkar while studying the stage discharge relation ship at a site on river Narmada. Moreover the structure is able to identify the patterns in testing data in a better way while applying the Back Propagation.

5.7 PHYSICAL INTERPRETATION OF THE RESULTS

The following analysis is to find the physical inference of the results obtained from the ANN. The following observations suggests that the ANNs consider the physics behind the rainfall-runoff process and they are not simply block box models.

1. The inclusion of PET has improved the performance while studying the Samakoi sub basin on monthly basis and the same affected slightly while studying on Ten daily basis. This implies that the most important element of the hydrologic cycle, the PET is rightly absorbed by the ANN. How ever the same is affected the results perhaps due to the delay in response of high consumption by plant when observed on ten daily basis besides the fact that there is noiseness in ten daily data sets.

2. The ANN structure of Paleru sub basin when applied to Musi sub basin and vice versa, both of the structures given the good performance. Further both of the structures give similar response for the common input vector when applied to Samakoi sub basin, though the performance is deteriorated as the area lies in hydro-meteorologically different region. These finding also suggests that the ANNs absorb the physics behind the rainfall-runoff process.

3. The performance improved consistently, when inputs are increased but beyond certain number of inputs, either the results are affected or saturated. This is in accordance to the physical laws in which the proper variables, boost the performance while shows negative response when some irrelevant inputs are included.

CHAPTER 6

CONCLUSIONS & RECOMMENDATIONS

6.1 CONCLUSIONS

1. ANNs are capable of recognising the patterns and the models developed on the basis of ANNs perform better than regression models irrespective of the catchment size, shape, slope and location of the study area and number of data considered as found in the study of Paleru , Musi and Samakoi sub basins considering monthly data. Further, the ANNs are stronger in capturing the peak flows.
2. The performance of ANNs slightly deteriorated when the study is made on Ten daily basis as found while studying the Samakoi sub basin. The findings of Tokar and Markus (2000) while applying the ANNs to American river systems also suggest that the ANNs are more accurate with monthly input vector than 10 daily.
3. The performance of ANNs is improved with the inclusion of PET while studying on monthly basis and slightly affected while the study is made on Ten daily basis.
4. The ANNs are adaptable if the area of the model structure and the area of the testing are located in hydro meteorologically same region.
5. Both of the training algorithms LLSSIM and Back Propagation gives comparable results while the latter takes more time for completing the training. Further in Back Propagation the performance improves consistently with the increase in variables whereas in LLSSIM the best performance is attained somewhere in the intermittent level.
6. The time consumed by the training process is inversly proportional to the quality of data and this is in accordance with the fact that the quality of the data influences the solution space.

6.2 RECOMMENDATIONS

To establish ANNs as rainfall-runoff models, further study is required and the following recommendations are made to work in this direction.

1. Number of basins/sub basins all over the country with different size and shape of are to be studied. Using the weights of these catchments for testing the various areas on the basis of size, shape, slope, location and with repeatedly changing variable pattern may tell exactly about the influencing physical parameters using the principle of mutual exclusion.
2. Changing the training and testing data sets judiciously, it may be possible to come out with an optimal data set for training the network. This is very essential as to avoid the over training that results in poor performance while testing.
3. The noiseness in data, whether reduces the performance, is needed to be studied further by artificially including the noise data keeping all other characteristics similar. This can be achieved by studying the monthly or ten daily data sets of good correlation with and without the noiseness in data sets. In this study, it is not conclusive whether the reduced performance with ten daily data sets is due to the noiseness in the data sets
4. The extensive use of the ANNs for different objectives may result in faster analysis and reduce the unnecessary delay in implementation of the water resources projects.

REFERENCE

Abrahart, R.J. "Neural networks and the problem of accumulated error: An embedded solution that offers new opportunities for modeling and testing" *Hydroinformatics'98*, Babovic and Laren(eds),1998 Balkema, Rotterdam,725-740.

ASCE Task Committee (2000), Application of Artificial Neural networks in Hydrology, " Artificial Neural Networks in Hydrology-I: Preliminary Concepts." *Journal of Hydrologic Engineering*, April 2000, 115-123

ASCE Task Committee (2000), Application of Artificial Neural networks in Hydrology, "Artificial Neural Networks in Hydrology-II: Hydrologic Applications." *Journal of Hydrologic Engineering*, April 2000, 124-137

Babovic,V.(1998), "A data mining approach to time series modeling and forecasting." *Hydroinformatics'98*, Babovic and Laren(eds) 1998 Balkema, Rotterdam, 847-856.

Maidment, David R., "Hand Book Of Hydrology" Tata *Mc Graw-Hall,* 1992, 17.30, 17.40

Govindaraju, R.S., and Ramachandra Rao, A. " Editorial" *Journal of Hydrologic Engineering*, July 2000, 225-226

Hamday A.Taha. " Operations Research An Introduction" *Prentice-Hall of India* , 1998

Hsu,Kuo-lin., Gupta, H.V., and Soroosh Sorooshian " Artificial Neural Networks modeling of rainfall-runoff process." *Water Resources Research*, 31(10), 1995,2517-2530

Jain,S.K.,and Chalisgaonkar, Setting up stage discharge relationship using ANN" *Journal of Hydrologic Engineering,* vol 5, No.4, 428-432

Khondker, M.ul-H., Wilson,G., and Klinting,A. " Aplication of Neural Neworks in time flash flood forecasting." *Hydroinformatics'98*, Babovic and Laren(eds), 1998 Balkema, Rotterdam, 777-781.

Lange, N.T.G., " Advantages of unit hydrograph derivation by neural networks." *Hydroinformatics'98*, Babovic and Laren(eds),1998 Balkema, Rotterdam, 783-789.

Liu,K.C., and Lin,S.C. " Artificial neural network forecasting for chaotic dynamical process in hydrology." *Hydroinformatics'98*, Babovic and Laren(eds),1998 Balkema, Rotterdam, 791-796.

Luis Silveira. " Large scale basins with small to negligible slopes part I&II." *Nordic Hydrology* 31(1), 2000,15-26

Luk,K.C., Ball,.J.E., and Sharma,A. " Rainfall forecasting through artificial neural networks." *Hydroinformatics'98*, Babovic and Laren(eds),1998 Balkema, Rotterdam, 797-804.

Minns,A.W., hall, M.J. " Artificial neural networks as Rainfall-runoff models." *Hydrological Sciences* - Journal- des Sciences Hydrologiques, 41(3) June 1996, 399-417

Sezin Tokar,A. and Momcilo Markus,. " Precipitation –Runoff Modeling using Artificial Neural Networks and Conceptual Models," *Journal of Hydrologic Engineering*, April 2000, 156-161

Van den Boogaard, H.E.P., Gautam, D.K., and Mynett, A.E., " Auto regressive neural networks for the modeling of time series," *Hydroinformatics'98*, Babovic and Laren(eds), 1998 Balkema, Rotterdam, 741-748

Yegnanarayana, B. " Artificial Neural Networks." *Prentice Hall of India,* 1999.

Zhang, B., and Govindaraju, R.S., " Using Modular Neural Networks to predict Watershed Runoff." *Water Resources Engineering*,98, 897-902

Paleru sub basin of Krishna basin

Appendix-A

Weighted raifall over the catchment

unit : mm

Year	June	July	Aug	Sept	Oct	Nov	Mon-soon	Dec	Jan	Feb	Mar	April	May	Non-mon	Annual
1965-66	60.3	279.8	101.6	154.9	1.1	0.5	598.2	0.0	53.0	0.0	0.0	13.1	0.2	66.3	664.5
1966-67	64.6	209.5	132.6	174.5	41.9	14.6	637.7	25.7	0.8	0.0	48.9	13.4	4.7	93.5	731.3
1967-68	112.9	260.4	138.4	146.9	7.5	0.0	666.1	19.4	6.2	9.4	3.0	34.3	12.0	84.3	750.4
1968-69	69.4	206.8	32.4	236.4	71.1	19.6	635.7	0.6	3.2	0.0	0.0	1.9	254.2	259.9	895.6
1969-70	74.9	231.3	158.0	151.1	128.0	103.1	846.4	46.3	0.1	4.2	53.0	38.0	76.0	217.6	1064.0
1970-71	252.4	117.8	304.9	155.4	65.4	0.0	895.8	0.0	0.0	13.7	13.1	2.3	56.4	85.4	981.2
1971-72	124.9	82.5	121.3	115.5	185.6	0.0	629.9	0.0	0.0	2.9	0.0	7.4	10.2	20.5	650.3
1972-73	82.4	85.8	73.1	77.8	90.6	81.5	491.2	2.5	0.0	0.0	5.4	4.7	10.0	22.7	513.8
1973-74	143.8	168.0	266.9	108.6	155.8	23.7	866.8	0.0	0.0	0.0	0.0	4.3	41.5	45.8	912.6
1974-75	123.9	177.0	155.1	165.2	387.1	9.6	1018.0	0.0	10.2	6.6	0.0	3.7	59.9	80.4	1098.4
1975-76	156.7	305.4	237.2	306.5	231.0	15.3	1252.1	0.0	0.3	0.4	0.3	5.0	52.6	58.6	1310.7
1976-77	127.2	257.1	290.9	113.8	29.8	74.2	893.0	0.0	0.0	0.0	0.7	20.8	43.8	65.3	958.3
1977-78	35.8	154.9	199.9	48.6	143.3	140.3	722.7	8.8	26.4	7.7	1.0	3.5	17.1	64.4	787.1
1978-79	255.8	283.2	441.0	226.7	60.2	34.7	1301.6	0.1	0.0	86.4	0.1	10.8	39.3	136.6	1438.2
1979-80	73.4	93.4	50.1	268.1	44.9	47.8	577.6	14.8	9.9	0.0	5.7	10.7	10.8	51.9	629.5
1980-81	179.3	174.4	146.2	76.8	20.9	2.3	600.0	10.2	3.0	0.0	49.3	9.1	30.7	102.3	702.3
1981-82	142.1	233.3	154.7	224.0	72.0	10.6	836.7	0.7	0.0	0.0	4.3	9.1	55.6	69.7	906.5
1982-83	128.3	217.4	114.4	128.1	91.7	39.8	719.7	0.0	0.0	0.8	0.0	1.6	7.4	9.9	729.6

Runoff over the catchment

Year	June	July	Aug	Sept	Oct	Nov	Mon-soon	Dec	Jan	Feb	Mar	April	May	Non-mon	Annual
1965-66	1.7	47.5	19.1	41.9	18.2	12.3	140.6	0.6	0.9	0.2	0.2	0.1	0.2	2.2	142.9
1966-67	2.7	10.4	13.4	19.8	10.4	3.7	60.3	0.4	0.2	0.1	0.1	0.1	0.0	0.9	61.3
1967-68	2.6	43.5	18.1	16.2	15.7	8.8	104.8	0.4	0.1	0.1	0.1	0.1	0.1	1.0	105.8
1968-69	1.4	10.1	1.9	19.8	9.2	2.9	45.4	0.1	0.1	0.1	0.1	0.1	24.0	24.6	70.0
1969-70	2.5	4.7	11.3	28.9	32.0	79.9	159.2	24.0	2.2	1.4	6.5	1.7	2.7	38.5	197.7
1970-71	11.3	4.7	131.6	34.1	20.1	10.9	212.8	2.0	1.4	1.1	1.8	0.9	1.2	8.5	221.2
1971-72	3.7	1.2	4.0	7.9	18.5	7.0	42.3	1.3	1.4	1.1	0.8	0.3	0.2	5.1	47.4
1972-73	0.5	0.7	1.8	7.9	8.5	12.5	32.0	1.2	1.1	0.8	0.7	0.4	0.2	4.4	36.4
1973-74	2.7	2.3	23.2	17.6	33.5	20.9	100.2	0.9	1.2	1.4	1.5	1.5	0.6	7.1	107.3
1974-75	1.2	0.9	6.2	18.9	110.1	25.6	162.9	5.5	7.3	7.3	7.4	7.2	2.0	36.7	199.6
1975-76	2.2	14.1	50.8	128.4	130.3	23.8	349.7	8.3	10.5	10.7	9.3	8.4	2.6	49.7	399.4
1976-77	2.6	23.1	150.4	74.0	19.8	29.9	299.7	2.8	1.5	1.0	0.7	0.5	1.5	8.0	307.8
1977-78	1.2	10.6	38.7	21.8	44.0	31.5	148.0	4.0	6.9	9.1	10.0	9.4	4.3	43.7	191.7
1978-79	23.1	49.9	196.4	53.0	24.1	14.1	360.6	4.2	2.3	1.9	1.7	2.2	1.4	13.8	374.5
1979-80	0.9	1.1	8.5	48.0	24.9	27.1	110.6	38.8	9.8	14.7	14.5	11.6	3.9	93.3	203.9
1980-81	10.6	36.1	49.6	28.0	30.3	20.1	174.8	5.0	1.5	1.4	1.7	2.0	1.1	12.7	187.5
1981-82	1.6	24.4	50.2	52.7	46.2	21.7	196.7	4.3	1.6	0.9	1.1	1.2	1.0	10.0	206.8
1982-83	0.9	4.8	35.8	29.3	35.1	26.8	132.8	7.9	8.3	4.4	1.8	1.3	1.2	25.0	157.7

Musi sub basin of Krishna basin

Weighted rainfall over the catchment

Appendix-B

Unit : mm

Year	June	July	Aug	Sept	Oct	Nov	Mon-soon	Dec	Jan	Feb	Mar	April	May	Non-mon	Annual
1968-69	89.7	136.5	29.6	276.7	67.6	20.5	620.7	0.4	3.1	0	1.8	9.6	64.8	79.7	700.4
1969-70	72.6	182.7	118.4	188.6	61.1	74.7	698.1	24.4	0.5	2.2	12.5	34.5	57.4	131.5	829.5
1970-71	174.8	75.3	284.2	174.8	58	0	767.1	0	0.3	3.9	2.3	15.4	37.8	59.7	826.8
1971-72	111.3	45.8	130.1	114	121.4	0	522.6	0	0	1	0	12.7	5.3	19	541.5
1972-73	90.3	92.2	33	78.2	89.7	45.6	429	2.3	0	0	3.1	9.6	11.1	26.1	455.1
1973-74	124.7	96.4	203.2	113.7	222.1	21.9	782.1	0.1	0	0	1.4	6	44	51.4	833.5
1974-75	62	72.5	131.6	154.4	260.9	6.2	687.6	0	19.7	11.2	20.5	5.2	33.1	89.6	777.2
1975-76	88.1	202.6	173.9	400.9	360	15.8	1241.4	0	0	0	0.9	27.8	12.3	41.1	1282.5
1976-77	118	295	240.6	82.7	6.1	67.6	810	0	0	0	2.6	20	31.1	53.7	863.7
1977-78	77.6	167	194.8	25.8	84.5	71.7	621.3	8.4	39.9	23.5	1	16.4	52.1	141.4	762.7
1978-79	169.4	225.6	315.1	181.3	59.3	45	995.6	0	0.6	47.2	0	18	51.4	117.2	1112.9
1979-80	82.7	81.6	70.9	266.8	20.1	55.9	578	10	3.5	0	5.1	17.4	10.9	46.9	624.9
1980-81	187.5	111.7	146.9	82.7	6.3	6.8	541.9	5.9	7	0	64.1	30.8	29.1	136.9	678.8
1981-82	157.9	136.2	162.9	243.2	99.2	1.1	800.6	0.4	0	0	3.9	19.2	46.5	70	870.6
1982-83	121.6	142.2	103.1	130.9	106.8	38.3	642.8	0	0	1.6	4.7	7.8	22.2	36.3	679.1

Runoff over the catchment

Year	June	July	Aug	Sept	Oct	Nov	Mon-soon	Dec	Jan	Feb	Mar	April	May	Non-mon	Annual
1968-69	0.1	3.3	18	28.7	26.6	23.8	100.5	13.1	13.7	13.4	14.5	8.6	5.7	69	169.5
1969-70	1.9	8	23.7	33.8	30.7	28.7	126.8	9.4	9.6	12.1	16.5	12.4	0.6	60.6	187.4
1970-71	6.7	21.8	43.4	42.1	28.4	20.1	162.4	5.3	7.1	7.5	7.2	2.3	0.5	30	192.4
1971-72	1.3	3	13.9	18.1	26.6	13.8	76.7	4.3	5.3	4.1	3.4	1.2	0.3	18.6	95.3
1972-73	0.1	0.7	3.5	8.9	14.8	7.4	35.3	2.3	4.3	3	3.8	1.8	0.3	15.4	50.7
1973-74	1.2	1.7	23.2	15.8	37.8	12	91.8	1.7	5.6	5.7	6.9	4	0.5	24.4	116.2
1974-75	1	1.4	17.2	21.6	31.1	14.6	86.9	4.7	8	8.3	6	3.6	0.6	31.2	118.1
1975-76	0.8	8.4	20.7	89.8	168.7	44.9	333.3	6.4	9.4	7.8	7.1	3.8	0.6	35.2	368.5
1976-77	2.1	10	51.9	48.3	12.9	15.8	141	2.7	3.6	1.6	2.2	1.9	1.6	13.7	154.7
1977-78	0.4	3.9	13.6	10.2	15.9	11.4	55.5	1.9	3.1	4.3	4.3	2.7	0.8	17.1	72.6
1978-79	2	12	91.4	33.4	27.1	15.1	181	3.8	7.1	4.4	4	2.7	1	23.1	204.1
1979-80	0.4	4.9	4.7	29.2	10.7	10.7	60.5	5.6	4.6	4.6	5.2	4.1	0.9	25.1	85.5
1980-81	2.3	10.5	14.4	12.7	11.2	8.1	59.2	1.8	0.7	0.3	0.3	0.4	0.2	3.6	62.8
1981-82	0.3	2.5	16.6	26.5	43.2	13.5	102.6	2.3	0.5	0.3	0.1	0.1	0.1	3.3	106
1982-83	0.4	0.7	8.3	19.4	22.5	14.9	66.2	3.4	2.4	1.5	0.4	0.3	0.1	8.1	74.3

Appendix-C

Samakoi sub basin of Brahmani basin

Weighted rainfall over the catchment

Unit: mm

Year	June	July	August	Sept	Oct	Mon
1985	299.1	245.2	585.9	396.8	280.7	1,807.60
1986	520.7	478.6	219.6	175.4	174.5	1,568.90
1987	105.9	324.6	362.6	196.3	72.1	1,061.60
1988	287.7	443.1	550.6	320.2	47.6	1,649.10
1989	163.7	240.7	437.4	242.1	57.1	1,141.00
1990	315.7	436.6	546.1	367.1	172.7	1,838.20
1991	385.1	719.4	574.3	141.1	92	1,912.00
1992	115.6	485.6	288.7	292.8	80.4	1,263.10
1993	355	441	630.6	419.6	146	1,992.20
1994	411.8	642.6	566.8	166.3	95.8	1,883.30
1995	106.6	465.9	287.5	296.7	101.9	1,258.70

Runoff over the catchment

Unit : mm

Year	June	July	August	Sept	Oct	Mon
1985	33.3	63.9	303.2	217.4	156.2	774
1986	77.8	237.1	126.4	48.7	92.2	582.3
1987	12.8	120.4	161.4	98.2	41.1	433.9
1988	53.1	196.6	335.3	234.5	33.1	852.7
1989	142.3	200.1	424.9	174.1	35.3	976.8
1990	58.1	263.2	217.2	390.1	218.4	1146.8
1991	24.9	274.1	440.5	93.1	102.2	934.7
1992	18.1	90	236.8	143.2	27	515.1
1993	55.6	61.7	336.9	289.7	57.5	801.4
1994	114.6	145.7	261.9	195	41.1	758.3
1995	22.2	110.7	230.5	132.8	49.4	545.7

Samakoi sub basin of Brahmani basin (Ten daily)

Appendix-D
Unit : mm

Weighted rainfall over the catchment

Year	1-Jun	2-Jun	3-Jun	1-Jul	2-Jul	3-Jul	Augt-1	2-Aug	3-Aug	1-Sep	2-Sep	3-Sep	1-Oct	2-Oct	3-Oct	Monsoo
1985	22.7	52.5	223.8	116.0	83.1	46.1	275.7	102.6	207.6	134.8	117.5	144.5	80.2	150.5	50.0	1807.6
1986	45.6	60.3	414.8	138.3	157.6	182.7	63.3	97.8	58.6	36.3	56.4	82.7	133.2	27.7	13.6	1582.5
1987	9.3	17.2	79.5	54.5	180.0	90.0	69.1	107.4	186.1	90.4	73.4	32.5	27.1	24.4	20.6	1061.6
1988	101.6	68.5	117.6	177.0	96.4	169.6	428.5	37.6	84.5	166.0	81.2	73.0	18.6	8.4	20.6	1649.1
1989	64.5	48.3	50.9	22.0	91.6	127.0	194.3	128.6	114.5	136.7	21.1	84.4	4.7	31.8	20.6	1141.0
1990	9.6	164.5	141.6	165.6	178.9	92.1	171.9	308.8	65.5	146.0	183.7	37.5	56.3	98.7	17.7	1838.2
1991	35.9	213.2	136.0	157.0	327.7	234.7	186.2	171.3	216.9	76.4	61.1	3.6	47.6	14.2	30.2	1912.0
1992	19.0	23.3	73.2	128.1	252.2	105.3	186.3	67.9	34.5	168.9	41.3	82.6	18.1	51.2	11.1	1263.1
1993	11.2	184.9	159.0	133.3	194.2	113.5	230.3	363.3	37.0	189.0	193.3	37.3	45.6	83.4	17.0	1992.2
1994	28.8	240.1	142.9	166.5	305.7	170.3	190.6	144.6	231.6	85.7	72.9	7.7	54.5	5.4	36.0	1883.3
1995	13.5	20.2	73.0	134.7	259.2	71.9	212.6	29.4	45.5	144.5	55.0	97.2	30.8	57.0	14.1	1258.7
PET	69.05	69.05	69.05	46.11	46.11	50.72	42.86	42.86	47.15	40.83	40.83	40.53	42.07	42.07	46.27	

Runoff over the catchment

Year	1-Jun	2-Jun	3-Jun	1-Jul	2-Jul	3-Jul	Augt-1	2-Aug	3-Aug	1-Sep	2-Sep	3-Sep	1-Oct	2-Oct	3-Oct	Monsoon
1985	0.0	23.0	10.0	34.0	23.0	6.0	148.0	42.5	112.0	112.0	60.0	45.0	17.0	120.0	18.0	774.0
1986	0.0	8.0	70.0	47.0	66.0	124.0	30.0	50.2	46.0	14.0	18.0	17.0	59.0	27.0	6.0	582.0
1987	10.0	1.0	2.0	6.0	65.0	50.0	33.0	15.4	113.0	43.0	31.0	24.0	15.0	13.0	13.0	434.0
1988	0.9	13.2	39.1	60.8	97.1	38.8	209.8	62.4	63.1	95.5	71.8	67.2	11.1	14.2	7.8	852.7
1989	0.2	103.5	38.5	16.8	14.6	168.7	220.9	138.1	65.9	55.9	63.0	55.2	12.1	13.7	9.6	976.8
1990	7.4	34.8	15.9	44.0	167.8	51.4	40.1	48.4	128.7	153.6	113.3	123.2	74.4	113.6	30.3	1146.8
1991	1.7	13.3	9.9	15.4	51.4	207.3	51.1	199.4	190.0	62.0	4.2	26.9	38.6	47.5	16.0	934.7
1992	6.8	5.4	5.9	1.8	7.6	80.7	76.3	111.7	48.8	92.4	34.0	16.7	10.2	12.0	4.8	515.1
1993	0.0	12.7	42.8	17.6	29.5	14.6	73.3	203.2	60.4	95.6	143.6	50.5	20.1	22.3	15.1	801.4
1994	1.3	66.5	46.8	52.8	18.8	74.1	124.5	120.6	16.7	78.7	88.4	27.9	20.4	11.2	9.4	758.3
1995	1.1	8.2	13.0	17.3	23.3	70.0	143.9	51.3	35.3	66.1	31.5	35.2	17.0	16.9	15.5	545.7