RAINFALL-RUNOFF MODELING OF RIVER KOSI USING SCS-CN METHOD AND ANN

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Bachelor of Technology
In
Civil Engineering

By

Punit Kumar Bhola
and
Ashish Singh

Department of Civil Engineering

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CERTIFICATE

This is to certify that the project entitled, "Rainfall-Runoff modeling of river Kosi using SCS-CN method and ANN" submitted by 'Ashish Singh and Punit Kumar Bhola' in partial fulfillments for the requirements for the award of Bachelor of Technology Degree in Civil Engineering at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the report has not been submitted to any other University / Institute for the award of any Degree or Diploma.

Date:

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ABSTRACT

A rainfall-runoff model is a mathematical model describing the rainfall - runoff relations of a catchment area, drainage basin or watershed. In other words, the model calculates the conversion of rainfall into runoff. There can be used many methods to calculate the runoff among which the methods used in the current report are

- SCS-CN Method
- Artificial Neural Network (ANN)

In rainfall-runoff modeling SCS-CN uses the soil information, rainfall, storm duration, soil texture, type & amount of vegetation cover and conservation practices are considered while a new dimension has been added to the modeling approach through the adoption of the ANN technique as these models possess desirable attributes of universal approximation, and the ability to learn from examples.

The performance comparison of both the models is made with coefficient of determination (R^2) which is coming to be 0.82 in case of SCS-CN method and 0.89 in case of ANN. Further a comparison is made of both the models i.e. ANN and SCS-CN for the runoff of river Kosi in year 2009.

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CHAPTER -1

INTRODUCTION

1.1 General

A rainfall-runoff model is a mathematical model describing the rainfall - runoff relations of a catchment area, drainage basin or watershed. More precisely, it produces the surface runoff hydrograph as a response to a rainfall hydrograph as input. In other words, the model calculates the conversion of rainfall into runoff. A rainfall runoff model can be really helpful in the case of calculating discharge from a basin. The transformation of rainfall into runoff over a catchment is known to be very complex hydrological phenomenon, as this process is highly nonlinear, time-varying and spatially distributed. Over the years researchers have developed many models to simulate this process. Based on the problem statement and on the complexities involved, these models are categorized as empirical, black-box, conceptual or physically-based distributed models. Physically based distributed models are very complex and required too many data and tedious for the application purpose. The conceptual models attempt to represent the known physical process occurring in the rainfall-runoff transformation in a simplified manner by way of linear or nonlinear mathematical formulations but their implementation and calibration is complicated and time consuming. While black-box models, which establish a relationship between input and the output functions without considering the complex physical laws governing the natural process such as rainfall-runoff transformation. The unit hydrograph, which is a linear rainfall-runoff model, is one well-known example of such a relationship. However, these simpler models normally fail to represent the nonlinear dynamics inherent in the process of rainfall-runoff transformation which can be done by using Artifcial Neural Networks and fuzzy logic.

In the present work the KOSI river basin, which lies in Nepal and Bihar, India has been selected as the area of study. The modeling being simulated by two methods SCS-CN method and Artificial Neural Network (ANN) separately and results have been compared at the end. Both the methods have their own importance. In the SCS-CN method data defining the basin properties, like Rainfall data, soil conditions, topographical condition (i.e. the vegetation available above the earth surface, building and roads etc), population density and rainfall data collected from the rain-gauge stations are required. Kosi River emerges from Himalayas thus it can be really hard to get the required data on the upstream side due to the difficulties in establishment of the rain-gauge and discharge stations. Difficulties arise due to the financial conditions and adverse ground conditions available at such steep gradients. To avoid such conditions a method which can give good results without considering the basin conditions is required, thus the opted method is ANN which is based on a black box model. It basically creates a non-linear function by the rainfall and discharge of the historical data and forecasts future discharge using an optimum network suited for the given problem statement then the comparison of two methods i.e. SCS-CN and ANN have been done. SCS-CN method has been in use for a long time (Since 1969) and gives satisfactory result and ANN is relatively new but it gives a wide range of future development aspects and come to an optimum conclusion which one of the method is best suited in context of future development.

CHAPTER -2

STUDY AREA

2.1 KOSI RIVER

The Kosi River basin is the largest river basin in Nepal. It comprises of about 61, 000 sq.km. Out of a total catchment area of 27, 816 sq. km. (45.6%) lies in Nepal and the remaining 331845 sq.km. lies in Tibet. In addition to the Kosi River basin, the other two major basins are in Nepal namely the Karnali and Gandaki River basins. The River Kosi also commonly known as Sapta Kosi comprises of seven rivers namely (From west to east); Indrawati, SunKosi, Tama Kosi, Likhu, Dudh Kosi, Arun and Tamor. Out of these three major rivers or tributaries originates from Tibet; namely; the Sun Kosi, Tama Kosi and Arun. Broadly, the basin of Kosi can be divided into three major river sub-basins; the SunKosi, Arun and Tamor. The SunKosi River comprises of the Indarwati, Sunkhoshi, Tama Kosi, Likhu and Dudh Kosi rivers. The Kosi has an average water flow (discharge) of 1 564 m^3/s or55,000 cu ft/s. During floods, it increases to as much as 18 times theaverage. The greatest recorded flood was 24,200 m^3/s(850,000 cu ft/s) on August 24, 1954. The Kosi Barrage has been designed for a peak flood of27,014 m^3/s (954,000 cu ft/s). The Kosi river has laid waste large fertile tracts during frequent migrations and has caused extensive damage through overbank flooding and inundation. For this reason, it is often called “Sorrow of Bihar”.

2.1.1 SunKosi Basin

The catchment area of the SunKosi basin is about 19,000 sq. km. The SunKosi River originates in the mountain range east of Barhabise called Kalinchowk, and flows in a westerly direction with steep river gradients of 1:10 to meet the BhoteKosi at Barhabise. The BhoteKosi, originates from a glacier on the south slope of Mt. Xixabangma Feng, in the southern part of the Himalayan range in the Tibetan plateau. The catchment area at the confluence point is about 2,375 km2 of which about 2000 sq. km lies in Tibet. The average gradient in the upper reach is 1:8, while in the lower reach it is about 1:31. The SunKosi flows in a south-east direction up to Dolalghat, the confluence point of the SunKosi with the Indrawati River, with an average gradient of 1:130. The Indrawati River, one of the main tributaries of the SunKosi River, originates in the Himalayan range and flows in a south, south-east direction to meet with the River SunKosi at Dolalghat. The average gradient of this river is about 1:34 in the upper reach and 1:194 in the lower reach. The total catchment area of the Indrawati at the confluence with the SunKosi River is about 1,175 sq. km. The SunKosi River, after the confluence with Indrawati River, flows in a south-east direction up to Tribeni with an average gradient of 1:450. The TamaKosi River, which originates in the southern part of the Tibetan Plateau of China, flows in a southerly direction through the Rolwalin Himalayan range and enters Nepal. Within Nepal, the river flows in a southern direction through the mountainous and hilly areas with an average gradient of 1:20 in the upper reach and 1:110 in the lower reach to meet with SunKosi River at Khurkot. The TamaKosi River has total drainage area of 4,190 sq. km at Khurkot. About 40 km downstream of Khurkot, the SunKosi River joins with the Likhu Khola. The Likhu Khola originates in the mountain areas and flows towards the south to meet the SunKosi River. The average gradient of Likhu Khola is about 1:54. Its drainage area at the confluence point with the SunKosi is 1,070 sq. Km. The SunKosi River after the confluence with Likhu Khola, meets with the DudhKosi about 25 km downstream.The DudhKosi originates in the Khumbu and Nojumpa Glaciers located on the southern slopes of the Mahalangur Himalaya range and flows directly from north to south resulting in a rapid river gradient. The average gradient is about 1:30 in the upper reach and 1:250 in the lower reach. The total drainage area of the river (at the confluence with the SunKosi River) is about 4,140 km2. The SunKosi River flows in a south-eastern direction to meet the Arun and Tamur Rivers to form the SaptaKosi at Tribeni. The total length of the river is 330 km. The gradient of the SunKosi River is approximately 1:210 throughout the entire length of its course in Nepal.

2.1.2 Arun River Basin

The Arun River originates from a glacier on the northern slope of Mt. Xixabangma Feng (El.8012m), part of the Himalyan range in the southern part of the Tibetan highland. The river is called Pengqu within Tibet. It flows eastward almost parallel to the Himalyan range in upper reaches for a distance of about 280 km and then makes a sharp turn to the southwest at the junction with its tributary, the Yenuzangbu River Tibet), forming a big bend. The Arun then flows southward crossing the Himalyan range into Nepal. It continues to flow south and joins the SaptaKosi (Kosi) River at Tribeni. The total length of the river is about 510 km and the total drainage area is about 36,000 sq. km, out of which 25,310 sq. km lies in Tibet. In Tibet it has a gradient of 1:130 and 1:630 in upper and lower reach, respectively. When it enters in Nepal it has a steep slope in the range of 1:30 to 1:50 in upper reach. In the middle reach of Nepal it has a slope of 1: 96 and in lower reaches it has a slope of 1:300 to 1: 400.

2.1.3 Tamur River Basin

The river has its source in the High Himalayas. Near its source the Tamur is called Medalung Khola. Before becoming the Tamur River it is joined by a large khola called Yangma Khola. The north boundary of the Tamur catchment lies in high Himalayas and delineates the border between Nepal and Tibet. Similarly the eastern boundary lies in the High Himalayas and delineates the border between Nepal and India. Kanchanjanga (at an elevation of 8586m) the world's third highest peak lies in this basin. In addition, there are 13 other major peaks in the basin, ranging from 5938 m (Ganbul on northern border of Nepal with Tibet) to 7902 m (Kambachen inside Nepal).

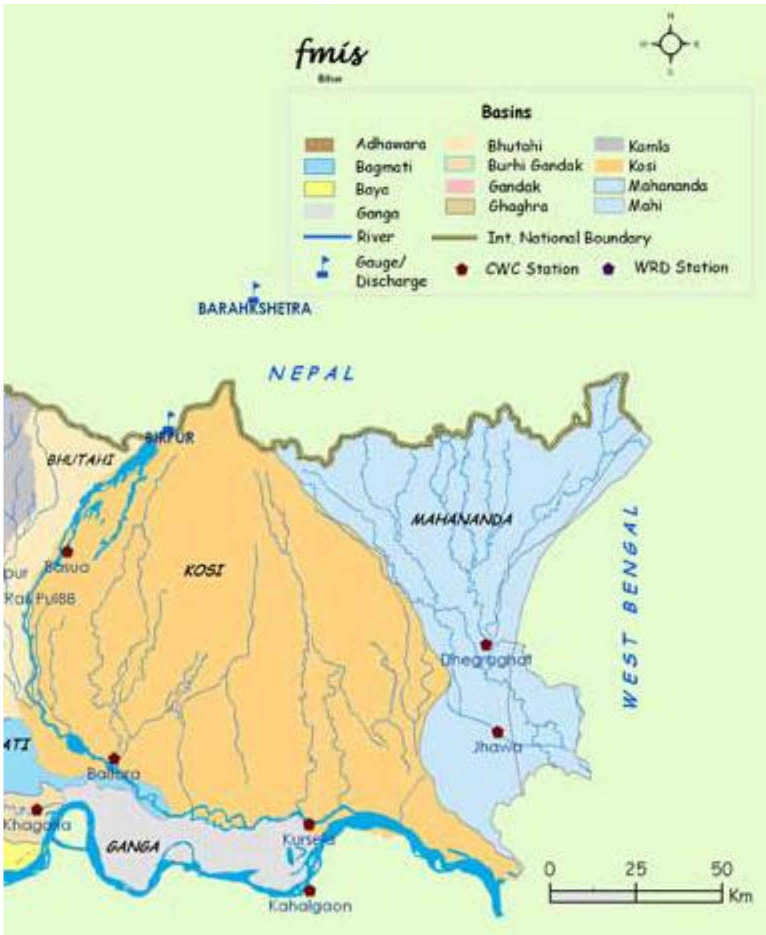


Figure 1: Kosi river basin in Bihar (Flood Management Information System (FMIS), Bihar).

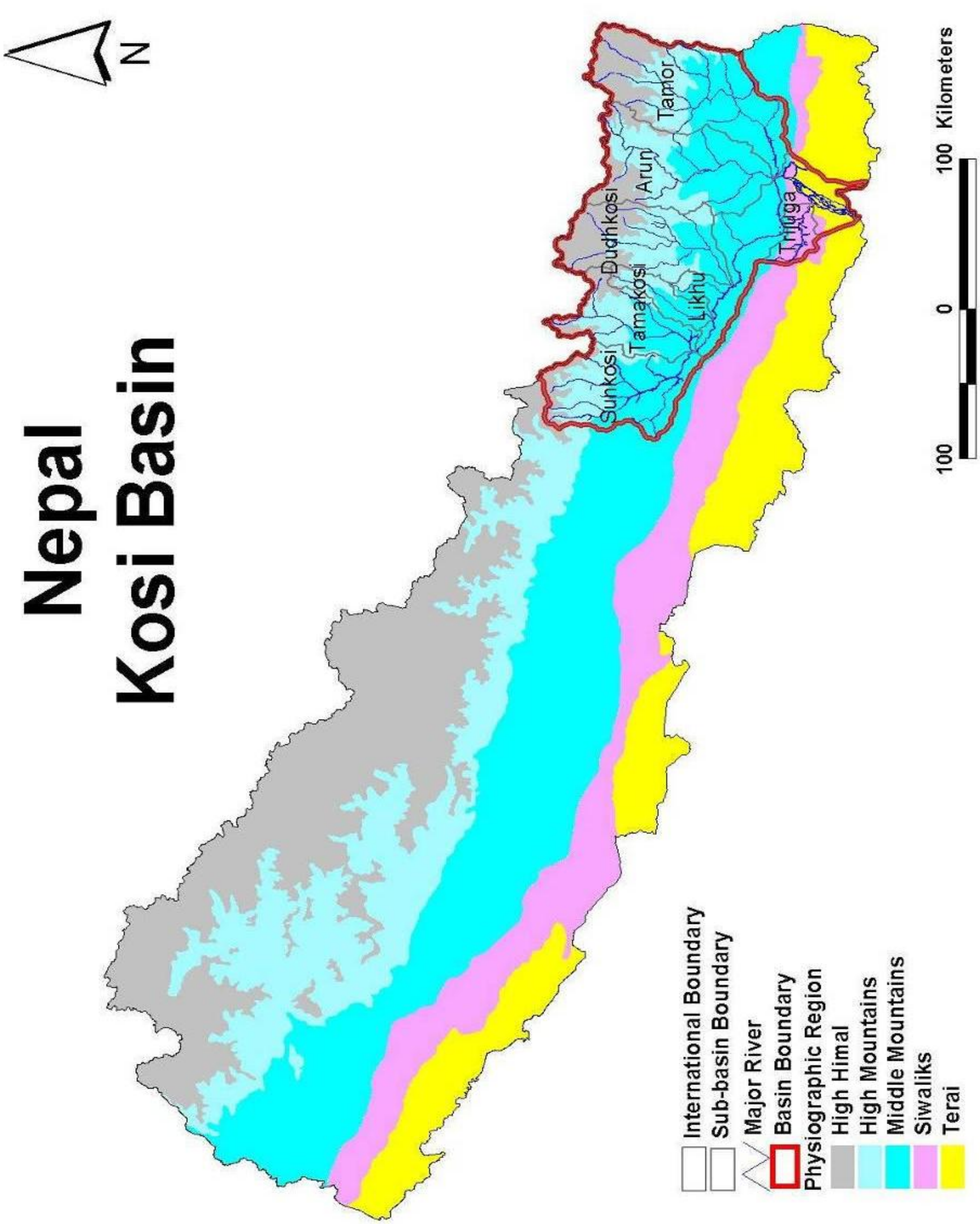


Figure 2: Kosi River basin in Nepal (Rapid hazard and risk assessment post-flood return analysis (2009) UNESCO on behalf of OCHA and UNCT, NEPAL)

In the present report the rainfall data of five years starting from 2005 to 2009 have been taken for five different rain gauge stations

- Okhaldunga, Nepal
- Taplejung, Nepal
- Dhankutta, Nepal
- Biratnagar, Nepal
- Dharan, Nepal

Rainfall data are considered only for monsoon period i.e. from July to October for each year so total 600 data sets are used and discharge for the two station for five years (2005-2009) is considered, two discharge stations are

- Bhimnagar, India
- Barah Kshetra, Nepal

Among which Barah Kshetra lies in the upstream hilly areas of Himalaya and Bhimnagar in downstream relatively planner area.

The rainfall and discharge data were collected from the Water Resources Department, Govt. of Bihar and then scaled. The data has been modified because the discharge data of River Ganga and its tributaries are confidential and may not be made public.

The Kosi basin is an alluvial which has been studied in detail by remote sensing techniques. The Kosi's alluvial fan has fertile soil and abundant groundwater in a part of the world where agricultural land is in acutely limited supply in relation to population. The basin area of river Kosi lies in hydrological soil group C with two type of moisture content i.e AMC II and AMC III, as the precipitation data considered is for the monsoon season.

CHAPTER -3

REVIEW OF LITERATURE

3.1 SCS-CN method

The SCS-CN method has been widely used to compute direct surface runoff. It originated from the (I) proposal of Sherman(1949) on plotting direct runoff versus storm rainfall; the subsequent work Mockus (1949) on estimation of surface runoff for ungauged stations using the soil information, rainfall, storm duration and average annual temperature and (II) the graphical procedure of Andrews (1982) for estimating runoff from rainfall for combination of soil texture and type amount of vegetation cover and conservation practices, also known as soil vegetation land use (SVL). Thus the empirical runoff relation of Mockus and SVL complex of Andrews founded SCS-CN method. Extensive work has been done to estimate discharge in rivers and the relevant literature review is given below

McCuen(1982), Hjelmfelt(1991), Hawkins(1993), Steenhuisetal.(1995), Bonta(1997), Mishra and Singh (1999,2002,2003,2004) and Mishra et al.(2004,2006), Sahu et al (2007) has done appreciable work in this field. SCS-CN method has wide application in fields like design of discharge system, irrigation system, spillways, sediment yield, non-point source pollution and many more. Besides them Stuebe and Johnston 1990; Ponce and Hawkins 1996; Michel et al 2005; Ramakrishnan (2008) used SCS-CN method in their analysis. Bhuyan et al. (2003) studied event based watershed scale antecedent moisture condition (AMC) values to adjust field-scale CNs, and to identify the hydrological parameters that provide the best estimate of AMC. Patil et al. (2008) has done work in this field using GIS based interface selected sites. Kosi River is selected as the study case by us as it has been in limelight due to its very uncertain behavior. It changes its path time to time thus cause many people to migrate. This is the reason why it’s called Sorrow of Bihar. Sinha (2008) had done a lot of work on this river.

3.2 Artificial Neural Network

A new dimension has been added to the system-theoretic modeling approach through the adoption of the artificial neural network (ANN) technique for rainfall-runoff modeling. Presently more and more researchers are utilizing ANNs because these models possess desirable attributes of universal approximation, and the ability to learn from examples without the need for explicit physics. In 1890, William James published the first work about brain activity patterns. In 1943, McCulloch and Pitts produced a model of the neuron that is still used today in artificial neural networking. In 1949, Donald Hebb published "The Organization of Behavior", which outlined a law for synaptic neuron learning. This law, later known as Hebbian Learning in honor of Donald Hebb is one of the simplest and most straight-forward learning rules for artificial neural networks.In 1951, Marvin Minsky created the first ANN while working at Princeton. In 1958 "The Computer and the Brain" was published posthumously, a year after John von Neumann's death. In that book, von Neumann proposed many radical changes to the way in which researchers had been modeling the brain.

The limitation of the linear unit hydrograph to represent the rainfall-runoff relationship, which is a nonlinear process, gives rise to the implementation of nonlinear black-box models. Amorocho (1973) summarized his previous works demonstrating that the functional series nonlinear models could be employed to simulate rainfall-runoff transformation. Diskin & Boneh (1973), Papazafiriou (1976) and many others have also explored the functional series as a catchment model for nonlinear black-box analysis. Muftuoglu (1984) proposed a physically realizable nonlinear runoff model, which was later applied to a larger catchment by Kothyari & Singh (1999). MINNS et al.(1996) shown how the application of different standardization factors to both training and verification sequences has underlined the importance of such factors to network performance. The multiple-input single output linear and nonlinear black-box models have also been studied in detail by Liang & Nash (1988), Papamichail & Papazafiriou (1992), Liang *et al.* (1994), Rajurkar *et. al* (2002), among others. Due to certain limitations for MLP use, Harun *et. al* (2001) and Kumar *et. al* (2004), have studied the performance of MLP- and RBF-type neural network models developed for rainfall-runoff modeling of two Indian river basins. The performance of both the MLP and RBF network models were comprehensively evaluated in terms of their generalization properties, predicted hydrograph characteristics, and predictive uncertainty. Many researchers have studied the impact of rainfall on runoff in previous few years. Atila et al (2010) studied the behavior of runoff using the Adaptive Neuro Fuzzy Interference Systems (ANFIS) and Artificial Neural Network (ANN) models at Flow Observation Stations (FOS) on seven streams where runoff measurement has been made for long years in Susurluk.

CHAPTER -4

METHODOLOGY

4.1 SCS-CN Method of Estimating Runoff Volume

SCS-CN method developed by Soil Conservation Services (SCS) of USA in 1969 is a simple, predictable and stable conceptual method for estimation of direct runoff depth based on storm rainfall depth. It relies on only one parameter, CN. Currently, it is a well established method, having been widely accepted for use in USA and many other countries. The details of the method are described in the section.

The SCS-CN method is based on the water balance equation and two fundamental hypotheses. The first hypothesis equates the ratio of the amount of direct surface runoff Q to the total rainfall P (or maximum potential surface to the runoff) with the ratio of the amount of infiltration F_c amount of the potential maximum retention S. The second to the potential hypothesis relates the initial abstraction I_a maximum retention. Thus, the SCS-CN method consisted of the following equations [Subramanya K. (2008].

(a) Water balance equation:

$$P = I_a + F_c + Q \qquad (1)$$

Proportional equality hypothesis

$$\frac{Q}{(P - Ia)} = \frac{Fc}{S} \qquad (2)$$

(b) I_a - S hypothesis:

$$I_a = \lambda S \qquad (3)$$

Where,

P is the total rainfall, I_a the initial abstraction, F_c the cumulative infiltration excluding I_a, Q the direct runoff, S the potential maximum retention or infiltration and λ the regional parameter dependent on geologic and climatic factors ($0.1<\lambda<0.3$).

Solving equation (2)

$$Q = \frac{(P - I_a)^2}{P - I_a + S} \qquad (4)$$

$$Q = \frac{(P - \lambda S)^2}{P - (\lambda - 1)S} \qquad (5)$$

The relation between I_a and S was developed by analyzing the rainfall and runoff data from experimental small watersheds and is expressed as I_a=0.2S. Combining the water balance equation and proportional equality hypothesis, the SCS-CN method is represented as

$$Q = \frac{(P-0.2S)^2}{P+0.8S} \quad (6)$$

The potential maximum retention storage S of watershed is related to a CN, which is a function of land use, land treatments, soil type and antecedent moisture condition of watershed. The CN is dimensionless and its value varies from 0 to 100.The S-value in mm can be obtained from CN by using the relationship

$$S = \frac{25400}{CN} - 254 \quad (7)$$

4.1.1 SOILS

In determining the CN, the hydrological classification is adopted. Here soils are classified into four classes A, B, C and D based on the infiltration and other characteristics. The important soil characteristics that influence the hydrological classification of soils are effective depth of soil, average clay content, infiltration characteristics and the permeability. Following is a brief description of four hydrologic soil groups:

- Group A (LOW RUNOFF POTENTIAL): Soils having high infiltration rates even when thoroughly wetted and consisting chiefly of deep, well to excessively drained sand or gravels. These soils have high rate of water transmission.
- Group B (MODERATELY LOW RUNOFF POTENTIAL): Soils having moderate infiltration rates when thoroughly wetted and consisting chiefly of moderately deep to deep, moderately well to well drained soil with moderately fine to moderately coarse textures. These soils have moderate rate of water transmission.
- Group C (MODERATELY HIGH RUNOFF POTENTIAL): Soils having low infiltration rates when thoroughly wetted and consisting chiefly of moderately deep to deep, moderately well to well drained soil with moderately fine to moderately coarse textures. These soils have moderate rate of water transmission.
- Group D (HIGH RUNOFF POTENTIAL): Soils having low infiltration rates when thoroughly wetted and consisting chiefly of clay soils with high swelling potential, soil with permanent high water table, soils with clay pan or clay layer at or near the surface and shallow soils over nearly impervious material.

4.1.2 Antecedent Moisture Condition (AMC)

AMC refers to the moisture content present in the soil at the beginning of the rainfall-runoff event under consideration. It is well known that initial abstraction and infiltration and are governed by AMC. For purposes of practical application three level of AMC are recognized by SCS as follows:

AMC-I: Soils are dry but not to wilting point. Satisfactory cultivation has taken place.

AMC-II: Average conditions

AMC-III: Sufficient rainfall has occurred within the immediate past five days. Saturated soil conditions prevail.

Table 1: Antecedent moisture conditions (AMC) for determining the values of CN

AMC Type	**Total rain in previous 5 days**	
	Dormant season	**Growing season**
I	Less than 13 mm	Less than 36 mm
II	13 to 28 mm	36 to 53 mm
III	More than 28 mm	More than 53 mm

4.1.3 Land use

The variation of curve number under AMC II called CN_{II} for various land conditions commonly found in practice are shown in table 2

Table 2: Classification of hydrological soil group

Land use	**Hydrological soil group**	**Treatment**	**Hydrological cover condition**
Row crops	C	Straight row	Poor
Paddy fields	C	Straight row	Poor
Forest land	B	NC	Fair
Farmsteads	D	NC	NC
Wasteland	B	NC	NC

The conversion of CN_{II} to other two AMC conditions can be made through the following correlation equations.

For AMC I

$$\frac{CN_{II}}{2.281-0.01281\,CN_{II}} \tag{8}$$

For AMC III

$$\frac{CN_{II}}{0.427+0.00573\,CN_{II}} \tag{9}$$

CN-II can be calculated from the given table

Table 3: Runoff Curve Number (CN_{II}) for Hydrologic Soil cover under AMC II conditions

Land use	**Cover**		**Hydrologic Soil Group**			
	Treatment or practice	Hydrologic condition	A	B	C	D
Cultivated	Straight row		76	86	90	96
Cultivated	Contoured	Poor	70	79	84	87
		Good	65	75	82	86
Cultivated	Contoured and terraced	Poor	66	74	80	83
		Good	62	71	77	82
Cultivated	Bunded	Poor	67	75	81	82
		Good	59	69	76	79
Cultivated	Paddy		95	95	95	95
Orchards	With understory cover		39	53	67	72
	Without understory cover		41	45	69	75
Forests	Dense		26	40	52	65
	Open		28	44	60	67
	Scrub		33	47	60	69
Pastures	Poor		68	79	86	88
	Fair		49	69	79	85
	Good		39	61	74	83
Wasteland			71	80	85	89
Roads (dirt)			73	83	88	91
Hard surface areas			77	86	91	95

4.2 Artificial neural network (ANN)

The relationship of rainfall-runoff is known to be highly non-linear and complex. The rainfall-runoff relationship is one of the most complex hydrologic phenomena to comprehend due to the tremendous spatial and temporal variability of watershed characteristics and precipitation patterns, and the number of variables involved in the modeling of the physical processes. Hydrologists are often confronted with problems of prediction and estimation of runoff, precipitation, contaminant concentrations, water stages, and so on. Although many watersheds have been gauged to provide continuous records of stream flow, hydrologists are often faced with situations where little or no information is available. In such instances, simulation models are often used to generate synthetic flows. The available rainfall-runoff models are HEC-HMS, MIKE-11, SWMM, etc. These models are useful for the hydrologic and hydraulic engineering planning and design as well as water resources management; e.g., hydropower generation, flood protection and irrigation. The existing popular model is considered as not flexible and they require many parameters. Obviously, the models have their own weaknesses. Therefore, in view of the importance of the relationship between rainfall-runoff, the present study was undertaken in order to develop rainfall-runoff models that can be used to provide reliable and accurate estimates of runoff.

ANN models have been used successfully to model complex non-linear input output relationships in an extremely interdisciplinary field. The natural behavior of hydrological processes is appropriate for the application of ANN method. In terms of hydrologic applications, this modeling tool is still in its nascent stages. Several studies indicate that ANN have proven to be potentially useful tools in hydrological modeling such as for modeling of rainfall-runoff processes flow prediction, water quality predictions, operation of reservoir system groundwater reclamation problems etc. The objective of the present study is to develop rainfall-runoff models using ANN methods.

4.2.1 NEURAL NETWORK MODEL

An ANN can be defined as ‘a data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain’. The ANN tries to mimic the functioning of the human brain, which contains billions of neurons and their interconnections. Two types of neural network architectures, namely multilayer perceptron (MLP) and radial basis function (RBF) network are implemented. The architecture of an ANN is designed by weights between neurons, a transfer function that controls the generation of output in a neuron, and learning laws that define the relative importance of weights for input to a neuron. The objective of ANN is to process the information in a way that is previously trained, to generate satisfactory results. Neural network can learn from experience, generalize from previous examples to new ones, and abstract essential characteristics from inputs containing irrelevant data. The main control parameters of ANN model are interneuron connection strengths also known as weights and the biases. In all cases, the output layer had only one neuron, that is, the runoff.

4.2.1.1 Multilayer Perceptron

The first technique of neural network modeling is the MLP model, and the architecture of a typical neuron with single hidden layer is shown in Figure 3. Basically the MLP consists of three layers: the input layers, where the data are introduced to the network; the hidden layer, where the data are processed (that can be one or more) and the output layer, where the results for given inputs are produced.

Each layer is made up of several nodes, and layers are interconnected by sets of correlation weights. Each input node unit ($i=1,\dots,m$) in input layer broadcasts the input signal to the hidden layer. Each hidden node ($j=1,\dots,n$) sums its weighted input signals according to

$$z\_in_j = w_{oj} + \sum_{i=1}^{m} x_i w_{ij} \qquad (10)$$

applies its activation function to compute its output signal from the input data as

$$z_j = f\,(z\_in_j) \qquad (11)$$

and sends this signal to all units in the hidden layer. Note that w_{ij} is the weight between input layer and hidden layer, w_{0j} is the weight for the bias and x_i is the input rainfall signal. The net of a neuron is passed through an activation or transfer function to produce its result. Therefore, continuous-transfer functions are desirable.

The transfer function, denoted by $\xi(\mu_k)$, defines the output of a neuron in terms of the activity level at its input. Six commonly used functions are predefined as below

- The Sigmoid function, ranged from 0 to 1, is defined as

$$\xi(\mu_k) = \frac{1}{1+ e^{-a\mu_k}} \tag{12}$$

- The Hyperbolic Tanh function, ranged from -1 to 1, is defined by

$$\xi(\mu_k) = \frac{1-e^{-a\mu_k}}{1+ e^{-a\mu_k}} \tag{13}$$

- The Gaussian function, ranged from 0 to 1, defined as

$$\xi(\mu_k) = e^{-a(\mu k)^2} \tag{14}$$

- The Linear function: ranged from -∝ to +∝

$$\xi(\mu_k) = a.\mu_k \tag{15}$$

- The Threshold Linear function: ranged from 0 to +1

$$\begin{cases} \xi(\mu k) = 0 & \text{if } \mu k < 0 \\ \xi(\mu k) = 1 & \text{if } \mu k > 1 \\ \xi(\mu k) = a.\mu k & \text{if } 0 < \mu k < 1 \end{cases} \tag{16}$$

- The Bipolar Linear function: ranged from -1 to +1

$$\begin{cases} \xi(\mu k) = -1 & \text{if } \mu k < -1 \\ \xi(\mu k) = 1 & \text{if } \mu k > 1 \\ \xi(\mu k) = a.\mu k & \text{if } -1 < \mu k < 1 \end{cases} \tag{17}$$

Where, a is a parameter called "Slope" of transfer functions.

The transfer function used in the present report is sigmoidal which has the property being continuous, differentiable everywhere, monotonically increasing, and it is the most commonly used in the backpropagation networks. The output is always bounded between 0 and 1, and the input data have been normalized to a range 0 to 1. The Slope a is taken assumed to be 1.The sigmoid activation function will process the signal that passes from each node by

$$f(z\_in_j) = \frac{1}{1+ e^{-z\_in\, j}} \tag{18}$$

Then from second layer the signal is transmitted to third layer. The output unit (k =1) sums its weighted input signals and applies its activation function to compute its output signal. The output node (k =1) receives a target pattern corresponding to the input training pattern, computes its error information, calculates its weight correction (used to update c_{kj} later), and its bias correction (used to update c_{0k} later) term. Note that, c_{jk} is the weight between second layer and third layer; c_{ok} is the weight for bias, and y_k is the neural network output. The error information is transfer from the output layer back to early layers. This is known as the backpropagation of the output error to the input nodes to correct the weights.

Back-propagation is the most commonly used supervised training algorithm in the multilayer feed-forward networks. The objective of a backpropagation network is to find the weight that approximate target values of output with a selected accuracy. The network weights are modified by minimizing the error between a target and computed outputs. The error between the output of the network and the target outputs are computed at the end of each forward pass. If an error is higher than a selected value, the procedure continuous with a reverse pass, otherwise, training is stopped. The weights are updated continuously until minimum error is achieved. The least Root mean square error (RMSE) method is used to optimize the network weights in backpropagation networks.

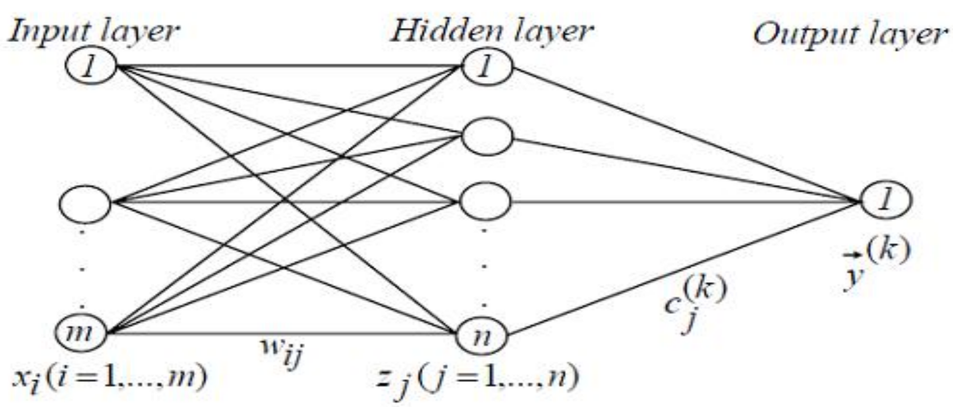


Figure 3: Structure of a MLP model with single hidden layer

4.2.1.2 Radial Basis Function

The second technique of the neural network modeling is the RBF. RBF is supervised and feed forward neural network. Figure 4 illustrates the designed architecture of the RBF. The RBF can be considered as a three layer network. The hidden layer of RBF network consists of a number of nodes and a parameter vector called a ‘center’ which can be considered the weight vector. The standard Euclidean distance is used to measure how far an input vector from the center is. In the RBF, the design of neural networks is a curve-fitting problem in a high dimensional space. Training the RBF network implies finding the set of basis nodes and weights. Therefore, the learning process is to find the best fit to the training data. The transfer functions of the nodes are governed by nonlinear functions that is assumed to be an approximation of the influence that data points have at the center. The transfer function of a RBF network is mostly built up of Gaussian rather than sigmoids. The Gaussian functions decrease with distance from the center. The transfer functions of the nodes are governed by nonlinear functions that is assumed to be an approximation of the influence that data points have at the center. The Euclidean length is represented by r_j that measures the radial distance between the datum vector y (y_1, y_2 ,..., y_m) ; and the radial center can be written as

$$\mathrm{Rj} = \left\| y - Y^j \right\| = \left[\sum_{i=1}^{m} \left(y_i - w_{ij} \right)^2 \right]^{1/2} \qquad (19)$$

A suitable transfer function is then applied to r_j to give,

$$\Phi(\mathrm{r_j}) = \Phi\left(\left\| y - Y^j \right\| \right) \qquad (20)$$

Finally the output layer ($k = 1$) receives a weighted linear combination of Φ_{rj} ,

$$y^k = w_0 + \sum_{j=1}^{n} c_{kj}\, \Phi_{(rj)} = w_0 + \sum_{j=1}^{n} c_{kj}\, \Phi\left(\left(\left\| y - Y^j \right\| \right) \right) \qquad (21)$$

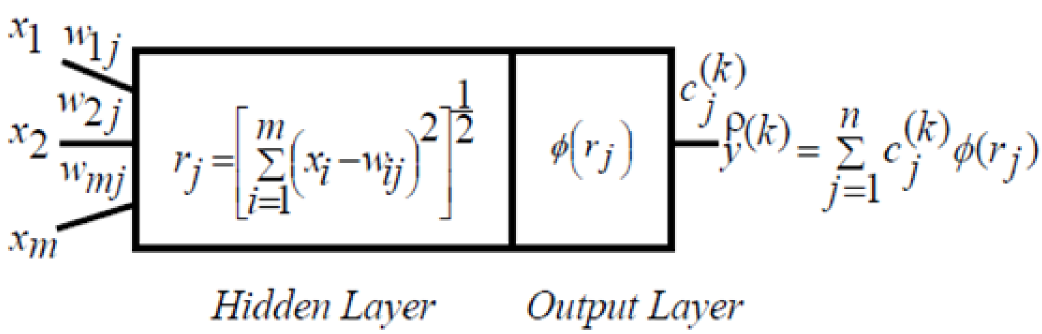


Figure 4:Structure of a RBF model

4.2.2 Rainfall-Runoff Modeling Using ANN

This is a real engine problem. The Natural rainfall-runoff relationship is very complicated and can be affected by many watershed factors. Figure 5 illustrates a typical relationship between effective rainfall and runoff. Runoff produced by rainfall, always has a time lag as compared to actual rainfall. It is why direct mapping between rainfall and runoff cannot be constructed. In this case, time series have to be applied for correctly modeling rainfall-runoff relationships. The follow equation shows relationships of rainfall and runoff

$$Q = f\,(R_t, R_{t-1}, R_{t-2}, \ldots, R_{t-m}, Q_{t-1}, Q_{t-2}, \ldots, Q_{t-n}) \qquad (22)$$

where, Qt: runoff at time t; Q_{t-1}: runoff at time t-1; Q_{t-2}: runoff at time t-2; Q_{t-n}: runoff at time t-n;

n: maximum steps of time lag of runoff. R_t: rainfall at time t; R_{t-1}: rainfall at time t-1; R_{t-m}: rainfall at time t-m. m: maximum steps of time lag of rainfall

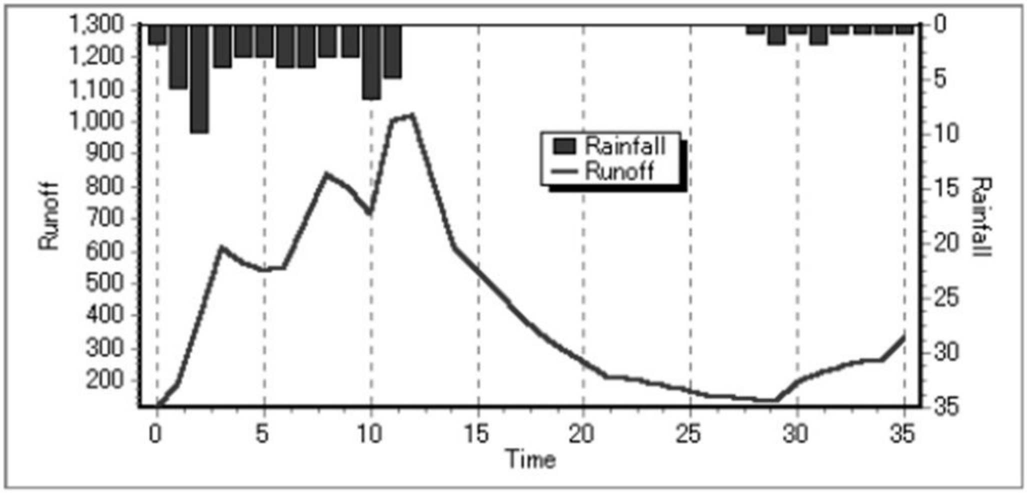


Figure 5: Typical Rainfall- Runoff relationship

Using Software tool NeuralPower, it is very easy to model such a problem with a time series. A unique feature of NeuralPower, is the application of multi-learning files which provides a greater advantage than other similar neural network software. which support only a single learning file. In the present project, there are five instances of rainfall-runoff processes observed from same watershed. It is almost impossible to arrange all them into one data file since they are independent processes and there are time lags between rainfall and runoff. In the present work, based on the analyses, modified discharge was found out to be a function of

$$Q=f(R_t, R_{t-1}, R_{t-2}, Q_{t-1}) \qquad (23)$$

So making all combinations total six input data files have been made

1. Input as rainfall at time t and output as modified discharge at time t
2. Input as rainfall at time lagged by 24 hrs or 1 day and output as modified discharge at time t
3. Input rainfall at time lagged by 2 days and output as modified discharge at time t
4. Two inputs, rainfall at time t and modified discharge lagged by 1day, and output as modified discharge at time t
5. Two inputs, rainfall at time lagged by 1 day and modified discharge lagged by 1day, and output as modified discharge at time t.
6. Two inputs, rainfall at time lagged by 2 day and modified discharge lagged by 1day, and output as modified discharge at time t.

CHAPTER -5

RESULTS & DISCUSSION

5.1 Estimation of missing rainfall data

Data for the rainfall and discharge of River Kosi are taken for the monsoon season (July-September 2005-2009). As many daily rainfall data were missing in the given data sheet the missing data needed to be generated. The missing data could be a result of

- Any interruption at the rain-gauge stations
- The absence of observer
- Instrumental failure

Different methods can be applied to fill the missing data

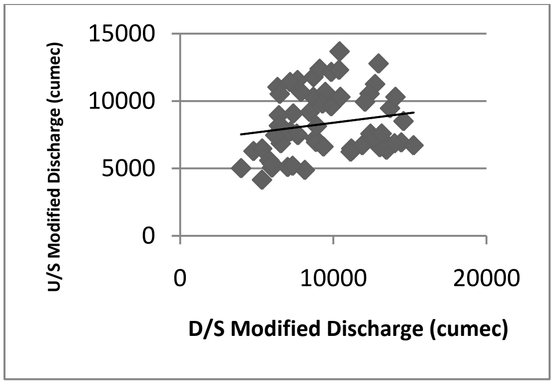
- Simple Arithmetic Average
- Normal Ration Method

It was essential to fill the missing data so we adopted **normal ratio method**. In this method the amount of rainfall at stations are weighted by the ratios of their average annual precipitation values. If we consider a case for 3 stations then missing precipitation data (P_x) will be given by

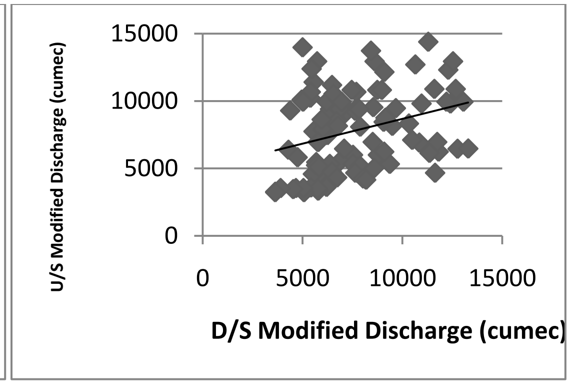
$$Px = \frac{1}{3}\left(P1\frac{Nx}{N1} + P2\frac{Nx}{N2} + P3\frac{Nx}{N3}\right) \quad (24)$$

5.2 Upstream and Downstream Discharge Relation

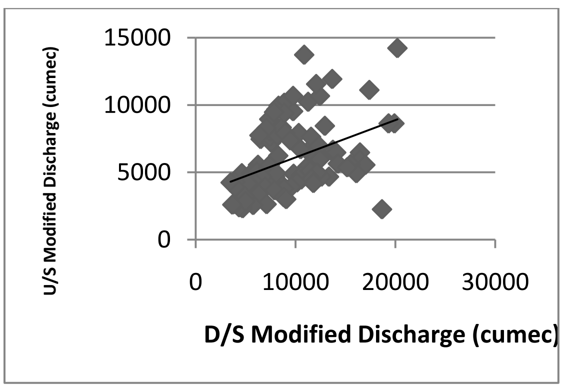
The two discharge stations considered, Barah kshetra, Nepal and Bhimnagar, India, of which Barah kshetra lies in the mountain regions and makes it upstream of the river Kosi whereas Bhimnagar lies in relatively Planner area and is far downstream very close to the India-Nepal Border. So relationships have been plotted between modified discharge of upstream and downstream. On the graph x-axis represent the modified discharge of downstream or Bhimnagar discharge station and y-axis as modified discharge of upstream or Barah kshetra discharge station. The purpose for the relation is to generate the discharge value for the upstream region with the help of downstream discharge data as it is relatively difficult to install the discharge measuring apparatus in the mountain regions so from this relationship an approximate value of discharge can be obtained.



(a)



(b)



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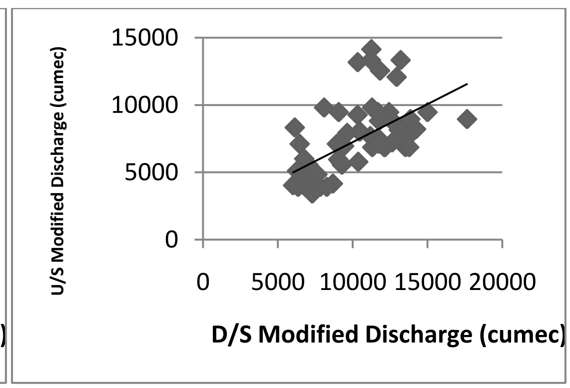

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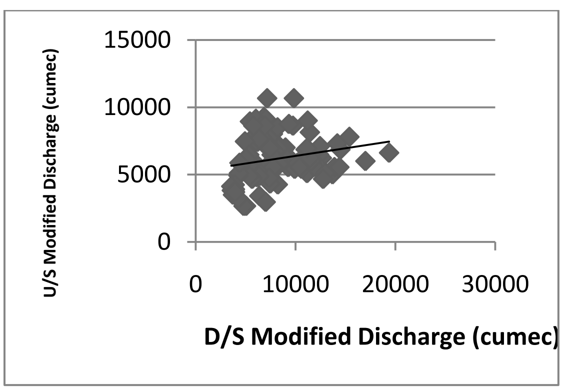


(e)

Figure 6: Upstream v/s Downstream Modified discharge relation of different years,

(a) 2005, (b) 2006, (c) 2007, (d) 2008 and (e) 2009.

5.3 Correlation Between the Raingauge Stations

Table 4 shows a correlation between the five rainguage stations, a Correlation matrix describes correlation among n variables. It is a square symmetrical nxn matrix with the ij^{th} element equal to the correlation coefficient r_{ij} between the i^{th} and the j^{th} variable. The diagonal elements (correlations of variables with themselves) are always equal to 1.00. The correlation matrix is generated using a programme in MATLAB, input data used are the average value of rainfall in five years from 2005 to 2009 of the five given stations. The input data set is a matrix of 106x5 which gives 5x5 correlation matrix. It can be concluded that the 3 stations Dhankutta, Biratnagar and Dharan shows fair inter dependency between them which is further more satisfied from the map as they lie close to each other. Whereas Okhaldunga doesn’t show good correlation with these three stations as it have a value 0.3451, 0.4246 and 0.4246 with Dhankutta, Biratnagar and Bharan respectively. Taplejung shows almost the same correlation with all the stations.

Table 4: Correlation Matrix between the Raingauge Stations

Stations	Okhaldunga	Taplejung	Dhankutta	Biratnagar	Dharan
Okhaldunga	1	0.55944	0.3451	0.42464	0.4246
Taplejung	0.55944	1	0.45178	0.4186	0.50846
Dhankutta	0.3451	0.45178	1	0.51272	0.54002
Biratnagar	0.42464	0.4186	0.51272	1	0.51704
Dharan	0.4246	0.50846	0.54002	0.51704	1

5.4 Rainfall v/s Downstream flow

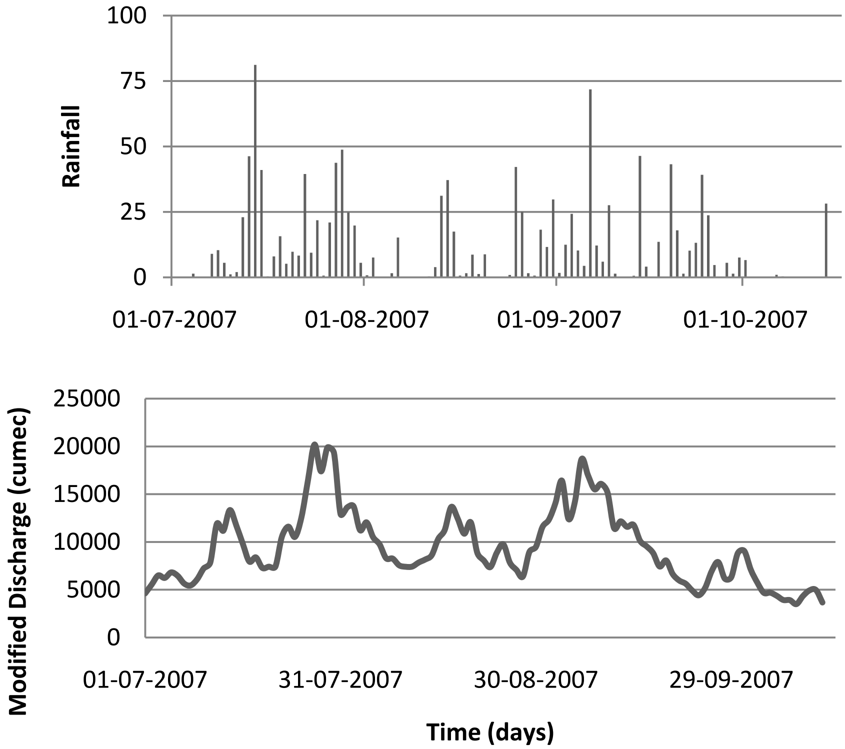
The graphs give an idea about the significance of a station in the basin. Rainfall and runoff or modified discharge in cumec have been plotted with respect to time starting from month 1st July to 13th October for each five years i.e. 2005 to 2009 at different station (Appendix I). The Runoff data are available for five consecutive years from 2005-09 for two discharge station

- Barah Kshetra, Nepal
- Bhimnagar, India

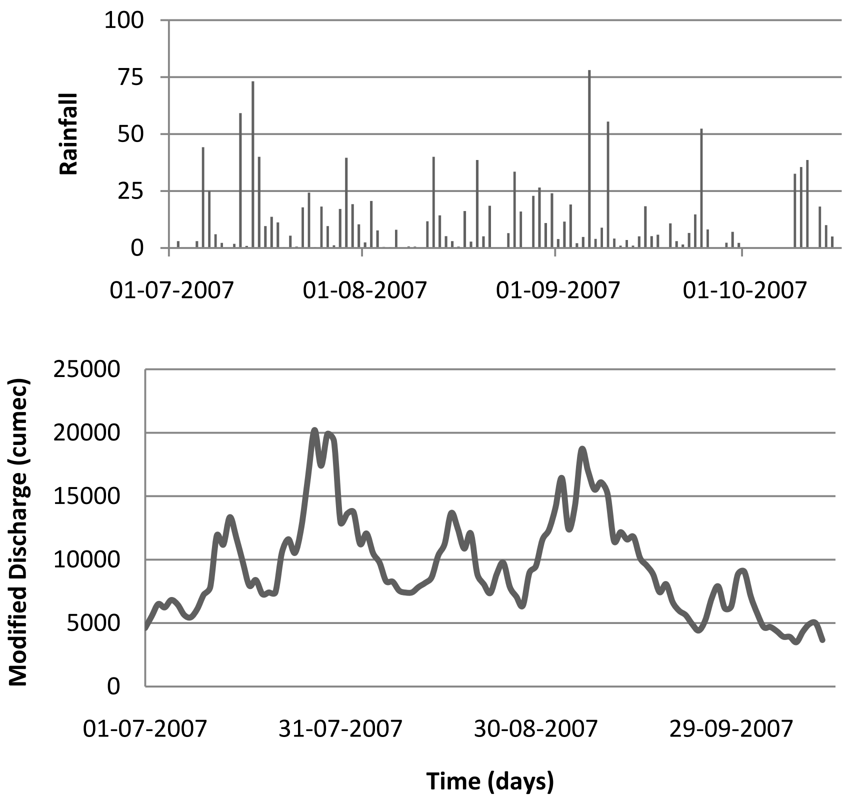
But from the basin maps Barah Kshetra lies well far upstream, in the Himalayas region, of the rainfall stations so for analysis purpose only Bhimnagar station which lies in India is considered. The five Rain gauge station being

a) Okhaldunga,
b) Taplejung,
c) Dhankutta,
d) Biratnagar and
e) Dharan

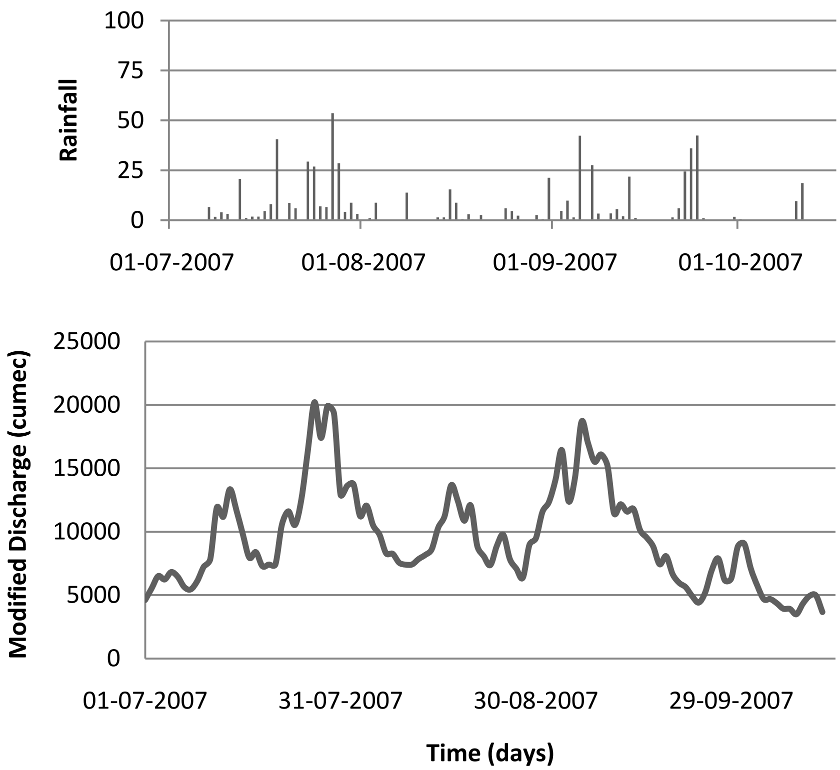
They all lies in Nepal and contributes to River Kosi but there significance at the desired discharge station i.e. Bhimnagar, India is matter of interest. As it can be seen from the graphs that storm in the basin gives its response after 1 or 2 days, which is called lag between rainfall and corresponding runoff. It depends on the type of basin, their distributaries and distance of the raingauge station to the discharge station and the time taken by surface runoff between these two stations is called travel time.As it is clear from the basin map the first station Okhaldunga lies too upstream and its contribution to runoff is suspected which is further clear from the Figures 7 (a) and Appendix I that in all years rainfall and runoff have no relation at all. So for the analysis purpose input data of rainfall is only taken for four stations.


100
75
50
25
0
Rainfall
01-07-2007
01-08-2007
01-09-2007
01-10-2007
25000
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2007
31-07-2007
30-08-2007
29-09-2007
Time (days)

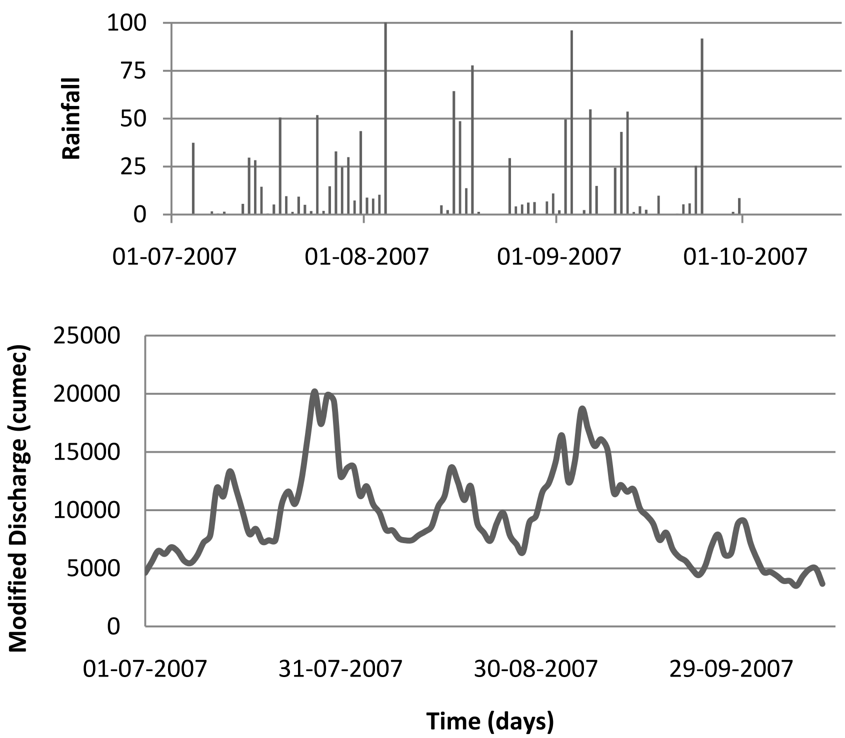
(a)


100
75
50
25
0
Rainfall
01-07-2007
01-08-2007
01-09-2007
01-10-2007
25000
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2007
31-07-2007
30-08-2007
29-09-2007
Time (days)

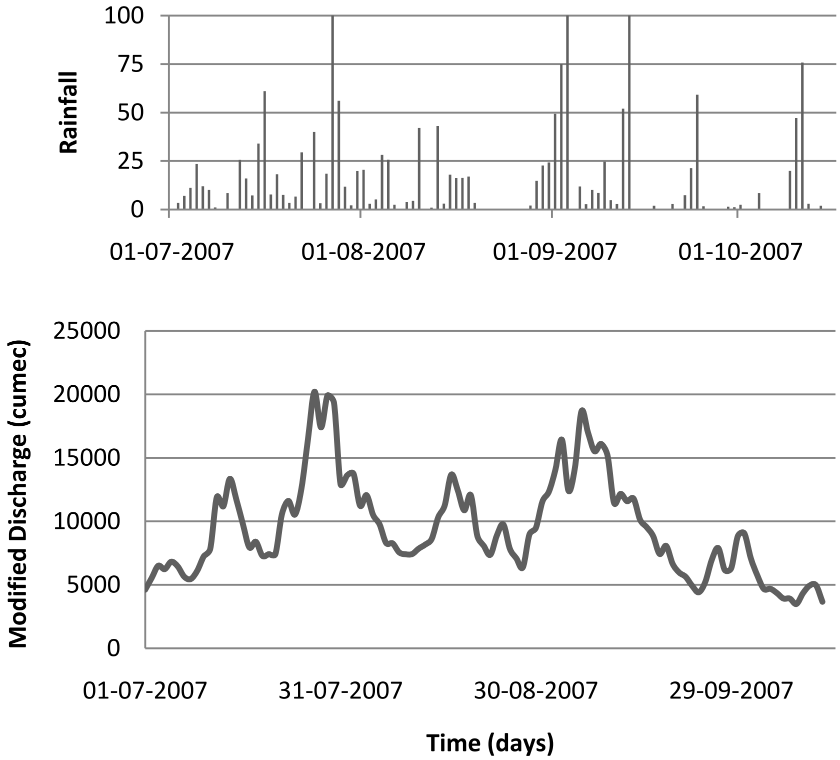
(b)


100
75
50
25
0
Rainfall
01-07-2007
01-08-2007
01-09-2007
01-10-2007
25000
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2007
31-07-2007
30-08-2007
29-09-2007
Time (days)

(c)


100
75
50
25
0
Rainfall
01-07-2007
01-08-2007
01-09-2007
01-10-2007
25000
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2007
31-07-2007
30-08-2007
29-09-2007
Time (days)

(d)



(e)

Figure 7: Rainfall v/s Downstream flow in year 2007 on different Rain gauge stations

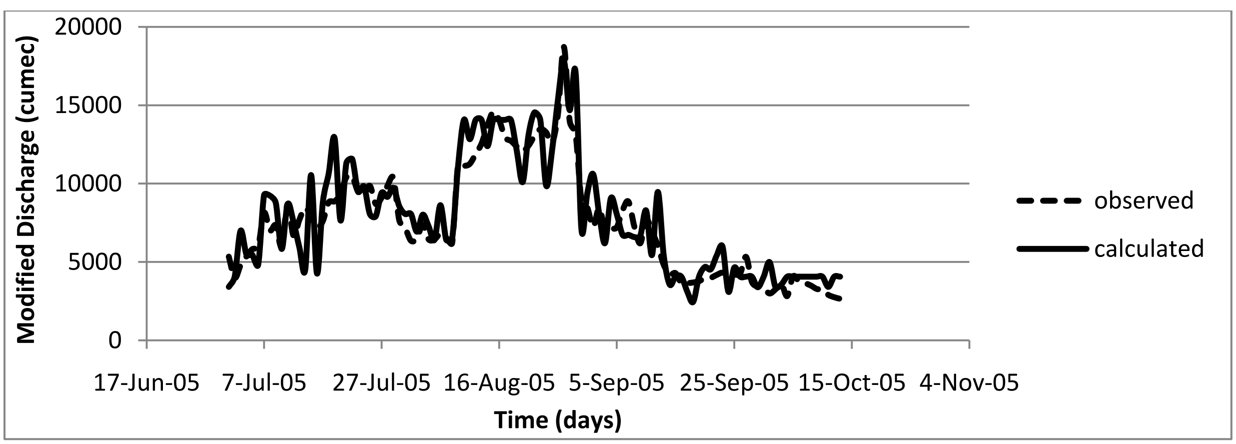
(a)Okhaldunga, (b) Taplejung, (c) Dhankutta, (d) Biratnagar and (e) Dharan

5.5 Analysis by SCS-CN Method

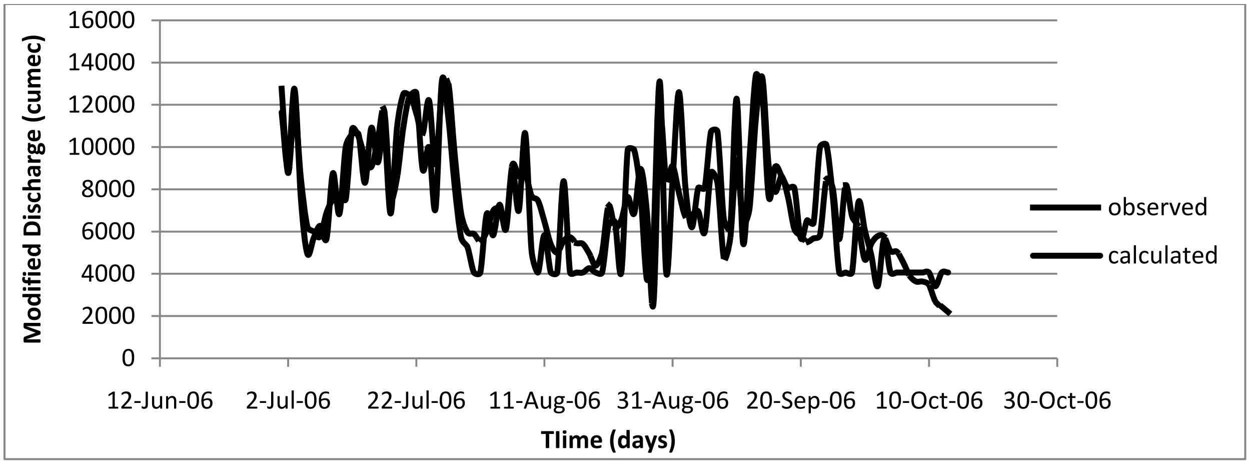
The five graphs represent the runoff comparison for years (2005-2009) between observed runoff data and calucuted runoff using the conceptual model SCS-CN. Daily raifall data is the input and the output is the runoff. As seen from table 5 R square value is higest for the year 2005 which means the error is least in that year so the accuracy of prediction of runoff is high for the year 2005 and for other years its almost 0.5 so it gives satisfactory reslts. It is clearly visible from the graph that there is lot of variation in runoff as caluclated with the help of SCS-CN method. The basin area is in hydrological soil group C with two kind of moisture content i.e AMC II and AMC III, as the data considered is in the monsoon season. The curve number is taken as 80 for AMC II conditions which is equivalent to 90 in AMC III conditions applying the equation (9). A slight change in rainfall is vulnerable to create crest and valley in the graph but in general it is showing good results for a year as a whole. This is possible as the area under the curve is nevertheless same as being observed, but when it comes to daily discharge the model is not showing satisfactory result as there is a large deviation from the daily runoff observed at many points.

Table 5: R^2 value of the observed and calculated modified discharge by SCS-CN method

Year	2005	2006	2007	2008	2009
R^2	0.8288	0.5256	0.5425	0.4953	0.5103

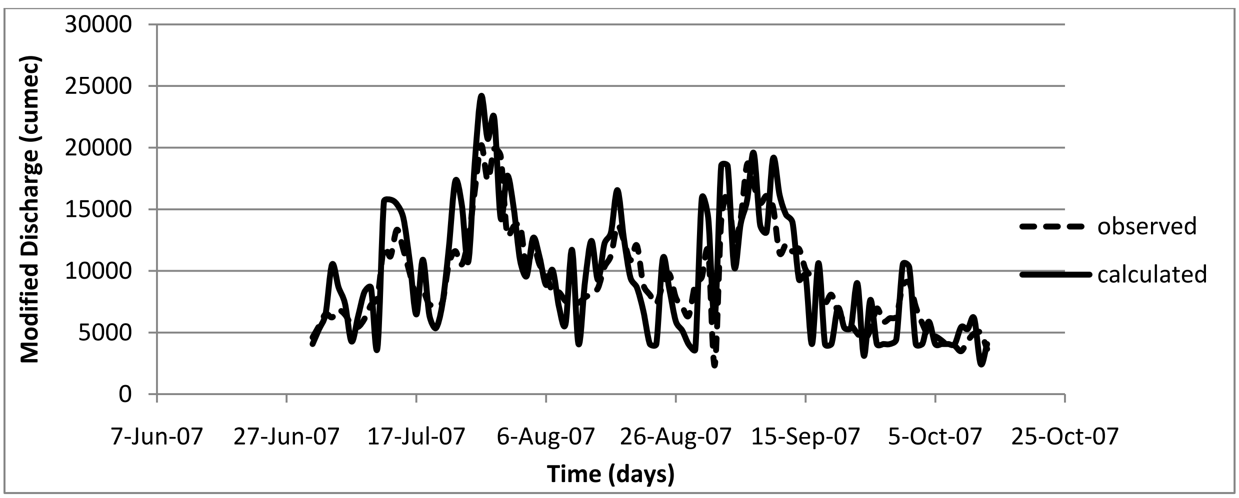


(a)



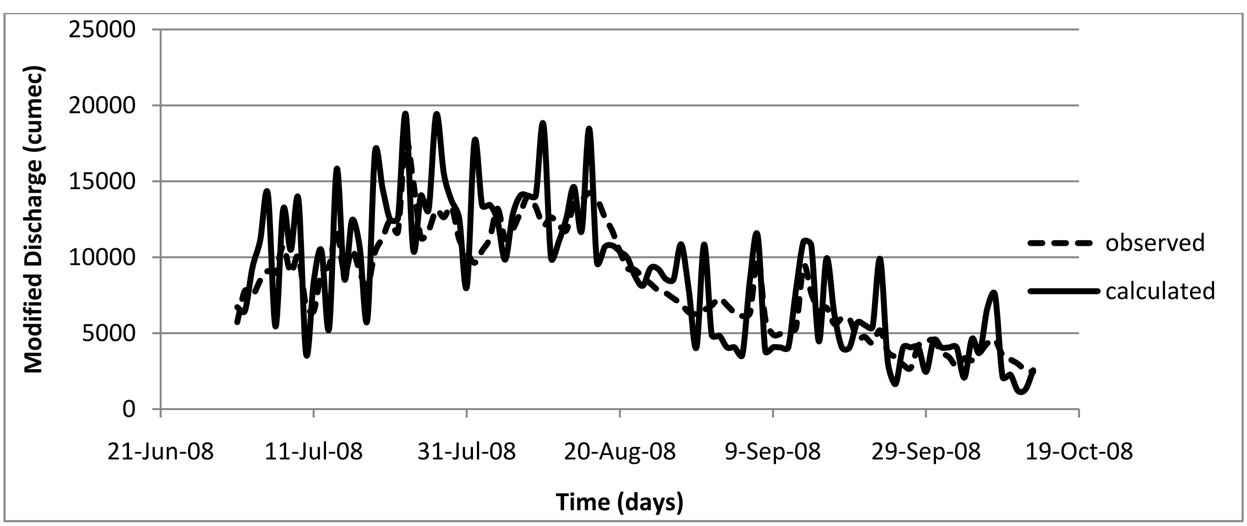
16000
14000
12000
10000
8000
6000
4000
2000
0
Modified Discharge (cumec)
12-Jun-06
2-Jul-06
22-Jul-06
11-Aug-06
31-Aug-06
20-Sep-06
10-Oct-06
30-Oct-06
TIime (days)
observed
calculated

(b)



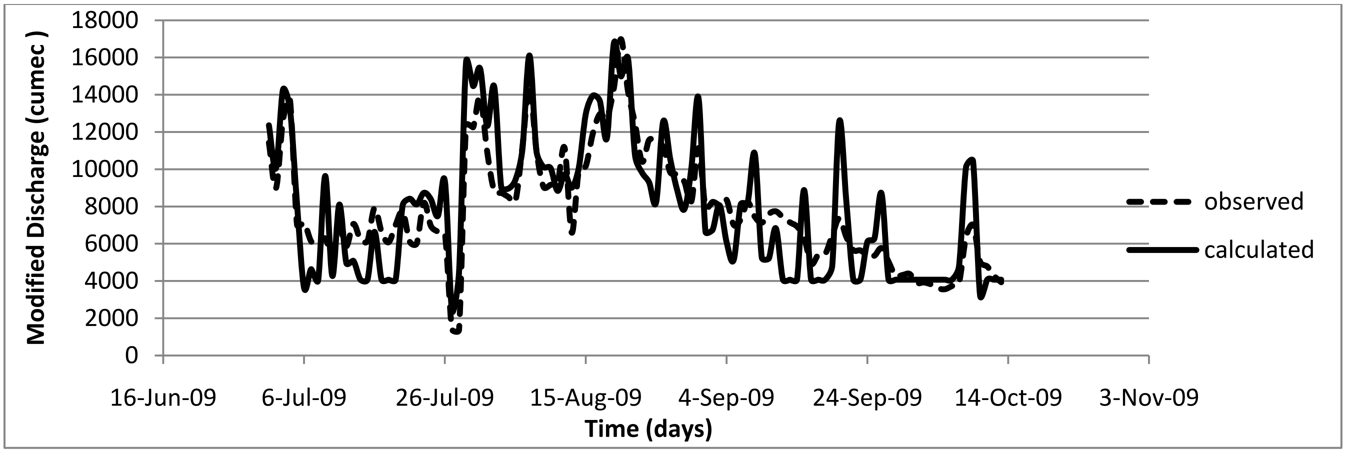
30000
25000
20000
15000
10000
5000
0
Modified Discharge (cumec)
7-Jun-07
27-Jun-07
17-Jul-07
6-Aug-07
26-Aug-07
15-Sep-07
5-Oct-07
25-Oct-07
Time (days)
observed
calculated

(c)



25000
20000
15000
10000
5000
0
Modified Discharge (cumec)
21-Jun-08
11-Jul-08
31-Jul-08
20-Aug-08
9-Sep-08
29-Sep-08
19-Oct-08
Time (days)
observed
calculated

(d)



(e)

Figure 8: Observed and calculated Modified discharge v/s time by SCS-CN method of five years (a) 2005, (b) 2006, (c) 2007, (d) 2008, (e) 2009

5.6 Normalization of Data

Before processing the data and introducing the ANN for training, normalization of the data must be applied in order to limit the range to the interval of 0 to 1, corresponding to the output limits of the nodes of the network. Normalization is required as ANN cannot correlate the rainfall values to higher values of runoff (ranges 2000 cumec to 20,000 cumec) in the training process. When different normalization factors are applied to the training and verification data set, the actual numbers represented by unity in the two data sets are different. In practice, a trained ANN can only be used in the recall mode with data that it has 'seen' before; the ANN should not be used for extrapolation. For example, if the maximum flow that the ANN has learned to predict is 2000 cumec, then it is impossible for the ANN ever to predict a flow value exceeding 2000 cumec. The choice of the range for normalization may therefore influence significantly the performance of the ANN. Normalization factor considered in the present work is given by equation

$$\frac{Q_i}{Q_{max} + 10} \tag{25}$$

5.7 Analysis by ANN

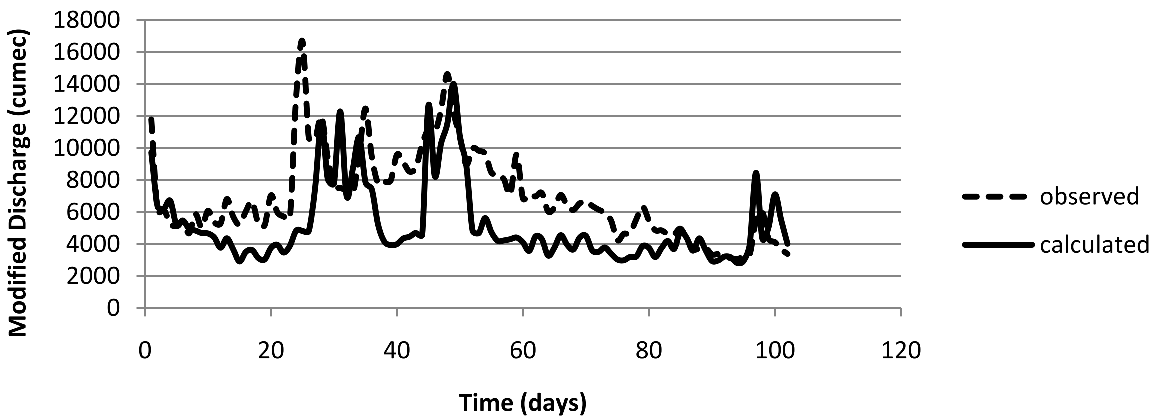
The analysis is carried out in the software Neural Power which required the input data rainfall and the output data modified runoff of the five years, out of which, for the Learning purpose the learning Algorithms used is Batch Back Propagation (BBP) and Connection type is Multilayer Normal Feed Forward. Input parameters o Rain t, Rain t-1, Rain t-2, Rain t and Flow t-1, Rain t-1 and Flow t-1 and Rain t-2 and Flow t-1. All variables were normalized, between zero and one and then split into annual data sets: 2005, 2006, 2007, 2008 and 2009. Flow values are reported here in normalized flow units (nfu). There are initially 3 no. Of layer, 1 input layer, 1 hidden layer and 1 output layer. Input layer has 11 neurons or nodes and the hidden layer has 15 nodes and transfer function for each node is sigmoid and slope of nodes is 1. Output layer has only 1 node with sigmoid transfer function so initial 11:15:1 and 11:15:15:1 network was trained for 4 years data and tested for 1 year data. As there is time lag between the rainfall and runoff, time series analysis with time step 3 for both rainfall and runoff. As described in the section 4.2.2, total 6 files are analyzed and the graph between the observed modified discharge and calculated modified discharge is plotted with respect to time (Appendix II) and other statistical parameter are tabulated in Table 6, which include following

1. Maximum, Minimum and Average Difference between the observed value and calculated value.
2. Root Mean Square Error (RMES) of the observed and calculated values.
3. Average mean or R value.
4. Coefficient of determination (DC).

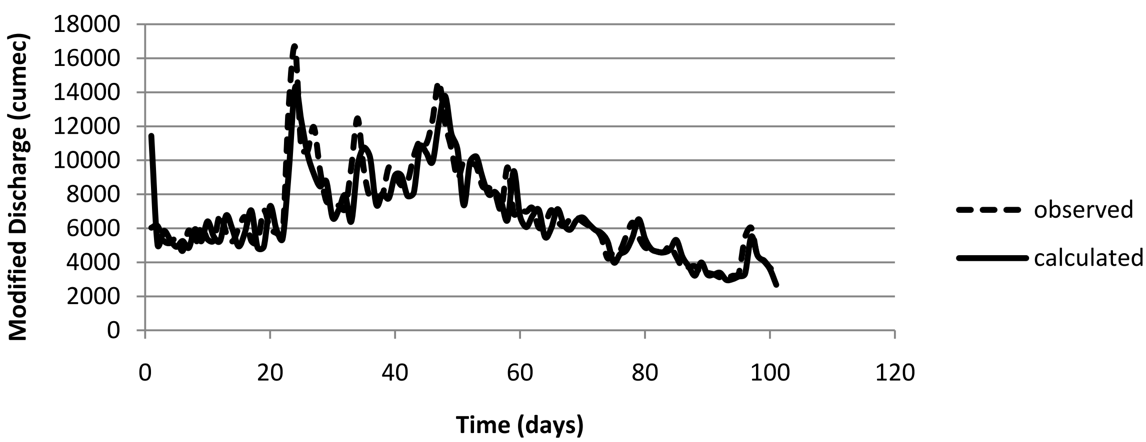
With only 1 input as rainfall at time t and output as discharge at time t doesn't show good results as RMSE for R_t is 0.1052 and average R 0.7012 and DC is 0.5812 which keep improving with lagging the time with 1 and 2 days, while for two input it shows better results without lagging the rainfall which again improves by lagging the rainfall by 1 day and further improves when it is lagged by 2 days, which means that surface runoff takes 1 or 2 days time to reach the discharge station at bhimnagar so there is lag of 1 or 2 days. The best result comes with the two inputs, rainfall lagged by 2 days and discharge lagged by 1 day and output as discharge at time t.

Table 6: Statistical Parameters of the observed and calculated modified discharge

S. No.	Input	Maximum Difference	Minimum Difference	Average Difference	RMSE	Average R	Average DC
1	R_t	11853	22	2239	0.1052	0.7012	0.5812
2	R_{t-1}	12449	34	2675	0.0942	0.7941	0.6861
3	R_{t-2}	11458	80	1381	0.0812	0.9024	0.8219
4	R_t & Q_{t-1}	10274	5	1191	0.0734	0.9411	0.8853
5	R_{t-1}&Q_{t-1}	8780	2	1092	0.0783	0.9558	0.8566
6	R_{t-2} & Q_{t-1}	6800	33	1080	0.0714	0.9636	0.9157



(a)



(b)

Figure 9: Observed and calculated modified discharge v/s time using ANN

(a) Input R_t, output Q_t, (b) Input R_{t-2} and Q_{t-1}, Output Q_t

5.8 Comparison

From the graph it is clearly visible that the results obtained by SCS-CN is showing much more deviation than obtained by the ANN. This outcome is justified as ANN is taking both discharge data and the rainfall data as input while SCS is considering the effects of rainfall only. The area under the SCS curve is much higher than the observed runoff value at the outlet point and it is showing too much deviation from the observed runoff this is due to the impact of high rainfall on the catchment area with a certain time lag. SCS method is not only showing the highest peak among three rather it is showing the deepest valley too, which is compensated by the fore coming peak. One more important result visible from the graph is that ANN is giving much better result for the daily runoff data or it can b concluded that ANN is more trustworthy than the SCS-CN .

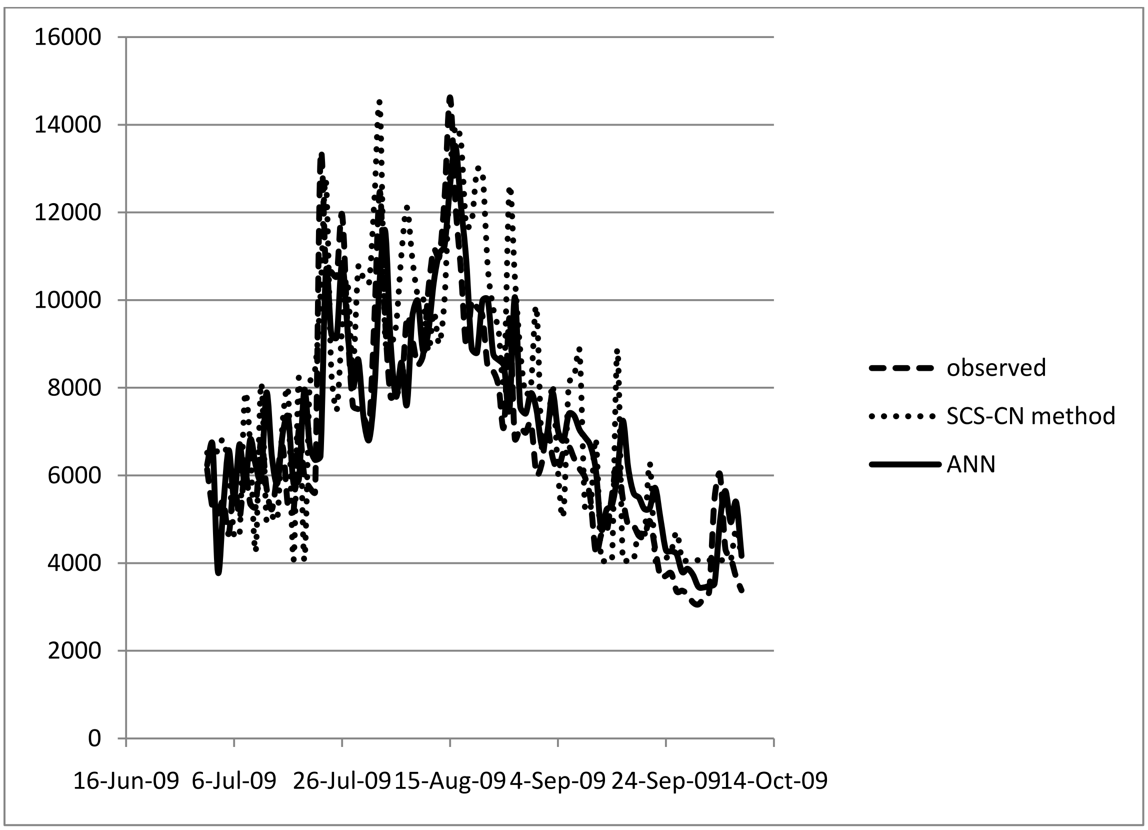


Figure 10: Comparison of two methods for the year 2009

5.9 Conclusion

Based on the analysis performed in Artificial Neural Network and SCS-CN Method following conclusions are drawn

1. A relationship between upstream and downstream modified flow (Figure 6) has been derived.
2. Correlation between the five different raingauge stations (Table 4) justify the dependency of the rainfall of other tributaries on the outlet.
3. Time series analysis shows the response of the storm on the discharge station lagged by 1 or 2 days.
4. SCS-CN method considers the infiltration losses and soil properties, so conceptually it is very sound.
5. SCS curve is covering a large area (figure 12) i.e. the modified discharge value coming out to be much higher than the observed value, so for designing purpose it is not economical rather safer.
6. SCS-CN method requires too many field data e.g. topography, Soil type, Moisture condition etc, which are sometimes not known so a lot of assumptions are to be made.
7. ANN required only rainfall and runoff data, and if we have RL of the river bed as input, it will give better solutions.
8. Optimum network possible for daily rainfall-runoff modeling is multi layer perceptron (MLP).
9. Normalisation of data is important for ANN analysis.
10. Selection of transfer function is very important.
11. ANN with two or more input layer gives better results instead using single input layer.
12. As ANN shows satisfactory results in comparison with SCS-CN method, it can be used for prediction of discharge at the remote places where establishment of stations economical.
13. For the learning curve ANN can use both the rainfall and runoff data of previous years while the input parameter in the SCS-CN method can only be rainfall and CN, thus gives better results.
14. If we have large number of data set then SCS-CN method is very good otherwise we can opt for ANN.

Reference

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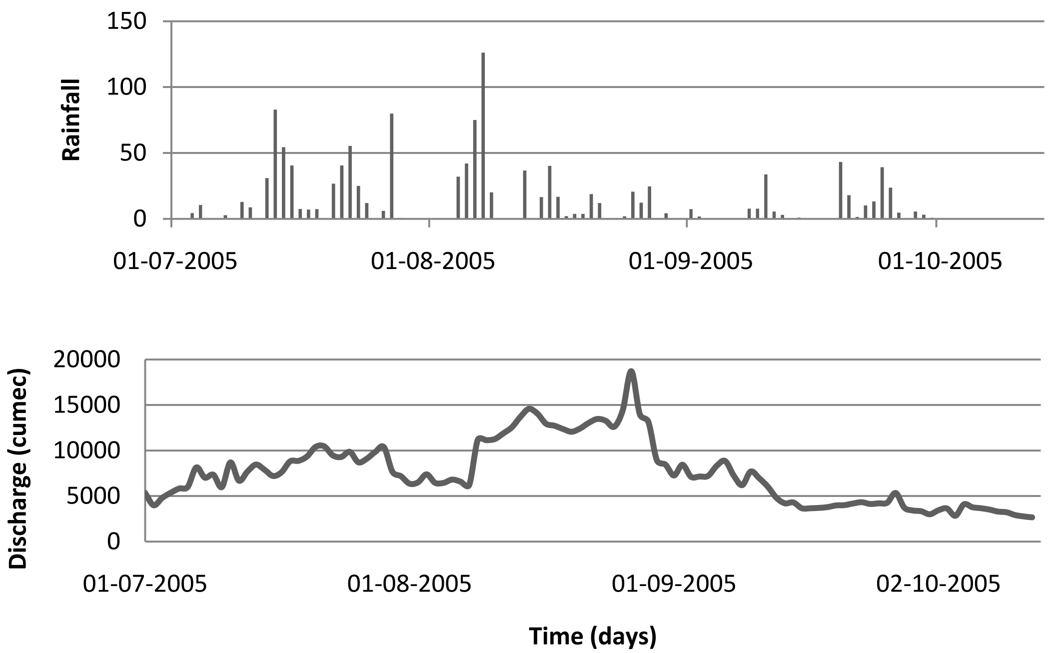
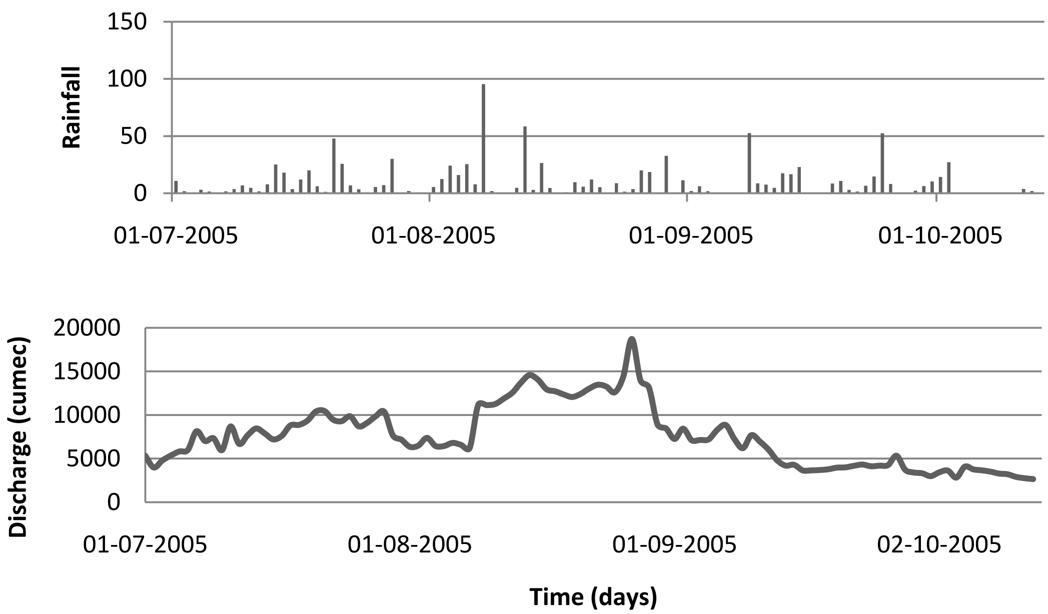
Appendix I

Rainfall-Runoff relationship

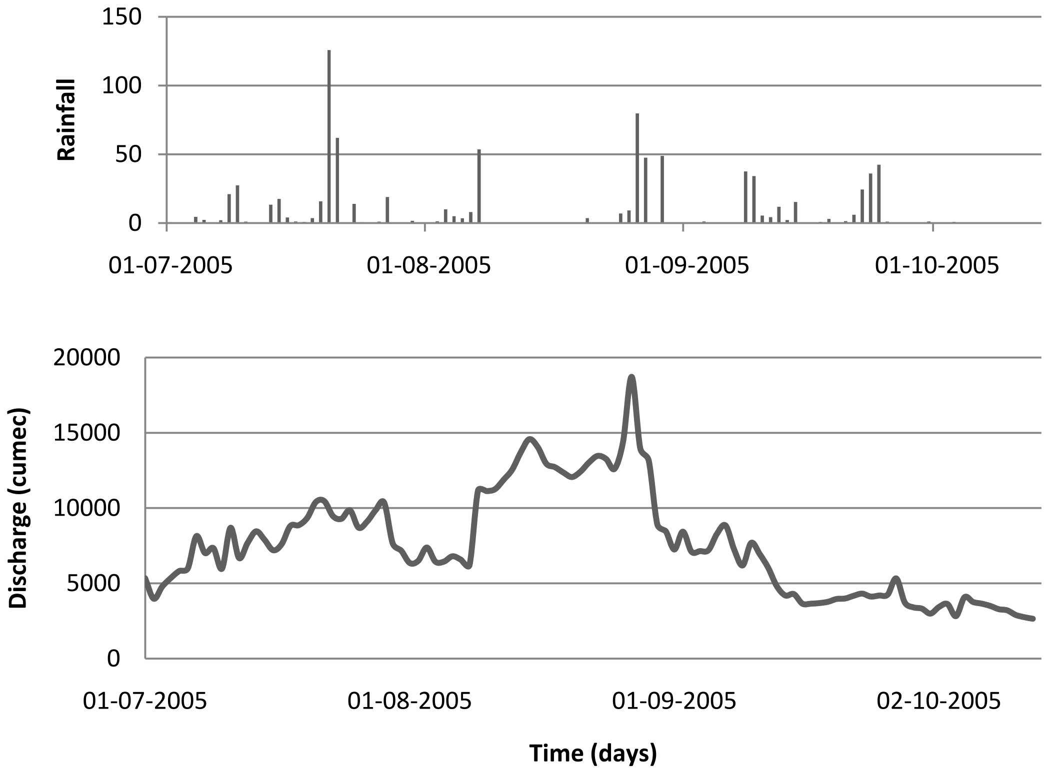
Rainfall v/s downstream modified discharge graphs for the different stations and four years:



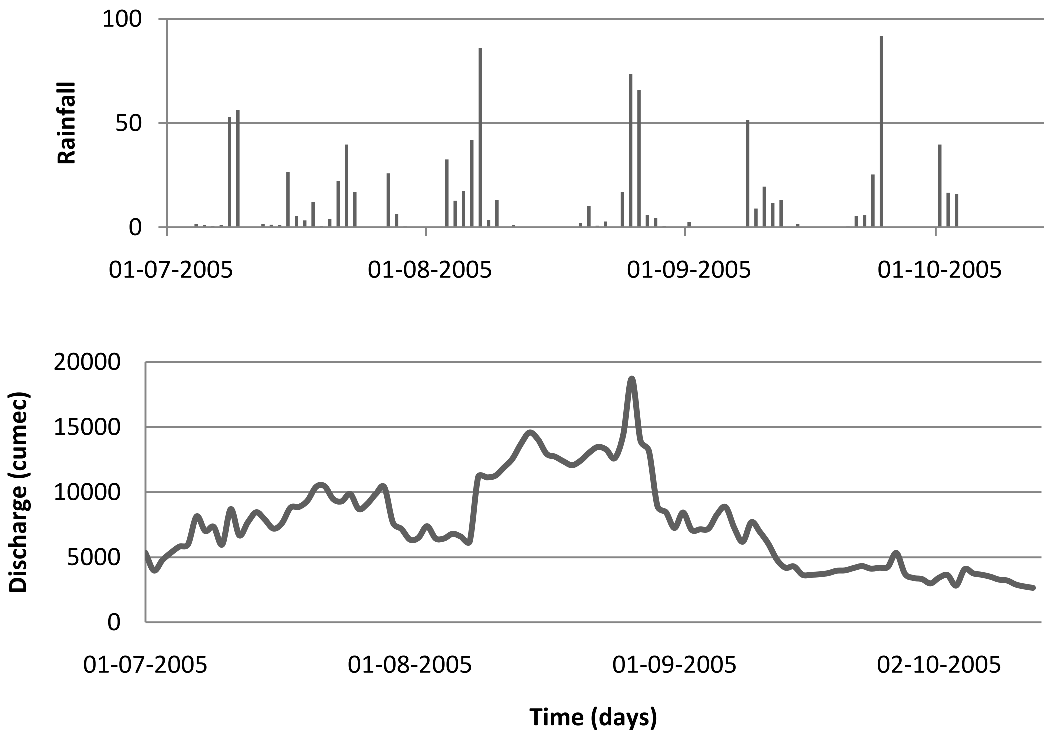
(a)



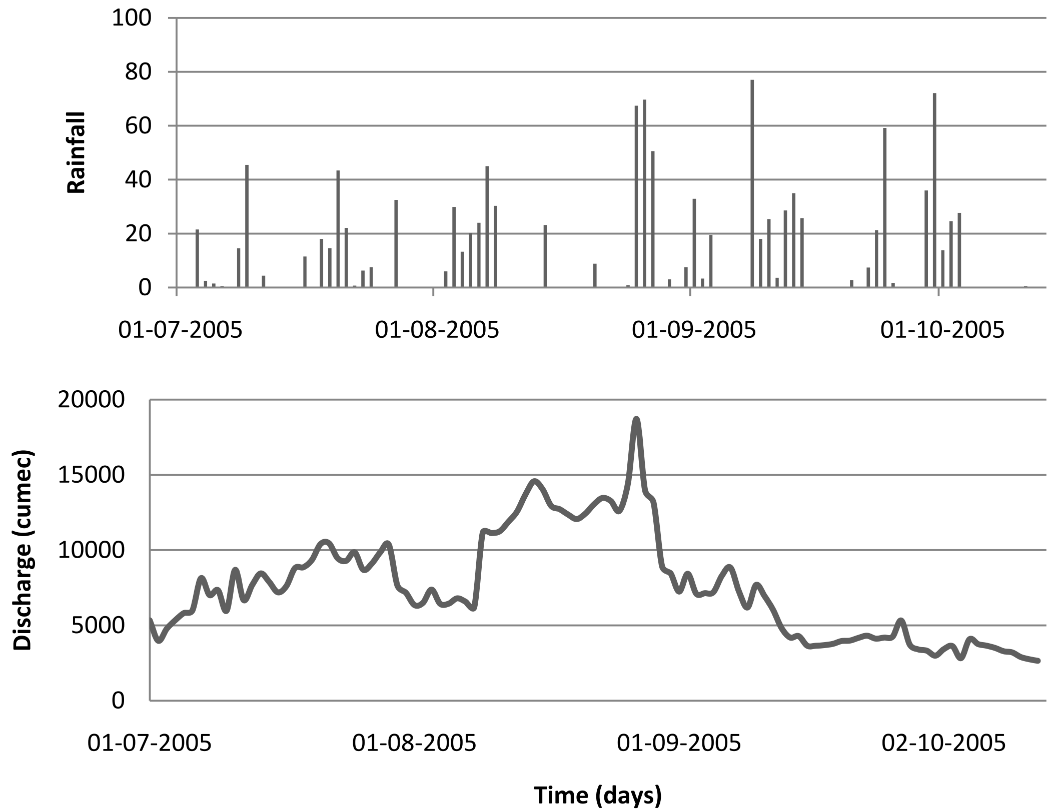
(b)


Rainfall
150
100
50
0
01-07-2005
01-08-2005
01-09-2005
01-10-2005
Discharge (cumec)
20000
15000
10000
5000
0
01-07-2005
01-08-2005
01-09-2005
02-10-2005
Time (days)

(c)


Rainfall
100
50
0
01-07-2005
01-08-2005
01-09-2005
01-10-2005
Discharge (cumec)
20000
15000
10000
5000
0
01-07-2005
01-08-2005
01-09-2005
02-10-2005
Time (days)

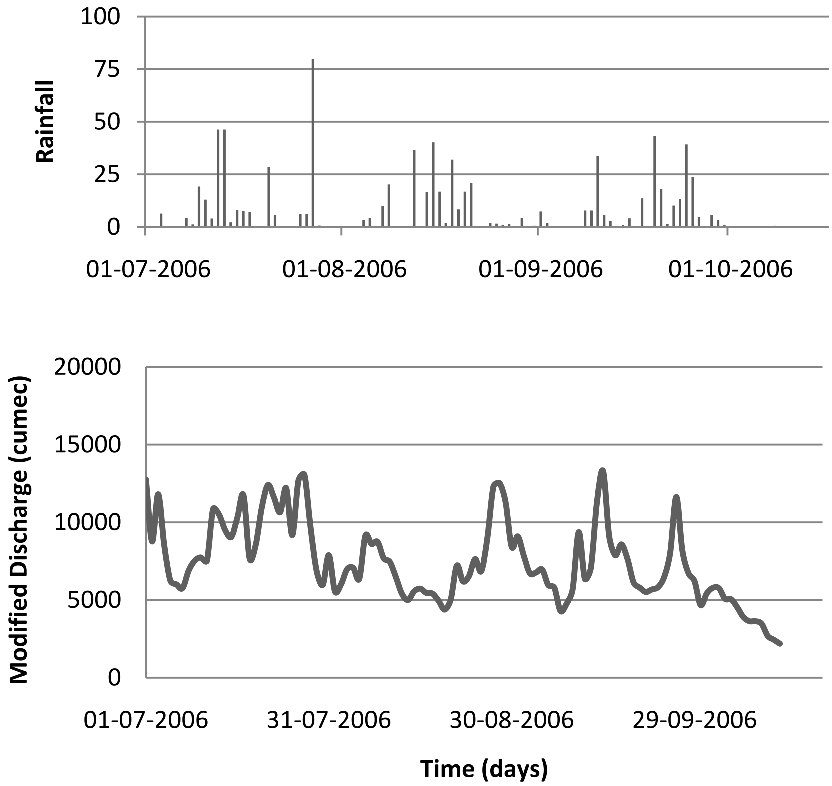
(d)



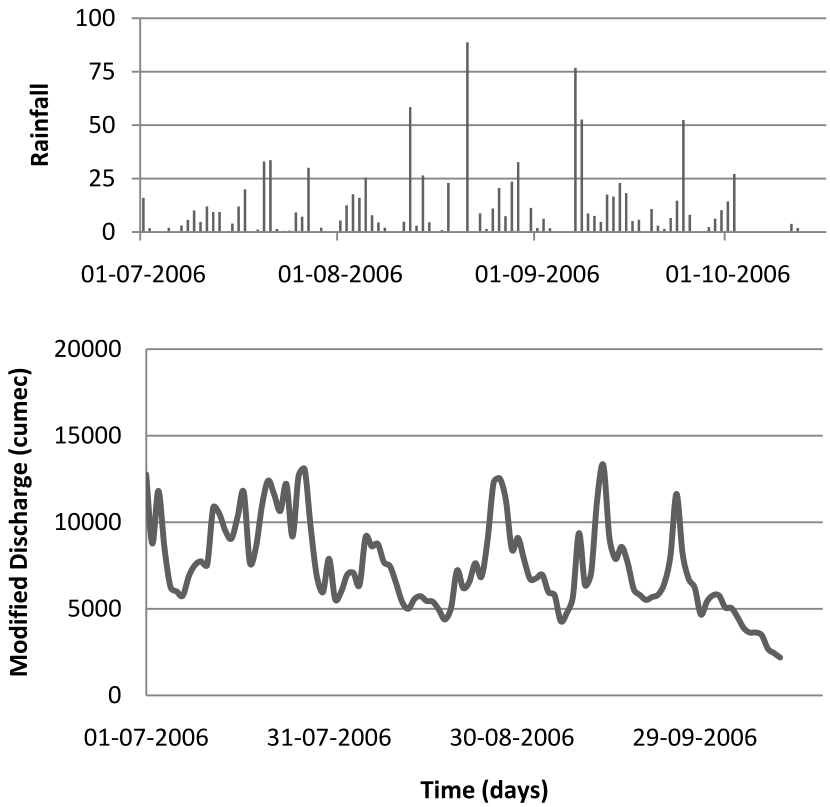
(e)

Figure 11: Rainfall v/s Downstream flow in year 2005 on different Rain gauge stations

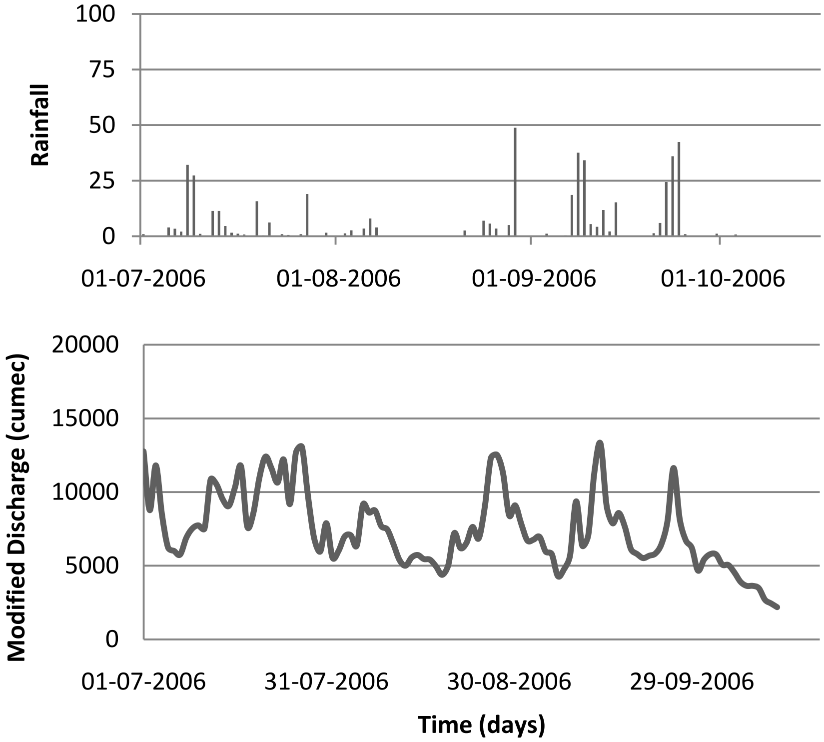
(a) Okhaldunga, (b) Taplejung, (c) Dhankutta, (d) Biratnagar and (e) Dharan


100
75
50
25
0
Rainfall
01-07-2006
01-08-2006
01-09-2006
01-10-2006
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2006
31-07-2006
30-08-2006
29-09-2006
Time (days)

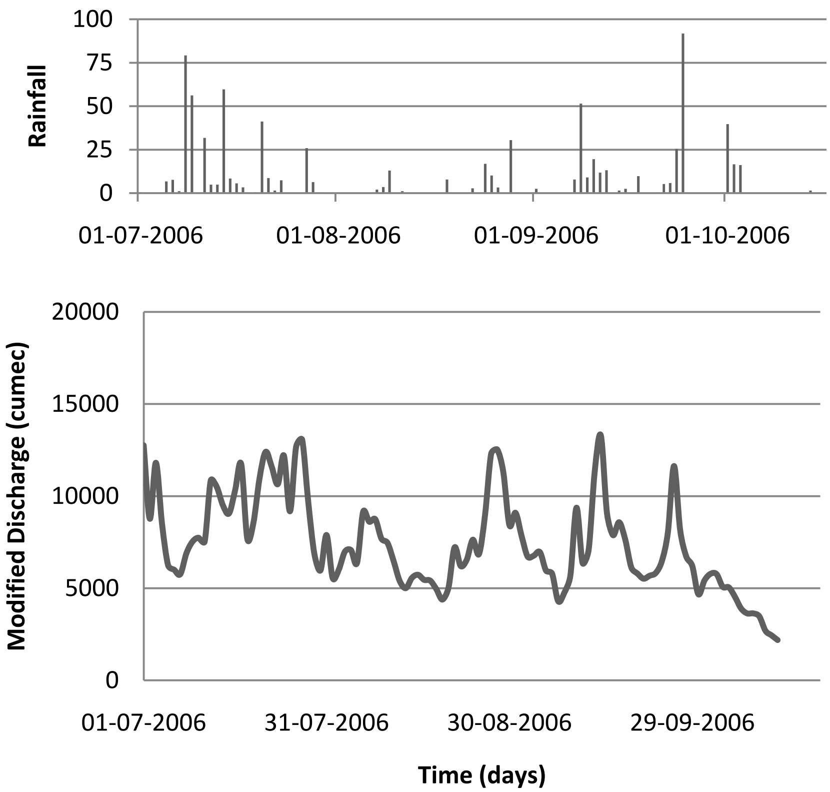
(a)


100
75
50
25
0
Rainfall
01-07-2006
01-08-2006
01-09-2006
01-10-2006
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2006
31-07-2006
30-08-2006
29-09-2006
Time (days)

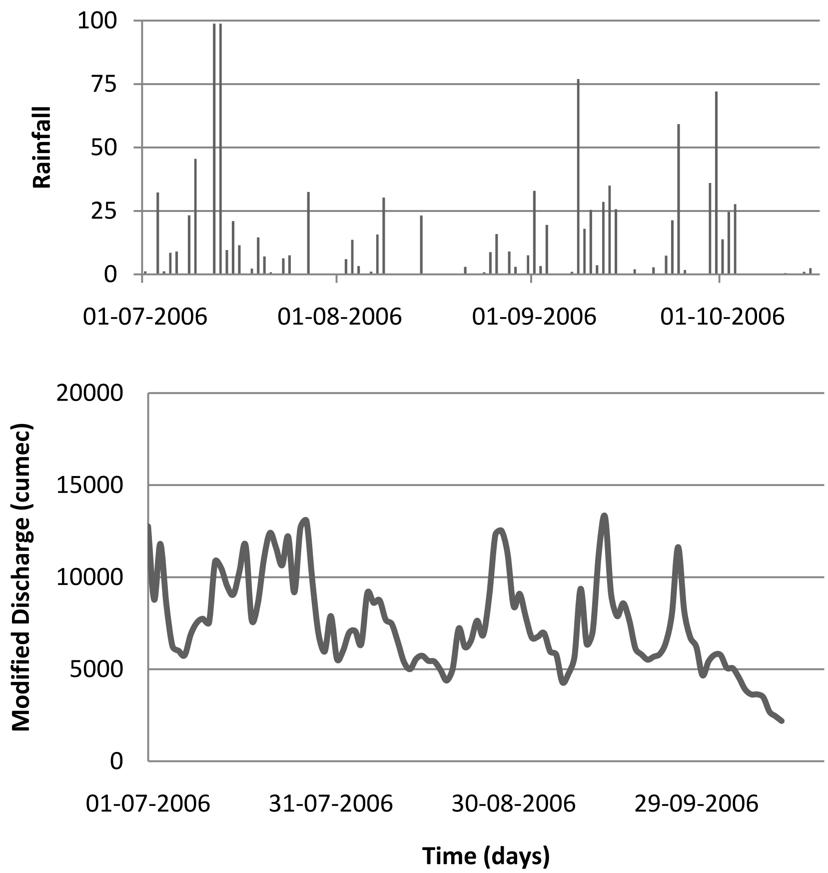
(b)


Rainfall
100
75
50
25
0
01-07-2006
01-08-2006
01-09-2006
01-10-2006
Modified Discharge (cumec)
20000
15000
10000
5000
0
01-07-2006
31-07-2006
30-08-2006
29-09-2006
Time (days)

(c)


Rainfall
100
75
50
25
0
01-07-2006
01-08-2006
01-09-2006
01-10-2006
Modified Discharge (cumec)
20000
15000
10000
5000
0
01-07-2006
31-07-2006
30-08-2006
29-09-2006
Time (days)

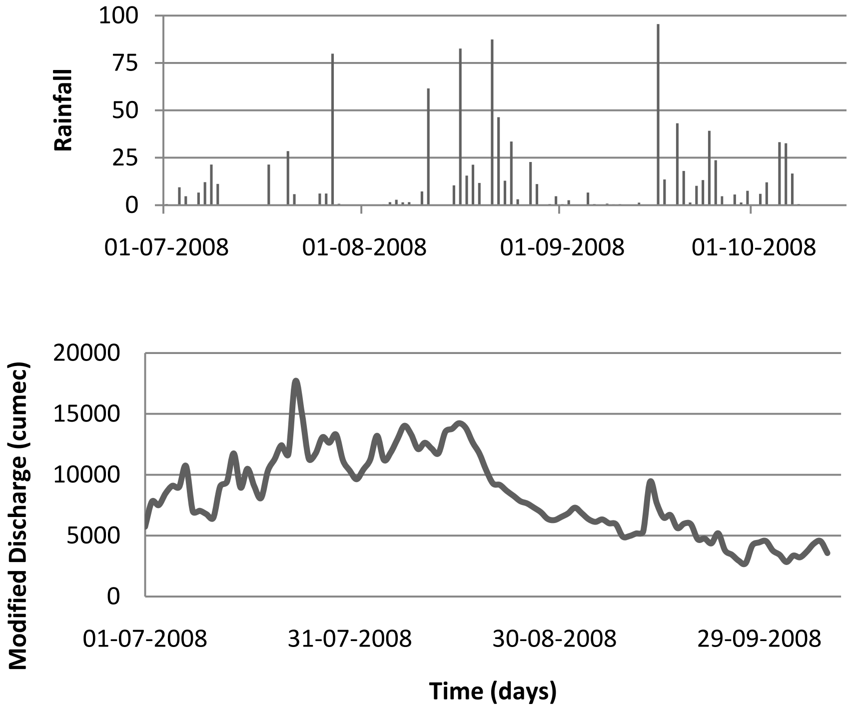
(d)



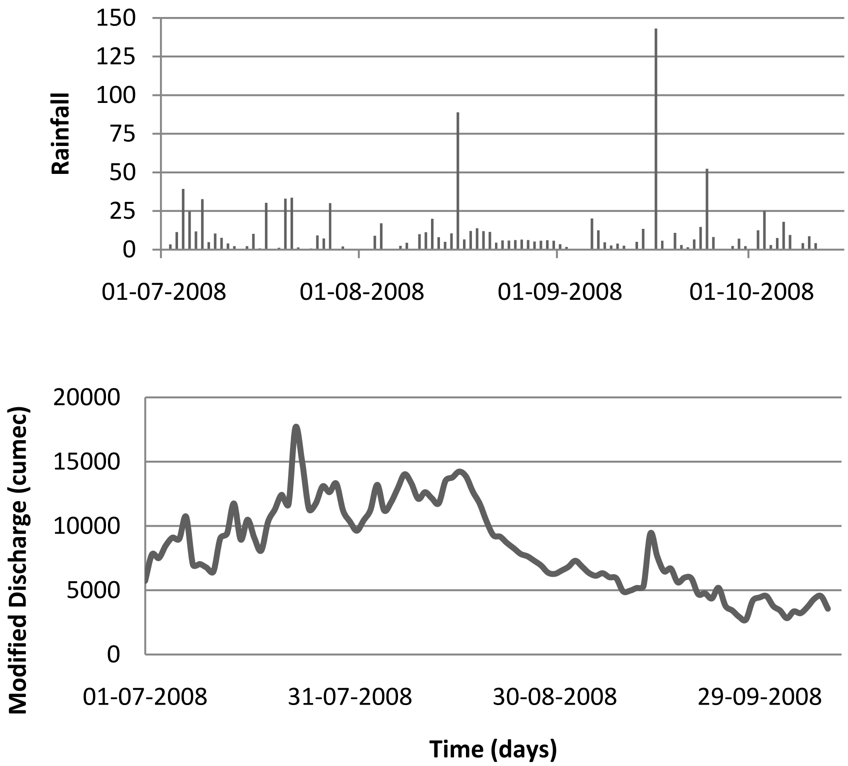
(e)

Figure 12: Rainfall v/s Downstream flow in year 2006 on different Rain gauge stations

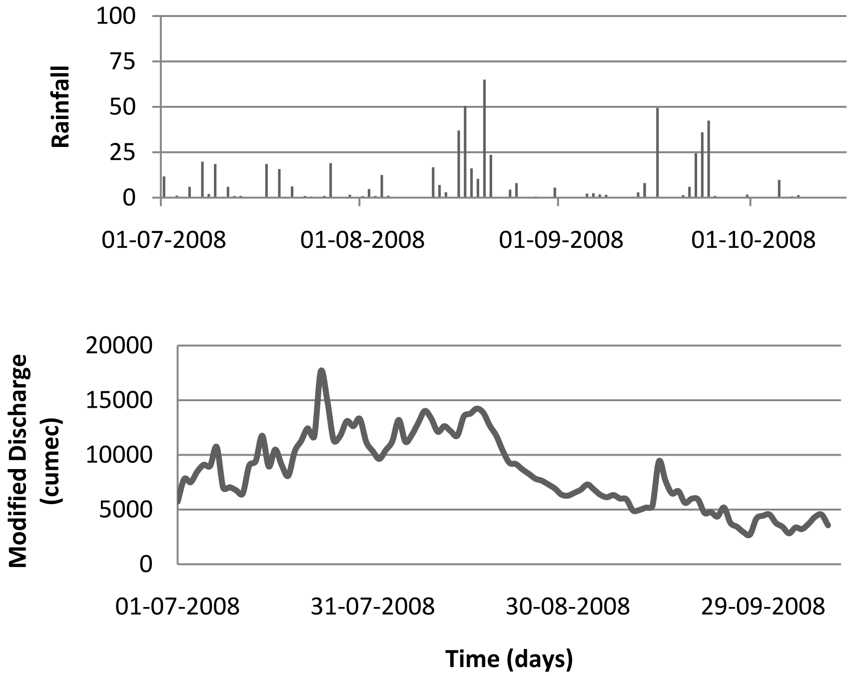
(a) Okhaldunga, (b) Taplejung, (c) Dhankutta, (d) Biratnagar and (e) Dharan


100
75
50
25
0
Rainfall
01-07-2008
01-08-2008
01-09-2008
01-10-2008
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2008
31-07-2008
30-08-2008
29-09-2008
Time (days)

(a)

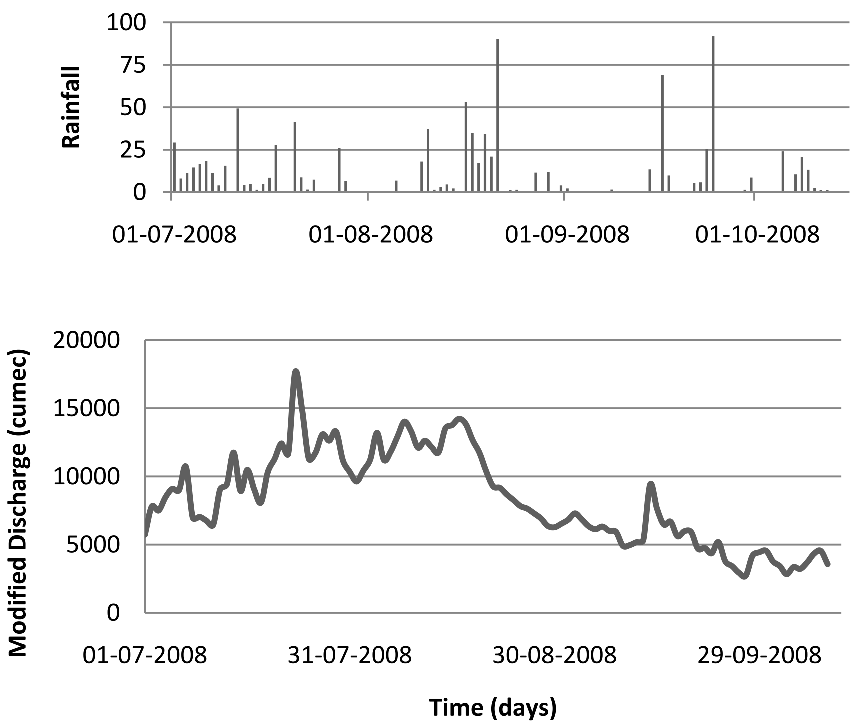

150
125
100
75
50
25
0
Rainfall
01-07-2008
01-08-2008
01-09-2008
01-10-2008
20000
15000
10000
5000
0
Modified Discharge (cumec)
01-07-2008
31-07-2008
30-08-2008
29-09-2008
Time (days)

(b)



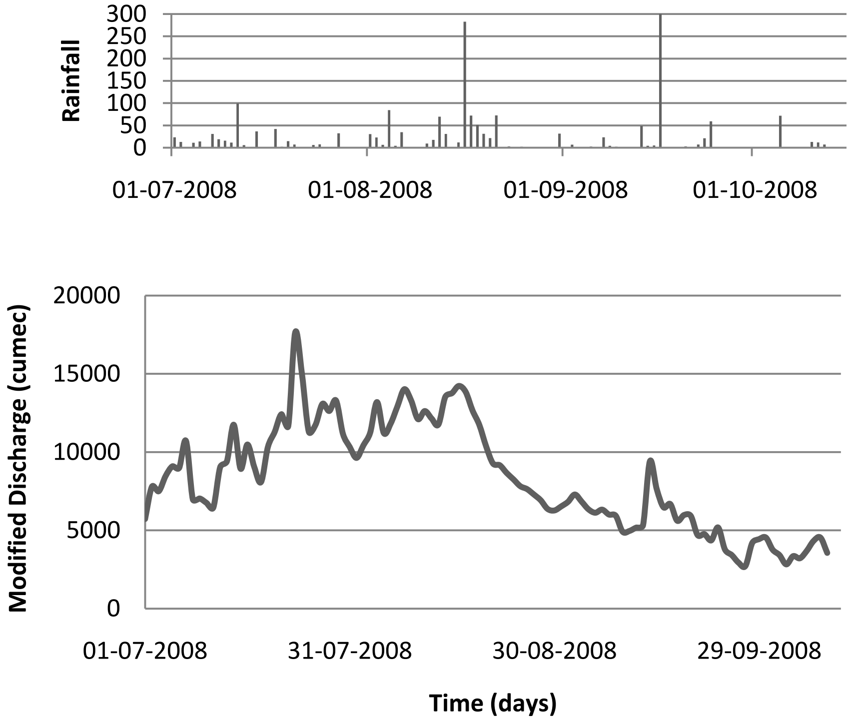
Rainfall
100
75
50
25
0
01-07-2008
01-08-2008
01-09-2008
01-10-2008
Modified Discharge (cumec)
20000
15000
10000
5000
0
01-07-2008
31-07-2008
30-08-2008
29-09-2008
Time (days)

(c)



Rainfall
100
75
50
25
0
01-07-2008
01-08-2008
01-09-2008
01-10-2008
Modified Discharge (cumec)
20000
15000
10000
5000
0
01-07-2008
31-07-2008
30-08-2008
29-09-2008
Time (days)

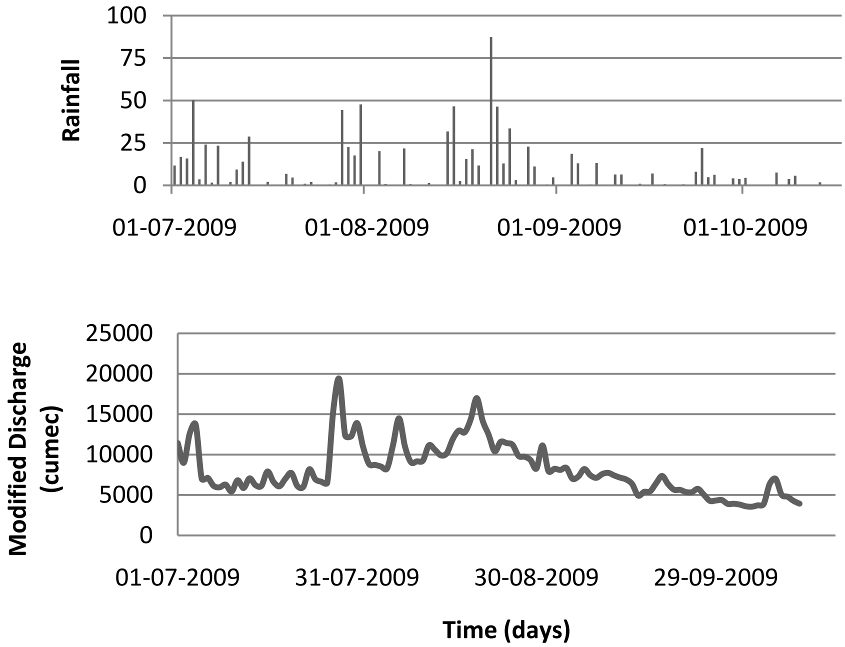
(d)



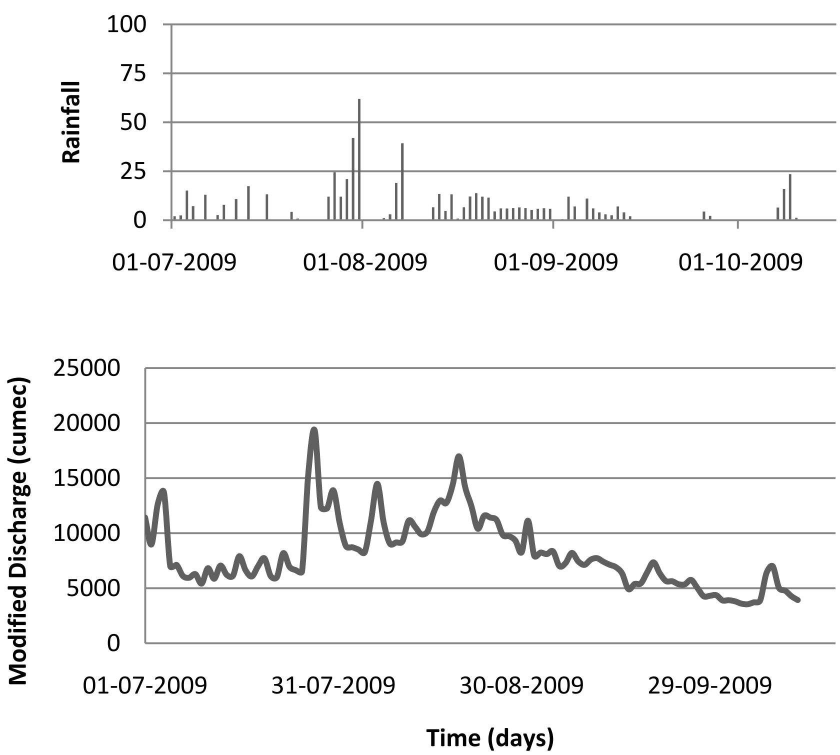
(e)

Figure 13: Rainfall v/s Downstream flow in year 2008 on different Rain gauge stations

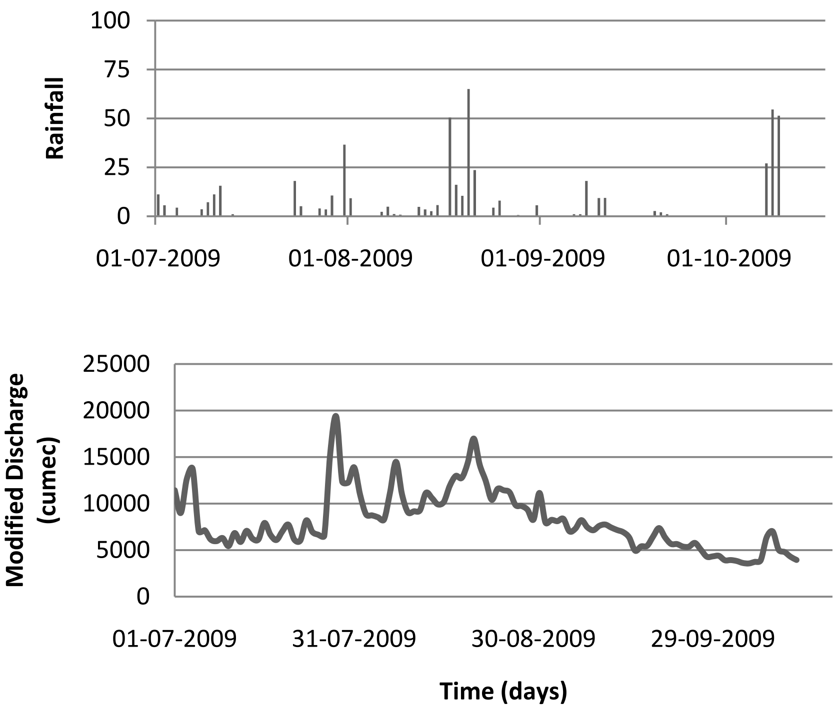
(a) Okhaldunga, (b) Taplejung, (c) Dhankutta, (d) Biratnagar and (e) Dharan


Rainfall
100
75
50
25
0
01-07-2009
01-08-2009
01-09-2009
01-10-2009
Modified Discharge (cumec)
25000
20000
15000
10000
5000
0
01-07-2009
31-07-2009
30-08-2009
29-09-2009
Time (days)

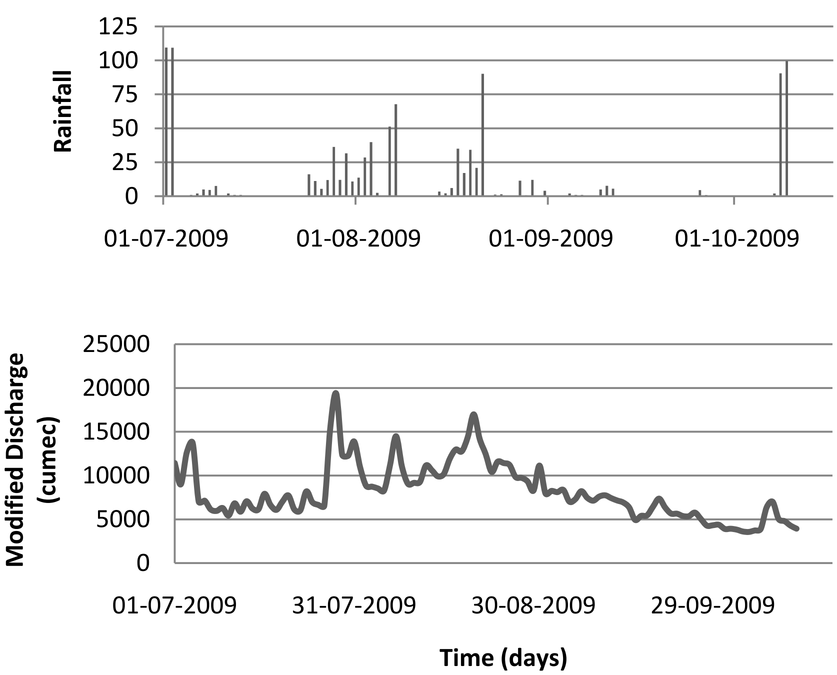
(a)


Rainfall
100
75
50
25
0
01-07-2009
01-08-2009
01-09-2009
01-10-2009
Modified Discharge (cumec)
25000
20000
15000
10000
5000
0
01-07-2009
31-07-2009
30-08-2009
29-09-2009
Time (days)

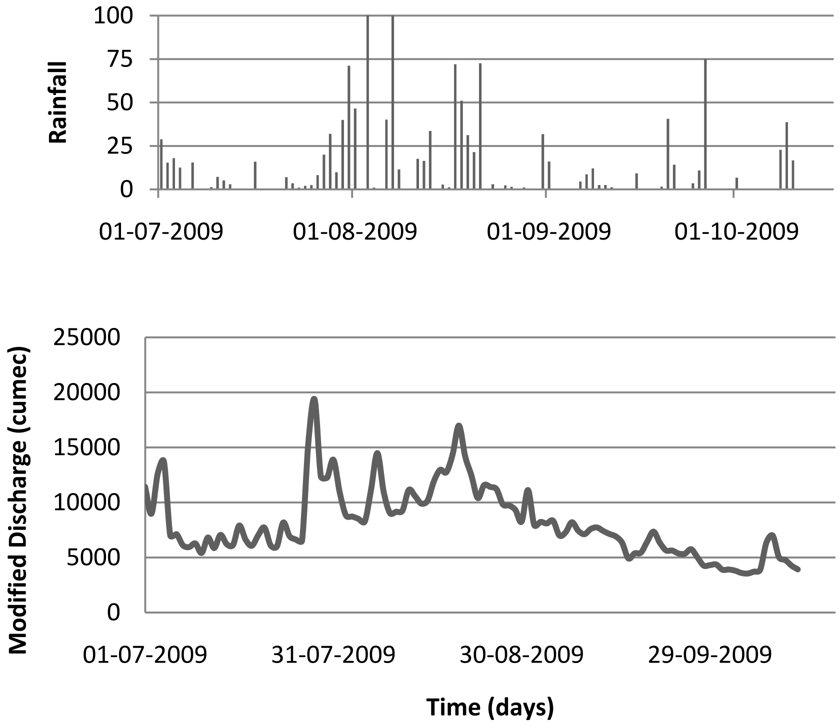
(b)


Rainfall
100
75
50
25
0
01-07-2009
01-08-2009
01-09-2009
01-10-2009
Modified Discharge (cumec)
25000
20000
15000
10000
5000
0
01-07-2009
31-07-2009
30-08-2009
29-09-2009
Time (days)

(c)


Rainfall
125
100
75
50
25
0
01-07-2009
01-08-2009
01-09-2009
01-10-2009
Modified Discharge (cumec)
25000
20000
15000
10000
5000
0
01-07-2009
31-07-2009
30-08-2009
29-09-2009
Time (days)

(d)



(e)

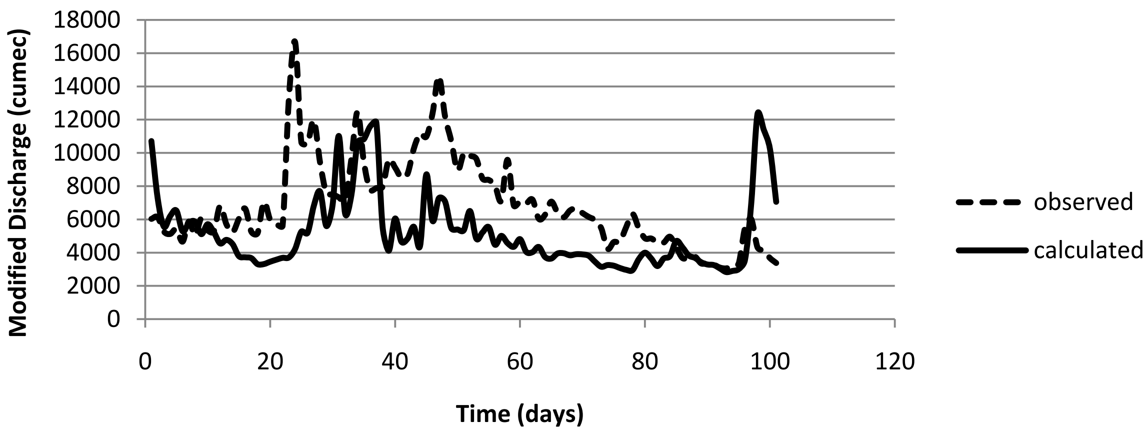
Figure 14: Rainfall v/s Downstream flow in year 2009 on different Rain gauge stations

(a) Okhaldunga, (b) Taplejung, (c) Dhankutta, (d) Biratnagar and (e) Dharan

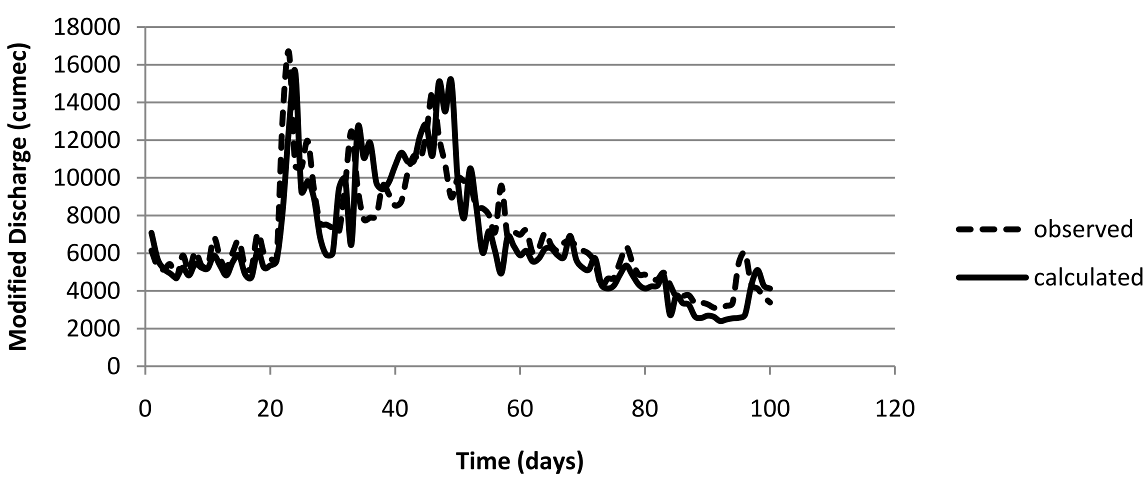
Appendix II

Optimized Network

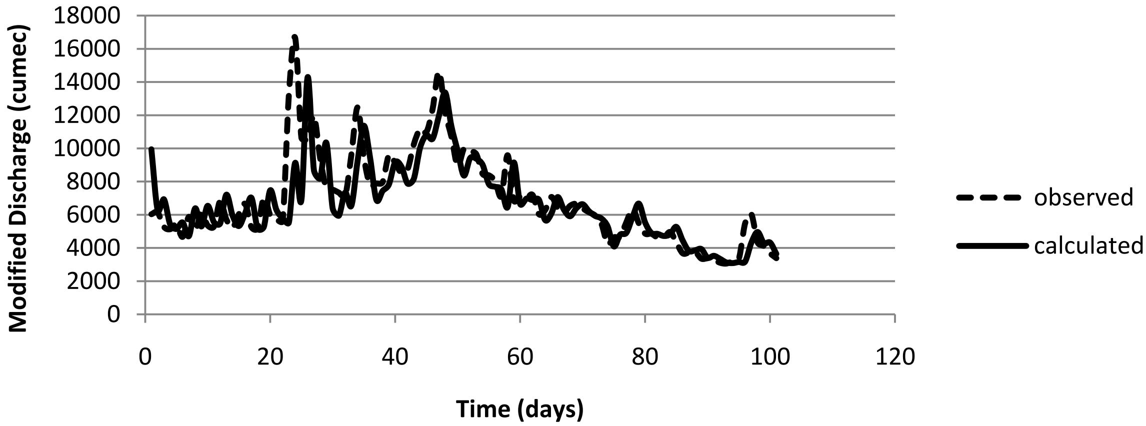
The network used in ANN has been optimised to give the best results using different trials and combinations e.g. increasing the no. of neurons in the hidden layers from 5 to 20 and increasing the no. of hidden layers in the network, changing the connection type and transfer function or increasing the time lag and then optimum results are discussed. Following are some remaining comparison.



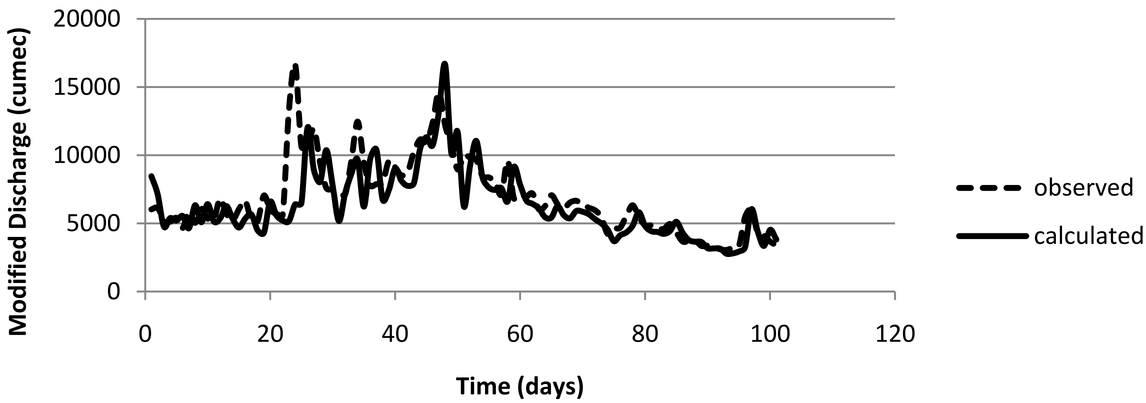
(a)



(b)



(c)



(d)

Figure 15: Observed and calculated modified discharge v/s time using ANN

(e) Input R_{t-1}, output Q_t,
(f) Input R_{t-2} Output $Q_{t,}$
(g) Input R_t and Q_{t-1}, output Q_t
(h) Input R_{t-1} and Q_{t-1}, Output Q_t