HYDROLOGICAL MODELING OF A TYPICAL UNGAUGED BASIN OF ODISHA

A

DISSERTATION

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE

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BY

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CERTIFICATE

This is to certify that the Dissertation entitled "**HYDROLOGICAL MODELING OF A TYPICAL UNGAUGED BASIN OF ODISHA**" *submitted by* **JANAKI BALLAV SWAIN** *to the* **National Institute of Technology, Rourkela**, *in partial fulfillment of the requirements for the award of* ***Master of Technology*** *in* ***Civil Engineering*** *with specialization in* ***Water Resources Engineering*** *is a record of bona fide research work carried out by him under my supervision and guidance during the academic session 2012-13. To the best of my knowledge, the matter embodied in this thesis has not been submitted to any other University or Institute for the award of any degree or diploma.*

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Date-

Place- **Janaki Ballav Swain**

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LIST OF ABBREVIATIONS

AMC- Antecedent Moisture Condition

ANN -Artificial Neural Network

CGWB-Central ground water board

DEM -Digital Elevation Model

GIS- Geographic Information System

IAHS- International Association of hydrological Sciences

MSL- Mean above Sea Level

PUB- Prediction in ungauged basin

SCS-CN- Soil Conservation Service-Curve Number

SRTM- Shuttle Radar Topography Mission

ABSTRACT

Drainage basins in most parts of the world are either partially gauged or completely ungauged. Estimation of hydrological parameters in ungauged basins is very difficult and also time consuming. Hydrological modeling is the tool which simulates the catchment behaviour by solving the equations that govern the physical processes occurring within the catchment hydrologic models are usually used to simulate the catchment response for a given input. The hydrologic models take time series data and produce another time series as output. In the present work a typical ungauged basin of Odisha having geographical area of 141.32km^2 has been selected as the study area. A small catchment has been chosen because the other catchments present around that area are similar to it or much less than that in terms of geographical extent. So the study was more focused in that aspect. Daily rainfall and discharge data were collected and time series analysis was done to check the correlation between them. Remote sensing and GIS techniques have been used as a tool to draw boundary map, drainage map, digital elevation map, flow direction map, flow accumulation map and land use/cover map of the ungauged basin, which were used as input for modeling through the conceptual SCS-CN model. Hydrological simulation model (HYSIM) is another distributed model used with catchment rainfall and potential evapotranspiration as its essential input parameters to simulate discharge. But it requires a large number of optimized parameters for simulation. ANN was also used to simulate runoff from the catchment rainfall. Simulated hydrographs were compared with the observed ones to look for a model that can be used with optimum input parameters and can provide best results. Results show that ANN model produced best result among the three used models and can be successfully used in an ungauged basin. ANN also takes very less parameter in comparison to the other two models as its input for simulation.

Key words-Rainfall-runoff; Ungauged basin; SCS-CN; HYSIM; ANN

CHAPTER 01

INTRODUCTION

1.1 General

Among the various natural resources available on earth, Water is one of the most important natural resource. Without it, life cannot be imagined on earth. 71% of the total Earth's surface is covered with water, and is mandatory for all known forms of life. On earth, Oceans have the major share of the total water i.e. 96.5%, 1.7% present in form of groundwater, 1.7% in glaciers and the ice caps of Antarctica and Greenland, a very small fraction in other large water bodies, and 0.001% in the air as vapor, clouds, and precipitation. Freshwater percentage is only 2.5, and out of it 98.8% is in form of ice and groundwater. So, less than 0.3% of all freshwater is in rivers, lakes, and the atmosphere (Gleick, 1993; CIA-The world fact book, 2008). Water is taken for granted because of abundance, but the problem with water is it is not always present in the proper place, at the proper time and of the proper quality.

Water on earth is not stagnant. It continuously moves from one place to another or one form to other. The continuous movement of water on, above and under the surface of the Earth can be explained through a cycle known as hydrologic cycle. The various aspects of water related to the earth can be explained in terms of this cycle (Chow *et al*., 1988; Subramanya, 2008). It is a continuous recirculating cycle which means that there is neither a beginning nor an end or a pause. Hydrologic cycle is a very vast and complex cycle in which a large number of paths are there with varying time scale. The various processes involved in this cycle are evaporation, interception, transpiration, surface runoff, infiltration and percolation. Figure 1.1 shows a schematic diagram of hydrologic cycle.

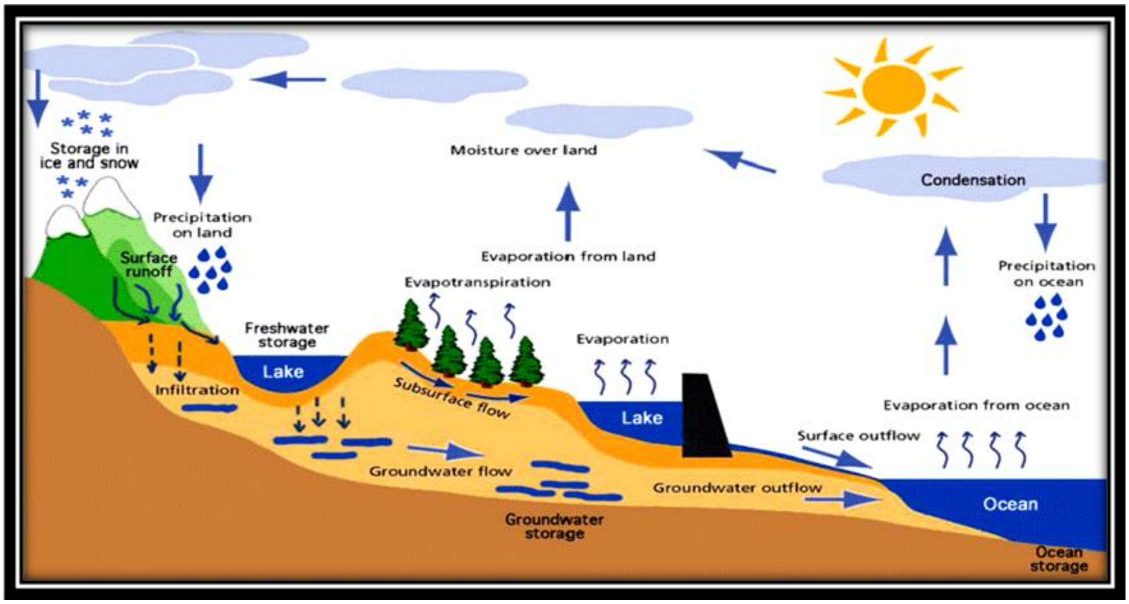


Figure 1.1: The Hydrologic cycle (Source: www.geofreekz.wordpress.com)

It can be seen from the above figure that, though the concept of the cycle seems simple, the whole phenomena is enormously complicated. It is not just a large single cycle but it is composed of many interrelated cycles.

Hydrology is the science with response to the intricate water cycle, which helps in solving many problems related to water. It gives you information about water on Earth and humans' involvement and use of water. A limited amount of water is available for our use. Hydrologists play a vital role in finding solutions to water related problems. People tap the water cycle for their own uses. Water is used either by pumping it from the ground or drawing it from a river or lake. Some of the common uses of water are daily household uses, industries, for irrigation of farms and gardens, and for production of electric power. After the above uses, water is allowed to flow on the ground or soaked in to the ground. The fundamental transport processes has been studied to describe the quantity and quality of water as it moves through the cycle.

1.2 Hydrology of ungauged basins

Drainage basins are a fundamental landscape unit for the cycling of water, sediment and dissolved geochemical and biogeochemical constituents. As such, they integrate all aspects of the hydrological cycle within a defined area that can be studied, quantified and acted upon. The drainage basin, thus, is a metaphor for integration of hydrological processes related to surface water, groundwater, evapotranspiration etc. and the explicit coupling of hydrology, geochemistry and ecology (Sivapalan *et al.*, 2003).

A drainage basin which has insufficient records of various hydrological observations in terms of both quantity and quality for analysis at the appropriate spatial and temporal scales and up to a good level of accuracy for application in practical fields is known as ungauged basins (Sivapalan *et al.,* 2003). If the parameter of interest is not available for the required period of time for prediction or modeling, that basin is an ungauged basin with respect to that variable. Variables of interest can be rainfall, runoff, erosion rates etc. so every basin is "ungauged" in some respect.

Accurate and timely predictions of high and low flow events at any ungauged watershed location can provide stakeholders the information required to make strategic, informed decisions. Whenever data is not available, hydrological models are important to establish baseline characteristics and determine long term impacts which are difficult to calculate (Lenhart *et al*., 2002). The aim of modeling is to reduce the uncertainty in hydrological predictions. Prediction of runoff water in an ungauged catchment area is vital for various practical applications such as the design of drainage structure and flood defenses, runoff forecasting and for catchment management tasks such as water allocation and climate impact analysis.

The IAHS Decade (2003-2012) on Predictions in Ungauged Basins, or PUB, is a new initiative launched by the International Association of Hydrological Sciences (IAHS), aimed at formulating and implementing appropriate science programs to engage and energize the scientific community, in a coordinated manner, towards achieving major advances in the capacity to make predictions in ungauged basins. (Sivapalan *et al*. 2003)

1.3 Hydrological modeling for ungauged basins & its importance

Hydrological modeling is a powerful technique of hydrologic system investigation for both the research hydrologists and practicing water resources engineer involved in the planning and development of integrated approach for management of water resources. Hydrologic models are symbolic or mathematical representation of known or assumed functions expressing various components of the hydrologic cycle (Schultz, 1993; Seth, 2008). The term hydrological model is often misunderstood to be only as a computer based mathematical model. The main function of these models are hydrologic prediction and to understand various hydrologic processes.

Hydrologic models for ungauged basins try to simulate the catchment behaviour by solving the equations that govern the physical processes occurring within the catchment. Therefore hydrologic models are usually used to simulate the catchment response for a given input. The hydrologic models take time series data and produce another time series as output. The importance of hydrological modeling in a catchment is

- To understand the spatial rainfall distribution over the catchment.
- To get information about catchment characteristics such as slope, soil type, land use, underlying geology, etc.
- Surface-groundwater interactions, water allocation, wetlands modeling, etc. can be better understood through hydrological modeling.
- Accurate stream flow forecasts are an important component of watershed planning and sustainable water resource management (Brooks *et al*., 2003).

One of the most frequently used events in hydrology is the relation between rainfall and runoff. It determines the runoff signal which leaves the watershed from the rainfall signal received by the basin (Kumar, and Bhattacharjya, 2011). In it a part of the hydrological cycle has been studied to express the runoff from the catchment as a function of the rainfall and other catchment characteristics. It helps to extend stream flow time series both spatially and temporally to evaluate management strategies and catchment response to climate.

Now a days number of approaches are available for prediction of basin responses. Methods which can be used for ungauged basins are extrapolation of response information from gauged to ungauged basins, information collected by remote sensing by satellites, application of process based hydrological models where the climate inputs are specified or are measured, and application of combined meteorological-hydrological models without the need to specify precipitation inputs (Sivapalan *et al*., 2003).

Singh *et al.*, (2001) developed regional flow-duration models for ungauged sites located in 13 states of the Himalayan region, covering almost the complete width of the country from Jammu and Kashmir in the west to northeastern states in the east.

Pandey and Ramasastri (2003) studied low flows in San and Barah rivers, tributaries of Indravati river system in Orissa using weekly flow data from two gauging sites.

A probabilistic distributed model structure was used for 127 catchments in United Kingdom using daily data and transformed the model to the ungauged catchments (Mclntyre *et al.*, 2005).

Kapangaziwiri and Hughes (2005) used Pitman model using estimates of physical basin properties in the selected ungauged catchments of South Africa. Hughes *et al.*, (2008) used commonly used estimation methods and typically available data for ungauged basins of South Africa.

Boughton, and Chiew (2007) used multiple linear regression to relate average annual runoff to average annual rainfall and areal potential evapotranspiration using data from 213 ungauged catchments of Australia. AWBM model was used to estimate daily runoff using daily rainfall.

Jha and Smakhtin described different range of techniques, which allow estimation of ungauged hydrological characteristics from climatic and physiographic catchment parameters. The parameters can be derived from maps, GIS, literature sources or observed climatic data which are normally more readily available than flow data.

Samuel *et al.*, (2011) used bias correction and regional climate models (RCMs), downscaling and global climate models (GCMs), dual regionalization method and hydrologic model to evaluate future flow variability and changes in 90 selected ungauged basins across the province of Ontario, Canada.

In the present work an attempt has made to establish relation between rainfall and runoff over the selected ungauged catchment as the study area using three different models: SCS-CN, HYSIM and ANN.

1.4 Objectives of the study

As mentioned above, hydrological modeling in any catchment; gauged, partially gauged or ungauged helps to understand about the catchment features and its responses. The specific objectives of the present study are:

1. Time Series, cross correlational and statistical analysis of daily rainfall and discharge data of the study area.
2. Delineation and development of Digital Elevation Model, land cover map and flow accumulation map of the study area for hydrological analysis.
3. Development of three models namely SCS-CN, HYSIM and ANN model for runoff estimation of ungauged basin.
4. Error analysis and correlation statistics for obtaining most suitable model for runoff simulation in ungauged catchments.

1.5 Thesis outline

Chapter 01 introduces the work related to hydrology of ungauged basins, importance of hydrological modeling in ungauged basins and objectives of the present work.

Chapter 02 focuses about the previous research works related to hydrological modeling in different ungauged basins around the globe by many researchers and hydrologists.

Chapter 03 describes about the geographical location of the study area, its characteristics, available hydrological data and time series analysis of rainfall and observed discharge.

Chapter 04 covers the use of remote sensing and GIS as a tool to delineate different maps, about the three hydrological models used in the study, and the input parameters required for these models.

Chapter 05 incorporates the results obtained from the present research work and analysis about the same.

Chapter 06 provides the summary, important conclusions derived from hydrological modeling of the ungauged basin.

CHAPTER 02

REVIEW OF LITERATURE

2.1 Drainage basin

A hydrologic system is defined as a structure or volume in a space, surrounded by a boundary that receives water and other inputs, operates on these parameters internally, and produces them as outputs (Chow *et al*., 1988).

The term 'precipitation' is referred as all forms of water that reach the earth surface from the atmosphere, and runoff is the draining or flowing off of precipitation from a catchment area through a surface channel after satisfying all surface and sub-surface losses (Dubayah *et al*., 1997).

If there is no runoff data available in catchments, these are termed as ungauged catchments. The parameters of rainfall runoff models can't be obtained by the calibration of direct runoff data and hence need to be obtained by other methods for these catchments (Bloschl, 2006).

2.2 Hydrological modeling

Hydrologic models are symbolic or mathematical representation of known or assumed functions expressing the various components of a hydrologic cycle (Beven *et al.*, 1979).

Ground water, rainfall and runoff are the major components of a water system in any given area. Complexity of these subsystems and their interactions depend on many factors such as geological, hydrological, environmental and geographical characteristics of the area (Cheng *et al*., 2001).

Hydrological modeling can be defined as a powerful technique of hydrologic system investigation for both the hydrologists and the practicing water resources engineers involved in the planning and development of integrated approach for water resources management (Schultz, 1993; Seth, 2008).

2.3 Rainfall-runoff modeling for ungauged basins

The first models that predicted runoff from rainfall were developed as early as halfway the nineteenth century (Mulvaney, 1851).

In 1932, Sherman introduced the concept of the unit hydrograph on the basis of the principle of superposition. Though this method was not yet very common at that time, but the superposition principle implied many assumptions.

The derivation of the unit hydrograph in the discrete form from input and output still remained a big problem, due to the assumed linear behavior of the system and errors in the data. Shape and volume constrained unit hydrograph with a smaller number of parameters was introduced to overcome these problems (Nash, 1958, 1959, 1960).

According to Dooge (1957, 1973), during the last part of the 19th century and earlier part of the 20th century, most engineers used empirical formulas derived for particular cases and applied them to the other cases under the assumption that condition were similar enough.

Box and Jenkins (1976) provided hydrologists with alternative methods of expressing the unit hydrograph in terms of autoregressive moving average (ARMA). This school of thought brought about the use of Artificial Neural Network (ANN) approach, a method applied widely in other fields of science and engineering to represent non-linear and dynamic system.

Traditional lumped, conceptual rainfall-runoff models attempt to represent hydrological processes by mathematical equations and multiple layers of storage, e.g., the Stanford Watershed Model IV (Crawford and Linsley, 1966), HEC-1 U.S. Army Corps of Engineers (Rockwood and Nelson, 1966), the SACRAMENTO model (Burnash *et al*., 1973), Tank model (WMO, 1975)and the XINANJIANG model (Zhao *et al*., 1980).

Mathematical modeling of the rainfall-runoff process possesses a very long history. However, progress was slow before the last half century. Hydrology advanced on all fronts during the

1930's and the groundwork for most of the present developments were laid during this period. The concept of physical hydrology was introduced and it led to an understanding of the physics of the hydrologic cycle. The modern burst of development in deterministic modeling of rainfall-runoff processes started from the 1930's, and the unit hydrograph concepts of Sherman (Dwady, 1983).

The lack of a one to-one relationship between the model and the reality gave rise to a development of a so called physical based model such as SHE (System Hydrologique European) (Abbot, 1986). This model is believed to be the state-art of the physically based model. A fourth generation model MIKE SHE (Refsgaard and Storm, 1995) is now being developed to apply for integrated water resource management. Typical areas of applications of this model are river basin planning, water supply, irrigation and drainage, effects of change of land use, and other ecological factors influencing surface and groundwater system.

To minimize the uncertainty lies with the parameters, lumped conceptual models are extended to handle basins as composites of sub basins, which are categorized according to homogeneity in topography and land use. Good examples of such development are TOPMODEL (Beven *et al*., 1979, Beven *et al*., 1995) and ARINO (Todini, 1996). The main concept behind these models is to give detailed account of very important topographic and hydraulic characteristics of a watershed.

Rainfall runoff models are a tool which contributes to the wider process of making decision on the most suitable strategies for river basin management. They are not replacements for direct data sources but they allow most to be made of existing data where such data are scarce (Seethapathi *et al*., 1997).

Bhaskar *et al*., (1997) derived the Geomorphological Instantaneous Unit Hydrograph (GIUH) from watershed geomorphological characteristics and then related it to the parameters of the Nash instantaneous unit hydrograph (IUH) model for deriving its complete shape.

Hydrological simulation model ‘HYSIM’ (Seth, 1997, 1998) has been used in Brahmani river basin and Rusikulya river basin of Odisha to generate daily flow.

Croker *et al.,* (2001) developed a set of techniques for estimating hydrological characteristics in the Himalayan part of Himachal Pradesh of India through the REFRESHA Project (Regional Flow Regimes Estimation for Small-scale Hydropower Assessment) using data from 41 gauged catchments in the study area of 56,000 square kilometers. They used multi-variate regression techniques to relate observed flow statistics to pertinent catchment characteristics and to derive regional prediction models.

Bhunya *et al*., (2003) introduced a simplified version of the existing two-parameter gamma distribution to derive accurate synthetic hydrographs.

Rees *et al*., (2004) developed a hydrological model using recession curves for estimating dry season flows in ungauged catchments of Himachal Pradesh and Nepal.

Holmes *et al*., (2004) examined the range of hydrological characteristics in Himalayan region of Nepal and Northern India. Statistics based regional hydrological model for estimation of average monthly dry-season flows in gauged and ungauged catchments for part of the region were developed. They describe the temporal sequence of flows during the critical dry season months.

The choice of modeling scale depends on modeling objectives, the available supporting data and the sought prediction accuracy, particularly rainfall and flow observations. It is common to have supporting flow observations at only one point in the catchment or to have no response record at all (Sivapalan *et al*., 2003; Wagener *et al*., 2005).

Mishra *et al*., (2007) used SCS-CN method for computation of direct runoff from long duration rains for five Indian watersheds. They derived curve numbers from long-term daily rainfall runoff data and Antecedent Moisture Condition (AMC) related with antecedent duration.

Rainfall-runoff modeling can be undertaken on different catchment discretization scales: starting from representative volumes of a few centimeters, going up to the whole catchment being treated as one element (Singh, 1996; Beven, 2008).

Patil *et al*., (2008) estimated runoff using curve number techniques (ISRE-CN) and validated with recorded data for the period from 1993 to 2001 of Banha catchment in Damodar valley, Jharkhand, India. They observed that the application of the modified CN I method in the ungauged watersheds that were hydrologically similar to the Banha watershed would result in an accurate surface runoff estimation.

Jha and Smakhtin (2008) described different range of techniques, which allow estimation of ungauged hydrological characteristics from climatic and physiographic catchment parameters. The parameters can be derived from maps, GIS, literature sources or observed climatic data which are normally more readily available than flow data.

2.4 Hydrological models of ungauged basins based on remote sensing, GIS and ANN

The type of models that have been applied with a GIS as a tool will be classified as Physical based, lumped parameters or some combination of the two. There has been a growing need to study, understand and quantify the impact of major land use changes on hydrologic regime, both water quantity and quality (Engman *et al*., 1991).

Remote sensing in runoff estimation generally provides a source of input parameters for the models. Satellite data provides thematic information on land use/land cover, soil, vegetation, drainage, etc., which, in combination with conventionally measured climatic parameters (temperature, precipitation etc.) and topographic parameters (elevation and slope), constitute the required input data for various rainfall-runoff models. The information, which is extracted from remote sensing and other sources, can be stored as a geo referenced database in a GIS. It provides efficient tools for data input into databases, retrieval of selected data for further processing, and computer based software modules that can analyze or manipulate the retrieved data in order to generate the desired information in a specific form (Miloradov and Marjanovic, 1991)

Runoff is one of the most important hydrological variables used in water resources studies. Reliable prediction of direct runoff for ungauged basins is difficult and time consuming. Conventional models used for prediction of stream discharge usually require considerable meteorological and hydrological data. Remote sensing and Geographic Information Systems (GIS), in combination with appropriate rainfall runoff models, provide ideal tools for the estimation of direct runoff volume, peak discharge and hydrographs (Miloradov and Marjanovic, 1991; Demayo and Steel, 1996; Bellal *et al.*, 1996).

Many researchers (Blanchard 1975; Jackson *et al*., 1977; Ragan *et al*., 1980; Slack *et al*., 1980; Bondelid *et al*., 1982; Hill *et al*., 1987; White, 1988; Muzik, 1988; Stuebe & Johnston 1990; Das *et al*., 1992; Tiwari *et al*., 1991, 1997) used land use/land cover information derived from satellite data of Landsat, SPOT, & IRS Satellite and integrated them with GIS to estimate SCS CNs and runoff.

Recently ANN has been considered as an efficient alternative tool which can model the complex hydrologic systems and therefore widely used for prediction. Some specific applications of ANN to hydrology include modeling rainfall-runoff process (Sajikumar *et al*., 1999).

A number of researchers (Zhu *et al*., 1994; Dawson and Wilby 1998; Tokar and Johnson 1999; Coulibaly *et al*., 2000) have investigated the potential of using neural networks in modeling watershed runoff based on rainfall inputs.

Sarkar *et al*., (2006*)* developed back propagation ANN runoff models to simulate and forecast daily runoff for a part of the Satluj river basin of India.

Remotely sensed data provide spatial information about the processes of the land phase of the hydrologic cycle. The land cover maps derived by the remote sensing are the basis of hydrologic response units for modeling units. For understanding of the hydrology of areas with little available data, a better insight in to the distribution of the physical characteristics of the catchments is provided by the image processing techniques. (Seth, 2008)

Geographic information system focuses on proper integration of user and machine for providing spatial information to support operations, management, analysis and decision making. Since GIS doesn't directly land itself to time varying studies, its features are utilized in hydrological studies by coupling it with hydrological models (Seth, 2008).

Artificial Neural Network (ANN) models have been used to model complex non-linear input-output relationships in an extremely interdisciplinary field successfully. The natural behavior of hydrological processes is appropriate for the application of ANN method (El-shafie *et al.,* 2011).

The behavior of rainfall-runoff process is very complicated phenomenon which is controlled by large number of climatic and physiographic factors that vary with the time and as well as space.

The relationship between rainfall and resulting runoff is quite complex and is influenced by factors relating the topography and climate (Kumar and Kumar, 2012).

Gajbhiye *et al*., (2012) determined the runoff depth using NRSC-CN method with Remote Sensing and GIS and the effect of slope on runoff generation for Bamhani catchment located in Mandla district of Madhya Pradesh. They determined the Effect of slope on CN values and runoff depth. The result showed that the CN unadjusted value are lower than CN adjusted with slope. Remote sensing and GIS is a very reliable technique for the preparation of most of the input data required by the SCS curve number model.

CHAPTER 3

THE STUDY AREA AND DATA COLLECTION

3.1 The study area

The study area for this present work is a catchment area in Sundergarh district of Odisha named as Samij nala catchment. It is a sub basin of Brahmani river present on the left side of the river. It is situated in Koira block. Nearest village to this area is Jamdihi. Rourkela railway station is the nearest railway station to the study area. Geographically it is on the south east part of Sundergarh district. It spreads from longitude 85^0 07’ to 85^0 14’E and latitude 21^0 52’ to 22^0 05’N.Geographical extent of this catchment is 141.32 km^{2}.The main channel which flows through the catchment is “Samij Nala”.

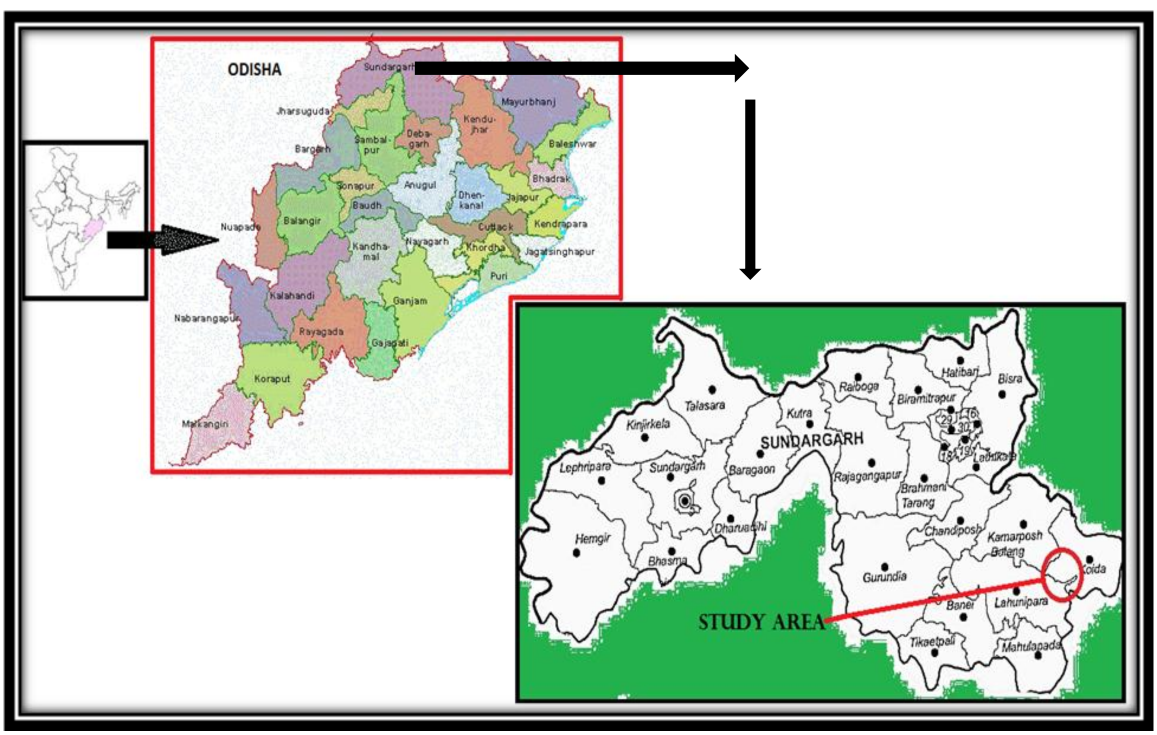


Figure 3.1: Location of the study area

As this portion of the district is a remote area, medium of communication to the place is road only. Location of the study area is shown above in Figure 3.1.Figure 3.2 shows the boundary of the study area.

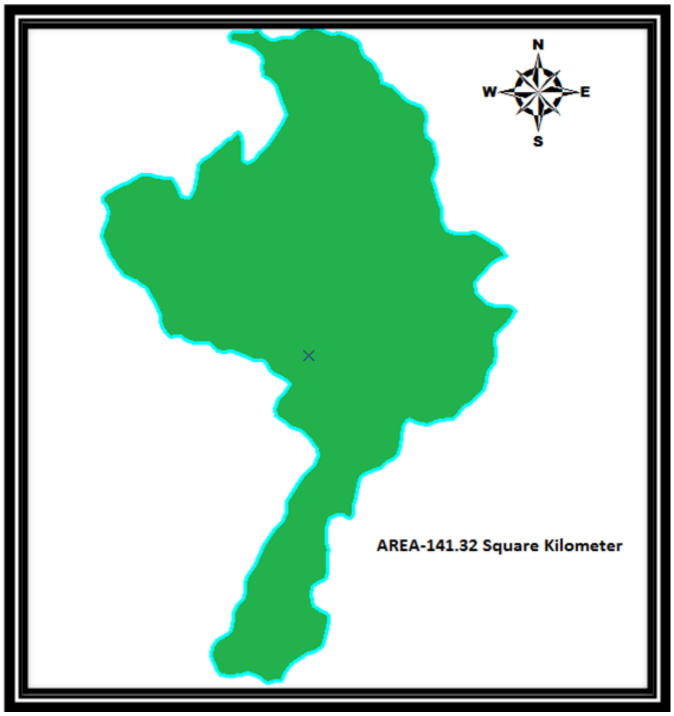


Figure 3.2: The Samij basin, an ungauged basin, a sub basin of Brhamani river basin

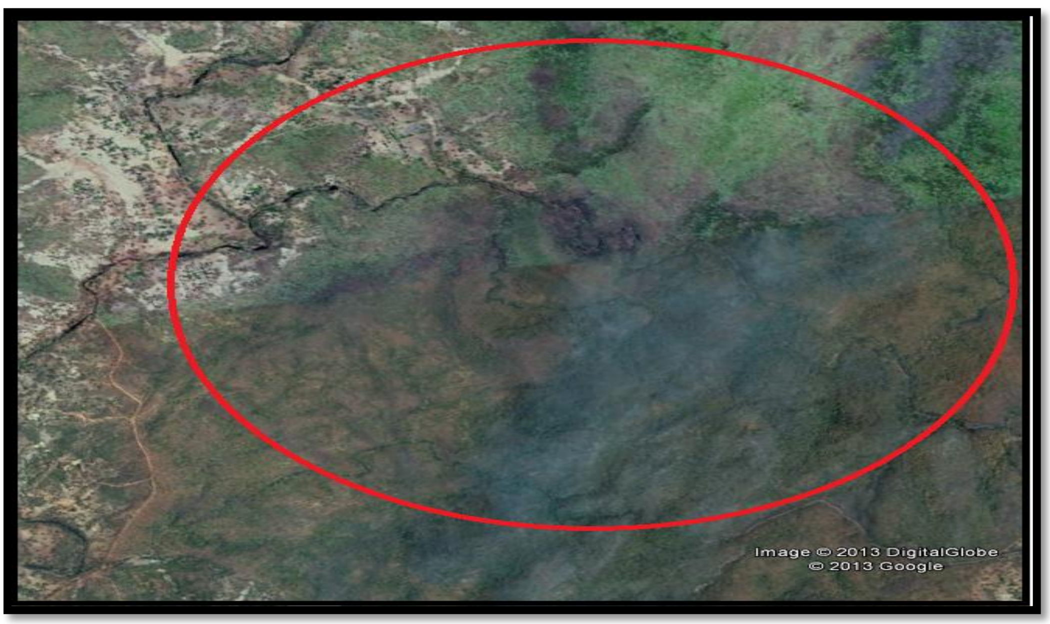


Figure 3.3: Synoptic view of the study area

3.1.1 Topography

The catchment area has a hilly topography. The elevation varies from 163m to 903m from mean sea level. So the slope in the area is high. Entire area is covered by undulating hilly tracts. The basin is surrounded by hills from the eastern side.

3.1.2 Land use/land cover

Catchment land cover is largely forested. Around 80% of the area is covered with dense forest. While moderate development is primarily located in the stream valleys. Barren lands are present in patches. Now days the forest cover is gradually decreasing due to rapid extension of mine areas around the basin. The soil in this catchment is red sandy soil and lateritic. Plenty of iron concentration is found in the soil.

3.1.3 Drainage

There are many dry drainage channels with in the area. The main channel which flows through the catchment is Samij nala. Besides many seasonal nala, samij nala is a perennial nala. Total length of the nala from its starting point up to the outlet is 30km. Samij nala is a tributary of Kurahi River which is a tributary of Brahmani River.

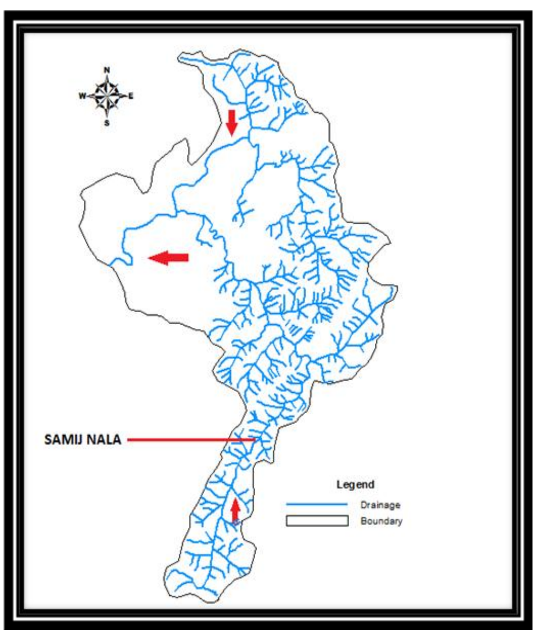


Figure 3.4: Samij nala & its tributaries in the catchment

Figure 3.5: The Samij nala

3.1.4 Soil

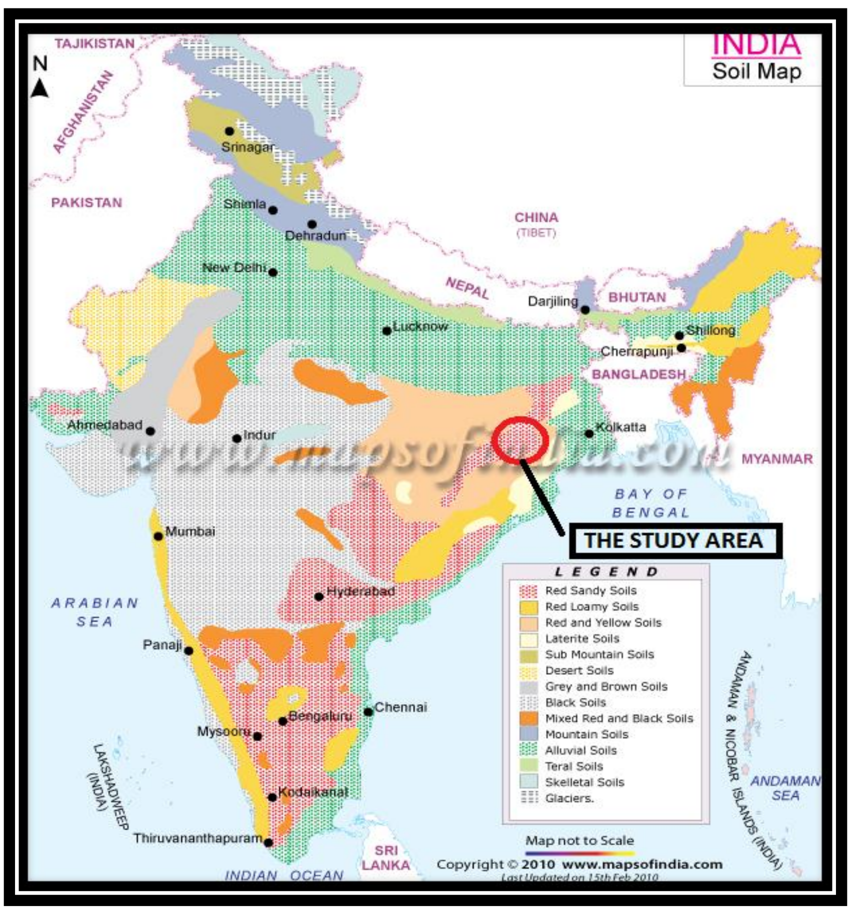


Figure 3.6: Soil map of the study area (Source: www.mapsofindia.com)

The soil of this catchment comes under the red soil group. It is of laterite origin. Red sandy loam is the main soil in the catchment.

Figure 3.7: Red Soil in the catchment

3.1.5 Agriculture

Within adverse climate, land used pattern, unreliable precipitation and light texture soil, the cropping pattern of the district mainly depend on rainfall. Medium irrigation, minor irrigation and lift irrigation schemes help people to grow paddy as the major crop in their fields in *Kharif* season. Blackgram, maize, and greengram are also grown by farmers.

3.1.6 Industry

Sundergarh district occupies an important position in the mineral map of the state. The available minerals are iron-ore, manganese, limestone, dolomite, mica, fire-clay, bauxite, lead copper, and zinc. Mainly Iron-ore and manganese-ore deposits are available around the study area. Based on these minerals many small and medium industries are established around the study area.

3.1.7 Ground water

During the pre-monsoon period the level of ground water varies in between 5 to 10m.After the monsoon season ground water level rises and varies between 2 to 5m.

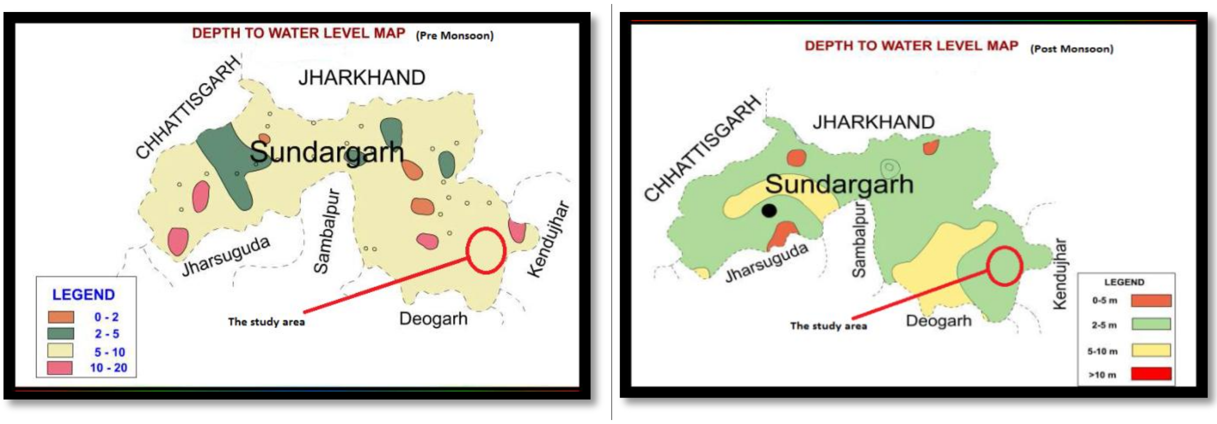


Figure 3.8: Ground water level in Sundergarh district (Source: CGWB, Bhubaneswar)

3.1.8 Temperature

The climate which prevails in and around the catchment area is sub-tropical. The climate of the area is characterized by an oppressively hot summer with high humidity. Temperature begins to rise rapidly attaining the maximum during the month of May. During the summer maximum temperature is around 40°C. The weather becomes more pleasant with the advent of the monsoon in June and remains as such up to the end of October. The temperature in the month of December is lowest i.e. around 10 °C. Sometimes it even drops down to 7 °C.

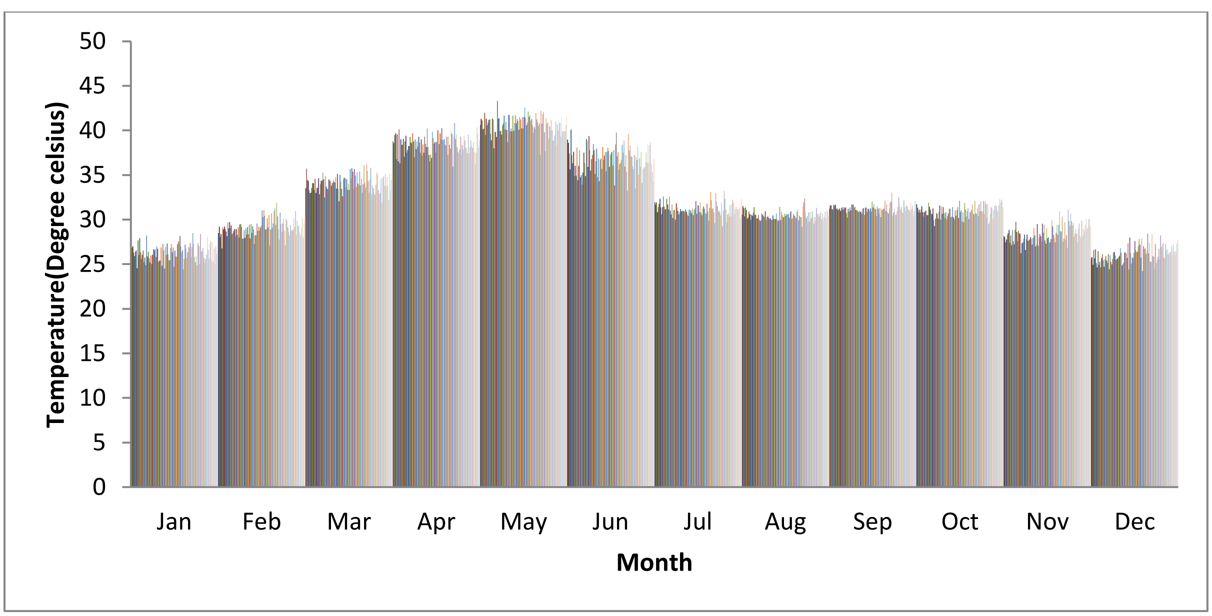


Figure 3.9: Mean monthly maximum temperature

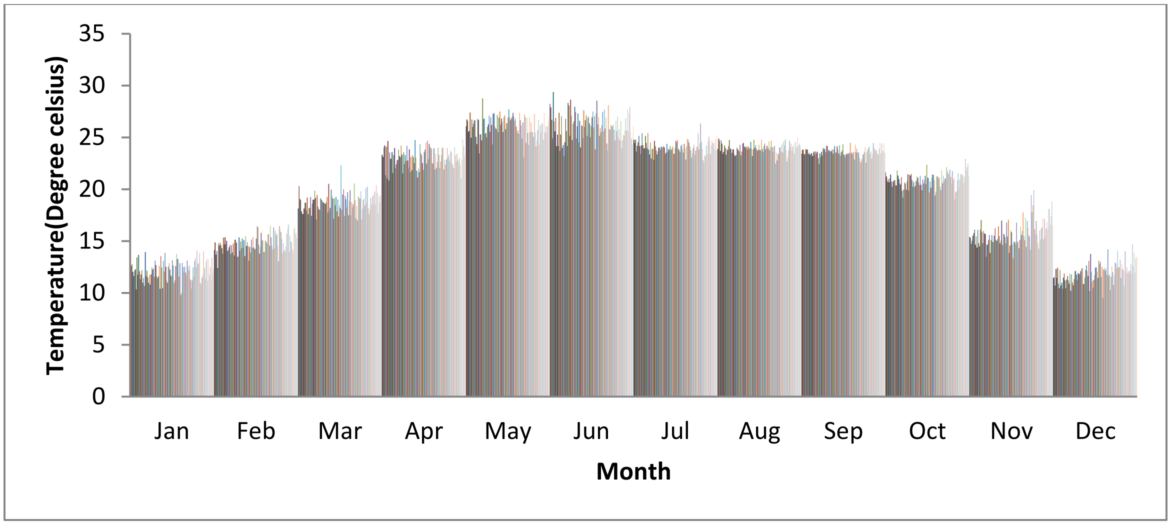


Figure 3.10: Mean monthly minimum temperature

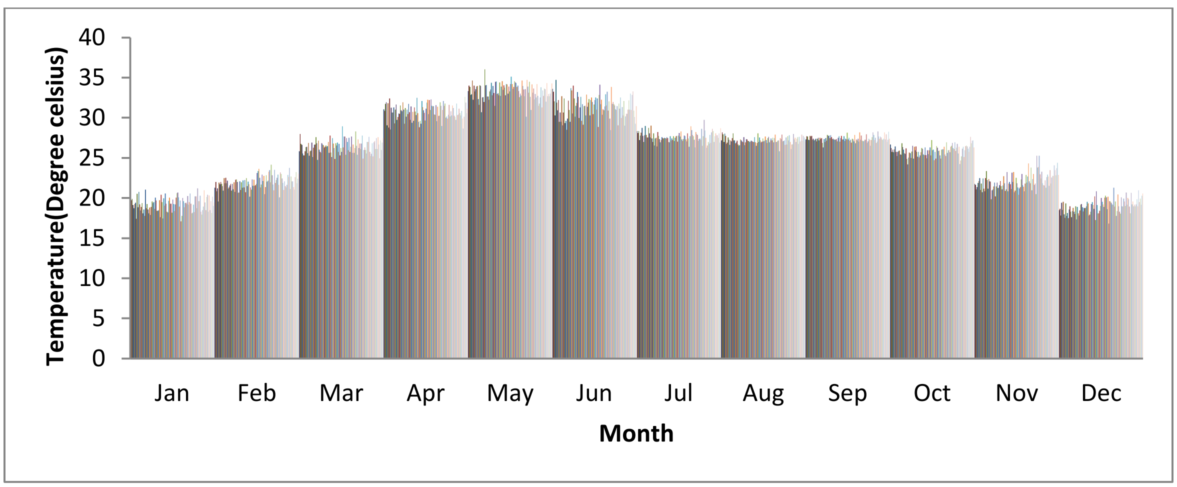
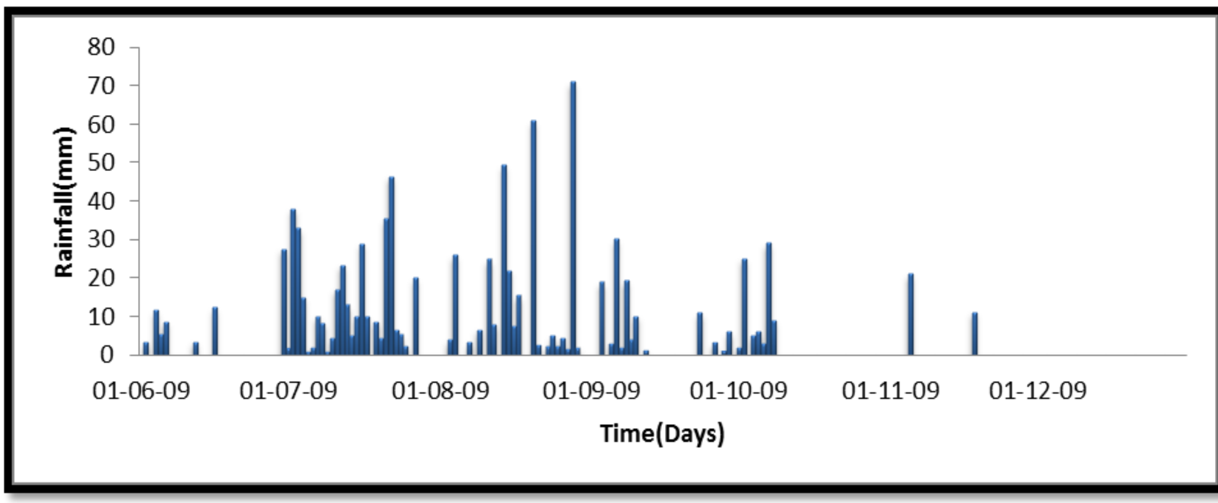


Figure 3.11: Mean monthly average temperature

3.2 Data collection & analysis

3.2.1 Rainfall

Monsoon season starts from June and it extends till September. Average annual rainfall In Sundergarh District is about 1400mm.Around 80% of the annual rainfall occurs during Monsoon period. During this period the intensity of rainfall is high. For the present study Daily rainfall data were collected from two rain gauge stations nearer to the study area which shows good co relation between each other. The two stations are at Lahunipara and at Bonei. Available rainfall data were from June 2009 to September 2012 (Source: Odisha rainfall monitoring system).Figure 3.12 and 3.13 show the daily rainfall of the Lahunipara and Bonei rain gauge stations respectively. From the observed data it is clear that rainfall during January to May is almost zero. During monsoon months the intensity is such high that on 23rd September of 2011 the rainfall measured at Bonei rain gauge station was 165mm.Total average annual rainfall of year 2011 is 1804mm which is around 400 mm more than the average annual rainfall of the district. As the slope in the catchment is on the higher side, high intensity rainfall causes heavy runoff in the flow channels. Thiessen-mean or Isohyetal method can't be applied over the catchment as not a single rain gauge station present inside the catchment. Therefore average rainfall was calculated using arithmetic mean method for further analysis.



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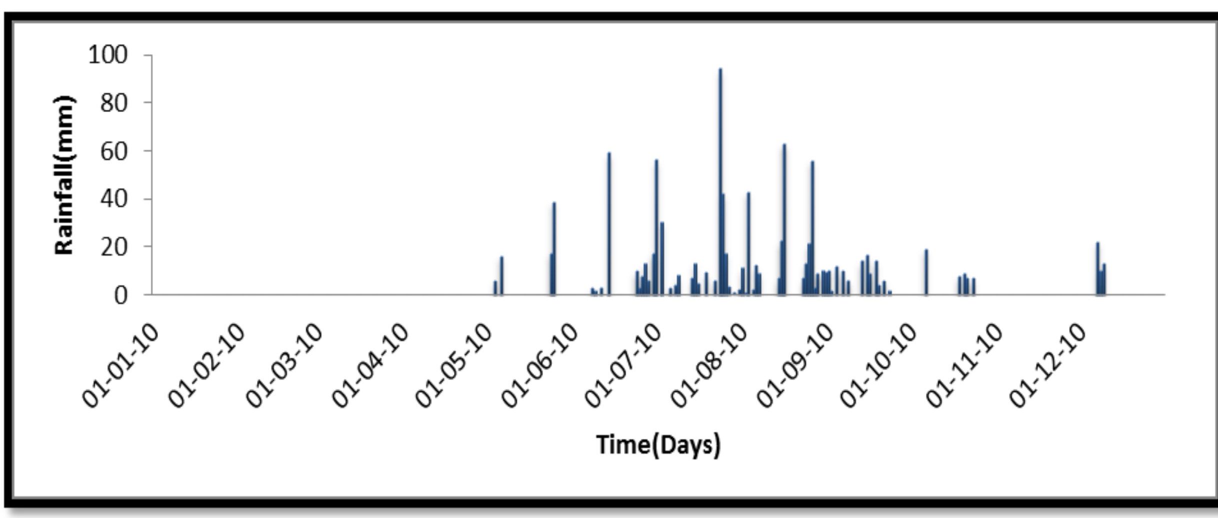

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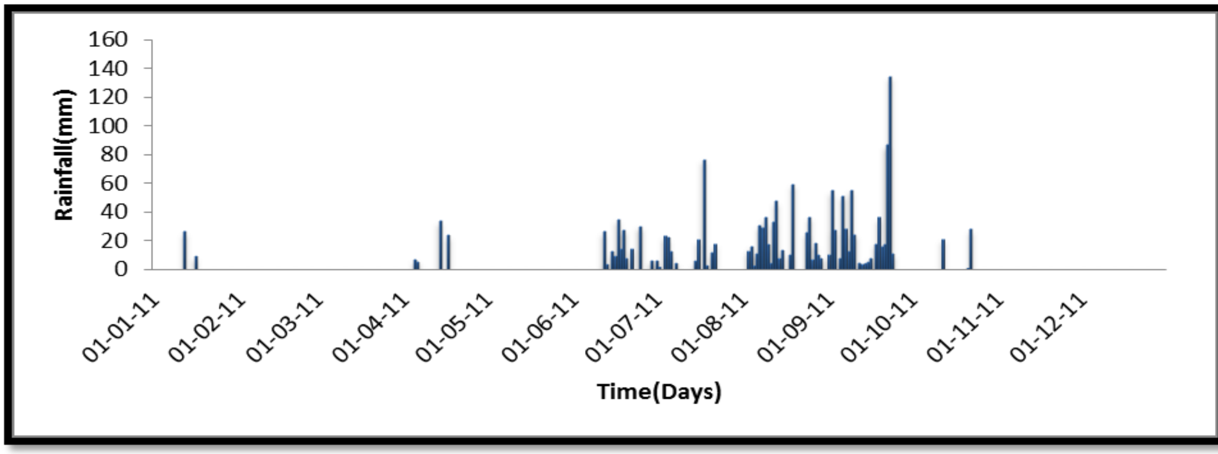

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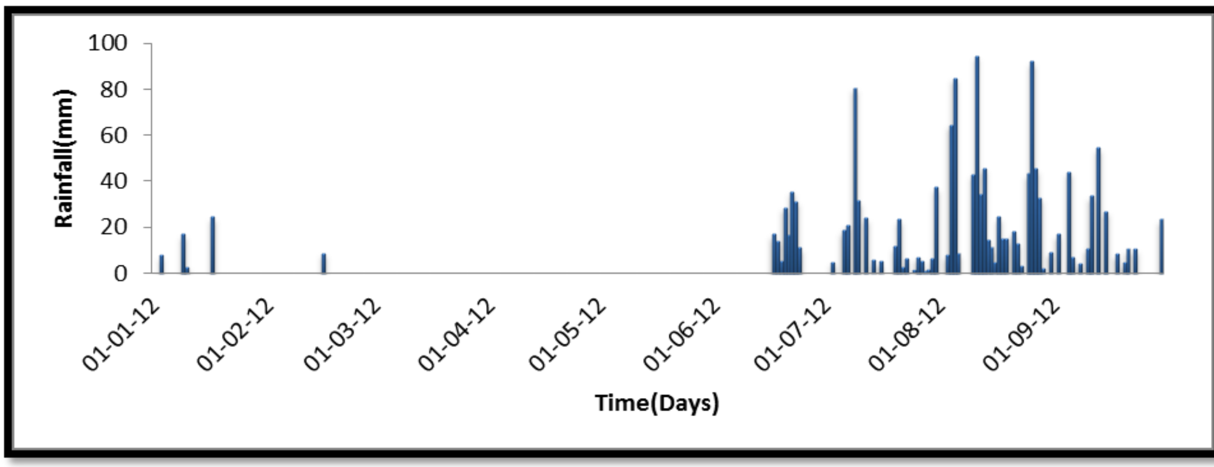
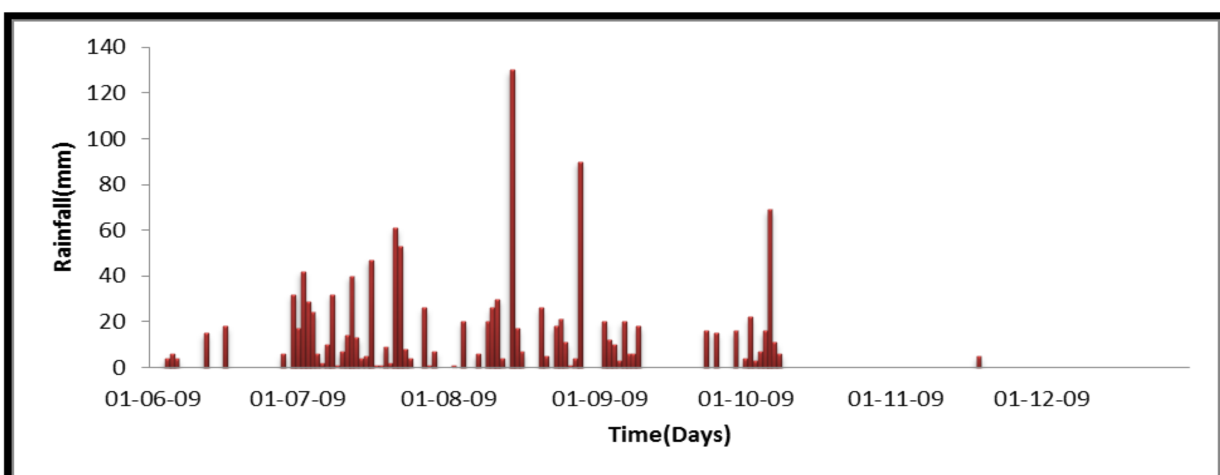


(d)

Figure 3.12: Daily rainfall at Lahunipara from June 2009 to September 2012



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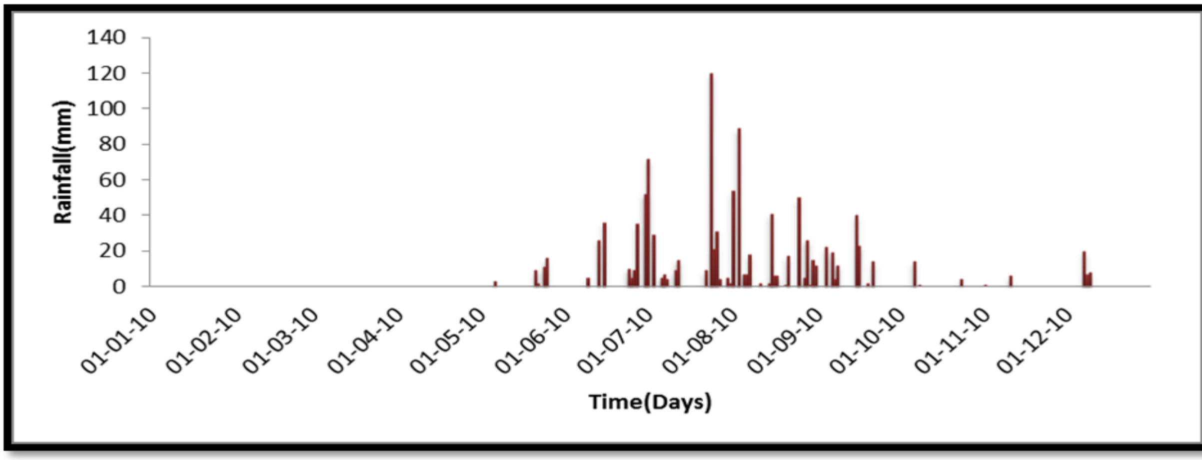

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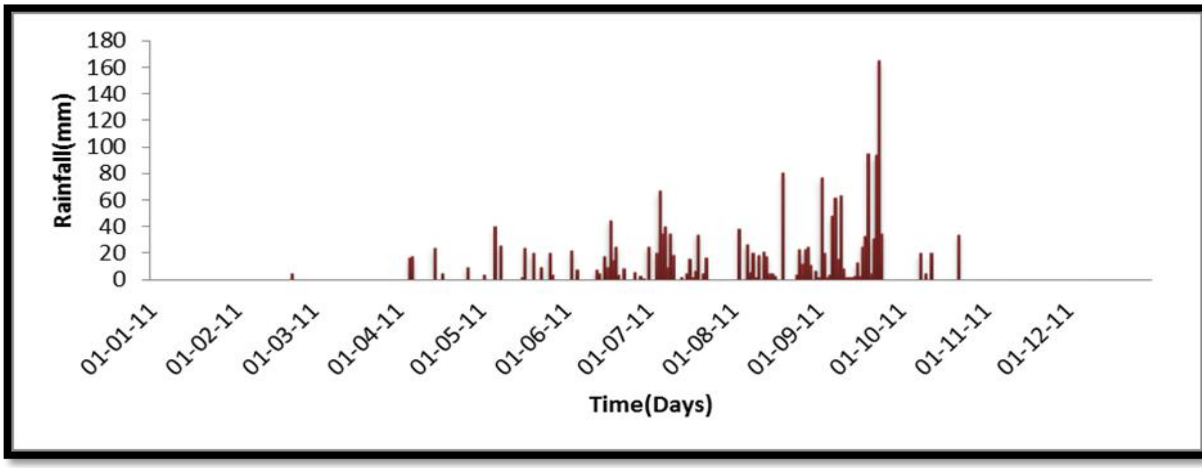

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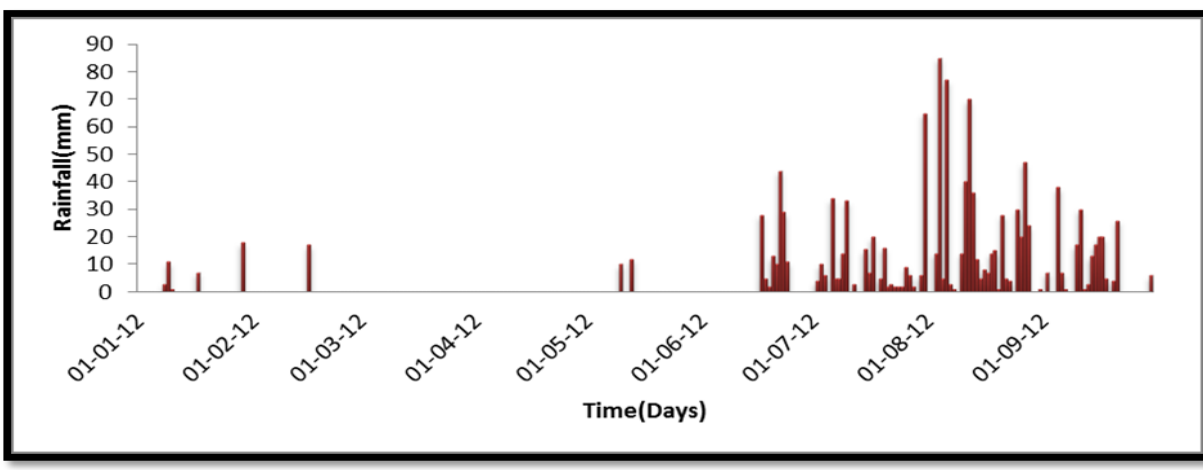

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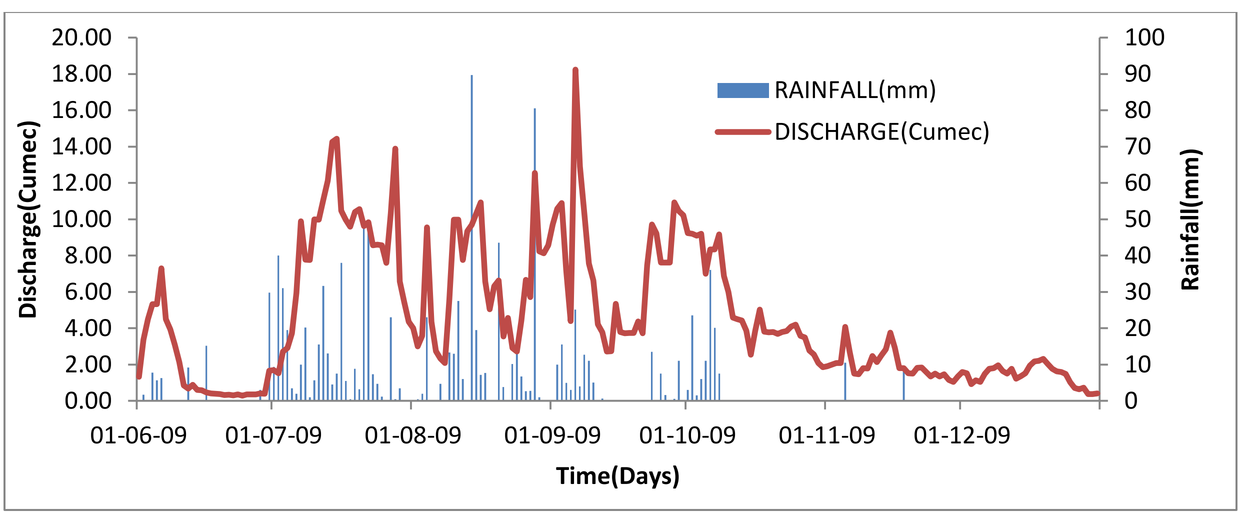
Figure 3.13: Daily Rainfall at Bonei from June 2009 to September 2012

3.2.2 Flow data

The study area is situated in a remote place. Measurement of flow velocity is not easy. Velocity was measured by use of a floating object. Floating object on the surface of a stream when timed can yield the surface velocity by the relation $v=s/t$ (1)

Where s =Distance travelled in time t.

The above method of measuring velocities while primitive still finds applications in special circumstances. Any floating object can be used for this purpose. It is easy to use and the mean velocity is calculated by multiplying the observed surface velocity by a reduction coefficient of 0.8. Velocity was measured at the outlet of the catchment. Length of the nala up to the outlet is 30km.At the outlet section stream is flowing straight. A straight section of 60m from the outlet towards the upstream of the nala was chosen for observation. Velocity was measured 3 times a day and the mean velocity for that day was calculated. At the measuring section the width of the channel was measured and it is 10m. Daily water level was also measured. The whole cross section was divided in to 5 parts by putting 4 rods across the channel. Area of each cross section was measured. Area of the whole cross section was calculated and multiplied with the mean velocity to know the discharge of the nala at the cross section. Daily discharge data is available from June 2009 to September 2012 (Source: Water Resources Department, Govt. of Odisha).Figure 3.14 shows the plot between average rainfall over the catchment and generated runoff from it.



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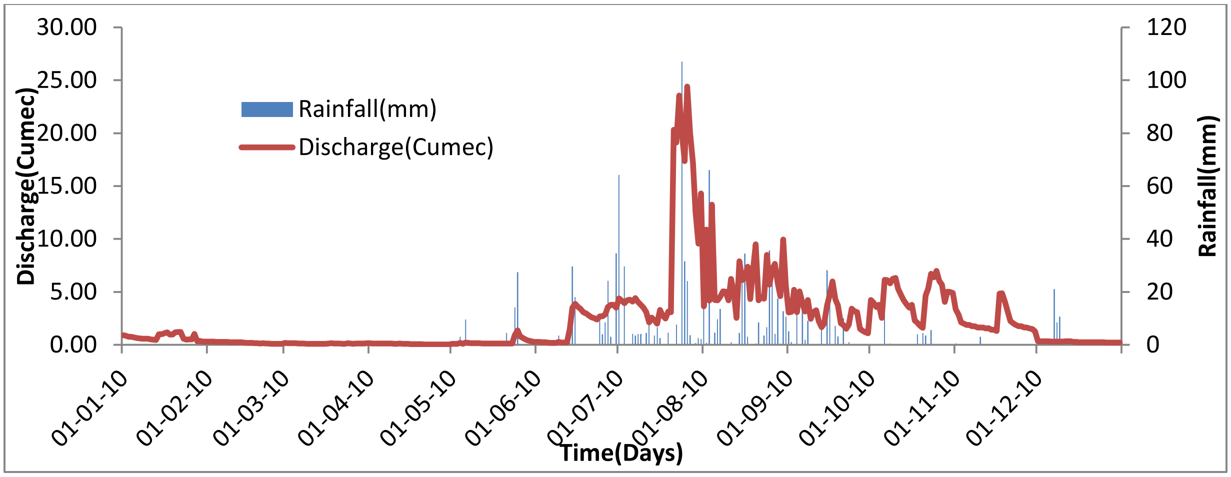

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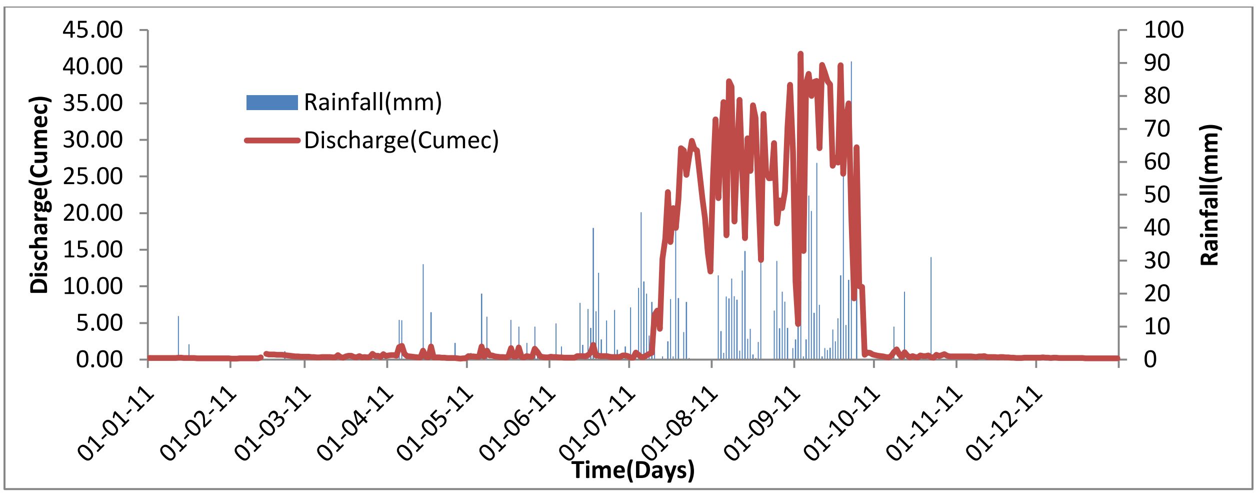

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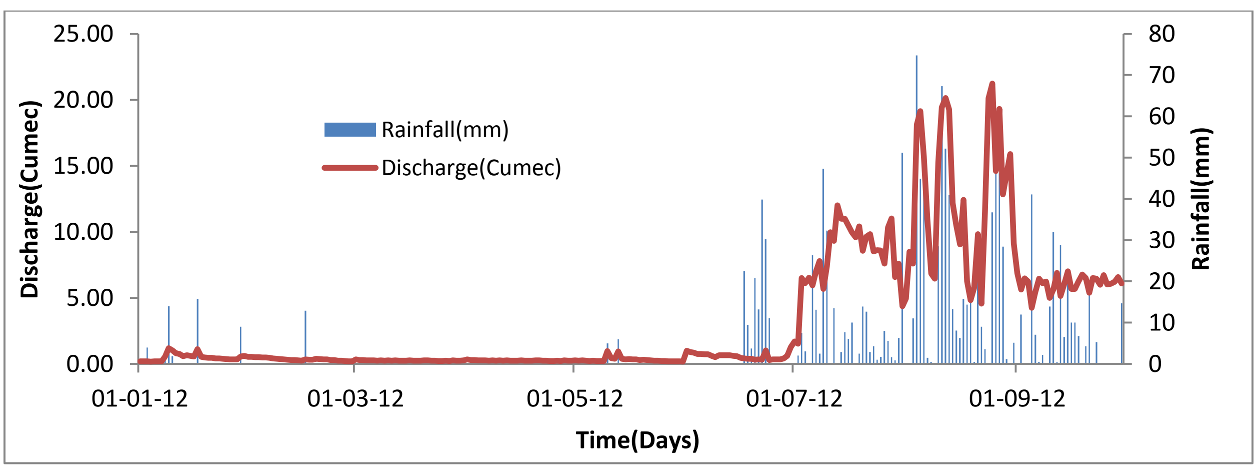

(d)

Figure 3.14: Average daily rainfall and observed daily discharge of Samij basin

3.3 Flow duration Curve

Flow of water varies over a year. Stream flow variability can be studied through flow duration curve. A flow duration curve of a stream is a plot of discharge against the per cent of time the flow was equalled or exceeded. It is also known as discharge-frequency curve.

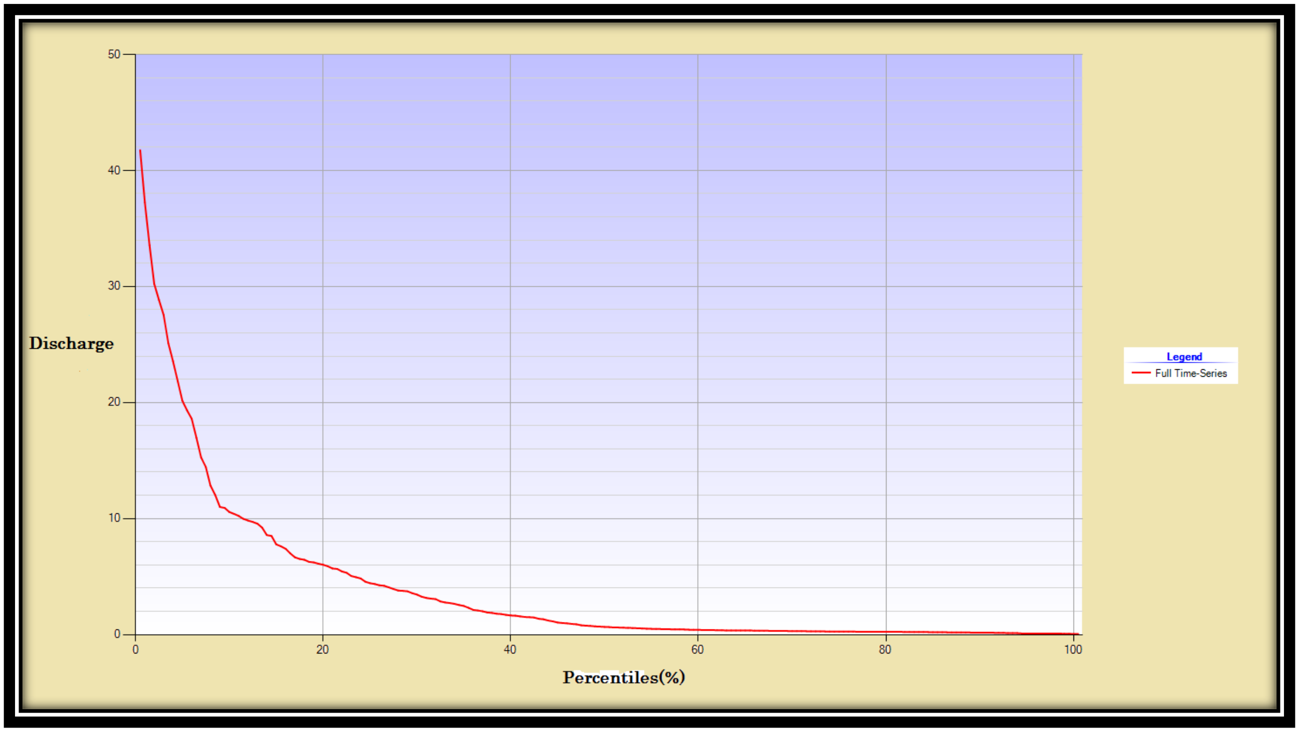

Figure 3.15: Flow duration curve of Samij nala

The flow duration curve shows that the Samij nala is a perennial stream though there is very little flow in the channel during summer season.

CHAPTER 04

METHODOLOGY

This chapter describes about the use of Arc GIS for delineation of different maps, deals with the three models and their input parameters used for estimation of runoff from the basin. The details of the models are described below.

4.1 Development of maps using Arc GIS

The toposheet, in which the study area comes, was collected and scanned. The scanned map was imported to Arc GIS software. Boundary of the basin was drawn using this software. Samij nala and its tributaries were drawn over the boundary map.

SRTM 90mm Digital elevation model (DEM) data were collected (Source: http://ws.csiss.gmu.edu/DEM Explorer/). Area of interest was cut from the map and imported to Arc GIS. Overlaying the previously drawn boundary map over the DEM, the required digital elevation model for the catchment was drawn.

Flow direction map was drawn taking DEM of the basin as input. It gives a clear idea about the direction of flow with in the catchment. Taking flow direction map as input, flow accumulation map was drawn using Arc GIS tools. It helps in identifying the most suitable sites for measurements of flow parameters, area contributing flow to that point and accumulation of flow at that point.

Land use/land cover map was collected (Source: swat.tamu.edu).Selected portion of the map was imported to Arc GIS and land use/land cover map of the basin was drawn.

4.2 Rainfall-Runoff modeling

4.2.1 SCS-CN Model

SCS-CN method, developed by soil conservation services (SCS) of USA in 1969.It is simple, can predict accurately, and a stable conceptual method for estimation of direct runoff depth based on rainfall depth. It depends on only one parameter, CN. Water balance equation of the rainfall in a known interval of time is the basis of this method, which can be expressed as

$$P = I_a + F + Q \tag{2}$$

Where P=total precipitation

I_a= initial abstraction

F=cumulative infiltration excluding I_a

Q=direct surface runoff

The first concept is that the ratio of actual amount of direct runoff (Q) to maximum amount of potential runoff ($=P-I_a$) is equal to the ratio of actual infiltration (F) to the potential maximum retention (or infiltration), S. The proportionality concept can be represented as

$$Q / (P-I_a) = F/S \tag{3}$$

The second concept is that the amount of initial abstraction ($Ia_)$ is some fraction of the potential maximum retention(S).Thus $Ia = \lambda S$ (4)

Combining equation (3) and (4)

$$Q = (P-\lambda S)^2/P + (1-\lambda) S \tag{5}$$

Where P= Daily Rainfall

Q=Daily Runoff from the catchment.

The parameter S represents the potential maximum retention. It depends up on the soil-vegetation-land use complex of the catchment and also up on the antecedent soil moisture content in the catchment just before the starting of the rainfall event. For convenience in practical application the soil conservation service of USA has expressed S (in mm) in terms of dimension less parameter *CN* (Curve number) as

$$CN = 25400/(S+254) \tag{6}$$

and it is in the range of 100 $\geq CN \geq 0$. A CN value of 100 represents a condition which has zero potential retention i.e. impervious catchment an CN=0 represents an infinitely abstracting catchment with $S=\infty$.The curve number CN depends upon

- Soil type
- Land use/cover
- Antecedent moisture condition

4.2.1.1 Soils

To determine the value of CN, the hydrological soil classification is adopted here. Soils are categorized in to four classes A, B, C, D based up on their infiltration and other characteristics. Effective depth of soil, average clay content, infiltration characteristics and permeability; these are some of the important soil characteristics that influence hydrological classification of soils.

1) Group A (Low runoff potential)

Soils, where the rate of infiltration is very high even when thoroughly wetted and consisting chiefly of deep, well to excessively drained sands or gravels can be categorised under group A. These types of soils have high rate of water transmission. Example - Deep sand, deep loess and aggregated silt.

2) Group B (Moderately low runoff potential)

Soils, where rate of infiltration is moderate when thoroughly wetted and consisting chiefly of moderately deep to deep, moderately well to well-drained soils with moderately fine to moderately coarse textures. These soils have moderate rate of water transmission. Example - Shallow loess, sandy loam, red loamy soil, red sandy loam and red sandy soil.

3) Group C (Moderately high runoff potential)

If, soils having low infiltration rates when thoroughly wetted and consisting chiefly of moderately deep to deep, moderately well to well drained soils with moderately fine to moderately coarse textures can be placed under group C. These soils have moderate rate of water transmission. Example-Clayey loam, shallow sandy loam, soil usually high in clay, mixed red and black soil.

4) Group D (High runoff potential)

Soils having very low infiltration rates when thoroughly wetted and consisting chiefly of clay soils with high swelling potential, soils with permanent high-water table, soils with clay pan, or clay layer at or near the surface, and shallow soils over nearly impervious material. Example - Heavy plastic clays, certain saline soils and deep black soils.

4.2.1.2 Antecedent moisture condition (AMC)

Antecedent moisture condition (AMC) refers to the initial moisture content present in the soil at the beginning of the rainfall-runoff event under consideration. It is well known that infiltration and initial abstraction are governed by AMC. For the purpose of practical application three levels of AMC are recognised by SCS as follows

AMC-I: Soils are dry but not to wilting point.

AMC-II: Average condition

AMC-III: Sufficient rainfall has occurred within the immediate last 5 days. Saturated soil condition prevails.

The limits of these three AMC classes, based on total rainfall magnitude in the previous 5 days are given in Table 3.1.This depends up on two seasons 1) growing season 2) Dormant season.

Table 3.1: AMC for determining the value of CN (Source: Engineering Hydrology)

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

The variation of CN under AMC-II, called $CN_{II.}$ The conversion of CN_{II} to other two AMC conditions can be made through the use of following equations.

For AMC-I: $CN_I = CN_{II} / (2.281\text{-}0.01281 CN_{II})$ (7)

For AMC-III: $CN_{III} = CN_{II} / (0.427+0.00573 CN_{II})$ (8)

Above two equations are applicable in the CN_{II}, range of 55 to 95 which covers most of the practical range. On the basis of extensive measurements in small size catchments SCS (1985) adopted $\lambda = 0.2$ as a standard value.

Considering the above mentioned parameters SCS-CN model was used in the ungauged basin.

4.2.2 HYSIM

HYSIM is a conceptual hydrologic simulation model which uses mathematical relationships to calculate the runoff from precipitation upon a catchment. The acronym HYSIM stands for Hydrologic simulation model. This model was originally developed by R.E.Manley in UK and has been widely used thereafter. Some of the important applications of this model include data validation, the extension of flow data records, generation of flow data for ungauged catchments, flood studies, simulation of ground water, and modeling of soil moisture. The rainfall-runoff model is only a part of the HYSIM system and other components deal with data preparation, parameter estimation and graphics. Figure 4.1 shows the linked parameters of HYSIM.

The model can use five types of input data as given below.

- Precipitation-It is the catchment areal average rainfall in mm per time increment.
- Potential evapotranspiration rate-Estimation of PET based either on empirical relationship or tank idea in units of millimetre per time increment.
- Potential snowmelt rate-This can be based on degree day method or a more complex one in mm per time increment.
- Discharge to/abstraction from river channel-The discharge from the channel represented in cumecs.
- Abstraction from ground water-It is given in cumecs.

In addition to the above listed five inputs, it can use measured flow record given in cumecs, as input. A measured flow record expressed in cumecs can also be compared with the simulated flow of the channel.

The data can be of monthly, daily or of any other shorter time increment. The time step for different types of data, both hydrologic and hydraulic calculations can all be independent of one another. The only issue to this is that the time increments for any data which is in time step of less than a day must be in an exact integer ratio to another.

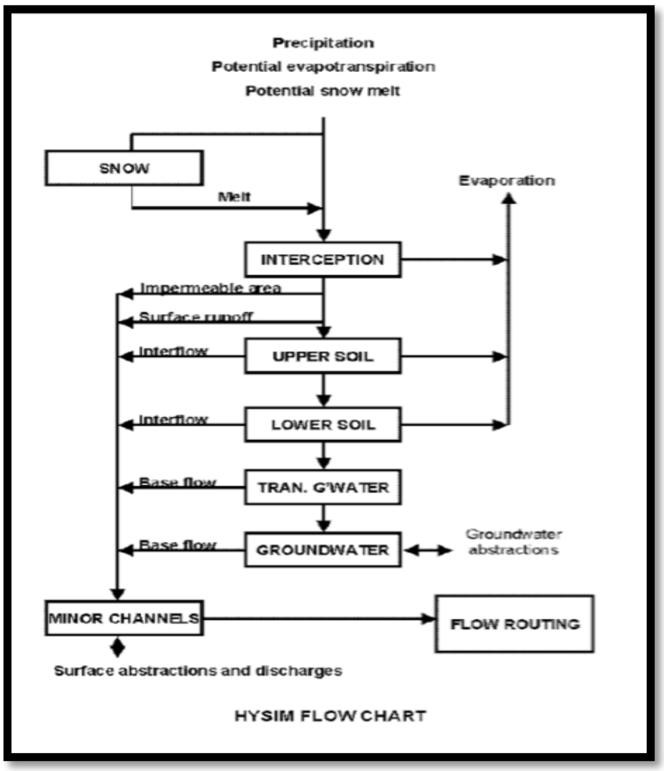

Figure 4.1: Structure of the HYSIM model

4.2.2.1 The Rainfall-runoff model

Hydrological simulation model (HYSIM) uses mathematical relationships to estimate runoff from rainfall over a catchment. Two types of parameters are there in the model, which govern the mathematical relationships; variable parameters which change with time to define the state of the catchment, and the time invariant parameters which define the nature of the catchment. The HYSIM model divides the catchment in to as many sub-catchments as required to have the reasonably homogeneous sub-catchments with respect to different features like soil types, land use or land cover and meteorology in order to reduce the inhomogeneity in the catchment. For the purpose of hydraulic routing river channels having reasonably uniform hydraulic characteristics are sub divided in to many reaches by the model. If more than one sub catchment is present, the runoff from upstream catchments is routed through the catchment, which is being modelled together with flows from local runoff. In this case, either the recorded flows from upstream catchments may be used or it may be simulated separately for each of the upstream catchments.

There are 2 main parts of this model, 1) Hydrology 2) Hydraulics. The hydrology part is the heart of the model. It deals with different hydrological processes occur in a catchment are responsible for generation of runoff in minor channels in a catchment. The hydraulics part deals with the routing of runoff through river channels in the catchment. HYSIM has the conceptual modularity that the hydrologic processes can be simulated without the hydraulic routing part and vice versa.

1) Hydrology

The model represents seven natural storages; these are snow, interception, upper soil horizon, Lower soil horizon, transitional ground water, ground water and minor channels.

I) Snow storage

Any precipitation in form of snow is held in snow storage, and then it is released in to interception storage. The potential melt rate is equal to the rate of release of snow.

II) Interception storage

When moisture is stored on the leaves of trees, grasses etc., it is called as interception storage. Moisture is added to this storage from rainfall or snowmelt. Evaporation is the first phenomenon which occurs on this storage. Experiments have shown, it can take place at more than the potential rate particularly on the leaves of trees. It is considered in this model. If moisture content exceeds the storage limit it is passed on to the next stage. A proportion of the moisture is diverted to minor channel storages after it leaves the interception storage, to allow for the impermeable proportion of the catchment. Subsequent transfer of the moisture is to the upper soil horizon storage.

III) Upper soil horizon

The moisture held in the top soil is represented through upper soil horizon storage. The depth of horizon multiplied by its porosity gives the capacity of this storage. Based on the potential infiltration rate a limit is applied on the rate at which moisture can enter this horizon.

IV) Lower soil horizon

Moisture below the upper soil horizon is represented through this storage. It is also in the zone of rooting. Any unsatisfied PET is subtracted from the storage at the potential rate, with the same limitation as for the upper horizon (capillary suction less than 15 atmospheres).

V) Transitional groundwater

This storage is an infinite linear reservoir and represents the first stage of ground water storage. As it is a linear reservoir the relationship between storage and time can be calculated explicitly.

VI) Ground water

If it is assumed to have a constant coefficient of discharge this is also an infinite linear reservoir. Ground water abstractions are made from this reservoir. The rate of runoff can be calculated explicitly for this storage also.

VII) Minor channel

Routing of flows in minor streams has been done by this component. Triangular shaped instantaneous unit hydrograph has been used with a time base equal to 2.5 times the time to peak.

2) Hydraulics

The runoff from minor channels is routed through the major river channels. The river channels are divided in to a number of reaches with reasonably uniform characteristics by HYSIM and the runoff is routed through each of these reaches of the river channel.

Simplified form of the Saint Venant equations known as the Kinematic wave method (Lighthill & Witham, 1955) is used for hydraulic routing in the river channels. The velocity of a Kinematic wave, V_w, is given by,

$$V_w = Q/A \tag{9}$$

Where, Q is the change in flow and A is the change in area.

The equations for Manning's formula when applied to a triangular and a broad rectangular channel can be given as,

$Q \alpha A^{4/3}$ for triangular channel

$Q \alpha A^{5/3}$ for rectangular channel

Since most channels fall in between these two, it has been assumed that

$$Q = CA^{1.5} \tag{10}$$

For flow in bank, area as a function of discharge is calculated by re-arranging the above equation. And for flow out of bank exponential relationships are developed at the start of the program. It is expressed as,

$$A = a\, Q^b \tag{11}$$

Where, a and b are constants. Geometry and roughness of the flood plain decides the values of a and b using Manning's equation. When the flood plain is filling up one such equation is used and another when it is full.

4.2.2.2 Optimization

There are 3 optimization options: i) No optimization ii) Single parameter optimization iii) Multiple parameter optimization. These options are used to get the optimized values of different hydrologic and hydraulic parameters.

For the present study the rainfall and potential evapotranspiration data were used for simulation of flow. Records of observed flows were used to compare with the simulated flow as it was required for calibration and validation of the model. In addition to it, the information on hydrologic, topographic, and soil characteristics of the catchment area and the hydraulic characteristics of the nala was also required for estimation of model parameters. In the present study, the following data and information as available with various field agencies were collected and used.

Along with the rainfall and flow, potential evapotranspiration data was used for simulation. Since the actual daily PET data were not available, the mean monthly PET values were used for the study area.

4.2.2.3 Method

The modeling of daily flows was carried out for a catchment area of 141.32sq.km. The whole drainage area up to the measurement site has been considered as a single unit while applying the model. According to the available record of the observed flows, the model was calibrated using the continues data of the period from June 2009 to December 2010.The model validation was carried out for two years of data sets i) January 2011 to December 2011 and ii) January 2012 to September 2012.The catchment data files for mean areal rainfall, potential evapotranspiration, and observed flows were prepared in the required format for calibration and validation periods separately.

4.2.2.3.1 Calibration

The aim of the model calibration is to obtain a unique and conceptually realistic parameter set which closely represents the physical system and gives the best possible fit between the simulated and observed hydrographs (Sorooshian, 1988). 21 hydrologic parameters are there in HYSIM which define the nature of the catchment and are used by the model to compute the transfer of moisture. These parameters don’t change with time. Assigning suitable values to these parameters is crucial for the accuracy of the simulation. Similarly, ten parameters which control the hydraulic characteristics of the channel were used by the model for routing through the nala. These parameters along with their possible values are discussed below.

Interception storage-It varies from 1mm for grass land and urban areas up to 5mm for wood land.

Proportion of impermeable area – It ranges from0.02 for rural areas and up to 0.20 or even more for urban areas.

Time to peak in minor channel- $T_p = 2.8\left(\frac{L}{S}\right)^{0.47}$ (12)

Where L is stream length in Km, S is stream slope in m/km, and T_p is time to peak in hours. The value used for this parameter should be the average value obtained from 4 or 5 small streams.

Total available soil moisture storage - Total soil moisture storage=Rooting depth × Porosity × (1-residual saturation).

The residual saturation is the moisture content below which a soil cannot be dewatered by capillary suction and is approximately equal to that of the wilting point. Its value ranges from 0.1 for sand to 0.25 for clay soil.

Saturated permeability at the top of the upper horizon - Generally a value of 1000mm/hr. can be adopted for a wide range of soils. Lower value can also be used for clayey soils.

Saturated permeability at the base of the lower horizon - This parameter controls the rate at which the moisture leaves the soil layers. In a catchment with no ground water it should have a value of zero. In catchments where ground water is present its value can vary from 1mm/hr. for heavy soils to 100mm/hr. or more for sandy or gravelly soils. This parameter has to be adjusted during calibration.

Saturated permeability at the horizon boundary - This parameter controls the rate at which moisture moves between the two horizons. Its value can vary from 5mm/hr. in clay up to 500mm/hr. or more in sandy or gravelly soils. This parameter also has to be adjusted during calibration.

Pore size distribution index- This parameter is one of the most important parameters in the model and controls the way in which the soils respond, appearing as an exponent in both the moisture/capillary suction and moisture/effective permeability relationships. Its value ranges from 0.09 for clay soils up to 0.25 for sandy soils.

Porosity - Its value ranges from 0.40 for sandy soils to 0.50 for silty clay type soils.

Bubbling pressure - Its value ranges from 80mm for loamy sand up to 630mm for clay loam.

Discharge coefficient for transitional ground water storage - This parameter represents recession from lower ground water storage and its value can be assessed by studying periods in a dry summer where little or no rain has fallen. Its value is given by

$$DCAG2=log_e (f_1/f_2)/T \tag{13}$$

Where, DCAG2 is equal to the discharge coefficient, f_2 is the flow at the end of the time period chosen, f_1 is the flow at the start of the time period and T is the time period being studied in hours.

Interflow runoff from upper soil horizon at saturation - This parameter is given in mm/hr. controls the direct or lateral runoff from the upper soil horizon. It has to be adjusted during calibration process. However, as an initial climate it can be set equal to the permeability at the horizon boundary.

Interflow runoff from lower soil horizon at saturations - This parameter controls the direct runoff from the lower horizon. Initially this too can be set equal to the permeability at the horizon boundary which has to be adjusted later during calibration.

Precipitation correction factor - This parameter is adjusted to allow for the fact that the rain gauges used may over or under estimate the true catchment rainfall. As a standard rain gauge collects less than a ground level gauge this parameter is normally given a value of 1.04.

Potential evapotranspiration correction factor- This parameter is adjusted during the initial fitting period to obtain water balance.

Ratio of contributing ground water catchment area to surface catchment area

Proportion of surface catchment without ground water

The following Hydraulic parameters are required for channel section

Base width, top width, flood plain width, channel depth, flood plain depth, maximum flood depth, Manning's n for channel, Manning's n for flood plain, Channel gradient and length of channel.

4.2.3 Artificial Neural Network model

An ANN is the densely interconnected parallel structure and is a collection of mathematical or analytical model that can emulate the observed or given properties of biological neuron systems and draws the analogies of adaptive biological learning system by using the learning rules and hybrid algorithm. Neurons of ANN are in a group forming a layer, it operates in logical parallelism. Here, information is transmitted from one layer of neurons to another in serial operations (Hecht-Nielson, 1990). A network can vary from single to many layers, but the basic structure of a network usually consists of three layers, where data are provided to the network of ANN, the data are processed in hidden layers and the results of input layer are produced in output layer.

ANNs were usually assumed to be powerful tools for functional relationship establishment or nonlinear mapping in various applications. Cannon and Whitfield, found ANNs to be superior to linear regression procedures. ANN is often good at solving complex problems for conventional technologies. There are several ways to use ANN, in the present study, used as back propagation neural network with several numbers of neurons and hidden layers. A dynamic model for Rainfall-Runoff modeling is identified by following steps:

- Selection of Input and Target data for calibration and validation.
- Model structure selection and estimation of its parameters.
- Validation of selected model.

4.2.3.1 Back Propagation Network

Back propagation, an abbreviation for "backward propagation of errors", is a very common method of training networks. ANN is the most widely used pattern recognition tool for both supervised and unsupervised algorithm, The three layer feed forward network is the most commonly used ANN by using back propagation algorithm (Rumelhart and MeCleland,1986).The back propagation neural network with three layer is adopted in present study. The typical back propagation architecture is given in Figure 4.2.

The back propagation algorithm by ANN involves forward propagating step and back propagating step. The forward and backward steps are executed for each step during training of BPN.As the input data is given to BPN, the forward step starts with formation of input layer of the network, goes through hidden layers to give the output layer. In each layer of the BPN, every processing unit sums its inputs and the transfer function by this input help to compute output. As the back propagation network started, it goes with the comparison of networks output pattern to target vector. The back propagation calculates the error values of hidden units in hidden layer for their incoming weights. Again it starts with the output layer and moves backward through hidden layer. During this back propagation it corrects its weights to decrease the observed error.

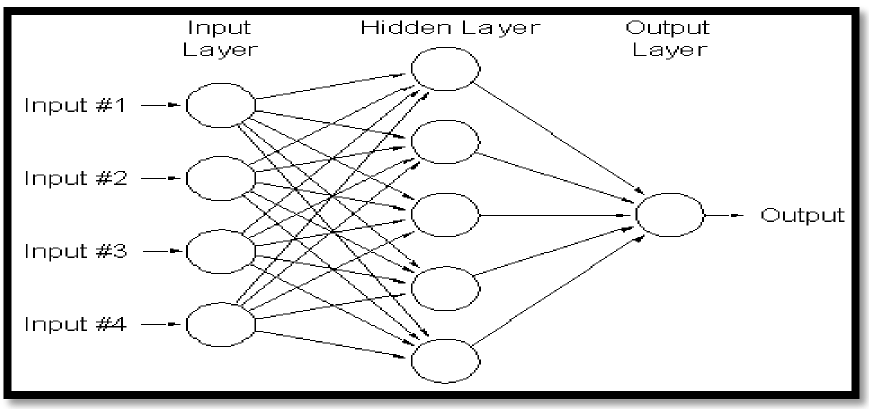

Figure 4.2: A typical back propagation Network Structure

The back propagation algorithm for ANN is described in three equations. The weight connections of neurons in each layer can be changed in each learning step (k) with the following equation.

$$\Delta W_{ij(k)}^{s} = \eta(t)\delta_{pj}^{s} x_{j}^{(s-1)} + m\Delta W_{ij(k-1)}^{s} \qquad (14)$$

For output layer, the following equation is used;

$$\delta_{pj}^{o} = (d_{j} - o_{j}) f(I_{j}^{s}) \qquad (15)$$

And the following one is used for the remaining nodes;

$$\delta_{pj}^{s} = f_{j}^{1}(I_{j}^{s}) \sum_{k} \delta_{pk}^{(s+1)} W_{jk}^{(k+1)} \qquad (16)$$

Where,

$X_{j}^{(s)}$ = Actual output of node *j* in layer *s*

$W_{jk}^{(s)}$ =Weight of the connection between node j and node k at layer (s-1) and s respectively

$\delta_{pj}^{(s0}$ =Measure of the actual error for the node j

I_j^s =Weighted sum of the inputs of node j in layer s

$\eta(t)$ =Time dependent learning rate

$f(t)$ = Transfer function.

m = The Momentum factor between 0 and 1

d_j & o_j = desired and actual activity of node j (for output nodes only).

The Artificial Neural Network is generally used for modeling non-linear input-output relationship such as time series prediction of rainfall to runoff. The main objective of this ANN study is to predict the discharge from observed rainfall and discharge data collected from 2009 to 2012.

4.2.3.2 Radial Basis Function Network

In the mathematical modeling field, a radial basis function network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks are used in many ways such as, time series prediction, function approximation, system control and classification.

The RBF has its state Gaussian function as the non-linearity for hidden layer and it only responds to small region of the input space where the Gaussian function is centred. The successful implementation of RBF is done with right Gaussian function and supervised learning.

In hybrid learning procedure, one layer is in unsupervised way followed by one or more layers trained by back propagation. The hidden units network architecture by the Moody and Darken in 1989, the network are neither linear, nor sigmoid, they have normalized Gaussian activation function of the form given below:

$$g_j(\varepsilon) = \frac{\exp[-(\varepsilon - \mu_j)^2 / 2\sigma_j^{\ 2}]}{\sum_k \exp[-(\varepsilon - \mu_k)^2 / 2\sigma_k^{\ 2}]} \qquad (17)$$

Where $g_j(\epsilon)$ is the input vector. μ_j is the receptive field centre which decide the unsupervised part of learning and σ_{ij} are the weights of unsupervised part of learning. The Gaussian function is an example of radial basis functions. RBF are consists of two layers; a hidden RBF function and an output linear neuron layer. Therefore the Gaussian function is a best example of Radial Basis functions. The typical network architecture of Radial Basis function is given below in Figure 4.3.

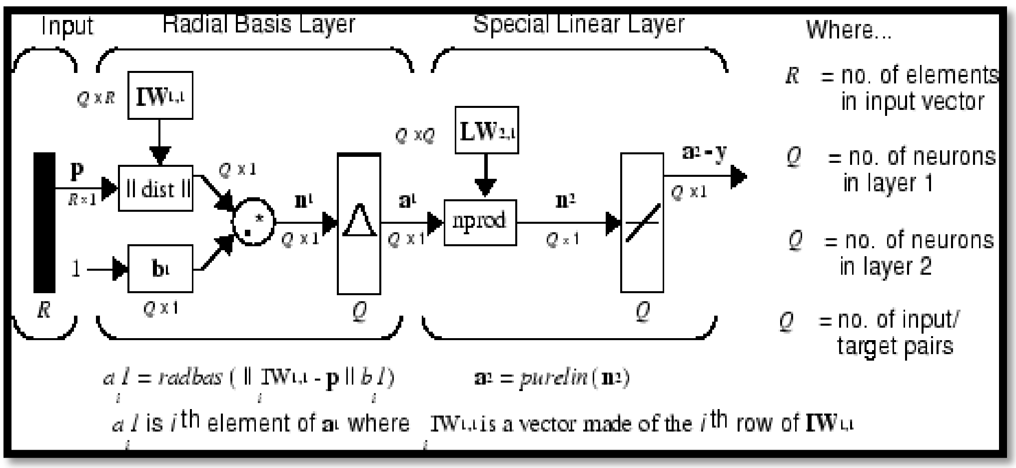

Fig4.3: A typical Network for Radial basis function in ANN

The Radial Basis function can find the input to output maps using local approximators, The supervised segment is always a combination of the approximators. Since, the linear combinations have weights; the RBF network needs training samples and it trains them very fast.

4. 3 Time series analysis of recorded data

A time series data contains periodic components that tend to repeat over a period of time intervals which generally depends upon the seasonal changes. This behaviour of time series is known as periodicity. According to periodicity in time series, statistical characteristics also change periodically in different seasons with in the year. In order to develop a model the periodic component must be removed from the time series. The periodic component in time series must be removed by the following formulation;

$$z_{v,\tau} = \frac{PET_{v\tau} - \mu_\tau}{\sigma_\tau} \tag{18}$$

Where $z_{v\tau}$ is the standardized flow; v is the year, τ is the time interval with in the year; μ_τ and σ_τ are respectively the population periodic mean and standard deviation of the flow time series. The standard deviation method uses the mean and standard deviation of historical series. The sample periodic means of the observed time series of data and standard deviation of the data can be estimated for each day of the season and are substituted to obtain the standardized flow series of data. (Salas *et al*., 1988) observed that the estimation of mean and standard deviation of the time series are subjected to large errors. The use of too many estimated time series parameters also violates the principle of statistical parsimony in the numbers of the estimated parameters. Therefore, before doing the Fourier, Auto correlation and Partial autocorrelation analysis, the rainfall and observed discharge was checked using STATISTICA 9. In this time series, the number of estimated parameters, standard deviation model parameters was 1218 in numbers. To reduce the number of estimated parameters of the time series, Fourier series can be used for the estimation of periodic parameters like discharge in this case. Estimations of periodic parameters were obtained by using Fourier series as described below:

Let u_τ is the periodic statistical characteristics of the flow series, such as daily mean or standard deviation. It can be also a sample estimate of the unknown population.

Population Periodic parameter denoted by v_τ .It can be obtained by:

$$v_\tau = \bar{u} + \sum_{j=1}^{h} \left[A_j Cos(2\Pi j\tau/\omega) + B_j Sin(2\Pi j\tau/\omega)\right] \quad \tau=1, 2,3\ldots\ldots\ldots\ldots\ldots\omega \tag{19}$$

Where $\bar{u}$ is the seasonal mean of u_τ , A_j, B_j are the Fourier series coefficients, *j* is the harmonic, and h is the total number of harmonics, which is equal to $\omega/2$ or $[(\omega-1)/2]$ respectively, it depends upon ω, odd or even.

The mean $\bar{u}$ and Fourier coefficients A_j and B_j can be calculated as followed;

$$\bar{u} = \frac{1}{\omega}\sum_{\tau=1}^{\omega} u_\tau \tag{20}$$

$$A_j = \frac{2}{\omega}\sum_{\tau=1}^{\omega} u_\tau Cos(2\Pi j\tau/\omega) \quad \text{and} \tag{21}$$

$$B_j = \frac{2}{\omega}\sum_{\tau=1}^{\omega} u_\tau Sin(2\Pi j\tau/\omega) \qquad (22)$$

When v_τ from the above equation is determined considering all the harmonics j=1, 2 …h. Here, u_τ is exactly same as v_τ for Ʈ=1, 2….ω. To reduce the estimation error of the estimated parameters from the observed parameters, the smaller number of harmonics h*< h is used.

Considering, all these theories and descriptions about Fourier or spectrum analysis, the analysis is done in STATISTICA 9 by taking the input time series data of rainfall and observed discharge data from 2009 to 2012. The figure 4.4 shows the Imaginary and predicted values of observed data by Fourier analysis of observed time series data from 2009 to 2012. The frequency of discharge depends upon the rainfall upon a catchment; a Fourier analysis for frequency of rainfall is also conducted with its sine and cosine coefficients which are given in Figure 4.5 and 4.6.

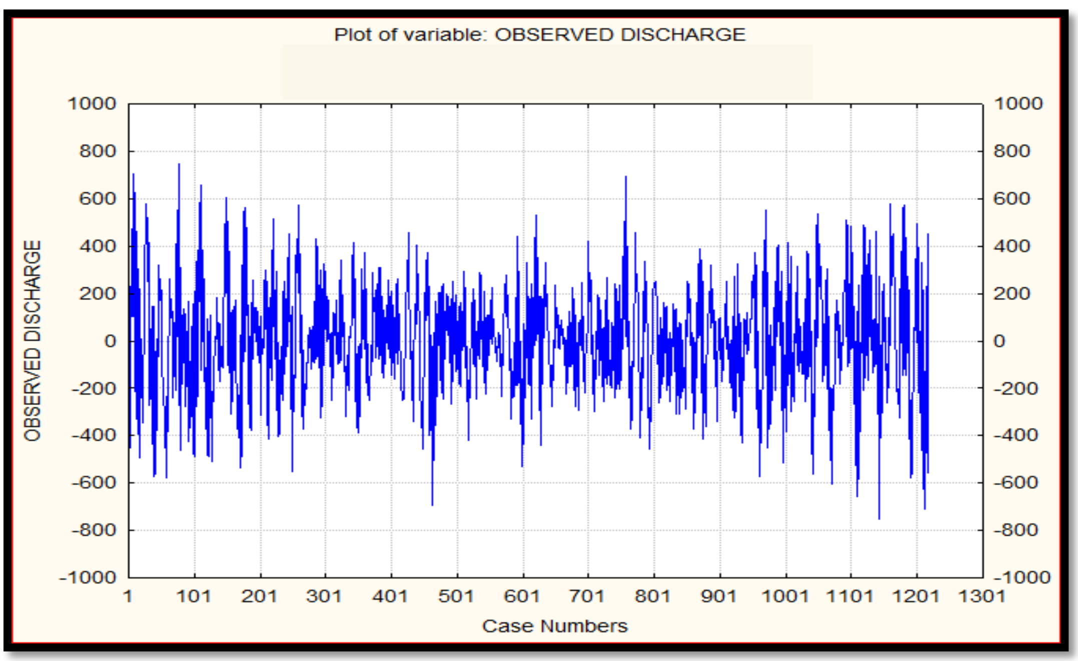

Figure 4.4: Fourier analysis for imaginary and predicted discharge by observed discharge

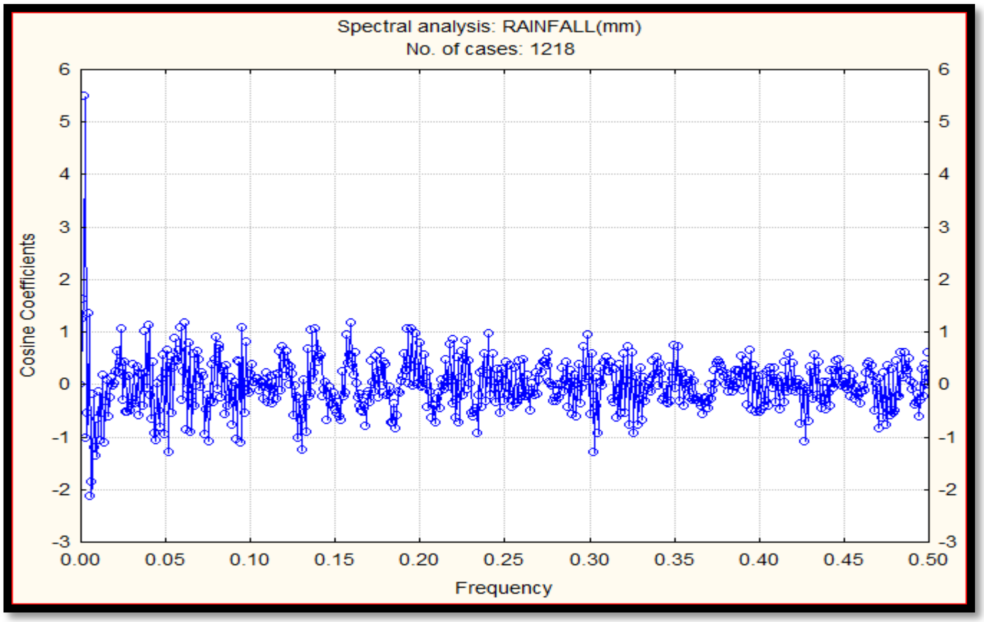

Figure 4.5: Fourier analysis between cosine coefficients and frequency of rainfall

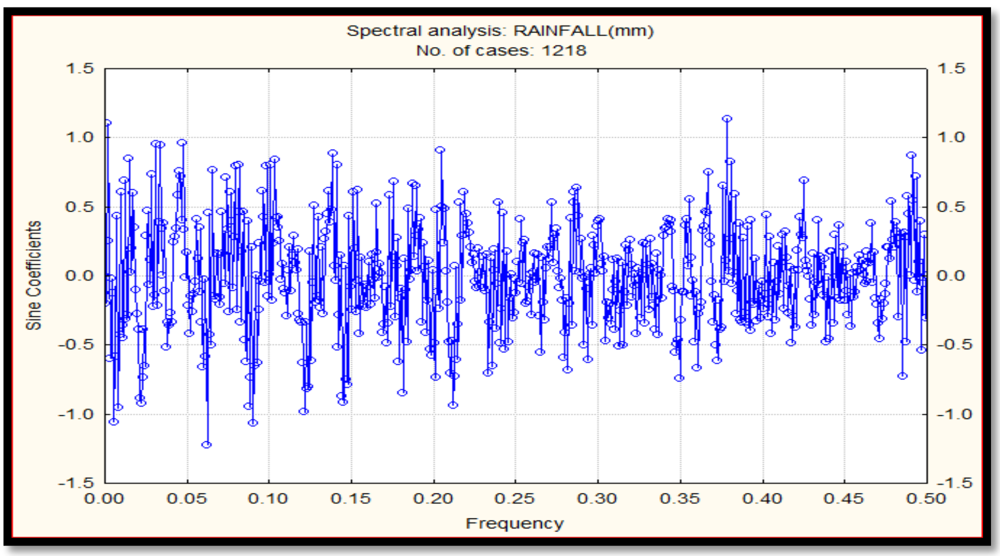

Figure 4.6: Fourier analysis between Sine coefficients and frequency of rainfall

Spectrum analysis is concerned with the exploration of cyclical patterns of data. The aim of the analysis is to decompose a complex time series with cyclical components into a few underlying sinusoidal (sine and cosine) functions of particular wavelengths. The term "spectrum" provides an appropriate metaphor for the nature of this analysis of the given data. In essence, performing spectrum analysis on a time series is like putting the series through a prism in order to identify the wave lengths and importance of underlying cyclical components. After a successful analysis one might uncover just a few recurring cycles of different lengths within the time series of interest, which at first looked like random noise. From the Fourier or spectrum analysis of time series data, it is concluded that there is a variation in the range of the data but are in particular range, which makes easy to go further for ANN modeling.

4.3.1 Auto Correlation and Partial Correlation Analysis

The correlation of a time series data with its own past and future values can be referred as autocorrelation. It is also sometimes called as "lagged correlation" or "serial correlation", which means the correlation between members of a series of numbers arranged in time sequence. Positive autocorrelation might be taken as a specific form of "persistence", which refers a tendency for a system to remain in the same state from one observation to the next. Autocorrelation complicates the application of statistical tests by reducing the number of independent observations. It can also complicate the identification of significant covariance or correlation between time series (e.g., precipitation with a tree-ring series). Autocorrelation can be used for predictions: an auto correlated time series is predictable, probabilistic, because future values depend on current and past values. Three tools used for estimating the autocorrelation of a time series are (1) the time series plot, (2) the lagged scatter plot, and (3) the autocorrelation function.

Partial correlation is a method used to describe the relationship between two variables whilst not considering the effects of another variable, or several other variables, on this relationship. Partial correlation is best thought of in terms of multiple regressions. Statistical analysis shows the partial correlation coefficient r with its main results from multiple linear regressions.

Auto correlation and partial correlation functions shows the correlation structure and are helpful in determining the stochastic process. The theory of correlations based on assumptions of second order stationary. According to the assumptions, z_t and $z_{(t+h)}$ are a pair for flow measurements at t and t+h respectively in time separated by a vector h(lag).Here, z_t is the random variable. The variable is said to be of second order stationary when; The expected value of $E(Z_t)$ is within the time domain.

$$E(Z_t)=m \tag{23}$$

The covariance for each pair of random variable (Z_t ,Z_{t+h}) should be in same time and are depend upon h,

$$Cov(h) = E[Z_t , Z_{t+h}] - m^2 \tag{24}$$

Stationary of covariance is same as stationary of variance.

The Auto correlation is a process of self-comparisons of the linear correlation between an equally spaced series and the same series at a specified lag.

Let Z_0, Z_1, Z_2……Z_{N-1} be the stationary stochastic process. Then, the population autocorrelation can be the quotient of the population auto covariance, cov (Z_t, Z_{t+h}) and variance of (Z_t);

$$\rho(h) = \frac{\text{cov}(Z_t , Z_{t+h})}{\text{var}(Z_t)} \tag{25}$$

Where Z_t is the variable at t^{th} time and h is the time lag. The series is the realization of a stochastic process produced by probabilistic mechanism.

The population autocorrelation function can be estimated by using a simple auto correlation function given below:

$$r(h) = \frac{\sum_{t=1}^{N=h} (Z_{t+h} - \overline{Z})(Z_t - \overline{Z})}{\sum_{t=1}^{N} (Z_t - \overline{z})^2} \qquad -1 \leq r(h) \leq 1 \tag{26}$$

Where, $\overline{Z}$ is the sample mean. The 95% of confidence band for sample auto correlation functions is given by (Anderson and Jenkins, 1970):

$$r(h) = 0 \pm \frac{1.96}{\sqrt{n}} \geq \{1 + 2\sum_{j=1}^{q} r_j^2\}^{1/2} \qquad h>q \tag{27}$$

Where q is the order of the process and n is the number of observations of the data given in the series of data. Auto correlation function is an independent and also is a diagnostic of the moving average process. Therefore, the estimation of the value of variable at a given time depends upon the random series using weighted sum of the values at previous time steps.

The Partial autocorrelation function is used for diagnosis of autoregressive process and is also a way of representing time dependence structure of a series. The autocorrelation measures the correlation variable separated by assigned lags and is extended to the independent intermediate correlation. Mathematically, it can be explained as follow:

$$\phi_k = corr(Z_t, Z_{t-k} / Z_{t-1}, ..., Z_{t-k+1}) \tag{28}$$

Here, φ_k is the correlation between Z_t and Z_{t-k} excluding the effects of $Z_{t-1}, Z_{t-2}, ...Z_{t-k+1}$ where k is the distance or time lag measured between the measured quantities.

For an autoregressive process of order k, the partial autocorrelation, $\phi_k(k)$,is a linear combination of ρ_j and ρ_{j-k} i.e. autocorrelation lag at j and j-k respectively for j ≥ k. $\phi_k(k)$ also known a partial autocorrelation function at kth autoregressive coefficient for k=1,2,……..

Lag j autocorrelation for an autoregressive process [AR(k)] can be explained as follows:

$$\rho_j = \phi_1(k)\rho_{j-1} + \phi_2(k)\rho_{j-2} + ... + \phi_k(k)\rho_{j-k} \quad \text{j=1,2,….k} \tag{29}$$

Where $\phi_j(k)$ is the jth autoregressive coefficient of the AR (k) model. The above equation is a set of linear equations, which can also be written in terms of partial auto correlation functions $\phi_j(k)$ as follows:

$$\begin{bmatrix} 1 & r1 \dots\dots\dots. & rk-1 \\ r1 & 1 \dots\dots\dots\dots & rk-2 \\ rk-1 & rk-2 \dots.. & 1 \end{bmatrix} \begin{bmatrix} ø1(k) \\ ø2(k) \\ øk(k) \end{bmatrix} = \begin{bmatrix} r1 \\ r2 \\ rk \end{bmatrix} \tag{30}$$

Bartlett in 1996 gave the 95% confidence band for the sample partial autocorrelation function as given below:

$$\phi_k(k) = 0 \pm \frac{1.96}{\sqrt{n}} \tag{31}$$

Where n is the number of observations in a given series.

4.3.2 Goodness of Fit statistics and Performance Evaluation

In every model, the process from validation to testing was done by using a residual statistics and is known as the root mean square (RMSE), it is first used in Akaike information criteria by (Akaike, 1974) and also used in Bayesian information criteria by (Rissanen, 1978). The Root Mean Square Error (RMSE) is also called the root mean square deviation, RMSD. It is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. The RMSE of the time series data is calculated by the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{32}$$

X_{obs} is observed values and X_{model} is modeled values at time/place *i*.

Again the other index used to evaluate the goodness of fit of the model is the efficiency of the model and is defined by the following formula by Sutcliffe in 1970:

$$Efficiency = 1.0 - \frac{\sum(Q_o - \overline{Q_o}) - \sum(Q_C - Q_o)^2}{\sum(Q_o - \overline{Q_o})^2} \tag{33}$$

Where Q_o , Q_c are the observed and computed values of values of flow and $\overline{Q_o}$ is the mean flow over the period.

The RMSE values can be used to distinguish model performance in a calibration period with that of a validation period as well as to compare the individual model performance to that of other predictive models. The ANN model efficiency can be used to evaluate the capability of the model in predicting the next day river flow in time series, which is assumed to be the prediction of time series.

CHAPTER 05

RESULTS & DISCUSSION

This chapter describes the results obtained from rainfall-runoff modeling using SCS-CN model, HYSIM model and ANN model. Before proceeding for ANN model time series analysis of rainfall and observed discharge was done and the results were shown in this chapter.

5.1 SCS-CN Model

The data required to model through SCS-CN model were downloaded from various sources and maps were delineated using Arc GIS.

SRTM 90mm digital elevation model (DEM) of the Samij basin was drawn. Flow direction map, flow accumulation map and Land use/land cover map of the basin was also drawn by Arc GIS. Figure 5.1 shows the DEM of the basin. It shows the large difference in elevation in the topography of the basin. So the slope in the basin is high having very hilly topography. Figure 5.2 and 5.3 shows the flow direction and flow accumulation map of the basin. It helps in marking the best possible places where measurements, sampling can be done in the stream. Land use/land cover map of the basin (Figure 5.4) shows that more than 80% area of the catchment is covered with dense forest. Barren lands and cultivated lands are present in patches. According to the land use pattern, the whole catchment has been taken as a single unit for modeling. Red sandy Soil present in the catchment (Figure 3.6). So the soil class was taken as Group B, according to Hydrological soil classification. The curve number has been estimated as 40 for AMC-II condition (Appendix-I). Curve number for other two antecedent moisture conditions I AND III were calculated using equations 6 and 7 and was found out be 22.7 and 62.5 respectively. Value of λ has been considered as 0.2.

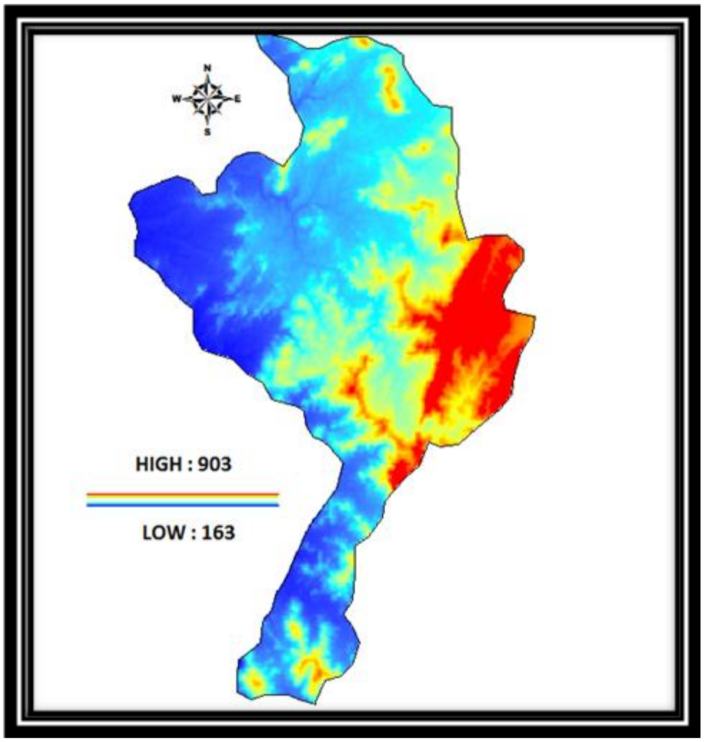

Figure 5.1: Digital elevation Model of the Samij basin

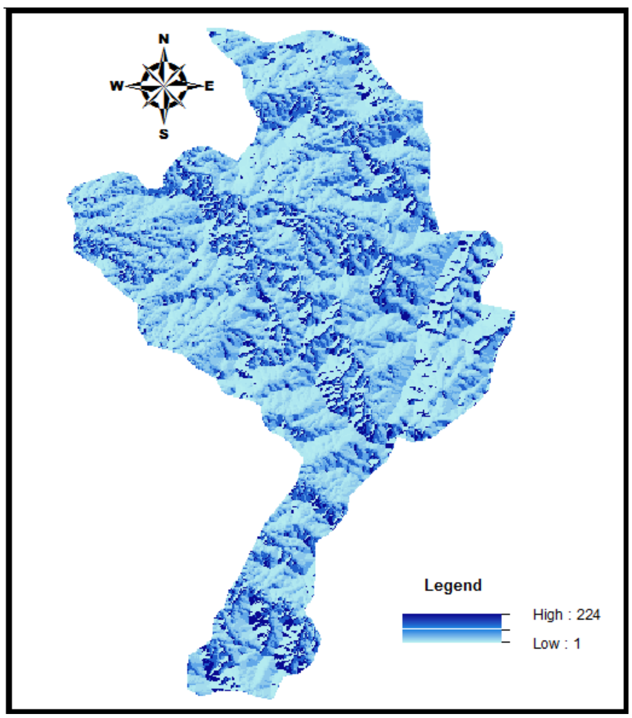

Figure 5.2: Flow direction map of the basin

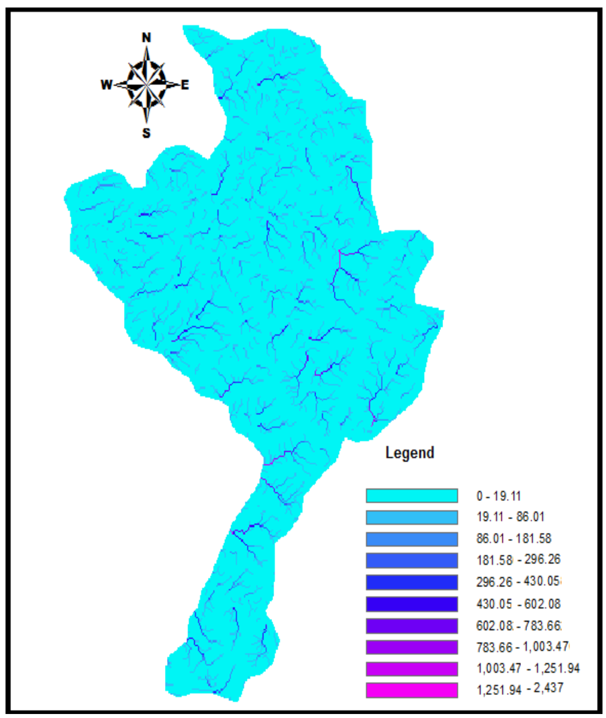

Figure 5.3: Flow accumulation map of basin

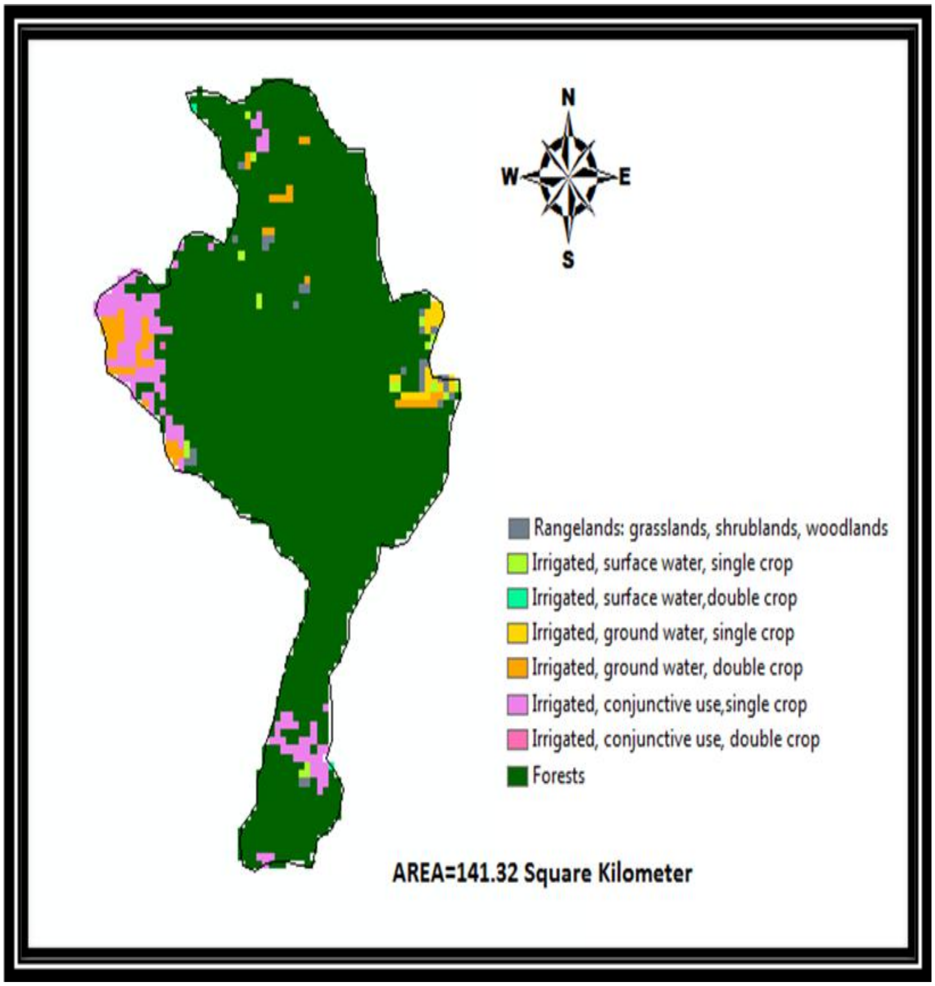

Figure 5.4: Land use/land cover of the Samij basin

Taking all these values of different parameters, SCS-CN model was applied for the Samij basin and daily discharge were calculated. A comparison has been drawn between the computed discharge and observed discharge.

Figure 5.5 shows the comparison between the observed and computed discharges for the year 2009.The correlation coefficient (r^2) value obtained here is 0.80, which is satisfactory. The r^2 value is 0.77 for the year 2010, shown in Figure 5.6.The result obtained for the year 2011 was the best among all 4 years.r^2 value is 0.90 for 2011(Figure 5.7).Figure 5.8 shows a comparison between the observed and computed discharge for the year 2012.0.87 is the correlation coefficient value for year 2012.

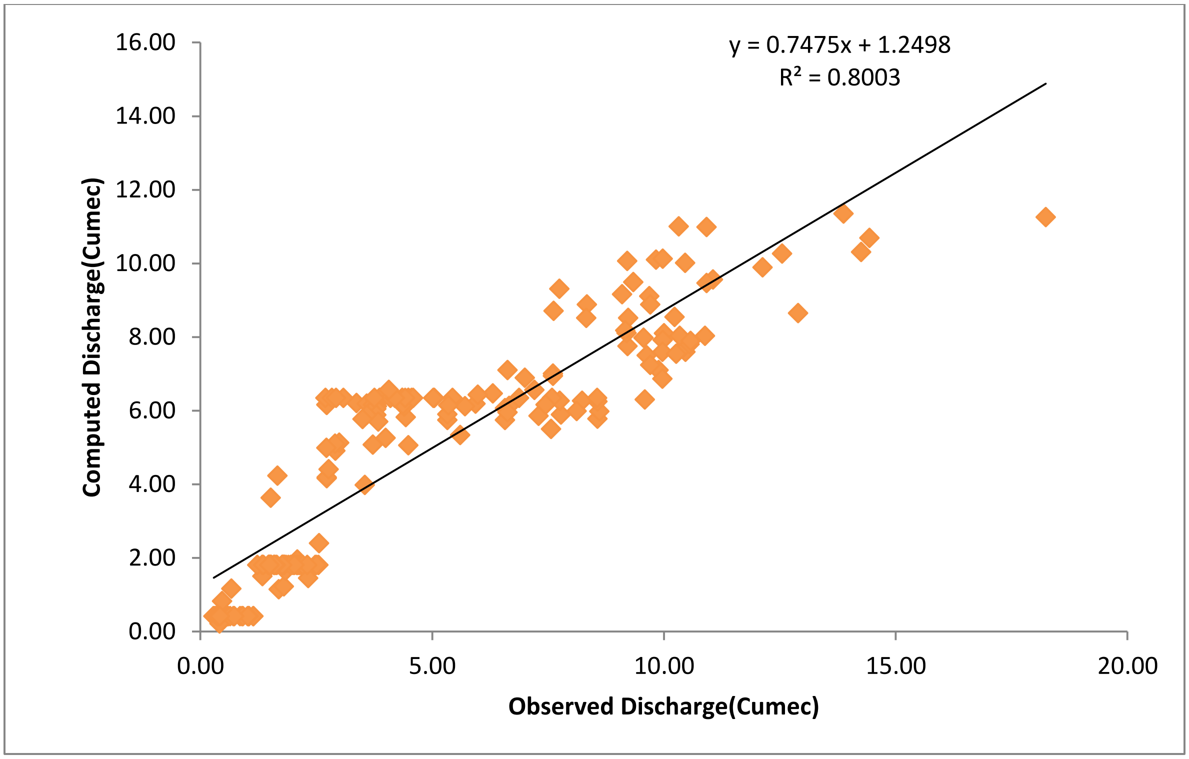

Figure5.5: Comparison between computed and observed discharge for year 2009

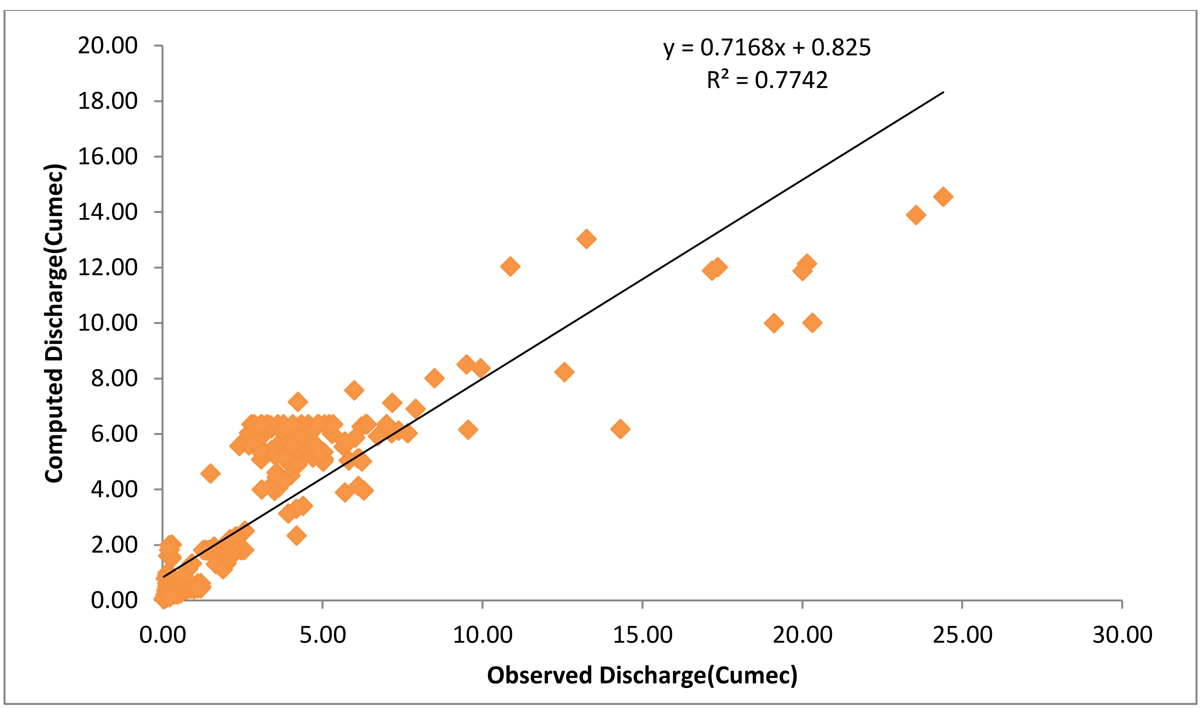

Figure 5.6: Comparison between computed and observed discharge for year 2010

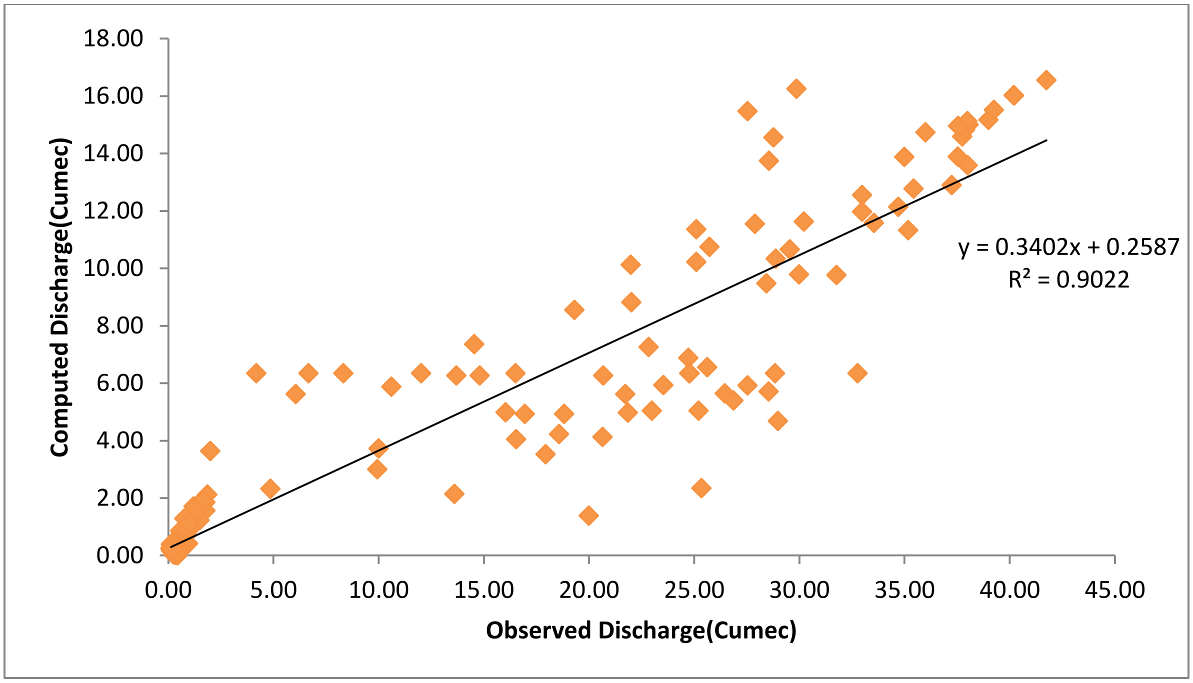

Figure 5.7: Comparison between computed and observed discharge for year 2011

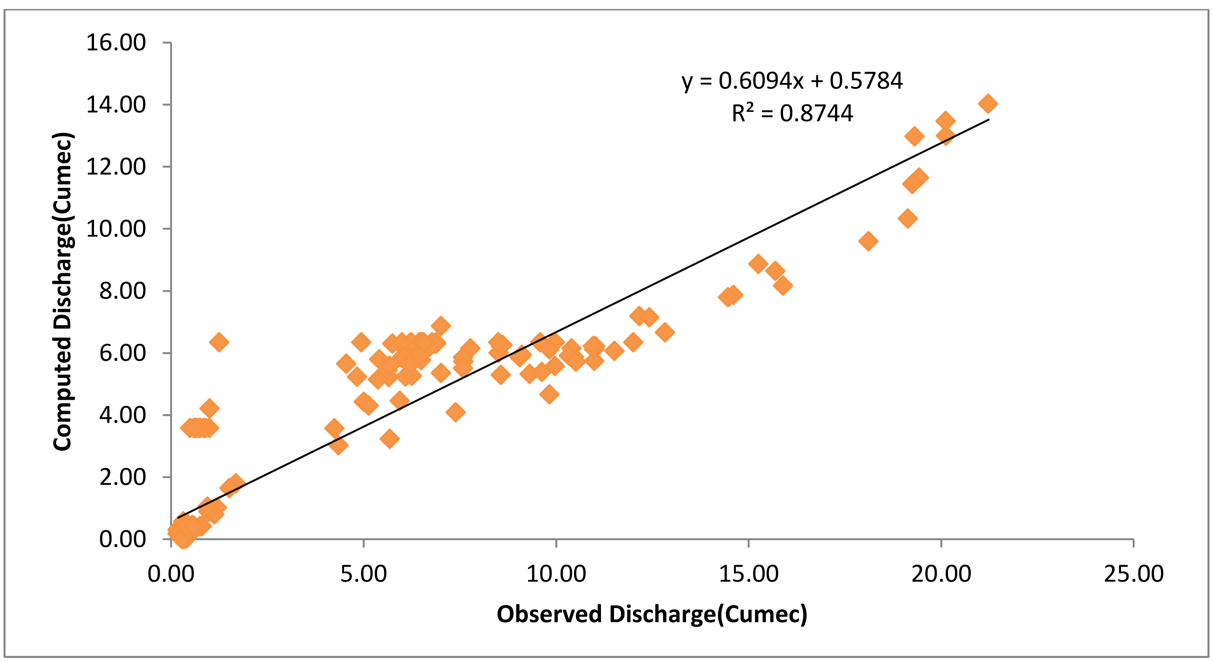

Figure 5.8: Comparison between computed and observed discharge for year 2012

From the above analysis, it is clear that the r^2 values for each case are good. So SCS-CN model used for the study area is showing good result.

5.2 HYSIM

HYSIM is a hydrologic simulation model which uses mathematical relationships to calculate the runoff from precipitation upon a catchment. Unlike SCS-CN model it uses the physically realistic approach to modeling the hydrological cycle. Antecedent soil moisture content is the important parameter for SCS-CN model. In addition to moisture content of the soil HYSIM uses potential evapotranspiration factor also as an essential parameter for modeling. HYSIM also considers the underground features of the catchment such as soil moisture in the upper and lower horizon, ground water storage etc.

According to the hydrologic and hydraulics features, the total basin has been taken as a single unit for modeling purpose. The parameters which were discussed in chapter 4 were optimized during the calibration of the model. The values of those optimized parameters were given below in Table 5.1.Rainfall and PET are only essential parameters to run the model. Data of 2009 and 2010 were used for calibration and next two years (2011 & 2012) of data were used for validation purpose.

The hydrographs of simulated and recorded flows for the calibration period was shown in Figure 5.9. It shows that the rising and the recession limbs of the simulated hydrographs match with those of the observed flow hydrographs. The simulated peak flow values in most of the cases are close to the observed peak value. The correlation co efficient between the observed and simulated flow is 0.83. During the initial period of calibration it can be seen from the Figure 5.9 that, there is slight variation between the simulated and observed discharge. It is due to the initialization of the model or warming up of the model which allows errors in assumed soil moisture condition to become ineffective. Afterwards when the conditions were stabilized it showed good correlation.

Table 5.1: Optimized values of HYSIM parameters

Sl. No	Parameters	Value
	Hydrologic Parameters	
01	Interception storage	10mm
02	Impermeable proportion	0.02
03	Time to peak for minor channels	4hrs
04	Soil moisture in upper soil horizon	265mm
05	Soil moisture in lower soil horizon	181mm
06	Rooting Depth	1500mm
07	Saturated permeability at the top of the upper horizon	500mm
08	Saturated permeability at the base of the lower horizon	10mm/hr.
09	Saturated permeability at the horizon boundary	18.23mm/hr.
10	Pore size distribution index	0.2
11	Soil porosity	0.65
12	Bubbling pressure	50
13	Recession from transitional ground water storage	0.02
14	Proportion of upper ground water runoff that enters channel	0.2
15	Interflow runoff from upper soil horizon at saturation	1mm/hr.
16	Interflow runoff from lower soil horizon at saturations	1.026mm/hr.
17	Correction factor for precipitation	1.26
18	Correction factor for PET	0.5
19	Ratio of ground water to surface catchment	1
20	Proportion of surface catchment without ground water	0
21	Catchment area	141.32
	Hydraulic parameters	
01	Average base width of nala	8m.
02	Average top width of nala	14m.
03	Flood plain width	20m.
04	Average depth of river	2m.
05	Flood plain depth	1m.
06	Maximum flood depth	1.5m.
07	Manning's n for nala	0.03
08	Manning's n for flood plain	0.15
09	Length of the nala	30km
10	Channel gradient	0.001

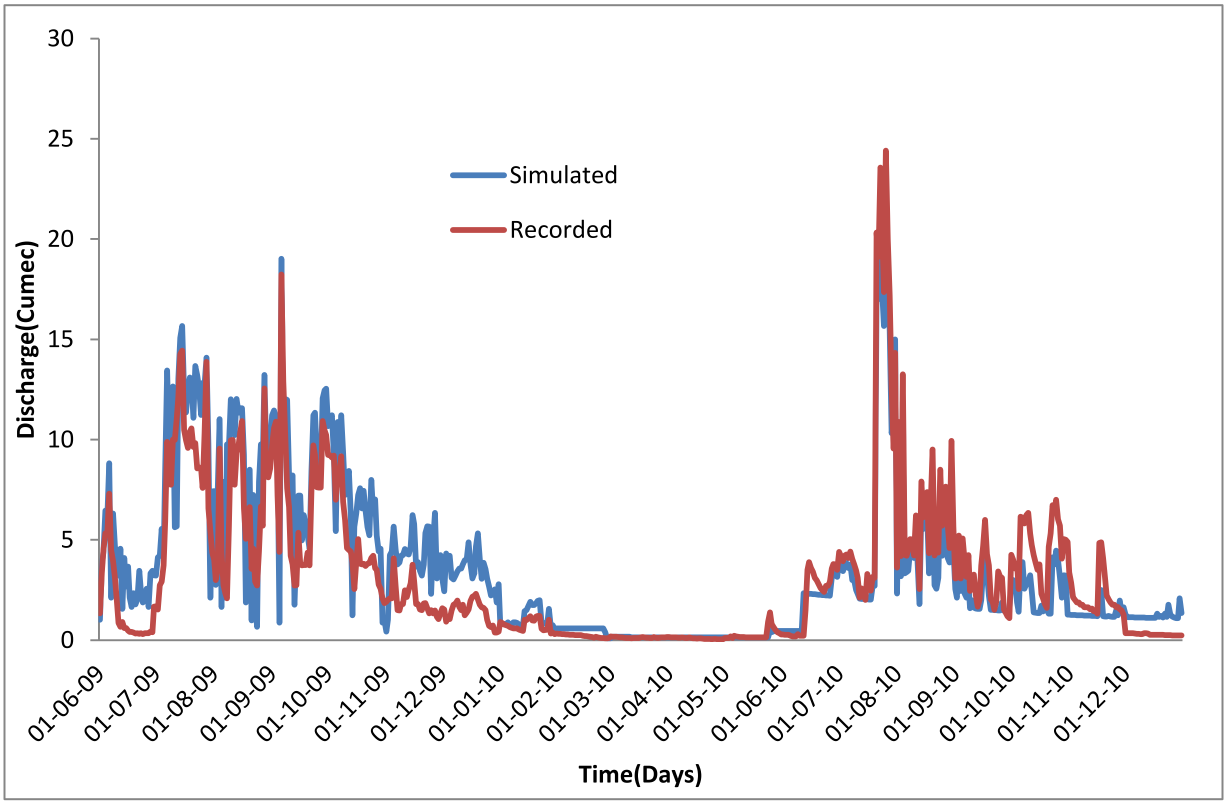

Figure 5.9: Simulated and recorded flows for calibration period (June 2009 to 2010)

The validation of the model has been done on 2 data sets (2011 & 2012) and the hydrographs of the simulated and recorded flows are shown in Figure5.10 and 5.11. The correlation coefficients between the simulated and recorded flows for the validation periods were 0.98 and 0.97 for 2011 and 2012 respectively. In 2011 monsoon season very heavy rainfall occurred as it can be seen from the hydrograph. The peak values of the simulated hydrographs in Figure5.10 seem to be slightly lower than that of the recorded. Still the correlation between the two hydrographs is good. Figure 5.11 shows the comparison between the simulated and recorded hydrographs for the validation period of January 2012 to September 2012.During the monsoon period it shows little variation between simulated and recorded values but the correlation is good.

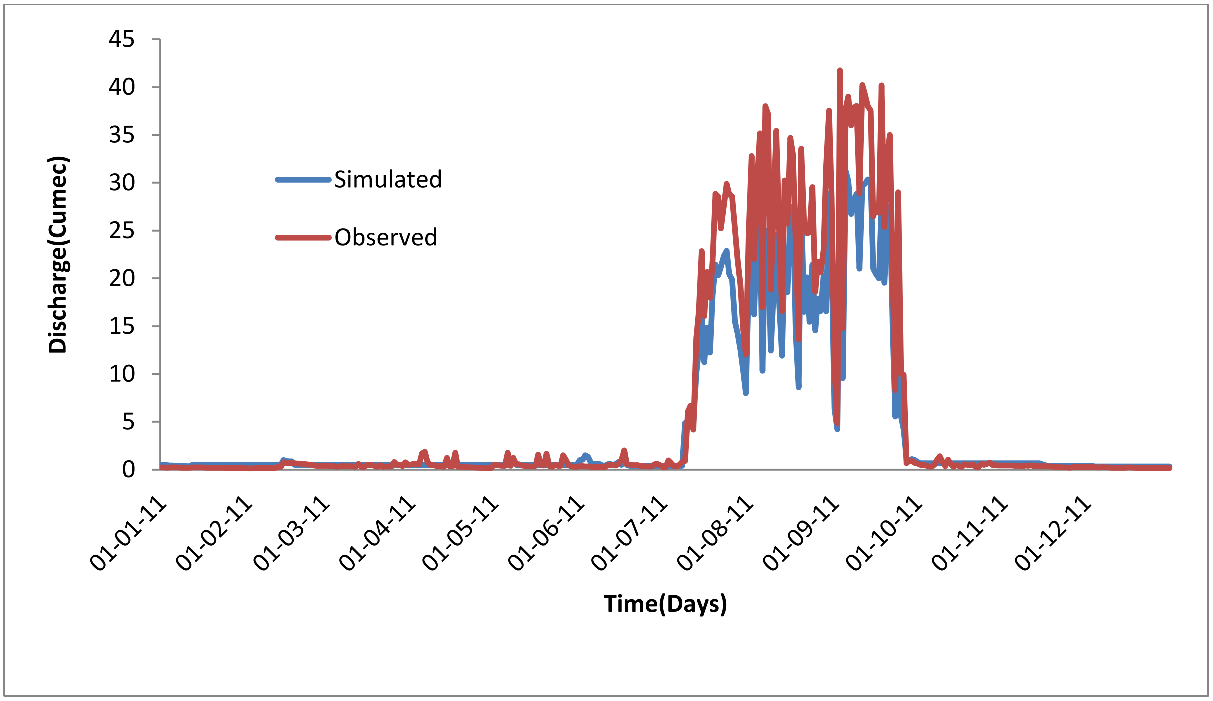

Figure 5.10: Simulated and recorded flows for validation period (January 2011 to December 2011)

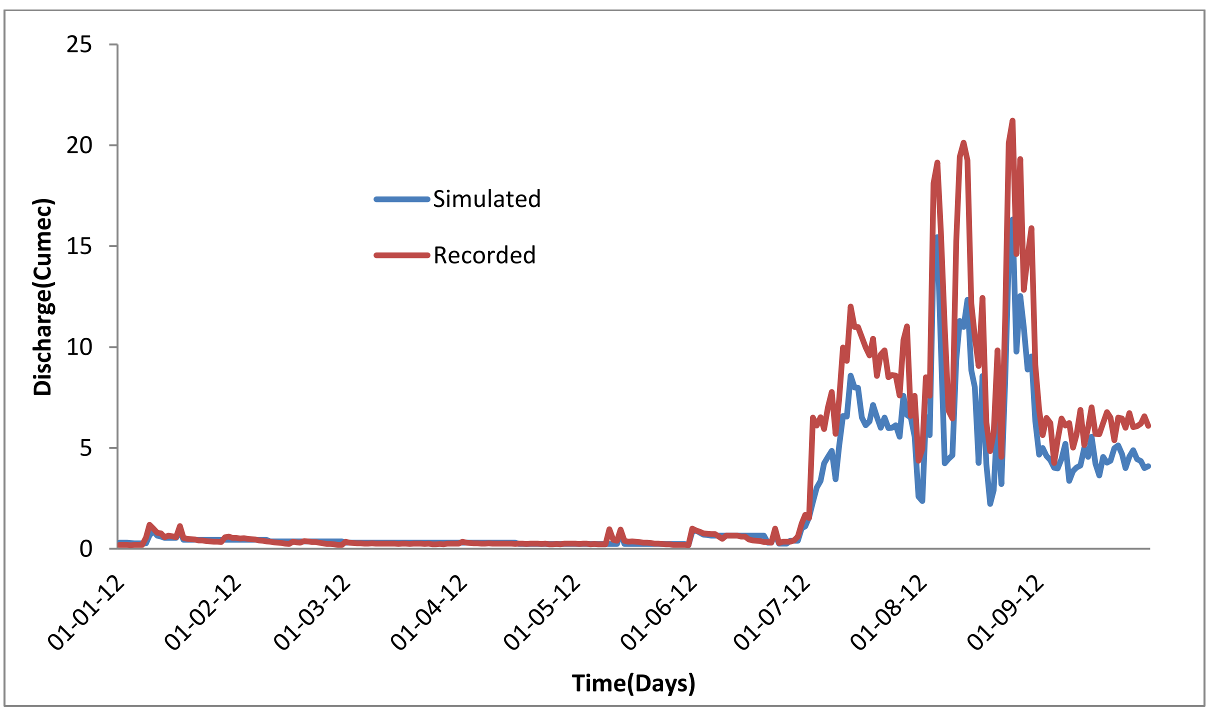

Figure 5.11: Simulated and recorded flows for validation period (January 2012 to September 2012)

Table 5.2: Correlation coefficients of the calibration and validation periods

TIME	Correlation coefficient
Calibration period(June 2009 to December 2010)	0.83
Validation period(January 2011 to December 2011)	0.98
Validation period(January 2012 to September 2012)	0.97

During analysis of the above obtained results for calibration and validation period, it is important to mention about the quality of the data used for the above procedure which directly affects the simulated results. The PET data used for the model was mean monthly PET values as actual values were not available. The flow data used for modeling purpose were daily average values, which may not give the actual peak values of that day. With certain limitations, still HYSIM model produced better results than SCS-CN model.

5.3 ANN

HYSIM requires a large number of parameters for modeling. The actual values of these parameters are also not easily available. To overcome this problem ANN model was used to simulate discharge as it requires less input parameters for modeling which is very good for an ungauged basin like Samij basin.

5.3.1 Time series analysis of rainfall and observed discharge

The Autocorrelation and Partial Autocorrelation analysis by STATISTICA 9 for the observed times series data of discharge and rainfall has been carried out to know the Correlation, Standardized Error and lag before proceeding for ANN modeling. Figure 5.12 and 5.13 show the auto correlation of the rainfall and observed discharge data. The self-explanatory Figure 5.14& 5.15 show the partial autocorrelation of the time series rainfall and observed discharge data from the year 2009 to 2012.From the figures shown below it is clear that the correlation between the observed discharge time series data is good while it is not the same for rainfall data.

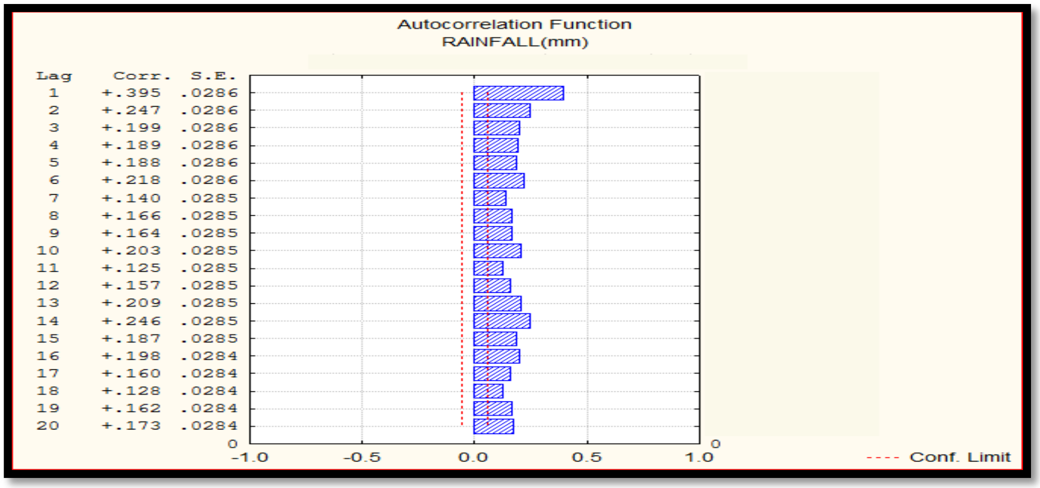

Figure 5.12: Autocorrelation analysis of Time series Rainfall data

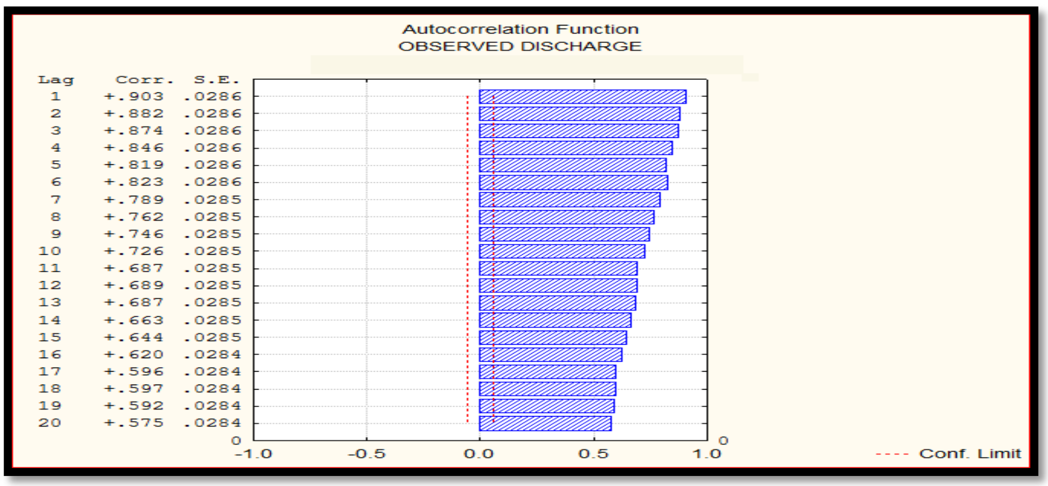

Figure 5.13: Autocorrelation Analysis of Observed time series discharge data

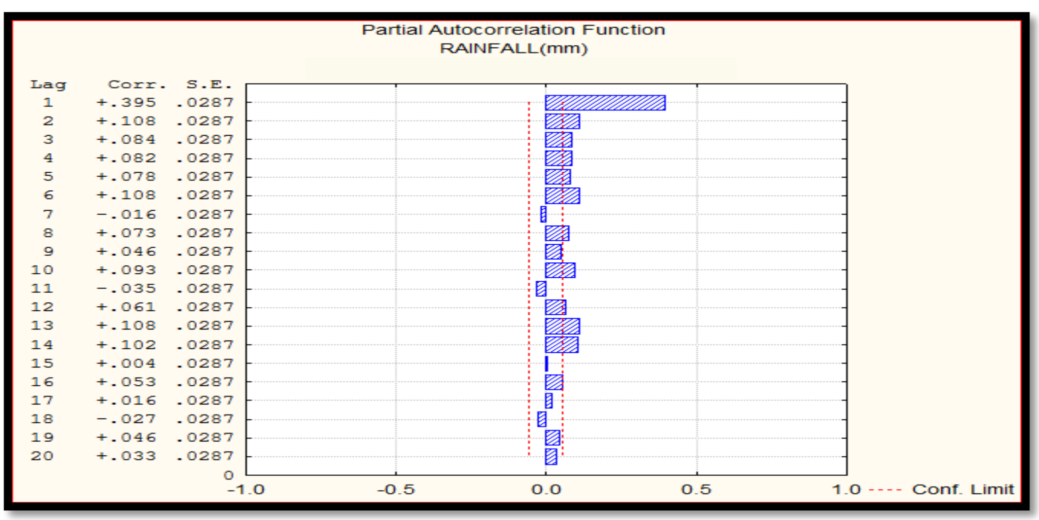

Figure 5.14: Partial Autocorrelation of Time series Rainfall data

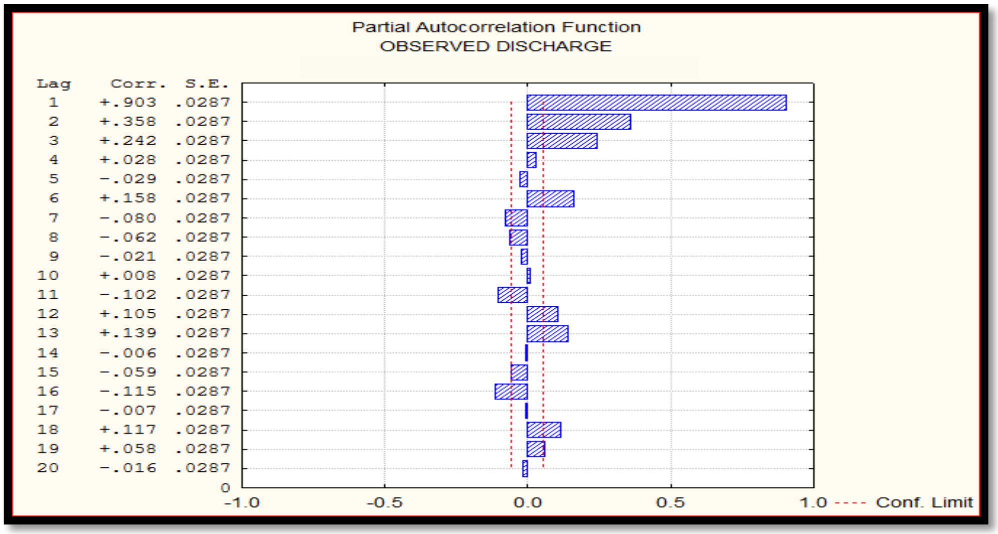

Figure 5.15: Partial autocorrelation of Observed Time series discharge data

Time series Prediction by ANN determines the input vector to the network by the two algorithms; those are back propagation network or BPN and radial basis function network or RBF. The trail of the given input data started with the network considered, the trial data consists of one previous day rainfall value and estimating the goodness of fit statistics, i.e. RMSE. The trial or training of data was continued with adding one more data in the input vector in the input layer and the performance of input layer is examined on the basis of statistical indices. As the number of hidden layer of the model increases or decreases there is a change in the goodness of fit statistics. Therefore, the goodness of fit statistics test has been done for training, validation and testing of time series data with fixing the hidden layers to 10 during the modeling.

The Target time steps are fixed for every year i.e. 30% for validation, 35% each for training and testing of the input and target data given to the model. The Target values are decided by the model after the target time steps are given to it. RMSE is the root mean squared error between output and target values. R is the measure of regression values between output and target data.

The Regression outputs are shown in Figure 5.16, 5.17, 5.18 and 5.19 for years 2009, 2010, 2011 and 2012 respectively. The RMSE and correlation coefficient (R) values for the years 2009, 2010, 2011 and 2012 are given in Table 5.3.It shows the RMSE values are less for all four years and R values are higher during validation than training or testing for each year. This is due to the radial basis function, during which the network reproduces the training pattern with least errors.

The regression analysis done by ANN model shows the regression coefficient nearest to 1 which shows there is good correlation between the target and output values for every year from 2009 to 2012.

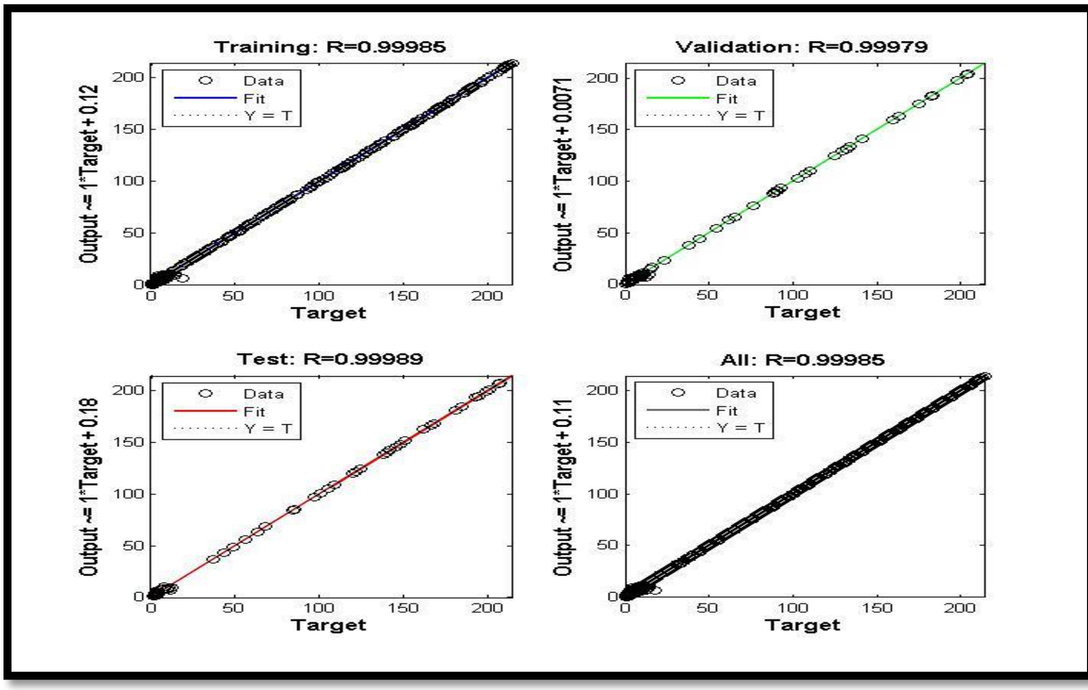

Figure 5.16: The regression output of ANN model for the year 2009

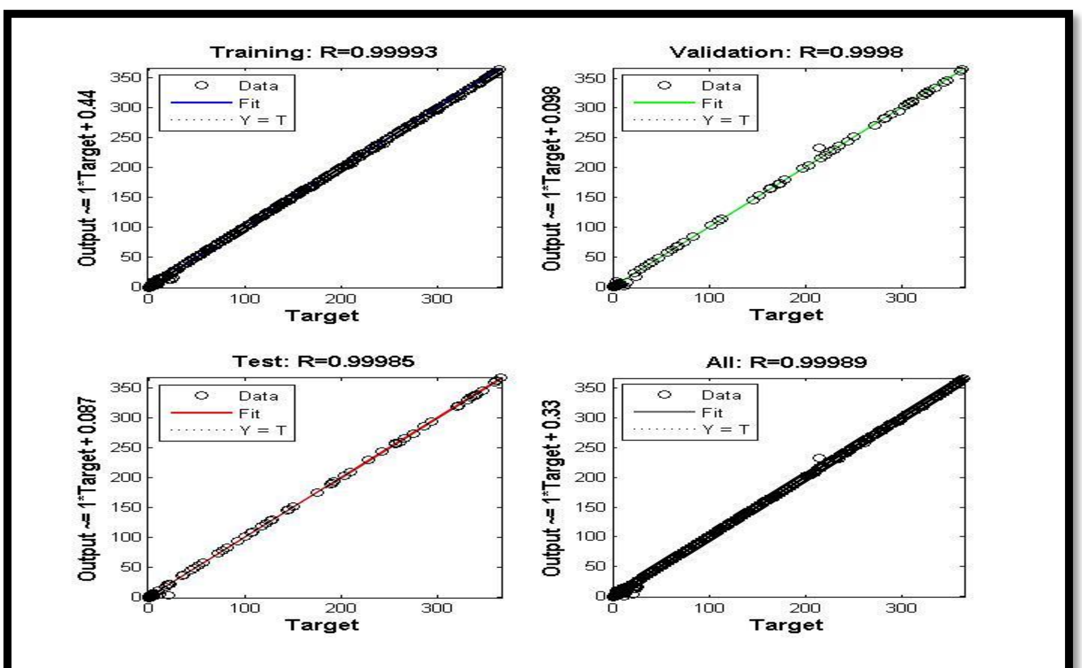

Figure 5.17: The Regression output of ANN model for the year 2010.

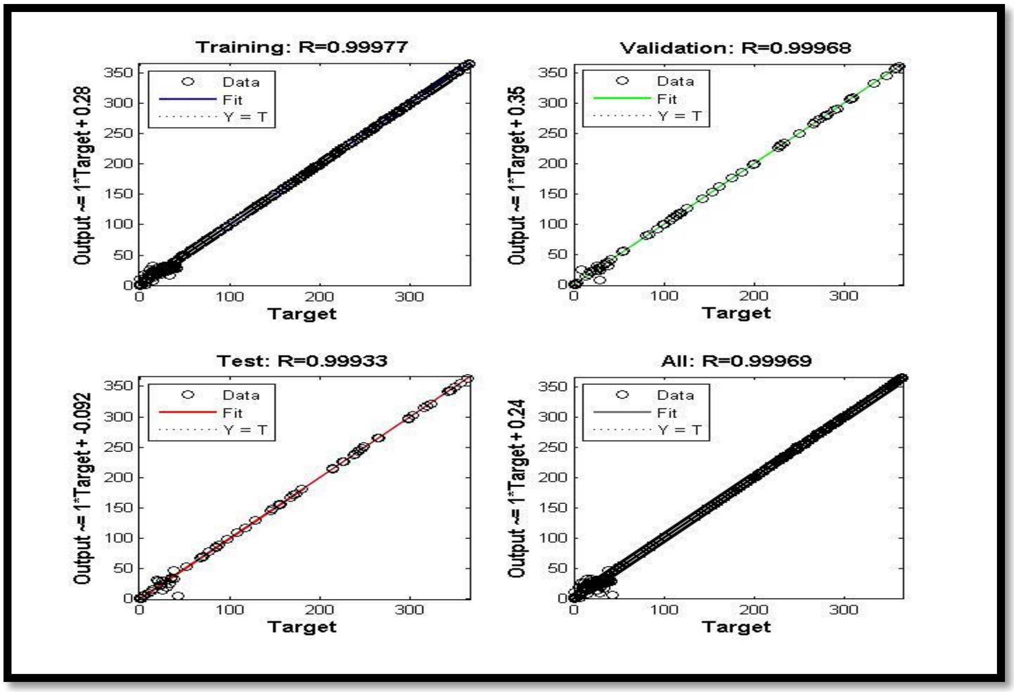

Figure 5.18: The regression Output by ANN model for the year 2011

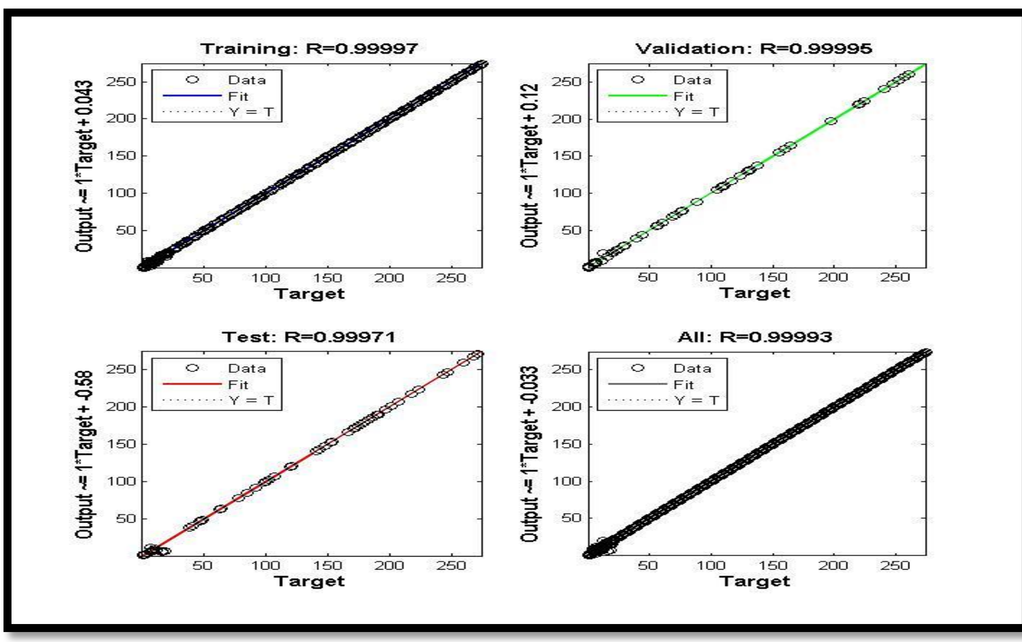

Figure 5.19: The Regression Output by ANN model for the year 2012

The graphs of regression output showed above for different years have the correlation coefficient (R) nearly equal to 1. It shows that there is less variation in the data and we can go for further analysis of prediction in artificial neural network (ANN).

The Response Outputs for the four years are shown in Figure 5.20, 5.21, 5.22 and 5.23 respectively. It shows the target values as input and the output values as output after the iterations in ANN during the analysis for prediction of discharge data.

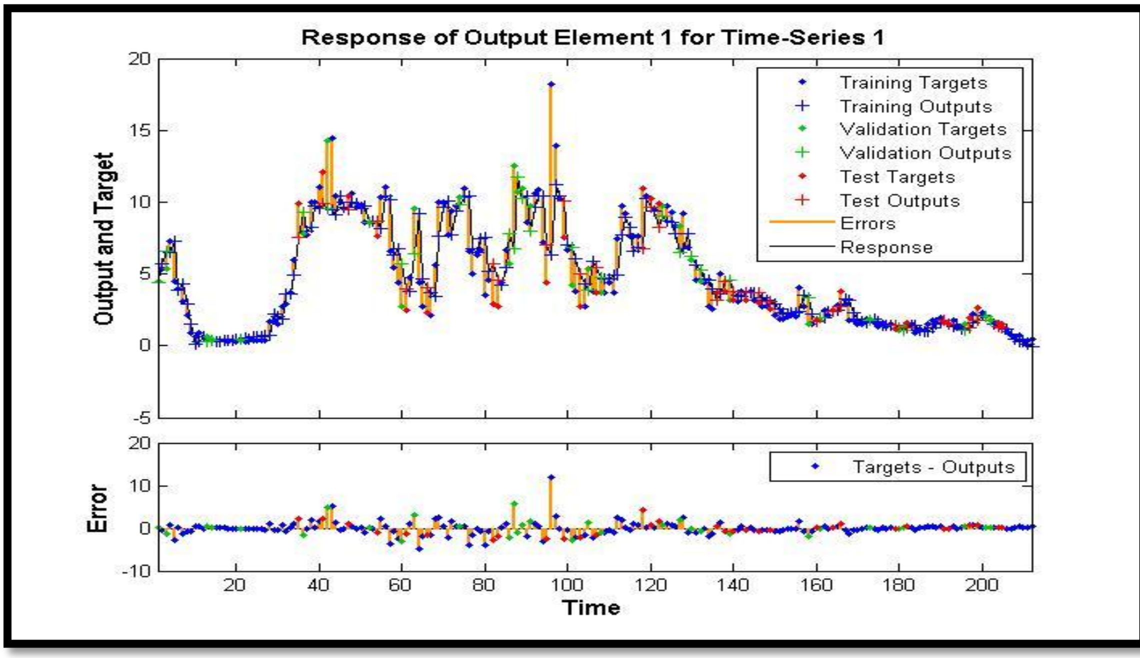

Figure 5.20: The Response Output by ANN model for the year 2009

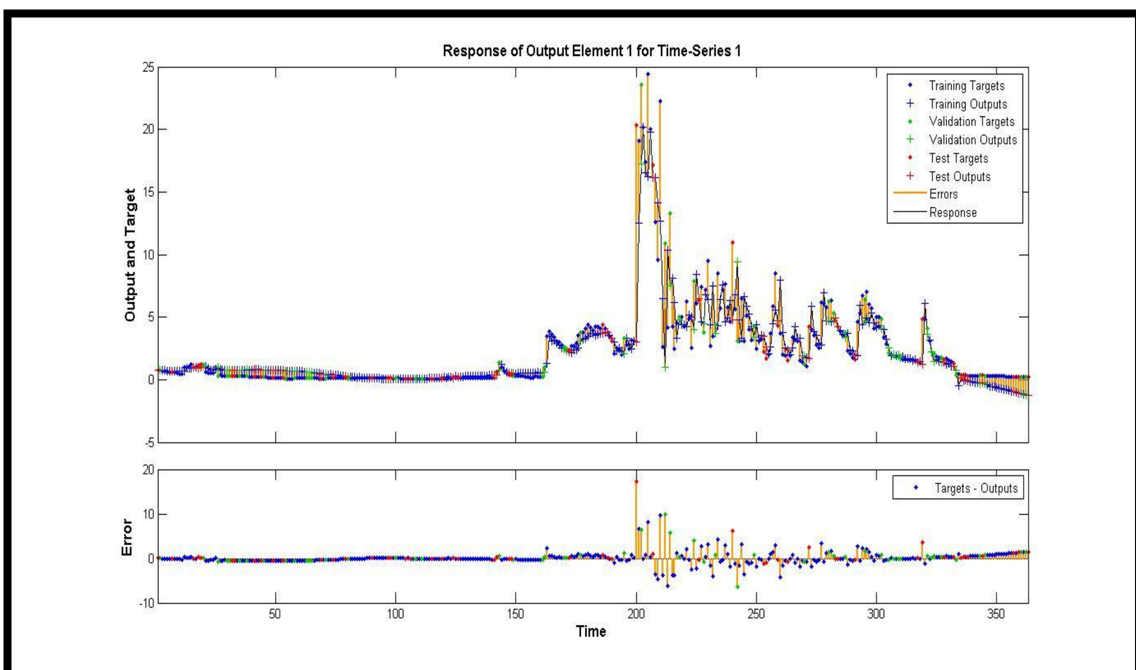

Figure 5.21: The Response Output by ANN model for the year 2010.

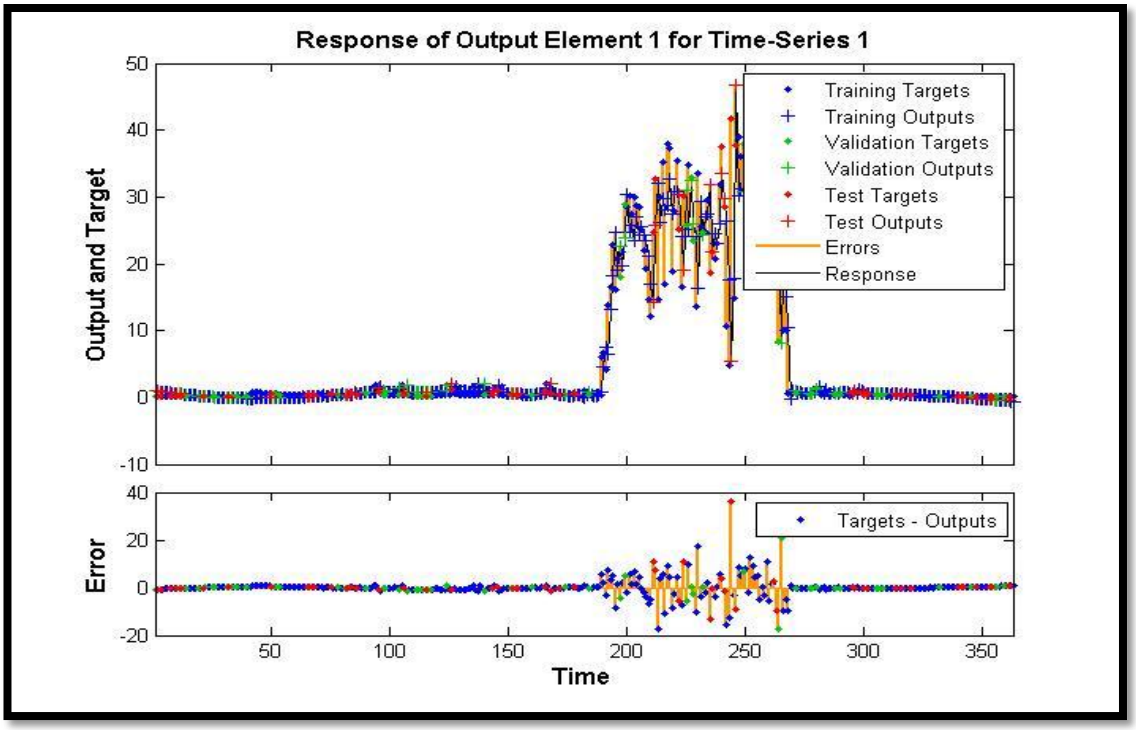

Figure 5.22: The Response Output by ANN model for the year 2011

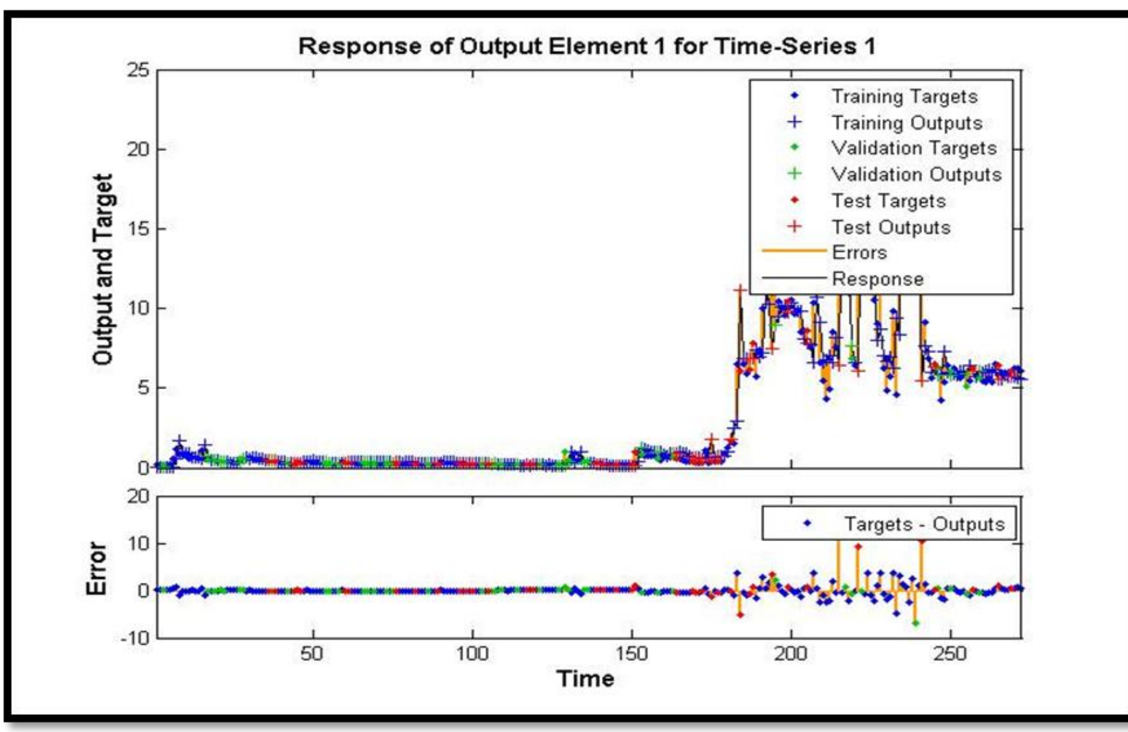

Figure 5.23: The Response Output by ANN model for the year 2012.

After the complete iteration by ANN model the predicted data is generated by the model and is recorded for correlation analysis for the validation of input time series data and the output of the model. The correlation graphs are given in Figure 5.24, 5.25, 5.26 and 5.27 for year 2009,2010,2011 and 2012 respectively, which are self-explanatory to know the correlation between the input and output data. The correlation analysis for the years 2009, 2010, 2011 and 2012 show strong correlation between the observed and predicted data having correlation coefficients of 0.979,0.991,0.997 and 0.991 respectively.

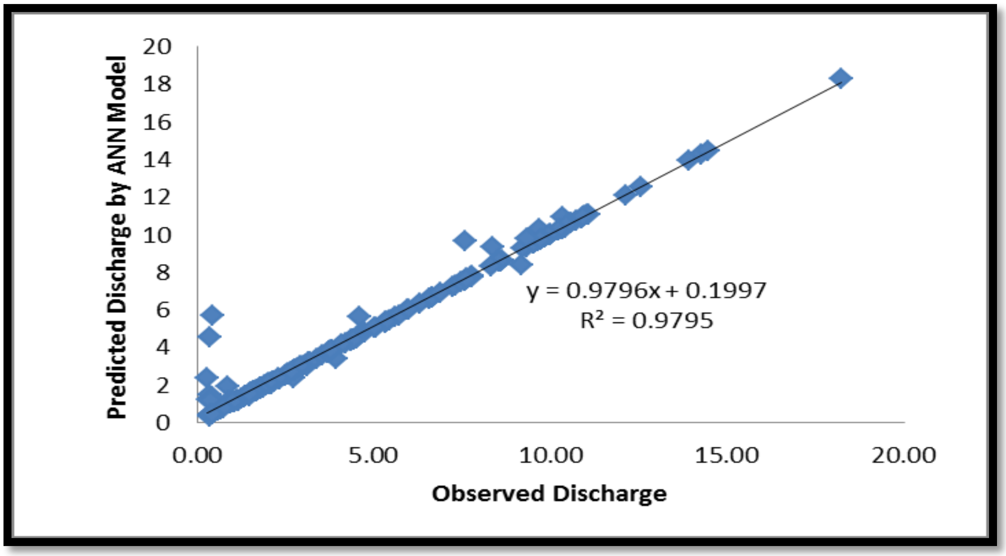

Figure 5.24: The comparison between Predicted and Observed discharge for year 2009

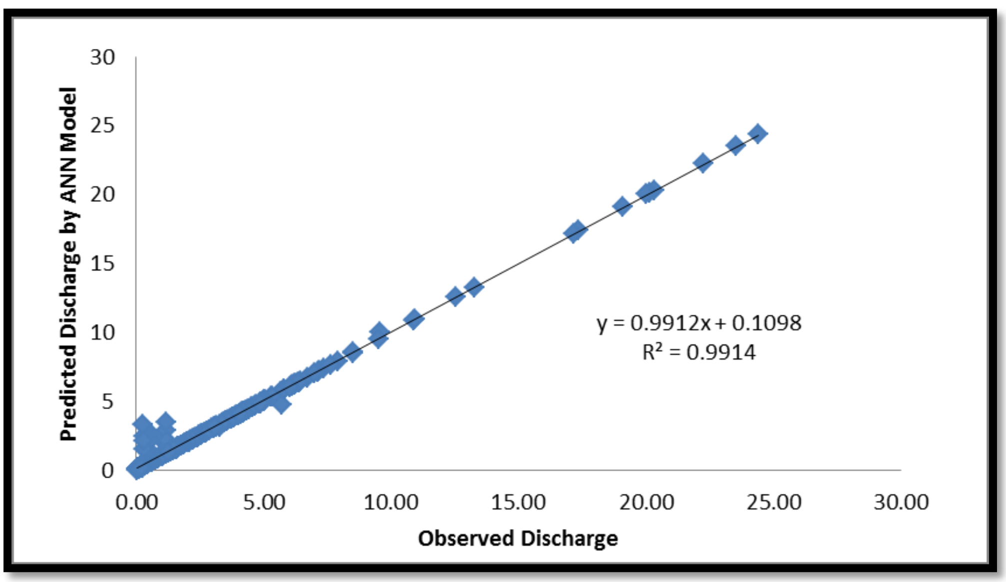

Figure 5.25: The comparison between Predicted and Observed discharge for year 2010

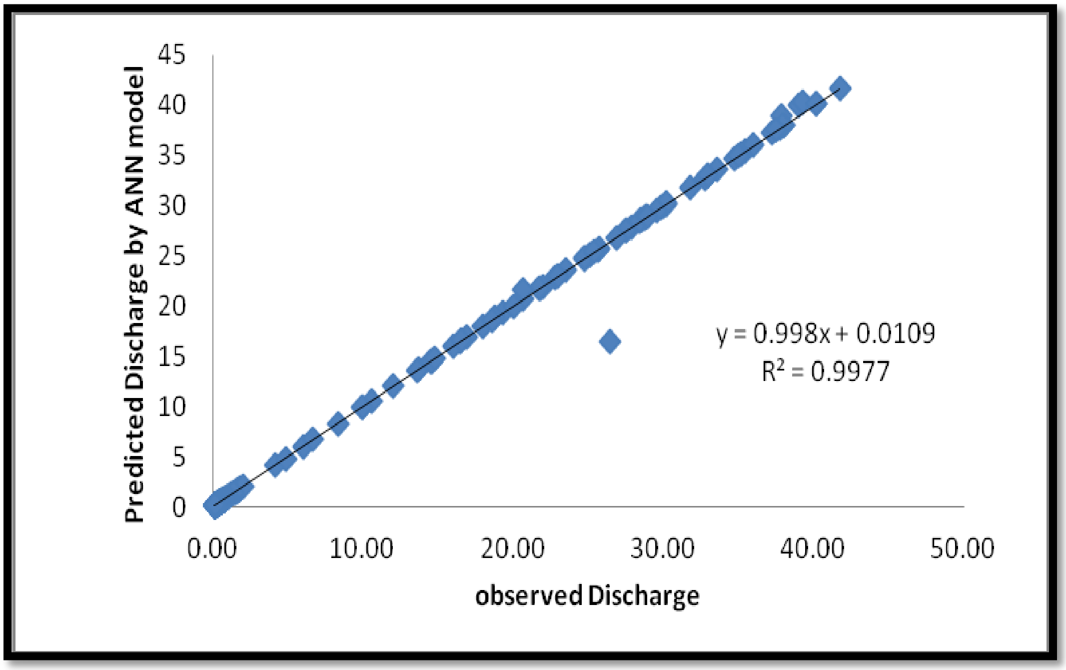

Figure 5.26: The comparison between Predicted and Observed discharge for year 2011

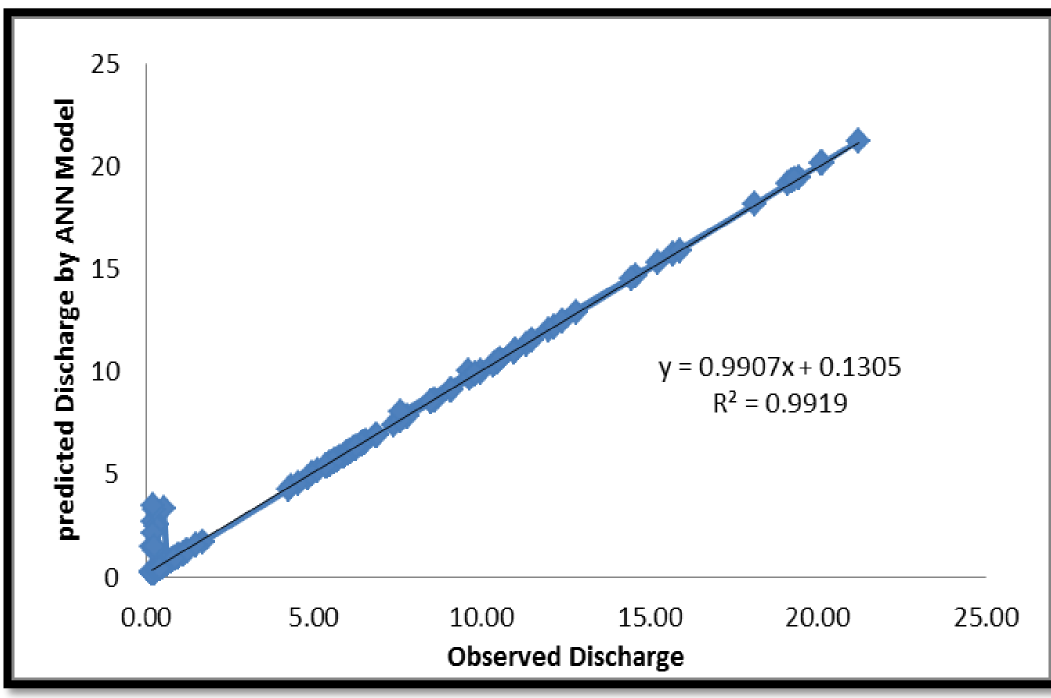

Figure 5.27: The comparison between Predicted and Observed discharge for year 2012

Table 5.3: Goodness of Fit Statistics for the time series data ANN model

	2009	2010	2011	2012
Target Time Steps				
Validation	30%	30%	30%	30%
Training	35%	35%	35%	35%
Testing	35%	35%	35%	35%
Target values				
Validation	128	218	218	164
Training	150	256	256	192
Testing	150	256	256	192
R (Correlation coefficient)				
Validation	9.99853E-1	9.99930E-1	9.99771E-1	9.99968E-1
Training	9.99791E-1	9.99795E-1	9.99675E-1	9.99945E-1
Testing	9.99889E-1	9.99847E-1	9.99334E-1	9.99711E-1
RMSE				
Validation	1.32199E-0	1.97029E-0	6.19924E-0	5.10990E-0
Training	1.75278E-0	6.30295E-0	8.38981E-0	6.81281E-0
Testing	1.19295E-0	4.35382E-0	10.09399E-0	4.54320E-0

Artificial Neural Network (ANN) models show the capability to modeling the hydrological process. They are useful and power full tools which can handle complex problems compared with the other traditional models. In this study, the results indicate clearly that the artificial neural networks by the use of BPN and RBF are capable of modeling rainfall-runoff relationship in any catchment. The used data in ANN were daily hydrometric and climatic data of four years from 2009 to 2012. The model structures were developed to investigate the probability impacts of enabling/disabling rainfall-runoff, rainfall and discharge in the above mention years in the catchment area. As indicated by the results, ANN model provided the highest performance. The results of this ANN study has shown that, with proper combination of computational efficiency, Statistical measures and ability of input parameters which generally describe the physical behaviour of hydro-climatologic variables, improvement can be made in the model predictability in artificial neural network study.

5.4 Comparison of models

SCS-CN, HYSIM and ANN are the three models used for modeling in the ungauged Samij basin. Each of the models are different to each other with respect to input data parameters.

SCS-CN uses the antecedent moisture content of soil, land use /land cover and soil texture as its main input parameters in addition to precipitation upon the catchment, while HYSIM uses rainfall and potential evapotranspiration as its basic input parameters. It also considers the soil moisture content of the soil and soil texture of catchment as its variables. ANN model used through back propagation and radial bias network as it requires very less input parameters.

The results obtained using the above three models were very good and a comparison was drawn between them which is shown below in Figure 5.28.The correlation coefficients obtained are 0.69,0.92 and 0.99 for SCS-CN,HYSIM and ANN model respectively. ANN emerged as the best fit model for this ungauged basin. The RMSE values were also calculated and given in Table 5.4.

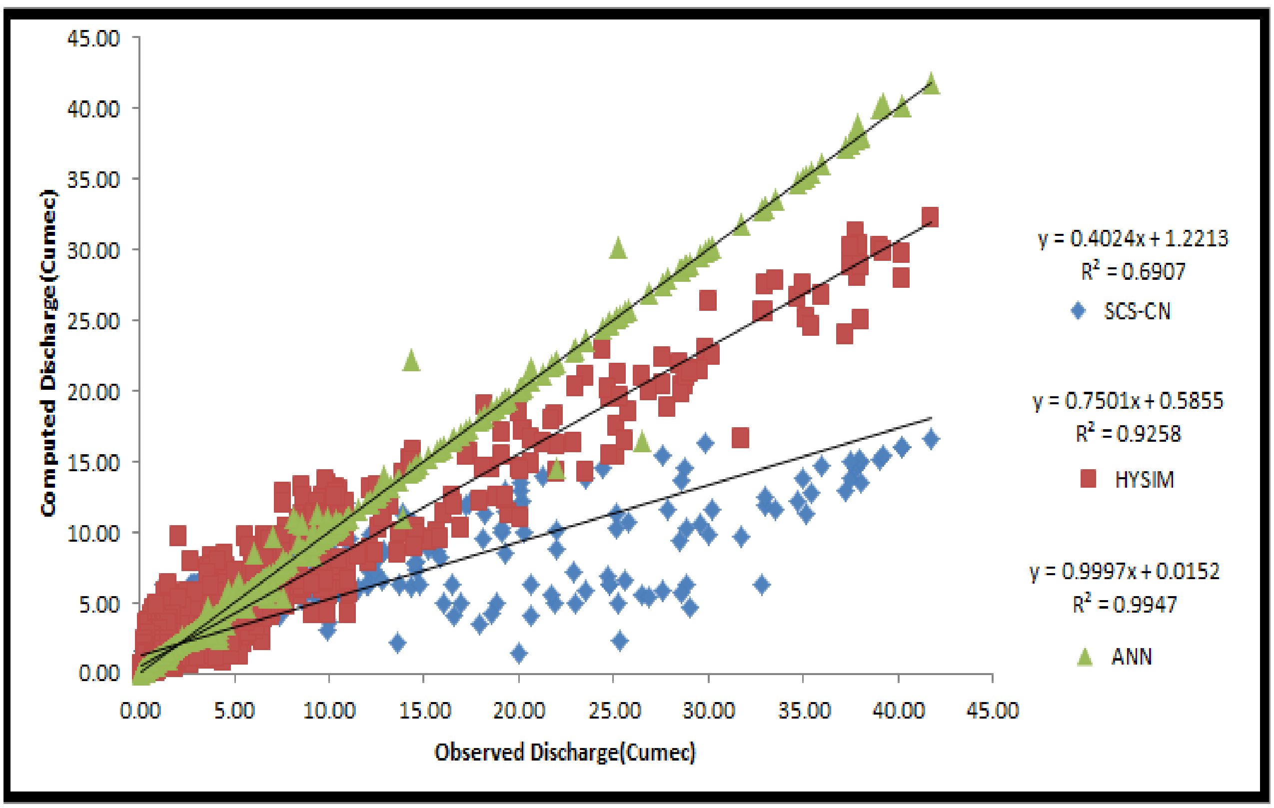

Figure 5.28: Comparison of the three models

Table 5.4: RMSE values in all 3 models

MODELS	RMSE Values			
	2009	**2010**	**2011**	**2012**
SCS-CN	1.65	1.73	8.34	2.25
HYSIM	2.04	1.04	3.4	1.92
ANN	0.69	0.48	0.71	0.27

Table 5.4 shows the RMSE values obtained using equation 31 of chapter 4 for each model and each year. In SCS-CN model the least error was found out during the year 2009 and most during 2011.HYSIM gave better result in comparison to SCS-CN model as the error values in each year is less than that of SCS-CN model. Highest error value of 3.4 was found out during 2011.ANN model gave the best result among the three models as the error values were less than 1 for every year. It clearly shows that ANN is the best model for this ungauged basin.

CHAPTER 06

CONCLUSION

The present work can be summarized in the following way:

The selected study area for the present work is an ungauged drainage basin having a nala called Samij nala as its main channel flowing through it. SCS-CN, HYSIM &ANN; the three models were used to model the ungauged basin. Each model used its own set of parameters as their input and discharge was predicted. Simulated discharges were validated with the observed discharges.

- The correlation obtained between the two rain gauge stations is not very good. This may be due to their topographic location or land use changes.
- Time series plot of the observed discharge data showed that, apart from monsoon season, flow in the nala is very low.
- The maps delineated using Arc GIS shows that the basin has a hilly topography; More than 80% of the basin is covered with forests. Elevation of the basin varies from 163m mean sea level to 903m mean sea level.
- SCS-CN model used for estimation of runoff in the basin. The comparison between the observed discharge and estimated discharge obtained using SCS-CN shows the correlation coefficients as 0.80, 0.77, 0.90 and 0.87 for year 2009, 2010, 2011 and 2012 respectively.
- A hydrological distributed model HYSIM was used to simulate discharge. It produced the flow hydrographs up to a good level of accuracy having correlation coefficients of 0.83 during calibration period and 0.98 and 0.97 for two validation periods. But this model requires a large number of parameters as their input to simulate the flow, which are not easily available.
- Artificial neural network model uses very less input parameters and shows the best results among all the three models having correlation coefficients as 0.99 for each year.

SCOPE OF THE STUDY IN FUTURE

- ❖ The study area of the present work is situated at a location which is surrounded by many mine areas. If each mine is considered as a small catchment, their size will be less than the catchment area of the Samij basin. Rainwater harvesting system is the need of the hour for these mines to meet their ever growing demand for water. The procedures followed in the Samij basin to estimate the runoff can also be applied to these mine areas to know the amount of runoff generated from its catchment. So that it can be stored at a proper location for future use.
- ❖ The results obtained from the present work are very good. These models can also be applied for very small, small, medium, large and very large basins with proper modification in the input parameters. All the three models used for the present work are flexible. According to the availability of the data in different basins, these models can operate accordingly.

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APPENDIX-I

Table 1: Runoff Curve numbers (CN_{II}) for hydrologic soil cover complexes under AMCII (Source: Engineering Hydrology)

Land use	Cover		Hydrologic soil group			
	Treatment or practice	Hydrologic condition	A	B	C	D
Cultivated	Straight row		76	86	90	93
Cultivated	Contoured	Poor	70	79	84	88
		Good	65	75	82	86
Cultivated	Contoured & Terraced	Poor	66	74	80	82
		Good	62	71	77	81
Cultivated	Bunded	Poor	67	75	81	83
		Good	59	69	76	79
Cultivated	Paddy		95	95	95	95
Orchards	With understory cover		39	53	67	71
	Without understory cover		41	55	69	73
Forest	Dense		26	40	58	61
	Open		28	44	60	64
	Scrub		33	47	64	67
Pasture	Poor		68	79	86	89
	Fair		49	69	79	84
	Good		39	61	74	80
Westland			71	80	85	88
Roads(dirt)			73	83	88	90
Hard surface areas			77	86	91	93