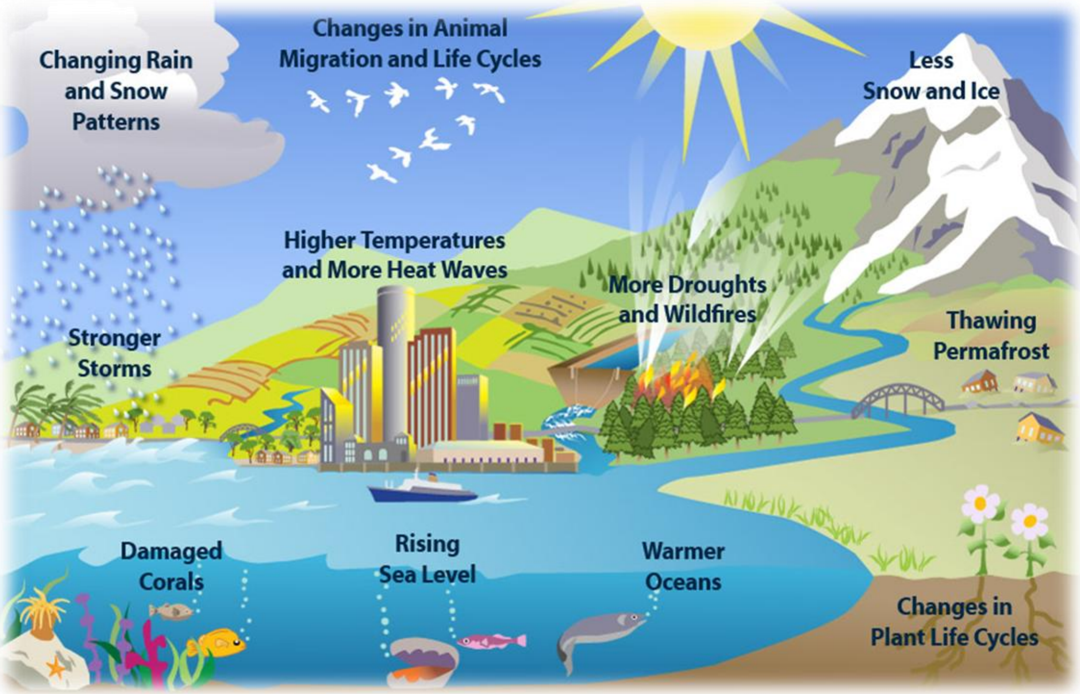
(Final Report)

STUDY OF HYDROLOGICAL CHANGES IN SELECTED WATERSHEDS IN VIEW OF CLIMATE CHANGE IN INDIA



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Preface

Water is the second essential element among the five elements of nature namely earth, water, air, fire and space with cold and wet sensible qualities. Available as a vital natural resource is of utmost important for the subsistence of any kind of life on the planet earth. Its availability is highly variable with space and time. Water is of paramount importance and precious for the livelihood, from crucial drinking water to food production, production of energy to development of industries and from management of natural resources to environment conservation. The scarcity of water resources and its tremendous increasing demand, which is outcome of growing population, intensification of agriculture sector, industrial and urban expansion, has necessitated its proper planning and management. Moreover, global warming and looming climate change in the region has further added more intricacy. The climate of earth has never been stable for any extended period but varying naturally on all time scales. Climate change has greatly affected the characteristics of climatic variables globally. These changes are not uniform but vary from place to place or region to region. Probable climate change and its perilous impacts on the hydrologic system pose a threat to global fresh water resources and aquatic ecosystems worldwide.

Hydrological modeling is the standard tool for investigating hydrological processes of river catchments, helps in flood forecasting, proper water resource management and evaluation of water quality, erosion and sedimentation, nutrient and pesticide circulation, land use and climate change etc. and have helped better appreciable understanding of hydrological problems and their possible solution. The present study is envisaged in this context to take up the study on the assessment of hydrological changes in different watersheds in India under changing environment.

The study entitled ‘Study of hydrological changes in selected watersheds in view of climate change in India’, being carried out at Surface Water Hydrology Division, National Institute of Hydrology, Roorkee. The study group comprises of Dr. L. N. Thakural, Sc-c, Er. D. S. Rathore, Sc-F, Dr. Surjeet Singh, Sc-C, Mr. Tanvear Ahmad¸ Sc-B, Dr. Sanjay Kumar Jain, Sc-G, Dr. Sharad Kumar Jain, Sc-G

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Chapter 1

INTRODUCTION

General

Water resources are the most important resources that are the basis for survival and advancement of humanity. Wise use of these resources is important for continuity of living on earth, which embrace both quantity as well as quality.

One of the major factor, which play a vital role in the decline of the water resources, is climate change. Climate change commonly refers to any change in climate over the time initiated by naturally or anthropogenic response. In another word, climate change means the changing of climatic or meteorological parameters viz. precipitation, maximum temperature, minimum temperature etc.

Precipitation is one of the main climatic variables that affect both the spatial and temporal patterns of stream water availability. One of the challenges posed by climate variability is ascertainment, identification, and quantification of trends in rainfall and their implications on river flows in order to assist in the formulation of adaptation measures through appropriate strategies for water resources management (De Luis et al., 2000).

In India, agriculture primarily depends on monsoon rainfall. Studies of large-scale changes especially in occurrence and distribution of rainfall are foremost factors in the planning and management of irrigation projects, reservoir operation, changes in water requirement and agricultural production. The variation of annual rainfall has great consequences in the planning of irrigation projects, and therefore, such studies are important for agricultural planning in India (Gadgil, 1986). Much of the recent public concern over climate change tends to focus on rising global mean temperatures and changing precipitation pattern, however, climate varies significantly on a regional scale, can be predominantly damaging the availability of water and causing drought (IPCC, 2007).

River basins are important for hydrological and environmental improvement. They generate runoff from snowmelt and rainfall if they are properly managed. Runoff is the water flow that occurs when soil is infiltrated to full capacity and excess water from rain, meltwater, or other sources flows over the land. Runoff occurs when the rate of rainfall on a surface exceeds the rate at which water can infiltrate the ground. Runoff is a major component of the hydrologic cycle and it is a source of surface water. Hydrology deals with the origin, distribution and circulation of water resources.

Surface water is the main reservoirs of water resource mostly used by a human. Surface water is the readily available freshwater resource used for various purposes, including household, agricultural and industrial purposes. People mostly use surface water because it is so easy to discover and utilizes.

Precipitation Trend Analysis

Precipitation trend analysis is one of the active areas of concentration to study the rainfall variability over the years. Trend analysis has proved to be a useful tool for effective water resources planning, design, and management. Investigating the long-term trends of rainfall is important and necessary in studying long-term impacts upon the environment of an area for water resources planning and management (Haigh, 2004). Mann-Kendall (MK) and Regression Analysis tests are the most commonly used tests for detecting trend analysis of rainfall.

Regression analysis is a parametric test conducted with time as the independent variable and rainfall/temperature as the dependent variable. The regression analysis can be carried out directly on the time series or on the anomalies (i.e. deviation from mean). Mann-Kendall (MK) test is a non-parametric test, widely used for the analysis of the trend in climatologic (Mavromatis and Stathis, 2011) and in hydrologic time series (Yue and Wang, 2004).There are two advantages of using this test. First, it is a non-parametric test and does not require the data to be normally distributed. Second, the test has low sensitivity to abrupt breaks due to inhomogeneous time series (Tabari *et al*, 2011).

Drought Characterization

Drought is a weather-related hazards. However, there is no universally accepted definition of drought. Perhaps the most general definition is the one which considers drought as a significant decrease of water availability during a long period of time and over a large area. In fact, drought is complex and least understood of all natural hazards, affecting more people than any other hazard (Wilhite, 2000). Drought is a natural hazard affects about one-third of the world’s population. On average more than 0.5 billion people in China and India are usually exposed to droughts, seriously affecting the economic development and environment of the region. Because of the slow development of a drought, people are often not aware of the emerging of droughts in time. More insight in the development of a drought can help the people to be aware of a drought in an earlier stage. Drought impacts the poorer economies to a larger extent and may cause fatalities as compared to developed countries. On an average, more than 30% of the population is exposed to drought annually in western African countries, thereby seriously threatening the livelihoods (ISDR, 2009; WWDR, 2009).

The drought has many facets and it always starts with the lack of precipitation, but may (or may not, depending on how long and severe it is) affect soil moisture, streams, groundwater, ecosystems and human beings. This leads to the identification of different types of drought viz., meteorological, agricultural, hydrological, socio-economic and physiological droughts, which reflect the perspectives of different sectors on water shortages (Smakhtin and Hughes, 2004).

In India drought- prone areas fall into three broad regions of the country: the plateau region, which embodies the state of Andhra Pradesh, Karnataka, Maharashtra, Madhya Pradesh, Orissa, Tamil Nadu, Bihar, West Bengal and Uttar Pradesh; the desert region, which embodies the states of Rajasthan and Gujarat; and a few districts in the states of Haryana and Jammu Kashmir (Ramasastri and Pandey, 2002).

Classification of Drought

Droughts are often classified into four different categories:

Meteorological drought (deficit in precipitation).

Agricultural drought (deficit in soil moisture).

Hydrological drought (deficit in surface water, groundwater, and reservoir storage) and Socio-economic drought (imbalance in water supply and demand).

Meteorological drought is defined usually on the basis of the degree of dryness (in comparison to some "normal" or average amount) and the duration of the dry period. Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth. Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (i.e., stream flow, reservoir and lake levels, groundwater). Socio-economic definitions of drought associate the supply and demand of some economic good with elements of meteorological, hydrological, and agricultural drought. It differs from the aforementioned types of drought because of its occurrence depends on the time and space processes of supply and demand to identify or classify droughts. The supply of many economic goods, such as water, forage, food grains, fish, and hydroelectric power, depends on the weather. The first three approaches deal with ways to measure drought as a physical phenomenon. The last deals with drought in terms of supply and demand, tracking the effects of water shortfall as it ripples through socioeconomic systems. Wilhite and Glantz (1985).

There are many indices to measure meteorological dryness, such as simple rainfall deviation from historic norms, Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI). Among these indices, SPI has been widely used in recent years because of its computational simplicity and reliable interpretation. SPI is a simple and more effective method for studying drought climatology (Lloyd-Hughes and Saunders, 2002).

Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) is a tool which was developed chiefly for describing and monitoring drought. It permits determining the rarity of a drought at a given time scale of interest for any rainfall station with historic data. It can also be used to determine periods of anomalously wet events.

The SPI (McKee *et al*, 1993) is a powerful, flexible index that is simple to estimate. Precipitation is the only required input parameter. In addition, it is just as effective in analyzing wet periods/cycles as it is in analyzing dry periods/cycles. Many drought planners appreciate the SPI's versatility. It is also used by a variety of research Institutions, Universities, and National Meteorological and Hydrological Services across the world as part of drought monitoring and early warning efforts. The SPI is the number of standard deviations that the observed value would deviate from the long-term mean, for a normally distributed random variable. Since precipitation is not normally distributed, a transformation is first applied so that the transformed precipitation values follow a normal distribution.

The SPI was designed to enumerate the precipitation deficit for multiple timescales. These timescales reflect the impact of drought on the availability of the different water resources.

The SPI estimation for any location is based on the long-term precipitation record for the desired period. This long-term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Edwards and McKee, 1997). Positive SPI values designate greater than median precipitation while negative values designate less than median precipitation. Because the SPI is normalized, wetter and drier climates can be represented in the same way; thus, wet periods can also be monitored using the SPI.

Role of Remotes Sensing and GIS in Hydrological Stream flow Modelling

Remote Sensing has been identified as a tool to produce information in a spatial and temporal domain, instead of point measurement, in digital form, with high resolution. The remotely sensed data acquired from spaceborne platforms, owing to its wide sensitivity and multispectral acquisition provides spatial information about the various processes of the land phase of the hydrological cycle. This spatial information can be used as input data for hydrological models and are extremely relevant as a means of estimating the number of key variables specifically in a situation where distributed hydrological models are used. In the present study, remote sensing has been used to generate input data of thematic maps such as land use land cover and geomorphology for a physically based fully-distributed hydrological model.

The use of remote sensing technology involves a large amount of spatial data management and requires an efficient system to handle such data. Hence, Geographic Information System makes it possible to store, analyze and retrieve data for large and complex problems.

Geographical Information System (GIS) is a computer-based system designed tool applied to geographical data for integration, collection, storing, retrieving, transforming and displaying spatial data for solving complex planning and management problems. This tool focuses on the proper integration of user and machine for providing spatial information to support operations, management, analysis, and decision-making. Two types of approaches are possible for this purpose. In the model-driven approach, a model or set of models is defined and thus the required spatial (GIS) input for the preparation of the input data and output maps. The other approach is the data driven approach. It limits the input spatial data to parameters, which can be obtained from generally available maps, such as topographic maps, soil maps etc. The possibility of rapidly combining data of different types in a GIS has led to significant increase in its use in hydrological applications. It also provides the opportunities to combine a data from different sources and different types. One of the typical applications is the use of a digital terrain model (DTM) for extraction of hydrologic catchment properties such as elevation matrix, flow direction matrix, ranked elevation matrix, and flow accumulation matrix. It also provides the ability to analyse spatial and non-spatial data simultaneously.

Hydrological stream flow Modelling

The history of scientific rainfall-runoff modelling started about three centuries ago with the report on quantitative measurements in hydrology published by P. Perreault in 1674 (Linsley, 1982 in Mishra and Singh, 2003). By comparing the measured annual rainfall (Pa) and the estimated annual stream flow (Q_a) of the Seine river near Paris, Perreault described a functional relationship as Q_a= Pa/6. In the context of modern hydrology, the development of this P_a-Q_a relationship is very primitive, but it was a major finding of the time. It is worth noting that concept of computing runoff as a percentage of rainfall is still in use after 325 years (Mishra and Singh, 2003).

The rainfall-runoff model is one of the most commonly used events in hydrology. Runoff signal which leaves the watershed from the rainfall signal received by the basin is determined by the rainfall- runoff model. Various methods have been developed by different researchers to simulate the rainfall-runoff process. A rainfall-runoff model is a mathematical representation of rainfall-runoff relations of a catchment area, drainage basin or watershed. This mathematical representation is used for simplifications of the actual process of runoff in nature. All models don’t possess the same simplification, some of the models are more simplified than others but at the base of each model, there is a mathematical description that simplifies the factors that are being considered and that enables models to make quantitative predictions (Beven, 2000; Rientjes, 2004). Factors involved in the process of runoff, such as soil characteristics, vary extensively over small distances. It is impossible to consider each variation in space in a mathematical model. Due to this, average values are taken for sets of variables that share similarities. The most common applied classification of rainfall-runoff models divides models into three classes: metric (also called data-based, empirical or black box), parametric (also called conceptual, explicit soil moisture accounting or grey box), and mechanistic (also called physically based or white box) model structures. Metric models, according to Wagener, Weather, and Gupta (2004) are empirical models which commonly derive both the model structure and the corresponding parameter values from available time-series. The tasks for which rainfall-runoff models are used are diverse, and the scale of applications ranges from small catchments, of the order of a few hectares, to that of global models (Wheather, Sorooshian, and Sharma, 2008). Typical tasks for hydrological simulation models include: modelling of gauged catchments (e.g. modelling of river behaviour, real-time flood forecasting, adjusting and evaluation of water resource management); runoff estimation of ungauged catchments; effects of rivers' activity (erosion, sedimentation); prediction of catchment response to changed conditions (e.g. land use change, climate change) and water quality investigations (e.g. nutrients, migration of microbes, salinity and alkalinity of soils, acid precipitation, nonpoint source pollution). In contemporary practice, rainfall-runoff models are standard tools routinely used for hydrological investigations in engineering and environmental science. Also, the topic of watershed management gains an increased attention. Some of the models are also employed in military operations (Singh and Frevert, 2006).

Soil and water Assessment Tool Model (SWAT)

The soil and water assessment tool (SWAT) is a watershed scale model developed by USDA-ARS for predicting the impact of land management practices on water, sediment and agricultural chemical yields in large complex watershed having varying soils, land use and management conditions over long periods of time (Arnold et al., 1998). Soil and water assessment tool released in 2009 and named as SWAT 2009. The model is a physical based, continuous time model, and simulates surface runoff evapotranspiration, infiltration, percolation losses, channel transmission losses, channel routing, lateral flow and shallow and deep aquifer flow. The SWAT model allows considerable flexibility in basin decomposition. The basin can be divided into a number of Hydrological Response Unit (HRU) or grid cells or sub-basins. Different parts of the basin can be divided differently. The new routing structure of the SWAT model routes and adds flows down through the basin reaches and reservoirs. Apart from this, changes were incorporated to simulate lateral flow, ground water flow, reach routing transmission losses, and sediment and chemical movement through ponds, reservoirs, streams and valleys. The SWAT model is capable of simulating hundreds of sub-basins for the periods of 100 years or more. The major components of the model include hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, pesticides, groundwater and lateral flow, and agricultural management.

The SWAT model was developed to predict the impact of land management practices on water, sediment yield, and agricultural chemical yield such as nitrogen, phosphorus and biological oxygen demand, chemical oxygen demand, runoff modelling, water balances modelling of a large basin. For the calibration analysis sequential uncertainty fitting (SUFI-2) program linked with, SWAT-CUP is used.

The SWAT-CUP (SWAT Calibration Uncertainty Procedures) is a computer program for calibration of SWAT models. SWAT-CUP is a public domain program, and it can use freely. SWAT-CUP contains different types of program. These programs include Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (Parasol), and Sequential Uncertainty Fitting (SUFI-2). It enables sensitivity analysis, calibration, validation and uncertainty analysis of SWAT model. The program links GLUE, parasol, SUFI-2, MCMC and PSO procedures to SWAT. SUFI-2 Various SWAT parameters for estimation discharge were estimated using the SUFI-2 program (Abbaspour *et al*., 2007). Uncertainty is defined as a discrepancy between observed and simulated variables in SUFI-2 where it is counted by variation between them. SUFI-2 combines calibration and uncertainty analysis to find parameter uncertainties while calculating smallest possible prediction uncertainty band. Hence, these parameters uncertainty reflect all sources of uncertainty, i.e. conceptual model, forcing inputs (e.g., temperature) and the parameters themselves. In SUFI-2, the uncertainty of input parameters is depicted as a uniform distribution, while model output uncertainty is quantified at the 95 % prediction of uncertainty (95PPU). In the new version of SWAT-CUP, a more powerful SWAT edit program is provided where all SWAT parameter are handled, including different soil layers and management rotation-operation, precipitation data etc. The users are also allowed 20 parameters placed at the end of their own program which linked into SWAT. SWAT-CUP includes parallel processing, visualization of outlet location using Bing Map, the creation of multi-objective function, extraction, and calculation of 95 PPU for all variables into output.rich, output.hru, output.sub files without measurements and one-at-a-time sensitivity analysis.

Nedbor-Afstromings Model (NAM)

NAM is an abbreviation for "Nedbor-Afstromings Model"," a Danish phrase meaning "precipitation runoff model." The hydrological NAM Model simulates the rainfall-runoff process that occurs at the watershed scale. The NAM Model forms part of the rainfall-runoff module of the MIKE 11 River modelling system and was originally developed at the Institute of Hydrodynamic and Hydraulic Engineering at the Technical University of Denmark. Over the past decade, the NAM Model has been extensively applied and modified by the Danish Hydraulic Institute in many projects.

The NAM model is a well-proven and broadly used hydrological tool that has been applied in a number of catchments worldwide, representing different hydrological regimes and climatic conditions (DHI, 2009). NAM is a conceptual model based on physical structures and equations used together with semi-empirical ones. Thus, some of the parameters can be evaluated from physical catchment data, but the final parameter estimation must be performed by calibration applying concurrent input and output time series. The NAM model (DHI, 2000) it is characterized by a deterministic, lumped conceptual rainfall–runoff model with limited input data requirements, which represents various components of the rainfall–runoff process by continuously accounting for the water content in five different and mutually interrelated storages whereby each storage represents different physical elements of the catchment (Madsen, 2000). These storages are snow storage, surface storage, lower zone storage, upper groundwater storage and lower groundwater storage. The resulting catchment runoff is divided conceptually into the overland flow, interflow, and baseflow components. The initial conditions required by the NAM model consists of initial water content in the surface and root zone storages and values of overland flow, interflow, and base flow. Based on simulation period, these values are estimated by the model. A lumped conceptual model of the MIKE11-NAM Model treats each sub-catchment as a unit. The MIKE11-NAM Model simulates the rainfall-runoff process in rural catchments and has 9 parameters: *U*max, *L*max, *CQ*OF, *CQ*IF, *T*OF, *T*IF, *CK*1, 2, *T*G, and *CK*BF. The various components of the rainfall-runoff process represent the average values for the entire sub-catchment by continuously accounting for water contents in 4 different but mutually interrelated forms of storage.

Statistical Downscaling (SD)

Downscaling refers to reduce in size or scale. Statistical downscaling involves development of statistical relationship between large-scale climate variables and local-scale hydrologic variable. Hence, an attempt has been made to use statistical downscaling technique in the present research. Statistical downscaling involves linking Global Climate Model (GCM) variables to local climate variables. The general circulation model is also popular by the name of global climate model. Considering IPCC, Global Climate Model/General Circulation Model (GCM) represents physical processes in the atmosphere, ocean, cryosphere and land surface. It is the most advanced tool currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. It has the potential to provide geographically and physically consistent estimates of regional climate change which are required in impact analysis.

Models are available on downscaling based on classification of circulation patterns (CP) and using this classified CP in estimation of precipitation. Bardossy et al. (1995) used a fuzzy rule-based technique for classification of CP into different states. Wetterhall et al. (2005) used analogue method for downscaling GCM output of circulation patterns to rainfall. A hard clustering-based analogue method for short-term weather forecasting may be found in Gutiérrezet et al. (2004). A review of different models used to simulate the effects of climate change on water resources is presented by Leavesley (1994).

In the past, very few scientific works relating to climate change by General Circulation Model (GCM) have been carried out in South Asian region. Therefore, in present research an attempt has been made for climate change scenario generation by using general circulation model and statistical downscaling technique. This study will be focused to generate the future climatic scenario in Gujarat. Application of statistical downscaling technique on GCM output for future climatic scenario generation is at beginning stage. Summing up, this kind of research has been initiated to fill up the gap existing in between large scale (GCM level) and local scale (basin level) variables.

It is a fact that research on climate change is one of the highly useful methodologies to understand the reality of the climatic condition whether it is at global level or local level. The predicted future climatic condition will be greatly useful to improve the matters related on planning, decision making systems etc. scientifically.

Statement of the Problem

The climate of earth has never been stable for any extended period but varying naturally on all time scales. Climate change has greatly affected the characteristics of climatic variables globally. These changes are not uniform but vary from place to place or region to region. Probable climate change and its perilous impacts on the hydrologic system pose a threat to global fresh water resources and aquatic ecosystems worldwide. These problems are happening in the basin scale because of lack of proper water resources management practices. therefore,analysis of spatiotemporal variability of rainfall and modelling the hydrology of the watersheds is necessary for effective water resource management strategy.

Hydrological modelling is the standard tool for investigating hydrological processes of river catchments, helps in flood forecasting, proper water resource management and evaluation of water quality, erosion and sedimentation, nutrient and pesticide circulation, land use and climate change etc. and have helped better appreciable understanding of hydrological problems and their possible solution. The present study is envisaged in this context to take up the study on the assessment of hydrological changes in different watersheds in India under changing environment. In the present study, Parametric and non-parametric approach has been used to understand the trend rainfall and temperature time series for the selected river basins, Standard Precipitation Index (SPI) for characterization of the drought event occurred in the area and the Soil and Water Assessment Tool (SWAT) and Nedbor-Afstromings (NAM) models to understand the hydrological process, in order to plan, develop and manage the water resource accordingly.

The present study is envisaged in this context to take up the study on the assessment of hydrological changes in four different watersheds located in different climatic regions in India under changing environment.

Objective of the Study

In the present study, SWAT and MIKE11 NAM models have been used for rainfall-runoff modelling in Bina basin. Further, the different analysis was taken place such as the investigation of precipitation trend and drought characterization, the objectives of the present research work are.

- Development of database related to hydro-meteorological data.
- Long-term spatio-temporal analysis of hydro-meteorological variables.
- Assessment of variation in surface water and groundwater availability.
- Drought characterization.
- Climate change impact on streamflow
- Inter-comparison of water resources variability in selected basins and suggestions for IWRM.

Chapter 2
LITERATURE REVIEW

Climate change refers to a statistically significant variation in either the mean state of the climate or in other statistics (such as standard deviations, the occurrence of extremes, etc.), persisting for an extended period particularly decades or longer. It is likely to affect the hydrology of river basin, especially those in Himalayan regions by intensifying the global hydrological cycle and have major impact on the streamflow of snow-fed rivers by influencing the snow/ice and glacier melt in the upstream part of the basins. It is therefore; essential to study the effects of climate change on streamflow and related variables of such river basins (both in space and time) to plan and manage the water resources effectively. This chapter deals with the review of literature on major fields related to this study namely trend and variability of long-term meteorological variables, drought characterization, hydrological modelling and climate change and statistical downscaling.

Trend Analysis

Many studies have tried to define the trend in precipitation on both country and regional scales. Most of these deal with the analysis of annual and seasonal series of rainfall for some individual stations or groups of stations.

Parthasarathy and Dhar. (1974**)** revealed that the annual rainfall for the period 1901–1960 had a positive trend over Central India and the adjoining parts of the peninsula, and a decreasing trend in some parts of eastern India.

Kripalani *et al*. (2003) examined the inter-annual and decadal variability in summer monsoon rainfall over India by using observed data for a 131-year period (1971–2001). They found random fluctuations in annual rainfall and distinct alternate epochs (lasting approximately three decades) of above- and below-normal rainfall for decadal rainfall. They also concluded that this inter-annual and decadal variability appears to have no relationship to global warming.

Jayawardene H.K. *et al*. (2005) in their study, an analysis was carried out to extract the trends of rainfall depth in Sri Lanka over the last century.

Goswami *et al*. (2006) used daily rainfall data to show the significant rising trends in the frequency and magnitude of extreme rain events, and a significant decreasing trend in the frequency of moderate events over central India during the monsoon seasons from 1951 to 2000.

Dash *et al*. (2007) investigated the trend of rainfall data for the period 1871–2002 indicated a decreasing trend in monsoon rainfall and an increasing trend in the pre-monsoon and post-monsoon seasons.

Ramesh and Goswami. (2007) analysed daily gridded observed rainfall data for the period 1951–2003 and found decreasing trends in both early and late monsoon rainfall and a number of rainy days over India.

Wing H Cheung *et al*. (2008) studied and investigated the temporal dynamics of rainfall and its spatial distribution within Ethiopia. Changes in rainfall were examined using data from 134 stations in 13 watersheds between 1960 and 2002. The variability and trends in seasonal and annual rainfall were analysed at the watershed scale. Similar analyses were also performed at the gauge, regional, and national levels. The gauge level analysis showed that certain gauge stations experienced recent changes in rainfall; these trends are not necessarily reflected at the watershed or regional levels.

Kumar *et al*. (2010) Trend analysis of rainfall data of 135 years (1871– 2005) indicated no significant trend for annual, seasonal and monthly rainfall on an all-India basis. Annual and monsoon rainfall decreased, and pre-monsoon, post monsoon, and winter rainfall increased over the years, with a maximum increase in the pre-monsoon season. Monsoon months of June, July and September witnessed decreasing rainfall, whereas August showed increasing trend on an all-India basis.

P. A. AZEEZ et al (2010) examines the general pattern of precipitation in the Palakkad fields (South India) utilizing month to month precipitation information gathered from four rain gage stations accessible in the zone. As the years continue, the yearly precipitation example of the considerable number of stations demonstrated a pattern of huge decline.

Arun Rana et al (2011) examines precipitation slants in Delhi and Mumbai and decided long haul inclines in Rainfall by Man-Kendall rank insights and direct relapse. Facilitate this review researches precipitation patterns amid storm period by various worldwide atmosphere wonders and utilized Principal part investigation and Singular esteem deterioration to discover connection between southwest rainstorm precipitation and worldwide climatic marvels using climatic indices.

Telemu Kassile et al (2013) inspects the development of precipitation and finds out whether the watched time incline in precipitation is critical in measurable terms. He utilized Linear relapse examination through OLS estimation and the Kruskal-Wallis and Mann-Kendall's tau test.

Rathore *et al*. (2013) investigated trends in seasonal and annual rainfall in all states of India and conclude that, State averaged annual rainfall trends have increased over Andhra Pradesh, Bihar, Gujarat, Haryana, Jammu and Kashmir, Jharkhand, Lakshadweep, Manipur, Meghalaya, Mizoram, Orissa, Rajasthan, Tamil Nadu, Tripura and West Bengal during 1951-2010. However, annual rainfall has decreased over Andaman and Nicobar, Arunachal Pradesh, Assam, Chhattisgarh, Delhi, Goa, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Nagaland, Punjab, Sikkim and Uttar PradeshA.C. Narayana et al (2014) gives an evaluation of environmental change inconstancy in light of examination of recorded information of precipitation and temperatures at Warangal region, Andhra Pradesh for the time of 1960-2012. Long haul changes in precipitation controlled by Man-Kendall, Sen's incline and relapse analysis.

Zaheed Hasan et al (2014) inspects fleeting changeability of precipitation for the area of south-east shoreline of Bangladesh over the time of 1949-2011 and utilized Mann-Kendall test and the Sen's incline estimators to distinguish precipitation slants and to comprehend extent of changes.

Adarsh et al (2014) concentrated long haul patterns of precipitation utilizing straight relapse, nonparametric Mann–Kendall (MK) test, Sen's incline estimator strategies and the successive MK (SQMK) strategy. At that point the pattern investigation in view of discrete wavelet change (DWT) in conjunction with SQMK technique is performed on the post-rainstorm precipitation time series of Kerala.

Chithra N R & Santosh G Thampi (2015) attempted to measurably identify climatic change motions in the month to month precipitation information of the Chaliyar stream bowl, Kerala, India and assesses the variables adding to it. He downscaled Precipitation information from the General Circulation Models factually to stream bowl scale utilizing ANN based models and recognized potential indicators by connection coefficient analysis.

Water resources systems are designed and operated on the basis of assumption of stationary hydrology, if these assumptions are erroneous then existing procedures for design needs to be amended. The changes in temperature, precipitation, and other climatic variables are likely to influence the amount and distribution of runoff in all river systems globally. The detection of trends in hydro-climatic data, particularly temperature, precipitation, and streamflow is essential for assessment of impacts of climatic variability and its change on the water resources of a region. Trend analysis may thus focus on the overall pattern of change over time, help temporal and spatial comparisons for deriving future projections. Estimates of temperature anomaly were better estimated using long-term series data. Several statistical methods apply parametric and non-parametric approach for the detection of trends. Mainly four stages are involved in the trend analysis; collection and preparation of suitable database, exploratory analysis of data, application of statistical tests, and interpretation of results.

Himalayan region aptly called the water tower of Asia is greatly to be affected due to change in climatic conditions and impact the streamflow of snow-fed rivers originating from the region. The Himalayan region, including the Tibetan Plateau, has shown consistent trends in overall warming during the past 100 years. Various studies suggest that warming in the Himalayas has been much greater than the global average of 0.74°C over the last 100 years (IPCC, 2007). Long-term trends in the maximum, minimum and mean temperatures over the north western Himalaya during the 20th century (Bhutiyani et al., 2007) suggest a significant rise in air temperature in the north western Himalaya, with winter warming occurring at a faster rate. Global warming has resulted in large-scale retreat of glaciers throughout the world. This has led to most glaciers in the mountainous regions such as the Himalayas to recede during the last century and influence runoff of Himalayan rivers. The climatic change/variability in recent decades has made considerable impacts on the glacier life cycle in the Himalayan region. Several studies have been carried out to investigate the changes in temperature and rainfall series and its association with climate change. Some of the important studies carried out for the Himalayas are reviewed and discussed here in brief.

Mirza et al. (1998) analyzed the trends and persistence in precipitation in the Ganges, the Brahmaputra and the Meghna river basins. Time series of annual precipitation of 16 meteorological sub-divisions covering these basins were examined for trends using Mann-Kendall rank statistic, student's t-Test and regression analysis, and first order autocorrelation analysis was used for persistence. The results indicated that precipitation was by-and-large stable in Ganga basin while sub-divisions of both Brahmaputra and Meghna basin had either increasing or decreasing trend. It was also concluded that persistence was not present in precipitation series of Ganga basin but existed in 2 common sub-divisions in Brahmaputra and Meghna basin.

Shrestha et al. (1999) analyzed the maximum temperature data of 49 stations in Nepal for the period (1971-1994). The results indicated warming trends after year 1977 ranging from 0.06 to 0.120C/year in most of the Middle mountain and the Himalayan regions whereas the Siwalik and Terai, southern plains regions showed warming trends less than 0.030C/year. It was observed from the distribution of seasonal and annual temperature trends that high rates of warming existed in regions at higher elevations (Middle Mountains and the Himalaya), whereas low warming or even cooling trends found in the southern region.

Fu et al. (2004) applied the Kendall's test to examine the hydro-climatic trends in the Yellow river watershed during the last half century. It was observed that watershed had become warmer with more significant rise in minimum temperature than maximum and mean temperatures. The change in precipitation trend was not found significant and the basin runoff depicted falling trend. These results were attributed mainly to the human activities, global warming, and changes in landuse/landcover along with other constraints such as accuracy in estimation of natural runoff, snowmelt, water transfer, groundwater exploitation and precipitation characteristics. The homogeneity analysis showed that precipitation, maximum and minimum temperature were all heterogeneous and the trends varied both monthly and regionally.

Bhutiyani et al. (2007) carried out a study to examine the trends in long-term instrumental air temperature data across the north western Himalayas during the last century. The study reported significant increase in air temperature by about 1.60C with winters warming at a faster in the twentieth century in the study region. It was concluded that the increasing significant trends in the diurnal temperature attributed to rise in both maximum and minimum temperatures, with maximum temperature increasing much more rapidly.

Dimri and Ganju (2007) simulated the winter time temperature and precipitation over the western Himalaya and found that temperature is underestimated and precipitation is overestimated in Himalaya. The changing trends of temperature and precipitation over the western Himalaya were examined and it was found that there was trend of increasing temperature and decreasing precipitation at some specific locations.

Basistha et al. (2007) assessed the spatial pattern trends of rainfall over Indian subdivisions. The decreasing trends of rainfall over North India excluding Punjab, Haryana, West Rajasthan and Saurashtra, and increased in the south India excluding Kerala and Madhya Maharashtra.

Cheung et al. (2008) reported studies on annual and seasonal rainfall at various spatial (gauge, watershed and national) and temporal scale to detect the trend and spatial distribution of rainfall in Ethiopia. The result showed no significant change in the annual rainfall at watershed scale and national level While, seasonal rainfall in some watershed shows decreasing trends and other did not show any significant change. There is need to analyze the other parameters also within the political and natural boundaries of countries/provinces/districts to clearly understand the effects of scale on climate change assessment.

Basistha et al. (2009) carried out a study to investigate changes in the rainfall pattern during twentieth century in the Indian Himalayas. The statistical tests were applied to detect trend and possible shift in rainfall using 80 years of data from 30 stations. The study suggested that 1964 was found to be the most probable year of change in monsoon and annual rainfall in the region. It was concluded that there was an increasing trend upto 1964 after which trend decreased during 1965-1980 for this region and changes were most explicit over the shivaliks and southern part of Lesser Himalayas.

Rai et al. (2010) used statistical test to investigate the persistence, trend and periodicity in hydro-climatic variables in Yamuna river basin. The results indicated significant difference in the patterns of monsoon and non-monsoon rainfall in terms of persistence and periodicity and about 20% of rainfall time series indicated the presence of persistence. The study concluded that overall declining trend was examined in the annual and monsoon rainfall, annual and monsoon rainy days and aridity index along with a rising trend in onset of effective monsoon.

Kumar et al. (2010) analyzed rainfall and rainy days' time series at five stations i.e Srinagar, Kulgam, Handwara, Quazigund and Kukarnag in Kashmir valley to decipher rainfall trends at seasonal and annual time scale. It was revealed that the during the year 1903-1982, annual rainfall showed decreasing trend at three stations (Srinagar, Kulgam, Handwara) and all three stations showed a decreasing trend in monsoon and winter and increasing trend in pre-monsoon and post-monsoon rainfall. It was also seen that all the stations experienced a decreasing trend in monsoon and winter rainy days. Other two stations experienced decreasing trend in annual rainfall during the period 1962-2002.

Xu et al. (2010) applied Mann–Kendall (non-parametric) test to detect the trends in main hydro-climatic variables in the Tarim River basin, China for a period of 1960-2007. The results indicated that both mean annual air temperature and precipitation experienced rising trend. The annual streamflow showed a mixed trend of increasing and decreasing. Moreover, it was found that the mountain region upstream illustrated a rising trend while region downstream showed a falling trend.

Khattak et al. (2011) examined trends in various hydro-meteorological variables based on nonparametric tests in the upper Indus river basin (UIRB) in Pakistan. The results indicated increased trend in winter maximum temperature for the upper, middle and lower region with the slopes of 1.79, 1.66 and 1.20 0C per 39 year, respectively. It was concluded that increased winter temperatures would possibly increase streamflow during winter and spring whereas flow will decrease during summer months.

Jain et al. (2012b) analyzed the trends in rainfall and temperature data series in northeast India for the period (1871-2008) at monthly, seasonal and annual time scale. It was examined that rainfall series at regional scale had no clear trend, although trends for some seasonal and hydro-meteorological sub-divisions existed. The temperature variables namely maximum, minimum and mean temperatures showed increasing trend and Sen’s estimator of slope for the minimum, maximum and mean temperature was found to be 0.011(°C/year), 0.019(°C/year), and 0.015(°C/year) respectively.

Choudhury et al. (2012) analyzed the long term data (1983-2010) to detect trend in the weather variables using non-parametric tests in Umiam located at mid altitude in Meghalaya. The results of the study indicated that there was non-significant increasing trend (3.72 mm/yr) in the total annual rainfall and maximum temperature depicted a linear increasing trend (0.086 0C/year) whereas minimum temperature showed non-significant decreasing trend (-0.0110C/year). A significant increasing trend (0.0310C/year) was also observed in the mean temperature over the period.

Mishra et al. (2013) identified trends in climatic variables using non-parametric methods in the Kaligandaki river basin located in Nepal Himalaya. It was revealed from the spatial distribution of temperature trend that there were greater warming trends at higher altitudes. The increasing trends in temperature (approx. by 0.03 to 0.080C/year) were found in different seasons whereas seasonal precipitation showed mixed trends in the study basin. It was seen that with the increasing trends in winter and spring temperature and decreasing trends in precipitation, a clear significant negative trend in SCA was identified during these seasons. The results indicated potential effect of global warming on the climatic variables, precipitation and snow cover area in higher mountainous region.

Kattel and Yao (2013) carried out a study to examine the recent trends at 13 mountain stations on the southern slope of the central Himalayas. The analysis was carried for temperature variables namely annual maximum, minimum and average temperature for a period of three decade (1980 to 2009) for the stations located between elevation range of 1304 and 2566 m amsl. From the spatial analysis of average temperature, it was found that most of the stations showed warming trends. It was observed that maximum temperatures had higher warming magnitude while the minimum temperatures showed larger variability. The temporal variations indicated a dramatic increase in temperature during the latest decade, especially in the average and maximum temperatures.

Sonali and Kumar (2013) observed that among the different influential atmospheric variables, temperature has a significant and direct effect upon nearly all hydrologic variables. A small shift in climatic pattern owing to escalating air temperature and changing precipitation is likely to affect mountainous river networks.

Standard precipitation Index (SPI)

A number of studies have been reported on the analysis of time series of rainfall data for characterizing drought events in terms of periodicity and magnitude.

Guttman (1997) compared spectral characteristics of the PMDI, which is used for real-time monitoring, to those of the SPI for time scales ranging from one month to three years. He recommended that the SPI be used as the primary drought index because it is simple, spatially invariant in its interpretation, and probabilistic so that it can be used in risk and decision analysis. It also can be tailored to time periods of concern to a user. He noted that in contrast, the modified PDSI is very complex, spatial and temporal comparisons made by users of the palmer values may, therefore, be misleading and lead to erroneous conclusions.

Guttman (1999) concluded that the Pearson type III, with parameters estimated using the method of L-moments, seemed as the more appropriate choice to describe dry and wet events.

Szalai *et al*. (2000) examined how strong the connection of SPI is with hydrological features, such as stream flow and groundwater level at stations in Hungary. Correlation of SPI with stream flow was the highest on a 2-month timescale while for groundwater levels the best correlations were found at widely different time scales. They also concluded that agricultural drought (proxied by soil moisture content) was replicated best by SPI on a scale of 2–3 months.

Lana *et al*. (2001) used the SPI to analyze spatial and temporal behaviors of rainfall shortage and excess for Catalonia, Spain.

Lloyd-Hughes *et al*. (2002) found that the 2-parameters gamma distribution seems to be the most appropriate approach to describe monthly precipitation over Europe and to calculate the SPI index. They have also compared for both the SPI and the PDSI and conclude that SPI provided a more appropriate spatial standardization than the PDSI.

Wu *et al*. (2005) indicated that the differences among the SPI values computed using different lengths of records were not considerable if the precipitation pattern is stable. In another effort, they claim that the SPI users should be careful when adapting short time scale SPI values in arid locations and they should concentrate on the duration of the drought rather than on its severity (2007).

Loukas *et al*. (2007), as well as Vasiliades *et al*. (2007), have used SPI as a forecasting tool for climate change impacts on droughts.

Livada *et al*. (2007) used monthly precipitation data from 23 stations to assess drought for Greece. Mishra and Singh (2010) pointed out that the greatest strength of the SPI is its ability to be used on multiple time scales. This ability makes the SPI useful in monitoring drought according to multiple definitions.

Chortaria *et al*. (2010) developed the SPI using 41 stations all over Greece for a time period from 1989 to 1994 and concluded that it described very closely the 1989–1990 severe drought.

Withey and Cornelis van Kooten (2011) studied the effect of climate change on optimal wetlands and waterfowl management in Western Canada. They relied on the Standardized Precipitation Index (SPI), which is a popular drought index based solely on precipitation.

Hydrological Modelling

So many researchers have successfully applied MIKE 11-NAM and Arc SWAT models to model the rainfall-runoff characteristics of various catchments such as

Dendrou (1982) identifies calibration, validation, and verification as the three crucial steps for the proper application of a model. Calibration is the process of modifying model parameters to reduce the error between the simulated stream flow and some portion of the observed flow record. Model validation tests the ability of the model to estimate runoff for periods outside that used to calibrate the model.

Sorooshian (1983) identifies two major purposes of calibration: 1) "to obtain a conceptually realistic and unique parameter set which closely reflects our understanding of the physical system", and 2) "to obtain an (any) parameter set which gives the best possible fit between the model-simulated and observed hydrographs."

Spruill *et al*. (2000) evaluated the SWAT model and parameter sensitivities were determined while modelling the daily stream flow in a small central Kentucky watershed comprising an area of 5.5 km^2 over a two year period. Stream flow data from 1996 were used to calibrate the model and stream flow data from 1995 were used for evaluation. The model accurately predicted the trends in daily stream flow during this period.

Francos *et al.* (2001) applied the SWAT model to the Kerava watershed (South of Finland), covering an area of 400 km^2. The temporal series comprised temperature and precipitation records for a number of meteorological stations, water flows and nitrogen and phosphorus loads at the river outlets. The model was adapted to the specific conditions of the catchment by adding a weather generator and a snowmelt sub model calibrated for Finland. Calibration was made against water flows, nitrate, and total phosphorus concentrations at the basin outlet. Simulations were carried out and simulated results were compared with daily measured series and monthly averages. In order to measure the accuracy obtained, Nash and Sutcliffe efficiency coefficient were employed which indicated a good agreement between measured and predicted values.

Tripathi *et al.* (2003) had applied the SWAT model for the Nagwan watershed with the objective of identifying and prioritizing critical sub-watersheds to develop an effective management plan.

Chekol *et al*. (2007) studied the efficiency of SWAT model in Upper Awash River watershed for the evaluation of water resources. The results indicated that SWAT model is a suitable tool for water resource analysis and planning such as simulating runoff and sediment yield. The model evaluated was based on Nash-Sutcliffe model efficiency; the values of efficiency were relatively high for both daily, weekly, and monthly discharges and monthly sediment yield.

Setegn *et al* (2008) developed a hydrological model for Lake Tana basin. SWAT 2005 model were used to examine the effect of land use, soil, topography and climatic condition on stream flow. Soil evaporation compensation factor ESCO and SCS curve number II were found to be the most sensitive parameters for the sub-basins. The results revealed successful application of SWAT 2005 model to Lake Tana sub-basins for the study of hydrological water balance.

Jain, *et al*. (2010) simulated the runoff and sediment load yield for part of the Satluj River extended from Suni to Kasol in Western Himalaya based on SWAT model. The model was calibrated and validated based on observed runoff and sediment load yields. They considered the values the have got rationally satisfactory for estimating runoff and sediment yield based on remote watershed and limited data.

Ahmed (2010) developed the hydrological model system of lower Rideau River sub-watershed, Ontario, Canada having 34 basins using MIKE 11 hydrological model system. The auto-calibration process was used to calibrate the model parameters for five years of stream flow data and performance of the model have been validated for the data of another five years. Furthermore, Ahmed (2010) successfully calibrated and validated for the six regional models of Rideau Valley watershed (4257 km2), Ontario, Canada and reported the satisfactory results with the comparison of published literature.

Lelis and Calijuri (2010) applied the SWAT model on Sao Partolimeu watershed in southeastern Brazil to recognize the sites of more affected by erosion for that soil type and land use.

Rahman *et al*. (2012) developed flood forecasting system for large Jamuneswari River basin, Bangladesh using MIKE 11 rainfall-runoff (NAM model).

Singh and Imtiyaz (2012) used SWAT, watershed scale model, to predict the monthly stream flow of the Nagwa watershed in eastern India. The model was calibrated and validated based on measured stream flow and quantification of the uncertainty in SWAT model output was assessed using a sequential uncertainty fitting algorithm (SUFI-2).

Mohammad *et al*. (2012) applied the SWAT model to estimate the surface runoff and sediment yield from the three main valleys on the right bank of Mosul Dam Reservoir for the period 1988-2008.

Milad *et al*. (2012) used the SWAT model with an integrated approach of curve number accounting procedure and plant evapotranspiration method (plant ET method) to simulate runoff in the Roodan watershed (10,570 km2) of Iran which had low storage soils.

Yan *et al*. (2013) used the SWAT model to assess the impact of land use change on watershed stream flow and sediment yield for the Upper Du watershed in China. The results indicated that changes in grassland did not show a significant influence on either stream flow or sediment yield.

Dendrou (2013) identified calibration, validation, and verification as the three crucial steps for the proper application of a model. Calibration is the process of modifying model parameters to reduce the error between the simulated stream flow and some portion of the observed flow record. Model validation tests the ability of the model to estimate runoff for periods outside that used to calibrate the model.

Zhou et al. (2015) analyzed the effects of the large-scale land use conversion to switchgrass as a bioenergy feedstock on water quality and economic feasibility in Oostanaula Creek watershed in East Tennessee. The soil and water assessment tool (SWAT) model was first used to simulate nutrient loadings of current land use in the watershed. Statistical criteria such as Nash-Suttcliffe efficiency (E) and R2 were calculated for model calibration and validation. The calibrated SWAT model was then used to simulate the effect of the land use conversion from the entire current crop and pasture/hay lands to switchgrass production. They found that the conversion reduces average annual watershed loadings of sediment, nitrate (NO3), total nitrogen (TN), and total phosphorous (TP) by an estimated 77%, 62%, 34%, and 46% respectively.

Perez-Valdivia et al. (2017) used SWAT model in the Prairie Pothole Region of North America to calibrate and validate daily and monthly time steps for the 1997–2009 period and assessed the impact of wetland drainage using three hypothetical scenarios that drained 15, 30, and 50% of the non-contributing drainage area. Results of these simulations suggested that drainage increased spring peak flows by about 50, 79 and 113%, respectively while annual flow volumes increased by about 43, 68, and 98% in each scenario. Years that were wetter than normal presented increased peak flows and annual flow volumes below the average of the simulated period. Alternatively, summer peak flows presented smaller increases in terms of percentages during the simulated period.

Statistical Downscaling

Tisseuil et al. (2010) tried to relate large-scale climate information from a general circulation model (GCM) to local-scale river flows in SW France for 51 gauging stations ranging from nival (snow-dominated) to pluvial (rainfall-dominated) river-systems and to select the appropriate statistical method at a given spatial and temporal scale to downscale hydrology for future climate change impact assessment of hydrological resources. The four statistical models used are generalized linear (GLM) and additive (GAM) models, aggregated boosted trees (ABT) and multi-layer perceptron neural networks (ANN). They showed the performance of each statistical method for downscaling flow at different spatial and temporal scales as well as the relationship between atmospheric processes and flow variability.

Wu et al. (2012) used an analog statistical-downscaling algorithm, k-nearest neighbors (KNN) to bridge the gap between the coarse forecasts from global models and the needed fine-scale information for the Southeastern Mediterranean and demonstrated its robustness by validating with NCEP/DOE reanalysis from 1981 to 2009 as hind casts before applied to downscale CFS forecasts. The downscaled predictions showed fine-scale information, such as station-to-station variability. This KNN method was found to be better than CFS model.

Chen et al. (2012) rigorously evaluated and compared the difference in water balance simulations resulted from using different downscaling techniques, GCMs and hydrological models is performed in upper Hanjiang basin in China. They concluded that NSC and RSR between simulated and observed rainfall can be used as key statistics to evaluate the statistical downscaling models.

Tareghian and Rasmussen (2013) downscaled precipitation employed quantile regression rather than traditional linear regression models to determine the conditional distribution for a given day. It was found that proposed method has distinct advantages over the conventional regression model for predicting summer precipitation, while for winter precipitation there is not much difference between the two methods.

Fu et al. (2013) compared three methods of applying statistical downscaling to catchment rainfall and evaluating their hydrological response with a hydrological model: (a) statistically downscaling to sites and then interpolating to gridded rainfall which is accumulated to catchment average rainfall; (b) statistically downscaling to catchment average rainfall directly; and (c) statistical downscaling to grid cells and then accumulating to catchment average rainfall. It was found that all three methods of application performed similarly for a range of rainfall characteristics, with directly downscaled catchment average rainfall producing a relatively better result for extreme daily rainfall indices. However, hydrological simulation indicated that the direct downscaling of catchment average rainfall did not have any advantages over the other two downscaling application methods in terms of the runoff statistics evaluated.

Shashikanth et al. (2014) applied a linear regression based statistical downscaling method for obtaining monthly Indian Summer Monsoon Rainfall (ISMR) projections at multiple spatial resolutions, viz., 0.05°, 0.25° and 0.50°, and compared them. The results showed that the changes in the mean for future time periods (2020s, 2050s, and 2080s) at different resolutions, viz., 0.05°, 0.25° and 0.5°, obtained with both Multi-Model Average (MMA) and Bayesian Multi-Model Average (BMA) are comparable. They highlighted that, a mere increase in resolution by a way of computationally more expensive statistical downscaling does not necessarily contribute towards improving the signal strength.

Laflamme et al., (2015) performed a statistical downscaling at 58 locations throughout New England, by applying a CDF transformation function to local-level daily precipitation extremes (from NCDC station data) and corresponding NARCCAP regional climate model (RCM) output to derive local-scale projections. They showed that very few New England locations with significant increases in 25-year return levels from the historical to projected periods.

Piras et al. (2016) used climate and hydrologic simulations produced within the Climate Induced Changes on the Hydrology of Mediterranean Basins to analyze how precipitation extremes propagate into discharge extremes in the Rio Mannu basin (472.5 km2), located in Sardinia, Italy. The basin hydrologic response to climate forcings in a reference (1971–2000) and a future (2041–2070) period was simulated through the combined use of a set of global and regional climate models, statistical downscaling techniques, and a process based distributed hydrologic model. They showed rainfall statistical downscaling algorithms produce more reliable forcings for hydrological models than coarse climate model outputs.

Hanel et al. (2017) used R package (musica package) to validate simulated runoff for the period 1970-1999 at the Cucice basin (861 km2) in the Czech Republic and shown that using conventional methods for downscaling of precipitation and temperature often leads to substantial biases in simulated runoff at all-time scales.

Chapter 3

METHOD AND MATERIAL

Four different watersheds located in different climatic regions namely Dhadhar river basin (Gujarat), Ramganga up to Kalagarh (Uttarakhand), Bina River basin (M.P) and Chaliyar river basin (Kerala) have been selected for the present study. The location map of study area is shown in Figure 3.1.

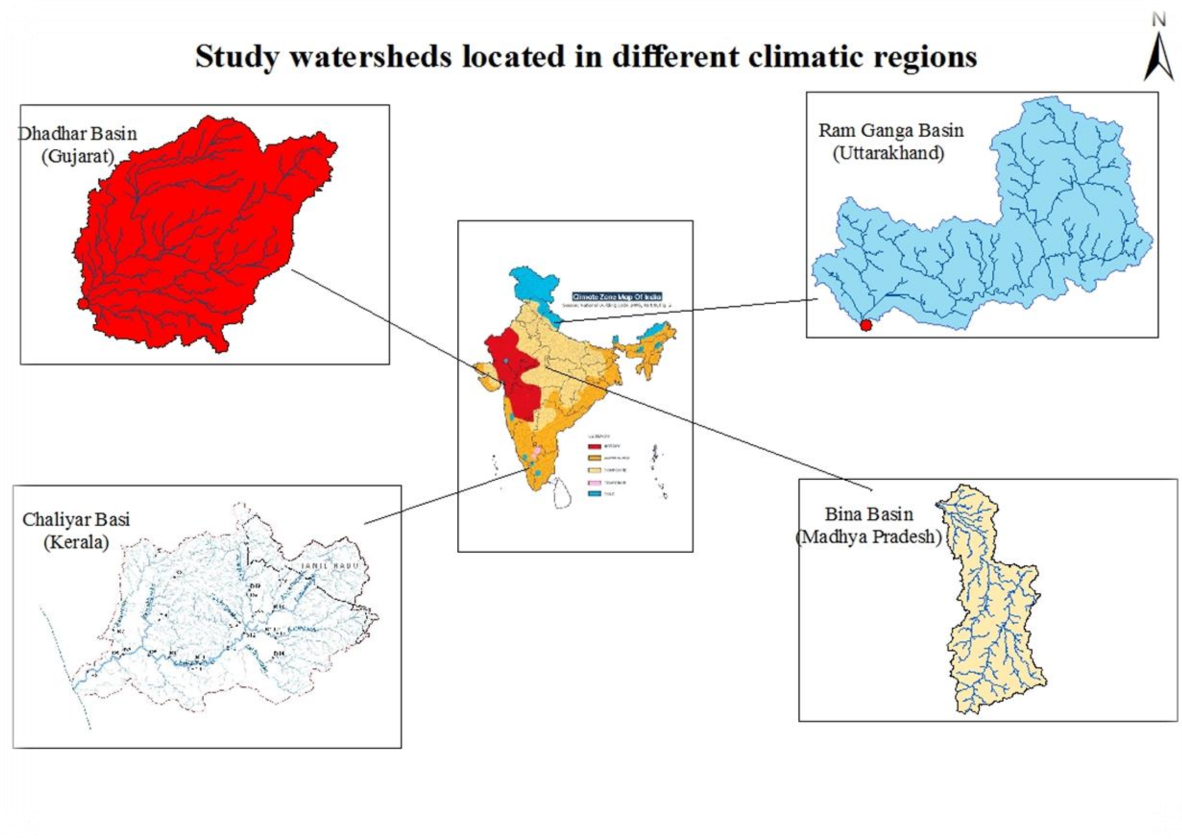


Figure 3.1: Location map of study area

Bina Basin

The selected study area, shown in Fig.3.1, is the river basin in Bina Province. Bina River is an important tributary of Betwa river of Madhya Pradesh, which originates from Begumganj block of Raisen district and enters Sagar district at Rahatgarh block and traverse through Khurai and Bina tehsil before the confluence with river Betwa near Basoda town in Vidisha district. Presently, domestic water supplies to Rahatgarh, Khurai and Bina town; railways requirement at Bina

Railway Junction and industrial supplies for Bina Refinery and proposed JP power project is met from this river beside limited irrigation from the river by direct pumping.

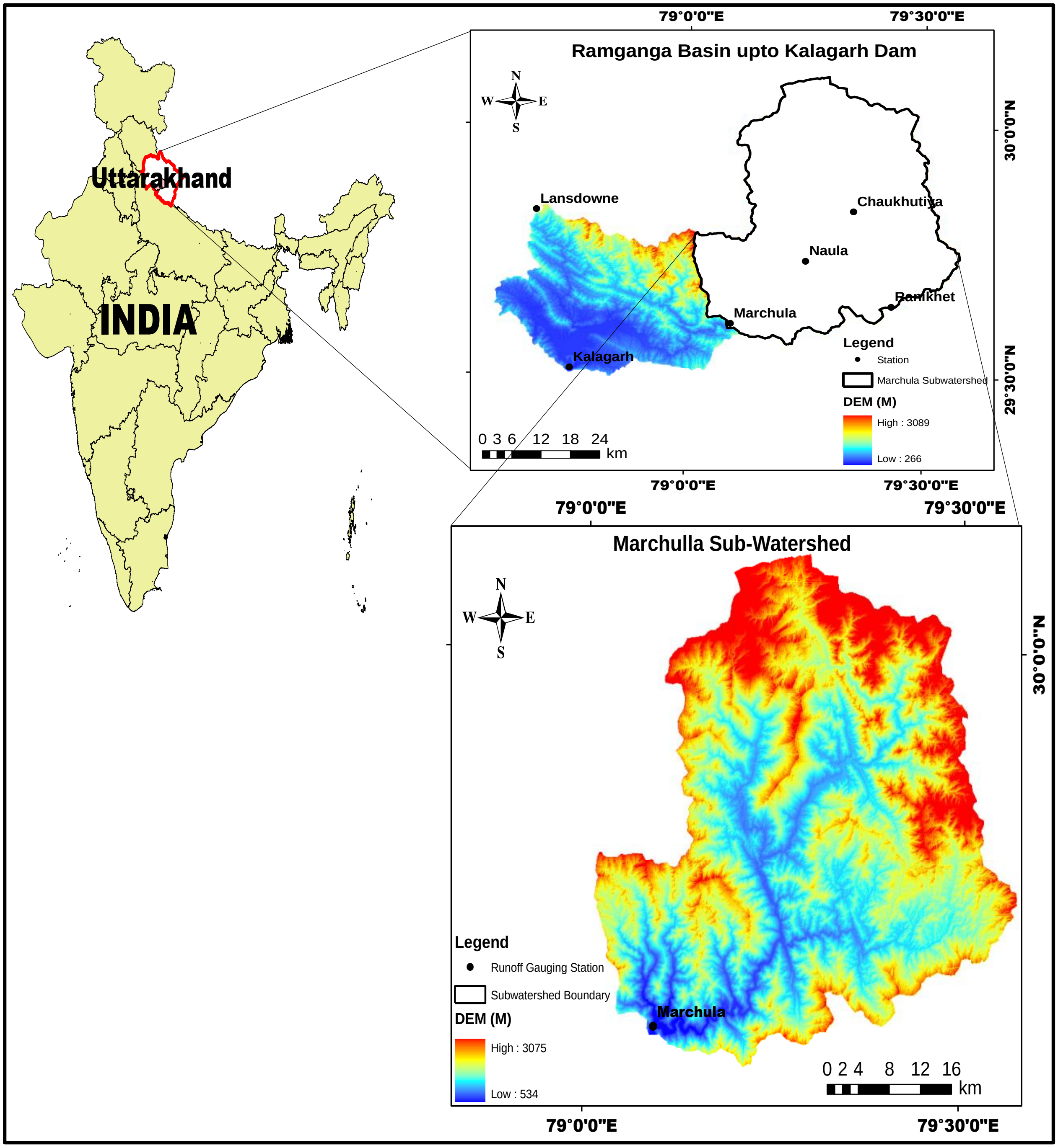


Figure 3.2: Location map of Ramganga basin

Bina basin falls between 23^0 3’ to 24^0 3’ N latitudes and 78^0 1’ to 78^0 6’ E longitudes having a total geographical area of 2822 sq.km. The catchment area highly adulated and covered by forests, barren lands and localized rain-fed agriculture. The drainage density is more in the upper catchment as compared to the lower part of the basin river basin, the later mostly gentle sloping to plain topography mostly covered with agricultural fields, the streams are dry after the monsoon months (June, July, August, and September).

Climate

Since Bina basin falls within three districts of Madhya Pradesh state namely Sagar, Raisen, and Vidisha. The climate of the basin is influenced by the climatic contribution of these three districts and accordingly the climate of this basin can be classified into four seasons. Summer season which starts from March and end in May. The monsoon season starts from June and ends in September and Post monsoon season laps from October to November. Winter season occurs in December and ends February. The average annual rainfall of the basin is 1236 mm and about 94.91% of the average annual rainfall takes place during the southwest monsoon period i.e. June to September. Nearly about 1.62% of average annual rainfall takes place during winter and only 0.81% of rainfall occurs during the summer months and 2.63% of rainfall is contributed by Post-monsoon season. During the winter season, the January is the coldest month with the temperature falling as low as 11.6^{o} C and max up to 24.5^{o}C. During the month of May, temperature goes up to 40.7^{0}C.

Physiography

The study area falls under Bundelkhand plateau as per broad physiographical classification. The topography of the area is rolling to undulating. The land slope is characterized by flat-topped hillocks. This topography is a result of the variation in hardness of different types of water flows. The valley land is moderate to poorly drain. The uplands having dendrite drainage pattern have limited natural drains and very low drainage density. The district has fairly extensive network of rivers which are mostly seasonal. Bundelkhand region has a network of rivers like Dhasan, Bebas, Bina, Bamner, and Sonar etc.

Soil and crop

The major types of soils of the region are black, alluvial and red soils. Black soil is popularly called black cotton soil because of its chemical association and suitability for cotton. This clayey soil has a distinct chemical composition and very high moisture retentive capacity. On getting wet the soil becomes extremely sticky and expands greatly due to high absorption of water, on drying up the soil contracts again and develops cracks on the surface. However, it has very high fertility status. The main crop grown in Kharif season are a Soybean, Urad and paddy and the main crop is grown during Rabi season are wheat, red gram. Other staple crops like linseed, chickpeas, sorghum, oilseeds and grown are also grown in the study area.

Location, extent and accessibility

Ramganga river is one of the major tributaries joining the Ganga river in the Ganga plains. The Ramganga river emerges from Dudhotoli range in Gairsain village of the Chamoli district, Uttarakhand and runs through the part of Central Himalayas and the Ganga Flood Plains before merging to the Ganga River. Ramganga basin is surrounded by ridges (water divide) like Chorara Khal Dhar (2363m amsl), Diwali Khal (2442 m amsl), Inora Khal (2557 m amsl) and Khankra Khet Ki Dhar (2784 m amsl) in the north, the water divide of Pindar and Ramganga rivers. Musa Ka Kotha (3119m amsl), Dudhatoli Dhar (3098 m amsl) and Malkhori Dhar (2488 m amsl) in the west, the water divide of Nayar and Ramganga river, Dhang ki Dhar (2591m amsl) and Agarni Dhar (2250 m amsl) in the east, and by the water divide of Kosi and Ramganga river, Chatkora Ka Tibba (1921m amsl) and Dhaniya Dhar (1951m amsl) in the south. After covering a length of 158 km from its starting point, the river emerges out from the mountains at Kalagarh into the Ganga Flood Plains, where the Ramganga dam (Kalagarh) was constructed at an elevation of 365 m (msl).

The main attractive feature of this river is its flowing patterns, in upstream its covers the Kumaon Himalayas including Jim Corbett National Park in Uttarakhand while in downstream of its course it flows through the highly industrialized district of Uttar Pradesh. The catchment is characterized by steep hills, deep and narrow valleys (CWC, 2012).

Index maps

The study area split into two parts as shown in Fig. 3.3 for modeling consider only 2036.09 km^2 and for trend analysis consider the whole area and covering major area of Almora, Garhwal, Cahmoli and Nainital districts and is a part of the Ramganga river basin of Uttarakhand of India. The present study is confined to $29^0 30'$ to 30^0 05’ N latitude and $78^0 36'$ to $79^0 34'$E longitude covering an area of 3183.20 km^2 from Chorara Khal Dhar and Dudhotoli Dhar near Gairsain village close to the origin of Ramganga river to Kalagarh (280 m amsl) where the river enters the plains.

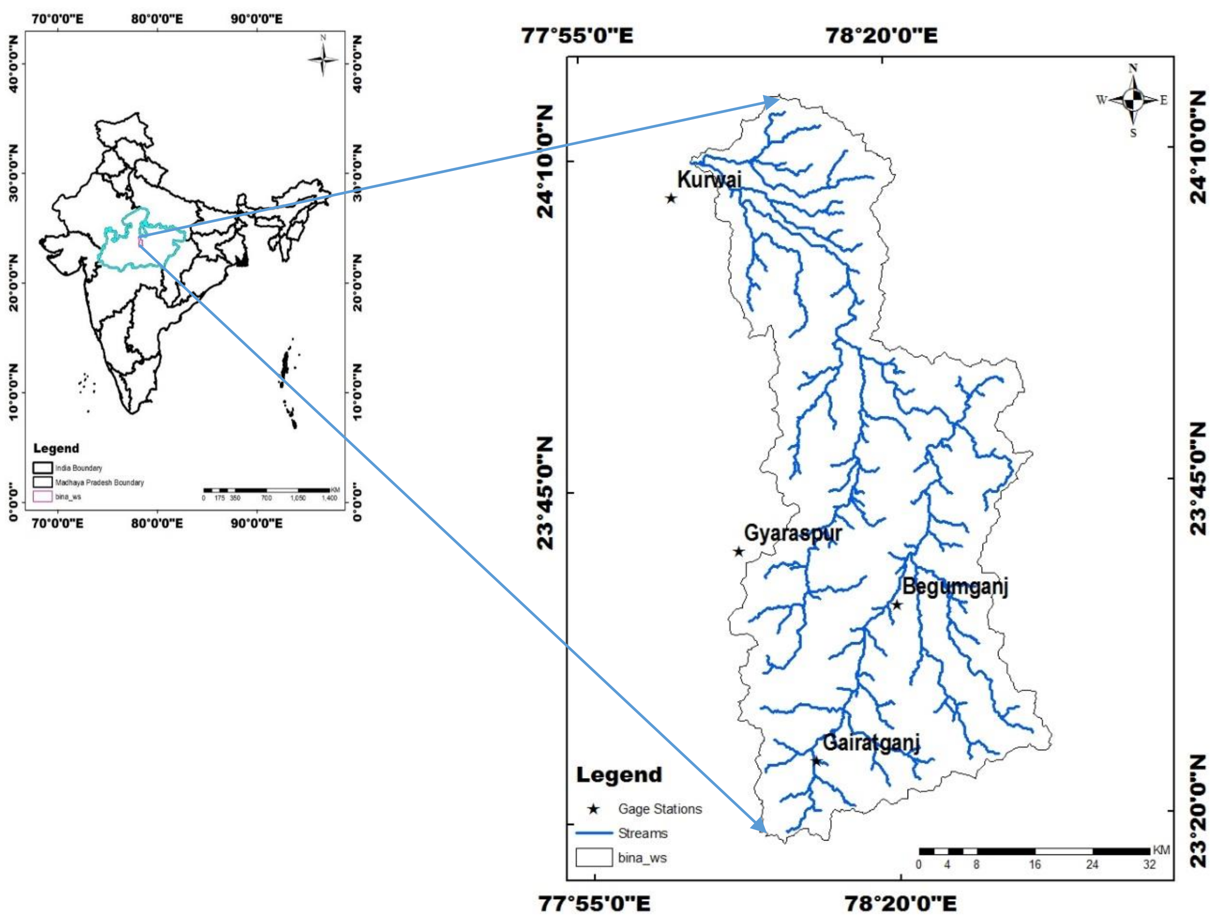


Figure 3.3: Location of Bina Basin

Climate

The climate varies from Sub-tropical monsoon type (mild winter, hot summer) to tropical upland type (mild winter, dry winter, short warm summer), the climate is sub-arctic type as the area is represented by lofty Himalayan Range. Severe winter and comparatively higher rainfall are the characteristic features of the area.The area studied witnesses three distinct seasons viz. winter, summer and rainy. Rainy season commences during the month of June and ends by September month. The temperature start rising from beginning of December and peak is reached in the month of May. The winter season commences with November following a brief spell of autumn beginning in mid-October when temperature drops drastically.

Rainfall

The whole catchment receives water mainly from a single climatic system, i.e. southwest (SW) or summer monsoon with little bit of snow fall during winter at higher reaches of mountain slope especially up to Kalimat and Gairsain areas of Ramganga basin.Monsoon currents can penetrate through trenched valleys, the rainfall reaches its maximal in the monsoon season that spans between June to September. March to May and October to November consider as pre monsoon and post monsoon respectively. Rainfall, spatially, is highly variable depending upon the altitude. In high altitude areas (1000-3000 m) maximum rainfall occurs about 70 to 80%, August is the rainiest month. Rainfall rapidly decreases after September and it is the least in November. About 17% of the annual precipitation occurs in winter season. The area receives about 1000 m. average rainfall annually (CWC 2012).

Six rain gauge station comes in study area namely Kalagarh, Marchulla, Naula, Ranikhet and Lansdowne (Fig. 3.4).

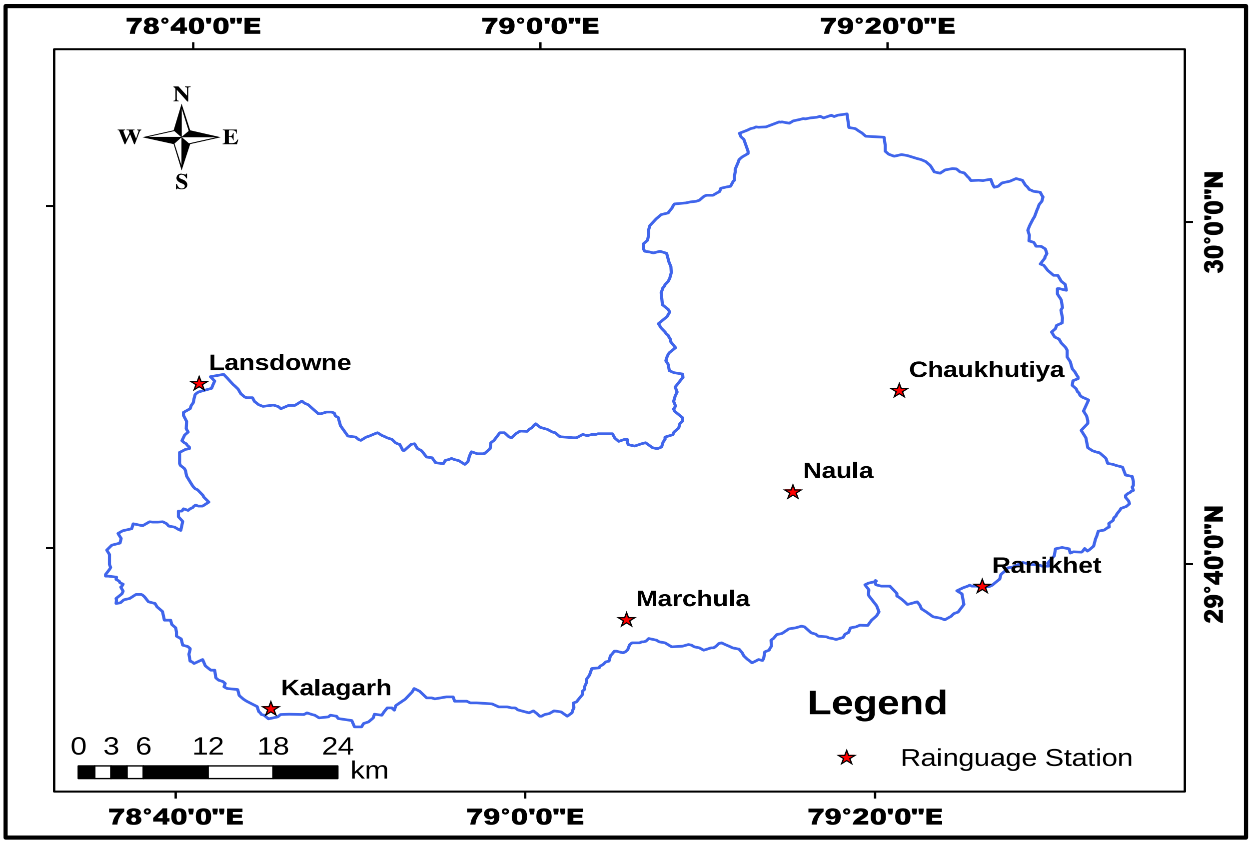


Fig. 3.4: Distribution of rain gauge station

Physiography and relief

The Ramganga basin lying entirely within the sub Himalaya and Lesser Himalaya, exhibits high differences in altitude with very narrow valleys, deep gorges having very high gradient. It has average elevation of 1677.5 m above mean sea level (amsl) and highest elevation of 3089 m amsl. The catchment is characterized by steep hills, deep and narrow valleys (CWC 2012). The slope generally varies from below 10% to above 40%.

The amount and direction of slope governs the runoff process. The slope amount was calculated from Digital elevation model (DEM). They were grouped into five classes- i.e. 0-5%, 5-15%, 15-45%, 45-70% and > 70% and shown in Fig. 3.3.

Soil texture

The soils are natural, dynamic, heterogeneous, non- renewable resource, which support plant and animal life. The spatial distribution of soil types depends on its physiography and Lithology. The tract of study area consists of outward succession of ridges viz, Greater Himalaya and Lesser Himalaya of decreasing height. These hills posse very little level land. The soils have developed from rocks like granite, schist, gneiss, phyllites, shales, slate etc. under cool and moist climate. Very steep to steep hills and Glacio-fluvial valleys are dominantly occupied with very shallow to moderately shallow excessively drained, sandy-skeletal to loamy-skeletal, neutral to slightly acidic with low available water capacity soils. They have been classified as Lithic or Typic Udorthents, Typic Ustipsamments and Dystric Eutrochrepts. These soils are in general under sparse vegetation. The Lesser Himalayan range is mainly composed of highly compressed and altered rocks like granite, phyllites, quartzite *etc*. and a major part of it is under forest. Intermittent sparse patchy terraced cultivation is also practiced on fairly steep hill slopes whereas dry and wet cultivation are prevalent on the uplands and low-lying valleys respectively. The broader valley slopes dominantly have deep, well drained, fine-loamy, moderately acidic and slightly stony.

Dhadhar Basin

The Dhadhar river is one of the west flowing rivers in Gujarat State. It originates from the Pavagadh Hills of Gujarat State and flows through Vadodara and Bharuch districts. The river Dhadhar after flowing 87 km receives Vishwamitri tributary from right bank at Pingalwada village 500m upstream of Gauge and Discharge site. After flowing another 55 km. It falls into the Gulf of Khambhat. The total length of the river from its source to an outfall in the Gulf of Khambhat is about 142 km. The important tributaries of the Dhadhar river are Vishwamitri, Jambu river, Dev and Surya river. The catchment area of the Dhadhar basin is 3423 Sq.km and catchment area up to the site is 2400 Sq.km. It lies between east longitude 72030’ and 73045’ and North latitude 210 45’ and 22° 45’.

Climate

Dhadhar basin experiences four major seasons – pre-monsoon (Mar-May), monsoon (June-Sep), post-monsoon (Oct-Nov) and winter (Dec-Feb). The major part of basin comprises tropical wet climate, caused mainly due to the existence of the Western Ghats. Due to a relatively high elevation in forest land, the area of the basin near the origin of the river experiences relatively cooler climate. The basin receives most of the rainfall from the south-west monsoon from June to September. The average annual rainfall in the Dhadhar basin is 900.1 mm. The rainfall is mainly influenced by the southwest monsoon. The monthly average wind speed in the Dhadhar basin varies about 1.7 km/h and 6.8 km/h. in the pre and post-monsoon periods respectively. The relative humidity in Dhadhar basin varies between 90.1 % to 66.8 % depending upon the season. The total population of the basin is about 11.23 lakh.

Chaliyar Basin

Chaliyar river basin in Kerala, India, situated between 110 30'N and 110 10'N latitudes and 750 50'E and 760 30'E longitudes falling in Survey of India (SOI) degree sheets 58A and 49M. Chaliyar River shapes the fourth biggest waterway in Kerala, starts from the Elambalari slopes, Nilgiri District of Tamil Nadu, at a height of around 2066m above mean ocean level (MSL). Chaliyar is an enduring stream and streams along the northern limit of Malappuram locale through Nilambur, Mambad, Edavanna, Areakode and Feroke and the waterway joins the Lakshadweep Sea south of Kozhikode close Beypore in the wake of streaming over a separation of around 169 kms in the name "Beypore" River. By taking kuniyal gage station as an outlate point add up to waste region of chaliayr waterway is 2013 km2. Six noteworthy streams Chaliyarpuzha, Punnapuzha, Kanjirapuzha, Karimpuzha, Iruvahnipuzha and Cherupuzha constitute the Chaliyar River seepage framework. Appropriately regular grouping of watershed Mar-May considered as a Premonsoon , June-Sep as a South west storm, Oct-Nov as a North east rainstorm and Dec-Jan considered as a Winter period by negligible darkness and precipitation (Ananthakrishnan et al. 1979)

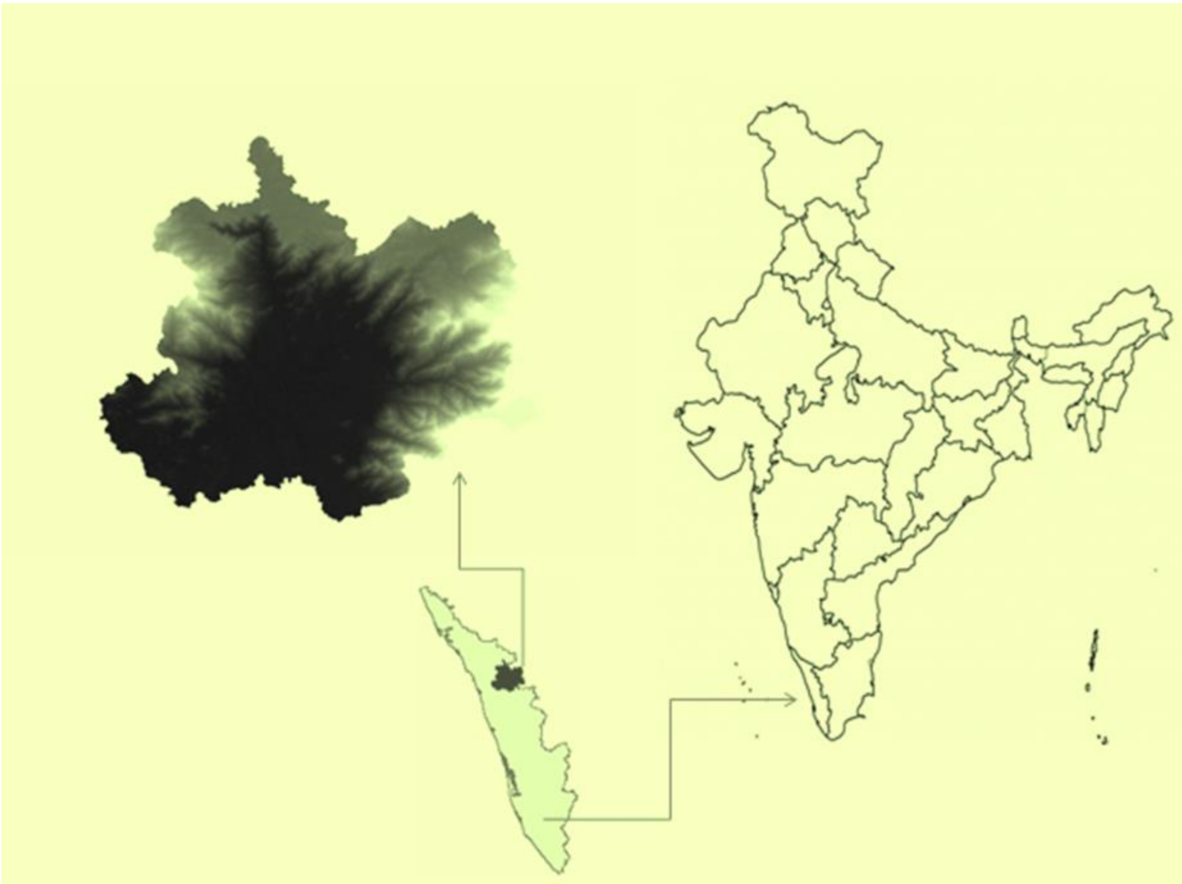


Figure: 3.5 Chaliyar River drainage

Climate

Kerala lies closer to the equator Compared to other Indian states, Yet Kerala is bestowed with a pleasant and equable climate through out the year Generally March and April are the hottest and December and January are the coolest. The maximum temperature ranges from 22ºC to 32.9ºC and the minimum temperature ranges from 22ºC to 25.8ºC. The average annual maximum temperature is 30.9ºC and minimum is 23.7ºC. The temperature begins ascending from January achieving the crest in April. It diminishes amid the rainstorm months. On a normal around 3000 mm of precipitation happens every year in the bowl. The main stormy seasons are the southwest (June-September) and upper east (October-November) rainstorm in India. The pre-storm months (March-

May) are portrayed by significant electrical storm action and the winter months (December-February) by insignificant darkness and precipitation (Ananthakrishnan et al. 1979). Sahyadri (Western Ghats) impacts the force and dispersion of precipitation over Peninsular India. As a mountain obstruction, the Sahyadri energizes precipitation along its peak. As soggy wind current amid the southwest rainstorm rises, the windward slant gets plentiful precipitation (Anu and Mohankumar, 2004). Accordingly, the Sahyadri shapes the watershed for a substantial number of waterways. These streams have high keep running off and dregs stack amid the rainstorm months. Southwestern India encounters a tropical atmosphere with regularly switching wind examples and huge varieties in precipitation. Along the west shore of India, the southwest (SW) monsoonal winds of maritime root are set up by mid-May. Amid the SW rainstorm, winds blow from southwest amid May-September, however alter to a north easterly course amid the upper east (NE) storm. These winds keep on growing solid until June, when there is a sudden blasted or fortifying of the southwest winds. The winds are the most grounded amid July and August, however end up noticeably feeble in September, in front of the NE rainstorm, which endures through October and November. The wind speed is by and large 15-20 km/hr amid the SW rainstorm, yet lower (10-12 km/hr) amid the NE storm. Summer (southwest) rainstorm (June-September) represents a noteworthy piece of the normal yearly precipitation (> 300 cm), while the winter storm (October-January) represents around 50-60 cm precipitation. Temperature in the area extends in the vicinity of 23° and 37°C (Narayana, 2006). The winds are the most grounded amid July and August, yet end up plainly feeble in September, in front of the NE rainstorm, which keeps going through October and November. The wind speed is for the most part 15-20 km/hr amid the SW rainstorm, yet lower (10-12 km/hr) amid the NE storm. Summer (southwest) rainstorm (June-September) represents a noteworthy piece of the normal yearly precipitation (> 300 cm), while the winter storm (October-January) represents around 50-60 cm precipitation. Temperature in the district goes in the vicinity of 23° and 37°C. Waterways in hilly territories usually convey higher silt loads and yields than do upland streams, whose heaps and yields thus, are higher than those of swamp streams. A superior relationship was reported between the yearly fluctuation of precipitation and silt transport. The positive relationship among precipitation, keep running off and dregs release recommends that precipitation and keep running off apply a first request control on the silt release of Kerala Rivers (Narayana, 2007). Tectonic uplift/subsidence alters the fluvial regime with resultant changes in rates of sediment erosion and deposition.

Physiography

The Chaliyar stream bowl can be physiographically isolated into four very much characterized units viz., good country, midland, swamp and seaside fields. In view of the help design and topographic arrangement, the bowl can be separated into five physiographic sub-units. (i) High ranges with a height extending from 600m to 2600m. This frame some portion of the Wayanad level and the high slope ranges with soak slants of the Western Ghats, (ii) Foot slopes of Western Ghat with height going from 300 to 600 m above MSL include rough hills and slant territories of the high slopes, (iii) Upland areas comprising of the edges and valleys, confined slopes with elevations going from 100-300 m. At spots these units are lateritic, (iv) Mid-arrive zone with height extending from 10 to 100 m described by moving geography with lateritic edges, disconnected slopes and alluvial valleys, and (v) Low-arrive portrayed by beach front extends and alluvial fields with an elevation of < 10 m.

Bina Basin Data Used

Hydrological Data

The daily discharge data of Bina river basin, observed at Bina station has been used for stream flow modelling using NAM and SWAT model. This observed daily discharge data was also collected from state data center, Bhopal. The details of hydro- metrological stations and available data are given in Table 3.1.

Table 3.1: Details of hydro- metrological stations and available data

Id	Stations	Lat dms	Long dms	Altitude	Rainfall	Discharge	Max and Min.Temp	Solar Radiation	Humidity	Wind Speed
1	Begumganj	23.60	78.34	505	1986-2008	-	-	-	-	-
2	Gairatganj	23.41	78.22	522	1986-2008	-	-	-	-	-
3	Gyaraspur	23.67	78.12	452	1986-2008	-	-	-	-	-
4	Kurwai	24.12	78.12	396	1986-2008	-	-	-	-	-
5	Sagar	23.83	78.75	525	-	-	1972-2003	1972-2003	1972-2003	1972-2003
6	Bina	24.18	78.20	417	-	1984-2014	-	-	-	-

Land use Land cover and Soil Map

The Landsat 8 ETM+ with a 30m resolution for Path/Row: 145/043 and 145/044 with the date of pass 6 march 2015 downloaded from earthexplorer.usgs.gov site. Landsat 8 ETM+ satellite images with optical bands with standard false color combination were used to prepare the land use land cover map of the basin, for which subsequent ground truth verification was carried out by carrying out extensive field visits. For the land use land cover, supervised classification using maximum likelihood classifier is applied.

Soil top sheets with sheet number of 1, 2, 4 and 5 prepared by the national bureau of soil survey and Land use planning (ICAR) on a scale of 1:250,000 and printed on a scale of 1:500,000 were used to prepare soil map of the watershed.

3.2.4. Aster Global Digital Elevation Model (ASTER GDEM)

Digital elevation model was downloaded from earthexplorer.usgs.gov site and used to delineate the watershed and to analyse the drainage patterns of the land surface terrain.

Ram Ganga basin-Data used

The hydro-meteorological data of temperature, rainfall and discharge used in the study have been collected from the office of Ram Ganga Dam Circle, Kalagarh, Govt. of Uttar Pradesh. The daily maximum and minimum temperature data series (2002-2015) for one stations namely Kalagarh was collected. The daily rainfall data series (1974-2014) of six stations Kalagarh, Marchulla, Naula, Chaukhutiya, Ranikhet and Lansdowne and the daily discharge data series for one station Marchulla were collected. The general details of hydro-meteorological stations is given in Table 3.1.

Table 3.2: Details of the meteorological stations located in the study area

S. No	Station	Latitude	Longitude	Altitude (m)
1	Kalagarh	78°45'24''E	29°31'7''N	278.6
2	Marchulla	79°5'37''E	29°36'20''N	564.8
3	Naula	79°14'47''E	29°44'7''N	903.7
4	Chaukutiya	79°20'55''E	29°50'10''N	1632.2
5	Ranikhet	79°25'50''E	29°38'44''N	1788.0
6	Lansdowne	78°40'36''E	29°49'57''N	1060.7

3.3.2 Data processing

The collected time series for the temperature, rainfall and streamflow was compiled and processed for the seasonal and annual analyses for the given period. The available daily maximum and minimum temperature data series has been used to compute the monthly time series of different variables; maximum (T_{max}), minimum (T_{min}) average (T_{avg}), for Kalagarh meteorological station. The monthly rainfall data series (1974-2014) of six stations namely Kalagarh, Marchulla, Naula, Chaukhutiya, Ranikhet and Lansdowne were used to form seasonal and annual series. Likewise, the monthly total time series was computed for the one stream flow station. For investigation of changes in hydro-climatic variables at different time scales, a year was divided into four principal seasons:

1. Pre-monsoon season prevailing from March to May
2. Monsoon season prevailing from June to September
3. Post-monsoon season prevailing from October to November
4. Winter season prevailing from December to February

The monthly data of temperature, rainfall and stream flow were further used to compute the annual and seasonal time series, which were in turn used for the investigation of trend on seasonal and annual time scale.

Methodology

Precipitation Trend Analysis

Precipitation, unlike stream flow, is little affected by works of man, precipitation records are invaluable in hydrologic studies involving trends. Factors such as location and exposure affect the consistency with which a rain gauge samples the rainfall in a particular area. The consistency is often affected when a gauge is moved to the yard of a new observer. Even at the same location, the exposure of a precipitation gauge can gradually change through the years, because of the growth of trees and other vegetation in the neighborhood or because of new buildings. Such changes sometimes go undistinguished in the station history. For example, moving a gauge from one part of a roof to another can affect the catch of the gauge greatly, even though the gauge is moved only a few feet. Also, construction of tall buildings in the vicinity of the gauge changes wind direction and affects thermal air currents, thus influencing the catch in the rain gage. If the changes detected are not due to meteorological causes, a precipitation record can usually be adjusted by coefficients determined from the double-mass curve.

When the double-mass curve of precipitation data from a particular station indicates a break in slope and the reason for the break is determined, the record for one set of conditions may be adjusted to what it would have been if it had been collected under the other set of conditions. The period of record to be adjusted depends on upon the use that is to be made of the records.

The theory of the double-mass curve suggests the method of adjusting an inconsistent record.

$$P_a = \frac{b_a}{b_o} * P_o \qquad (3.1)$$

Where,

Pa = adjusted precipitation

P0 =observed precipitation

ba = slope of graph to which records are adjusted

bo =slope of the graph at time P0 was observed

All precipitation records were used in this study, were tested by the double-mass curve technique to ensure that any trends detected are due to meteorological causes and not to changes in gauge location, in exposure, or in observational methods.

Trend analysis of a time series consists of the magnitude of trend and its statistical significance. In general, the magnitude of a trend in a time series is determined either using regression analysis (parametric test) or using Sen's estimator method (non-parametric method) (Sen, 1968). Both these methods assume a linear trend in the time series.

Parametric test (Regression analysis)

Regression analysis is conducted with time as the independent variable and rainfall as the dependent variable. The regression analysis can be carried out directly on the time series or on the anomalies (i.e. deviation from mean).

In this study, anomalies (deviation from mean) was used to determine the regression analysis. A linear equation, $y = mt + c$, defined by c (the intercept) and trend m (the slope), can be fitted by regression. The linear trend value represented by the slope of the simple least-square regression line provided the rate of rise/fall in the variable.

Non- parametric test (Mann-Kendall and Sen's Slope)

The most frequently used non-parametric test for identifying trends in hydrologic variables is the Mann-Kendall (MK) test. The non-parametric Mann-Kendall test is commonly employed to detect monotonic trends in series of environmental data, climate data or hydrological data. Non- parametric statistics are usually much less affected by the presence of outliers and other forms of non- normality (Lanzante 1996), and represent a measure of monotonic linear dependence (Davis 1986; Rossi et al.1992). The statistical significance trend detected using a non-parametric model such as Mann-Kendal (MK) test can be complemented with Sen's slope estimation to determine the magnitude of the trend.

The Mann-Kendall test is a statistical test widely used for the analysis of the trend in climatologic (Mavromatis and Stathis, 2011) and in hydrologic time series (Yue and Wang, 2004). There are two advantages of using this test. First, it is a non-parametric test and does not require the data to be normally distributed. Second, the test has low sensitivity to abrupt breaks due to inhomogeneous time series (Tabari *et al*, 2011).

The null hypothesis, H_0, is that the data come from a population with independent realizations and are identically distributed. The test returns the so-called H value, which is either 0, indicating that the null hypothesis is correct and no trend is detected, or 1, indicating the detection of a trend.

For a random variable $X(x_1, x_2... x_n)$, the Mann–Kendall test can be expressed as (Mann 1945; Kendall 1976):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(xj - xi) \qquad (3.2)$$

Where, n is the sample size and

$$\mathrm{sgn} = \begin{cases} +1 \text{ if } (xj - xi) > 0 \\ 0 \text{ if } (xj - xi) = 0 \\ -1 \text{ if } (xj - xi) < 0 \end{cases} \qquad (3.3)$$

In the Mann–Kendall test, a large positive value of the so-called S statistics in Eq. 3.2 implies an increasing trend while a large negative S indicates a decreasing trend.

Following (Yue et al. 2002), the significance of the trend is obtained using the z test, where Z denotes the standardized Z test statistic (Yue *et al*. 2002), and σ is standard deviation that can be approximated as (Kendall 1976):

$$Z = \begin{cases} S-1/\ \sigma(S) & \text{if } S>0 \\ 0 & \text{if } S=0 \\ S+1/\ \sigma(S) & \text{if } S<0 \end{cases} \qquad (3.4)$$

The test statistic Zs has used a measure of the significance of the trend. In fact, this test statistic was used to test the null hypothesis, H0. If | Zs| is greater than Zα/2, where α represents the chosen significance level (Eg: 5% with $Z_{0.025} = 1.96$) then the null hypothesis is invalid implying that the trend is significant. (Motiee and Mc Bean, 2009).

$$\sigma(S) = \sqrt{n\,(n-1)\,(2n+5)/\ 18} \qquad (3.5)$$

Sen's Slope Estimator Test*:* The magnitude of the trend in the time series was determined using Sen's estimator. Here, the Slope (Ti) of all data pairs is computed as *(Sen, 1968)*

$$Ti = \frac{Xj-Xk}{j-k} \quad \text{for } i= 1, 2, 3.........................., N \qquad (3.6)$$

Where, X_j and X_k are considered as data values at time j and k (j>k) correspondingly. The median of these N values of Ti is represented as Sen's estimator of slope which is given as:

$$Q_i = \begin{cases} T_{N+1/2} & \text{N is Odd} \\ \frac{1}{2}(T_{N/2} + T_{N+2/2}) & \text{N is Even} \end{cases} \qquad (3.7)$$

The sen's estimator was computed as Q_{med}= T (N+1)/2 if N appears odd, and it is considered as $Q_{med} =[T_{N/2} + T_{(N+2)}]/2$ if N appears even. At the end, Q_{med} is computed by a two-sided test at 100 (1- α) % confidence intervals and then a true slope was obtained by the non-parametric test. A positive value of Q_i indicates an upward or increasing trend and a negative value of Q_i gives a downward or decreasing trend in the time series.

In this study, both trend analysis methods were used i.e. Parametric (Regression analysis) and Non-parametric (Mann-Kendall and Sen's Slope) and daily precipitation records of four rain gauge stations of Bina basin for the period ranging from 1986-2008 have been used for analysis of rainfall trend on the monthly, seasonal and annual timescale.

Drought Characterization

Drought indices are employed to characterize drought and its statistical properties. Drought analysis from a stochastic point of view provides information required for the subsequent risk analysis (probabilities of drought occurrence and drought impacts). Drought indices provide spatial and temporal representations of historical droughts and therefore place current conditions in historical perspective.

Standardized Precipitation Index (SPI) is a tool which was developed primarily for defining and monitoring drought. It allows determining the rarity of a drought at a given time scale (temporal resolution) of interest for any rainfall station with historic data. It can also be used to determine periods of anomalously wet events.

The SPI is the number of standard deviations that the observed value would deviate from the long-term mean, for a normally distributed random variable. Since precipitation is not normally distributed, a transformation is first applied so that the transformed precipitation values follow a normal distribution.

The Standardized Precipitation Index (SPI; McKee et al. 1993), which is one of the most commonly used and recommended drought indicators, is used to describe meteorological droughts (WMO 2009; WCRP 2010). Generally, the SPI is calculated for 3, 6, 12, 24, and 48-month time scales. The drought time scales used in SPI calculation reflects effects on five water usable sources namely; soil moisture, stream flow, groundwater, snowpack and water in reservoirs. Meteorological and Agricultural droughts, which have an impact on precipitation and soil moisture respectively, are usually linked to short-term time scales which are 3 and 6 months SPIs. The long term time scale which is 12-month SPI or more are associated with hydrological droughts which have an impact on stream flow and reservoir levels. The short term durations are important to agricultural interest while long terms are important to water supply management interest. Negative and positive values of SPI indicate dry and wet periods, respectively. SPI values between−1 (≈20thpercentile) and −2 (≈5th percentile) refer to moderate to severe droughts while SPI below −2 indicates extreme droughts (McKee et al.1993).

The SPI is based on the probability of precipitation for any time scale. The SPI (McKee et al, 1993) is a powerful, flexible index that is simple to calculate. The probability of observed precipitation is then transformed into an index. Many drought planners appreciate the SPI's versatility. It is also used by a variety of research institutions, universities, and National Meteorological and Hydrological Services across the world as part of drought monitoring and early warning efforts In fact; precipitation is the only required input parameter. In addition, it is just as effective in analysing wet periods/cycles as it is in analysing dry periods/cycles.

The SPI was designed to quantify the precipitation deficit for multiple timescales. These timescales reflect the impact of drought on the availability of the different water resources. The SPI calculation for any location is based on the long-term precipitation record for the desired period. This long-term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Edwards and McKee, 1997) Positive SPI values indicate greater than median precipitation and negative values indicate less than median precipitation. Because the SPI is normalized, wetter and drier climates can be represented in the same way; thus, wet periods can also be monitored using the SPI.

(McKee et al, 1993) used the classification system shown in the SPI value Table 3.2. To define drought intensities resulting from the SPI. They also defined the criteria for a drought event for any of the timescales. A drought event occurs any time the SPI is continuously negative and reaches an intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event, therefore, has a duration defined by its beginning and end, and intensity for each month that the event continues. The positive sum of the SPI for all the months within a drought event can be termed the drought's "magnitude".

Sl. No	SPI Range	Classification
1	2.0 and Above	Extremely wet
2	1.5 to 1.99	Very wet
3	1.0 to 1.49	Moderately wet
4	-.99 to .99	Near normal
5	-1.0 to -1.49	Moderately dry
6	-1.5 to -1.99	Severely dry
7	-2 and less	Extremely dry

Table 3.3: Standard Ranges of SPI values and their classification

SPI algorithm application

The SPI algorithm development and application was achieved by the following rationale. Based on (Guttman, 1999) for the calculation of the SPI, the first step is to find the probability density function which best describes the distribution of the precipitation data over the different time scales. This pattern is applied separately for each month. The appropriate distribution function was selected by using the L-moments ratios diagrams (Hosking and Wallis, 1997) Thus; the gamma probability density function with two parameters was applied. And the pertinent parameters were estimated using the maximum likelihood approach Variable time scales of 1, 3, 6, 12, 24 months can be selected for the estimation of the index, which represents arbitrary time scales for precipitation deficits in relation to SPI application premises. Each of the data sets is fitted to the gamma probability density function with shape parameter α and scale parameter β to define the relationship of probability to precipitation. With the equal-probability transformation, the gamma cumulative distribution function converges to the standardized normal cumulative distribution function with a mean of zero and standard deviation of unity. This standardization gives the advantage of having consistent values in space and time for the frequency of extremely dry and wet events.

The gamma distribution has been found to fit precipitation time series well by Thom (1958). The probability density function defined gamma distribution for x>0

$$G(x) = \frac{1}{\beta^{\alpha}\,\Gamma(\alpha)}\, x^{\alpha-1} e^{-x/\beta} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.8)$$

Where α is shape and β is scale parameter, x is precipitation and Γ (α) is gamma function and

$$A = \frac{1}{4A}\left(1+\sqrt{1+4A/3}\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.9)$$

$$\beta = \bar{x}/\alpha \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.10)$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.11)$$

n is the number of observation.

For the station in question, to find the cumulative probability of an observed precipitation event for the given month and time scale the resulting parameters are then used. x=0 is undefined in gamma function and precipitation may contain zeros. The cumulative probability H(x) is calculated by:

$$H(x) = q + (1-q)\,G(x) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.12)$$

Where q is probability of zero G(x) the cumulative probability of incomplete gamma function

In the present study monthly precipitation records of four rain gauge stations in Bina basin were used to estimate SPI values for 3-, 6-, 12-, and 24-month time scale. Average SPI for the Bina province has been calculated for each time scale.

Hydrological Modelling

Stream flow modelling using SWAT model

The eco-hydrological model SWAT (Soil and Water Assessment Tool, Arnold et al., 1998) is a useful tool for a wide range of scales and environmental conditions. To set up a SWAT model, spatially distributed data (GIS input) are needed, which includes Digital Elevation Model (DEM), soil data, land use land cover and weather data (precipitation, maximum and minimum temperature, humidity, solar radiation, wind speed). Therefore, it is purely based on the information retrieved from the data and do not include any prior knowledge about catchment behaviour and flow processes, hence the name black box.

Input data for the model

The input data needed by SWAT include the Digital Elevation Model (DEM), soil type, land use land cover, and stream network layers. Daily weather data (precipitation and minimum and maximum air temperature, relative humidity, average wind speed and solar radiation) were used for simulating the stream flow. River discharge was also used for model calibration and validation purposes.

Spatial data

The spatial dataset used for the stream flow modelling in SWAT model were the DEM, land use land cover, and soil type layers. In this study, 30m resolution DEM, which was downloaded from earthexplorer.usgs.gov, was used to delineate the basin and to analyse the drainage patterns of the land surface terrain. We have used a watershed mask that was superimposed on the DEM since the model uses only the masked area for stream delineation. The land use land cover spatial data were reclassified into SWAT land cover/crop types. A user lookup table was created that identifies the SWAT code for the different categories of soil and land use land cover on the map as per the required format. The soil map was linked with the user soil database.

Weather and hydrological data

Eight years daily data of precipitation, air temperature (maximum and minimum), relative humidity, average wind speed and solar radiation of Bina basin were used to predict the stream flow at the catchment outlet. The daily weather data and weather generator location (wgnloc) were prepared into a separate excel sheet and converted into dbf format using Microsoft access before imported into the model setup. Hydrological data for the period 1991 to 1993 were used for calibration, whereas the period 1993 to 1996 was used for validation.

Model setup

The Soil and Water Assessment Tool (Arc SWAT 2009.93.4) having an interface with Arc GIS 9.3 software was selected for hydrological modelling in Bina Basin. To set up a SWAT model run, the watershed has been delineated and the spatial arrangement of the basin elements (e.g. sub-basin, reach segments and point sources) has been defined. Spatial data sets (DEM, land use land cover map, and soil map) were projected to UTM 43 North and WGS84 datum and were resampled to 30*30 pixel size. The land use land cover map layer was reclassified into SWAT land cover/plant types.

Re-projection and conversion were done using Arc GIS 9.3 raster and vector standard world re-project tool. The most popular setup is the sub-basin configuration, where the basin is divided into sub-basin and further sub-divided into hydrologic response units (HRUs). The HRUs represent percentages of the sub-basin area (Gassman et al., 2007). Individual areas of similar soil, topography and land use are lumped together within a sub-catchment to form an HRU while in reality they are scattered throughout the subbasin. In the present study for HRU's definition 8 classes of soil and 8 classes of land use land cover categories, and multiple slope discretization with 3 slope classes were used.

Curve numbers in SWAT were determined from USDA National Engineering Handbook (USDA-SCS, 1972). The SCS CN is a function of the soil permeability, land use, and antecedent soil water conditions. The SCS curve number method is a rainfall-runoff model that was designed for computing excess rainfall (direct runoff). This method assumes an initial abstraction before ponding that is related to curve number. SCS defines three antecedent moisture conditions: I – dry (wilting point), II – average moisture and III – wet (field capacity).The curve number method in SWAT relates runoff to soil type, land use, and management. The SCS-CN method is based on the principle of the water balance and two fundamental assumptions (Mishra and Singh, 2002). The first assumption is that the ratio of direct runoff to potential maximum runoff is equal to the ratio of infiltration to potential maximum retention. The second assumption states that the initial abstraction is proportional to the potential maximum retention. The water balance equation and the two assumptions are expressed mathematically:

$$P = Ia + F + Q \quad (3.13)$$

$$Q / P - Ia = F/S \quad (3.14)$$

$$Ia = \lambda S \quad (3.15)$$

Where, P is the total precipitation (mm), Ia is the initial abstraction before runoff (mm), F is the cumulative infiltration after runoff begins (mm), Q is direct runoff (mm), S is the potential maximum retention (mm), and λ is the initial abstraction coefficient. The combination of Eq. (3.13) and (3.14) leads to the popular form of the original SCS-CN method:

$$Q = (P - Ia)^2 / P - Ia + S \text{ for } P > Ia \quad (3.16)$$

$$Q = 0, \qquad \text{for } P \leq Ia$$

$$S = 25400/CN - 254 \quad (3.17)$$

Where the CN is a dimensionless variable, ranging from $0 \leq CN \leq 100$ and it depends on land use, hydrological soil group, hydrologic conditions, and antecedent moisture conditions. The standard values for curve number can be adjusted for drier or wetter antecedent conditions using the following equations:

$$CN_1 = CN_2 - \frac{20 *(100 - CN_2)}{(100 - CN_2 + \exp[2.533 - 0.0636(100 - CN_2)])} \quad (3.18)$$

$$CN3 = CN2 + \exp[0.00673(100 - CN2)] \quad (3.19)$$

Where, CN1 = moisture condition I curve number,

CN_2 = moisture condition II curve number,

CN_3 = moisture condition II curve number.

SWAT uses typical curve numbers for various soils with moisture condition II and a set slope of 5 percent. To adjust the curve number to different slopes, an equation developed by William (1995) was used, as given by Equation: 3.20

$$CN2s = \frac{CN2 - CN3}{3} * [1 - 2 * \exp(-13.6 * slp)] + CN2 \qquad (3.20)$$

Where,

CN2s = moisture condition II curve number adjusted for the slope,

CN3 = moisture condition III curve number for default 5 percent slope,

CN2 = moisture condition II curve number for default 5 percent slope,

slp = average percent slope of the sub-watershed.

The subdivision of the watershed enables the model to reflect differences in evapotranspiration for various crops and soils. Runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed. This increases accuracy and gives a much better physical description of the water balance.

The hydrologic cycle as simulated by SWAT is based on the water balance equation:

$$SW_t = SW_o + (R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \ldots\ldots 3.21$$

Where, SWt is the final soil water content (mm), SWo is the initial soil water content (mm), t is time in days, R_{day} is amount of precipitation on day i (mm), Q_{surf} is the amount of surface runoff on day i (mm), E_a is the amount of evapotranspiration on day i (mm), w_{seep} is the amount of percolation and bypass exiting the soil profile bottom on day i (mm), Q_{gw} is the amount of return flow on day i (mm).

The simulation part of the Bina catchment was finalized using the Arc SWAT interface of with Arc GIS 9.3 software, whereas sensitivity analysis, model calibration and validation have been done using SWAT-CUP tool. 20 parameters were considered and tested for the model parameterization and sensitivity analysis. The model uncertainties have been tested and analysed using SUFI-2 uncertainty analysis procedures.

Model parameters

The parameters responsible for stream-flow assessment for the Bina catchment, viz. r_CN2.mgt (curve number), v__ALPHA_BF.gw (base flow alfa factor), v__GW_DELAY.gw (groundwater delay time),v__GWQMN.gw (threshold depth of water in shallow aquifer required for return flow), v__GW_REVAP.gw (groundwater 'revap' coefficient), v__ESCO.hru (soil evaporation compensation factor), v__CH_N2.rte (manning roughness for the main channel), v__CH_K2.rte (effective hydraulic conductivity in main conductivity), r__SOL_ AWC.sol (soil available water capacity), r__SOL_K.sol (soil hydraulic conductivity) v_RCHRG_DP.gw (Deep aquifer percolation fraction), r_SOL_BD.sol (Moist bulk density), r_SOL_Z.sol (Depth from the soil surface to bottom of the layer), r_SLSUBBSN.hru (Average slope length), r_OV_N.hru (Manning's "n" value for overland flow), CANMX.hru (Maximum canopy storage), v_EPCO.hru (Plant uptake compensation factor), v_SURLAG.bsn (Surface runoff lag time) have been considered for model parameterization and calibration and validation process.

Objective function

The goodness of fit and efficiency of the model have been tested using the five main objective functions i.e. P-factor, R-factor, bR^2, R^2 and Nash-Sutcliffe coefficient. Nash-Sutcliffe efficiency approach is the most frequently used method for hydrological applications. The goodness of fit can be quantified by the R^2 and/or Nash-Sutcliffe (NSE) coefficient between the observation and best simulation.

The Nash-Sutcliffe coefficient is given by

$$N_{SE} = 1 - \frac{\sum_{t=1}^{T} (Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T} (Q_o^t - \overline{Q}_o)^2} \qquad (3.22)$$

The coefficient of determination is given by

$$R^2 = \frac{\left(\sum_{t=1}^{T} (Q_m^t - \overline{Q}_m)(Q_o^t - \overline{Q}_o)^2 \right)}{\sum^{T}} \qquad (3.23)$$

$$\sum_{t=1} Q_m^t-\overline{Q}_m)^2 (Q_o^t-\overline{Q}_o)^2$$

Where, N_{SE} = Nash-Sutcliffe coefficient,

Q_o = Observed discharge,

Q_m = Simulated discharge,

$\overline{Q}_o$ = Mean observed discharge,

Q^t = Discharge at time t.

Sensitivity analysis

The global sensitivity of stream flow parameters has been calculated using Latin hypercube regression systems. The t-Stat and p-Value are two factors to evaluate sensitivity in SWAT-CUP. The t-Stat provides a measure of sensitivity as its absolute values goes larger while the p-Values determine the significance of the sensitivity magnitudes with close to zero value as more significant.

Model calibration and validation

Six years of stream flow data were used for calibration and validation. The data of periods 1991-1993 and1993-1996 were used for calibration and validation respectively.

Model evaluation criteria

A variety of verification criteria which could be used for the evaluation models were proposed by the World Meteorological Organization (WMO) and other investigators (Nash and Sutcliffe, 1970; Aitken, 1973).

For the present study, the following suitable indicators were chosen to check the predictive capability of SWAT model, Santhi *et al*. (2001) and Coffey *et al*. (2004) recommended the use of the coefficient of determination (R^2) together with the Nash-Sutcliffe model efficiency coefficient (NSE) (Nash and Sutcliffe, 1970) as a method to evaluate and analyze simulated daily and monthly data. The R^2 (Eq.3.23) value is a measure of the strength of the linear correlation between the predicted and observed values. The NSE value, which is a measure of the predictive power of the model, is defined by Eq.3.22. A value of 1 for NSE indicates a perfect match between simulated and observed data values. A value of 1 for the R^2 also indicates a perfect linear correlation between simulated and observed data values.

Percent bias (PBIAS) measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias. PBIAS is calculated using the following equation:

$$PBIAS = \left(\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim}) * (100)}{\sum_{i=1}^{n} (Y_i^{obs})} \right) \qquad (3.24)$$

Where PBIAS is the deviation of data being evaluated, expressed as a percentage; Y_i^{obs} is the observed value; Y_i^{sim} is the simulated value and Y^{mean} is the mean of observed values.

Stream flow modelling using MIKE 11-NAM model

Many hydrological deterministic models have been developed to simulate the rainfall-runoff process for river watersheds, but most have complicated structures and need various observed data for calibration. The MIKE11 NAM model has been widely used in many Asian countries not only because of it is simple structures but also because of it is fewer data requirements (Ngoc et al, 2011). However, this hydrological model still needs extensive time and effort to calibrate various model parameters.

MIKE 11-NAM model treats each sub-catchment as a unit. The MIKE11- NAM Model simulates the rainfall-runoff process in rural catchments and has 9 parameters: Umax, Lmax, CQOF, CQIF, TOF, TIF, CK1,2, TG, and CKBF (snow storage was not considered in this study).The various components of the rainfall runoff process represent the average values for the entire sub-catchment by continuously accounting for water contents in 4 different but mutually interrelated forms of storage namely snow, overland flow, interflow, and base flow as shown in Fig 3.3.It is also based on the linear reservoir.

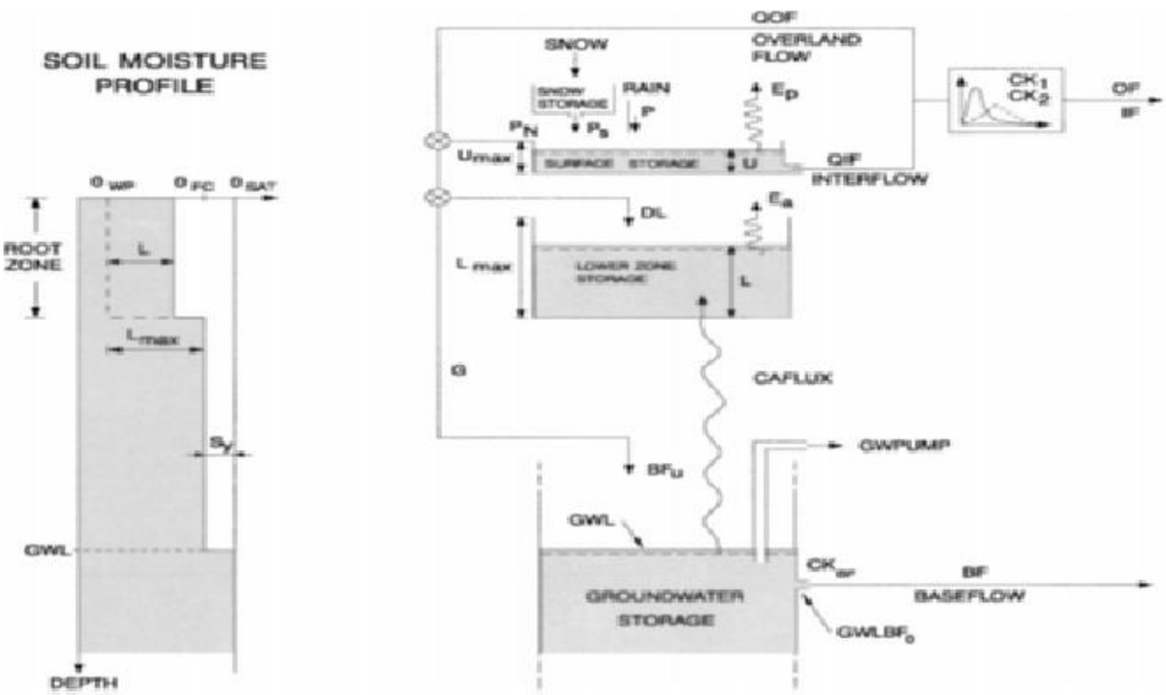


Figure 3.2: Structure of NAM model (Source: - DHI (2009) DHI MIKE 11 user manual)

Figure: 3.4 Structure of NAM model (Source: - DHI (2009) DHI MIKE 11-user manual)

Data requirements

The basic input requirements for the MIKE11-NAM model consist of model parameters are initial conditions, meteorological and hydrological data (Stream flow data for calibration and validation)

Initial conditions

Initial conditions represent the state of the basin at the beginning of the storm event. For the MIKE11-NAM, these conditions include the initial relative water contents of surface and root zone storages and initial base flow.

Meteorological data

Rainfall: The time resolution of the rainfall input depends on the objective of the study and on the time scale of the catchment response. In many cases daily rainfall values are sufficient, but in rapidly responding catchments where accurate representation of the peak flows is required, rainfall input on a finer resolution may be required. In this study daily rainfall (mm) data of four rain gauge stations of Bina basin i.e. Begumganj, Gairatganj, Gyaraspur and Kurwai for period of 1994 to 1998 were used for calibration and validation purpose, which were collected from state data centre, Bhopal and treated as step accumulated totals so the rainfall associated with any particular time was the rainfall volume since the last entered value.

Potential Evapotranspiration: When daily time steps are used, monthly values of potential evapotranspiration are usually sufficient. In this case, only minor improvements can be obtained by specifying daily values instead of monthly values. In the present study daily potential evapotranspiration (mm) data for a period of 1994 to 1998 were used for calibration and validation purpose and potential evapotranspiration treated as step accumulated totals where the evapotranspiration associated with any particular time was the evapotranspiration since the last entered value Daily data of maximum temperature, minimum temperature and radiation in Sagar station for the period of 1994 to 1998 were used for estimation of potential evapotranspiration. These data were collected from state data center, Bhopal. Hargreaves method has been employed to estimate the potential evapotranspiration using Eq. 3.25.

$$PET= mR\,(T_{avg}+17.8)\,(\sqrt{}T_{max}-T_{min}) \qquad (3.25)$$

Where, PET = Potential Evapotranspiration (mm/day)

T_{min} = Minimum Temperature (^{o}c)

T_{max} = Maximum Temperature (^{o}c)

$T_{avg} = \frac{Tmin+ Tmax}{2}$ (^{o}c)

R= Radiation (MJ/m^2)

m = Constant = 0.0009384

Areal precipitation

The MIKE11-NAM model simulates the rainfall-runoff process in a lumped fashion so provision is given for combining meteorological data from different stations within a single catchment or sub-catchment into a single time series of weighted averages. The resulting time series will represent the mean area values of rainfall for a catchment. In the present study Thiessen polygon method was used to estimate a weighted average of precipitation, and this Thiessen polygon was prepared using Arc GIS 9.3 software. In Thiessen polygon method, the precipitation recorded at each station was given a weight on the basis of an area closest to the station. If p_1, p_2, p3 ....p_n are the precipitation magnitude recorded by the stations 1, 2, 3.......n respectively, and A_1, A_2, A_3 ......A_n are the respective areas of the Thiessen polygons and average precipitation over the catchment P is given by

$$\overline{P} = \frac{\sum \overline{P}_{i} * A_i}{A} \quad \text{Thus, in general, for n stations} \qquad (3.26)$$

The ratio Ai/A is called the weighted factor for each station.

The Thiessen-polygon method of calculating the average precipitation over an area is superior to the arithmetic –average method as some weighted is given to the various stations on a rational basis. Further, the gauge stations outside the catchment are also used effectively.

Hydrological data

Discharge: Observed discharge data at the catchment outlet are required for comparison with the simulated runoff for model calibration and validation. In the present study daily discharge data of Bina basin in meter cube per second (m^3/s) for a period ranging from 1994 to 1998 were used and the discharge treated as Instantaneous.

3.5.3.2.6. Basic modelling components

MIKE11 NAM model components (DHI, 2009)

Surface Storage

Moisture intercepted on the vegetation as well as water trapped in depressions and in the uppermost, cultivated part of the ground is represented by surface storage. U_{max} denotes the upper limit of the water in the surface storage.

The amount of water (U) in the surface storage is continuously diminished by evaporative consumption as well as by horizontal leakage (interflow).When there is maximum surface storage, some of the excess water (P_N) will enter the streams as overland flow whereas the remainder is diverted as infiltration into the lower zone and groundwater storage.

Lower Zone or Root Zone Storage

The soil moisture in the root zone, a soil layer below the surface from which the vegetation can draw water for transpiration, is represented as lower zone storage. Lmax denotes the upper limit of the amount of water in this storage.

Moisture in the lower zone storage is subject to consumptive loss from transpiration. The moisture content controls the amount of water that enters the groundwater storage as recharge and the interflow and overland flow components.

Evapotranspiration

Evapotranspiration demands are first met at the potential rate from the surface storage. If the moisture content U in the surface storage is less than these requirements ($U<E_P$),the remaining fraction is assumed to be withdrawn by root activity from the lower zone storage at an actual rate Ea. Ea is proportional to the potential evapotranspiration and varies linearly with the relative soil moisture content, L/L_{max}, of the lower zone storage.

$$Ea= (Ep-U)\ L/L_{max} \qquad (3.27)$$

Overland flow

When the surface storage spills, i.e. when $U>U_{max}$, the excess water P_N gives rise to overland flow as well as to infiltration. QOF denotes the part of PN that contributes to overland flow.

It is assumed to be proportional to P_N and vary linearly with the relative soil moisture content, L/L_{max} of the lower zone storage.

$$QOF = \begin{cases} CQOF \dfrac{(L/L_{max} - TOF)}{1-TOF} PN & \text{for } L/L_{max} \leq TOF \\ 0 & \text{for } L/L_{max} \leq TOF \end{cases} \quad (3.28)$$

Where, CQOF is the overland flow runoff coefficient ($0 \leq CQOF \leq 1$)

TOF is the threshold value for overland flow ($0 \leq TOF \leq 1$)

The proportion of the excess water P_N that does not runoff as overland flow infiltrates into the lower zone storage. A portion, ΔL of the water available for infiltration, (PN-QOF), is assumed to increase the moisture content L in the lower zone storage .The remaining amount of infiltrating moisture, G is assumed to percolate deeper and recharge the groundwater storage.

Interflow

The interflow contribution, QIF is assumed to be proportional to U and to vary linearly with the relative moisture content of the lower zone storage.

$$QIF = \begin{cases} (CKIF)^{-1} \dfrac{(L/L_{max} - TIF)}{1-TIF} U & \text{for } L/L_{max} \leq TIF \\ 0 & \text{for } L/L_{max} \leq TIF \end{cases} \quad (3.29)$$

Where CKIF is the time constant for interflow, and TIF is the root zone threshold value for interflow ($0 \leq TIF \leq 1$).

Interflow and overland flow routing

The interflow is routed through two linear reservoirs in series with same constant CK12.The overland flow routing is also based on the linear reservoir concept but with a variable time constant.

$$\begin{cases} CK12 & \text{for } OF < OF_{min} \end{cases} \quad (3.30)$$

CK =

$$CK12\ (OF/OFmin)^{-\beta} \text{ for } OF \le OF_{min}$$

Where, OF is the overland flow (mm/hour), OF_{min} is the upper limit for linear routing (=0.4mm/hour), and β=0.4.

The constant β= 0.4 corresponds to using the manning formula for modelling the overland flow. Equation 3.30 ensures in practice that the routing of real surface flow is kinematic, while subsurface flow being interpreted by NAM as overland flow (in the catchment with no real surface flow component) is routed as a linear reservoir).

Groundwater Recharge

The amount of infiltrating water G recharging the groundwater storage depends on the soil moisture content in the root zone

$$G = \begin{cases} (PN - QOF)\dfrac{L/Lmax-TG}{1-TG} & \text{for } L/Lmax > TG \\ 0 & \text{for } Lmax \le TG \end{cases} \qquad (3.31)$$

Where, TG is the root zone threshold value for groundwater recharge (0≤TG≤1).

Soil moisture Content

The lower zone storage represents the water content within the root zone. After apportioning the net rainfall between overland flow and infiltration to groundwater, the remainder of the net rainfall increases the moisture content L within the lower zone storage by the amount ΔL

$$\Delta L = P_N - QOF - G \qquad (3.32)$$

Baseflow

The baseflow BF from the groundwater storage is calculated as the outflow a linear reservoir with time constant CK_{BF}.

Objective function

In general term, the objective of model calibration can be stated as below: Selection of model parameters so that the model simulates the hydrological behavior of the basin as closely as possible (Madsen, 2000). MIKE 11-NAM uses multi-objective approach to answering the question. This means that several numerical performance measures are accounted in the optimization process including (1) a good agreement between the average simulated and observed basin runoff volume; (2) a good overall agreement of the shape of the hydrograph; (3) a good agreement of the peak flow with respect to timing, rate and volume; and (4) a good agreement for low flows. In this study, three first objectives were preferred.

3.5.3.2.8. MIKE 11-NAM model setup

The first step in NAM modelling is to investigate the correlation between the rainfall and discharge, which is important for accurate modelling of stream flow. One of the most common methods is to correlate seasonal or annual observed runoff values (R) with corresponding rainfall Values (P). A commonly adopted method is to fit a linear regression line between R and P and to accept the result if the correlation coefficient is nearer unity. The equation of the straight-line regression between runoff R and rainfall P is

$$R = aP + b \qquad (3.33)$$

And the values of the coefficient a and b are given by

$$a = \frac{N (\sum PR) - (\sum P)(\sum R)}{N (\sum P^2) - (\sum P)^2} \qquad (3.34)$$

$$b = \frac{\sum R - a (\sum P)}{N} \qquad (3.35)$$

And in which N= number of the observation sets R and P. The coefficient of correlation r can be calculated as

$$r = \frac{N(\sum PR) - (\sum P)(\sum R)}{\sqrt{[N(\sum P^2)-(\sum P)^2][N(\sum R^2)-(\sum R)^2]}} \quad (3.36)$$

The value of r lies between 0 and 1 as Runoff can have an only positive correlation with Precipitation. The value of $0.6<r<1.0$ indicates good correlation. Further, it should be noted that $R>0$.The term r^2 is known as the coefficient of determination.

The input data of daily rainfall, runoff and potential evapotranspiration for the period of five years from 1994 to 1998 were converted to *dfso* format using MIKE ZERO software which was then used for the model development.

Model calibration

The parameters of MIKE11 NAM could not be found direct from measurable quantities of basin characteristics and therefore, model calibration is necessary. In MIKE 11-NAM model, manual way of model calibration is practiced. In manual calibration, a trial-and-error parameter adjustment is done based on a visual judgment by comparing the observed and the simulated discharge.

Auto-calibration, the default model parameters were kept the same and model was run in auto-calibration mode. The calibration method we use was manual calibration. Simply adjusting one of the parameters and seeing if the results get better. After several manual calibrations have been made the calibration was done again with very small changes. To check the quality of the results, the calibration were checked for the coefficient of determination (R^2) value and graphically analysed for the degree of agreement between simulated and observed runoff. The optimization method used by MIKE11-NAM is shuffled complex evolution (SCE) algorithm. The SCE method is a global search method in the sense that it specially designed for locating the global optima of the objective function and not being trapped in local optima.

Model validation

Model Validation means evaluating the capability of the calibrated model. According to Refsgaard (1996), a model is said to be validated if its accuracy and predictive capacity in the verification period have been proven to lie within acceptable limits. The verification is implemented by using the new set of observed data and the parameters that have been calibrated in the previous step.

Model performance

The performance of the model can be examined on the basis of the coefficient of determination (R^2), the use of the coefficient of determination is to test the goodness of fit of the model and to assess how well a model explains and predicts future outcomes. Efficiency Index (EI) was another hydrological model assessor as described by Nash and Sutcliffe (1970) which had been widely used to detect the model error for the long term simulation. The EI was developed to evaluate the percentage of accuracy of the simulated values with respect to their observed values. EI values equal to 1 signifies the accurate performance of the model. EI and R^2 are defined as:

$$EI = \frac{\sum (Oi-\overline{O})^2 - \sum (Oi-Pi)^2}{\sum (Oi-\overline{O})^2} \quad (3.37)$$

$$R^2 = 1 - \frac{\sum (Oi-Pi)^2}{\sum (Oi-O)^2} \quad (3.38)$$

In these equations, O_i and P_i are observed and simulated values, respectively, O is mean value for observed and n is the number of samples.

Sensitivity analysis

The MIKE11 NAM model thus developed was run by selecting one parameter as a variable and keeping other parameters constant to identify the most sensitive model parameters. It is noticed that the way to analyze sensitivity depends on the restricted ranges of each parameter. The model parameters were selected one by one and were increased and decreased by 10% and 20% to both sides from their values obtained during calibration of the model. As the sensitivity of the each parameter is dependent on how and to what extent it affects the EI and R^2 of the model, thus the EI and R2 were estimated for each model run. The output results were analysed by plotting selected parameter values against the EI and R^2 and the most influencing and sensitive model parameters were identified.

Cmip5 acquired from NEX-GDDP website

Chapter 4

RESULTS AND DISCUSSION

Rainfall Trend Analysis

4.1.1. Rainfall Characteristics of Bina basin

The average annual rainfall of the basin for the period of 1986-2008 is 1236 mm and Seasonal distribution of mean (Thiessen-Mean) precipitation in the study area is shown Fig 4.1. On the average, most precipitation occurs during the monsoon season with 1173 mm (95%) total precipitation, and June, July, August, and September are commonly the months (monsoon) with the highest observed precipitation.

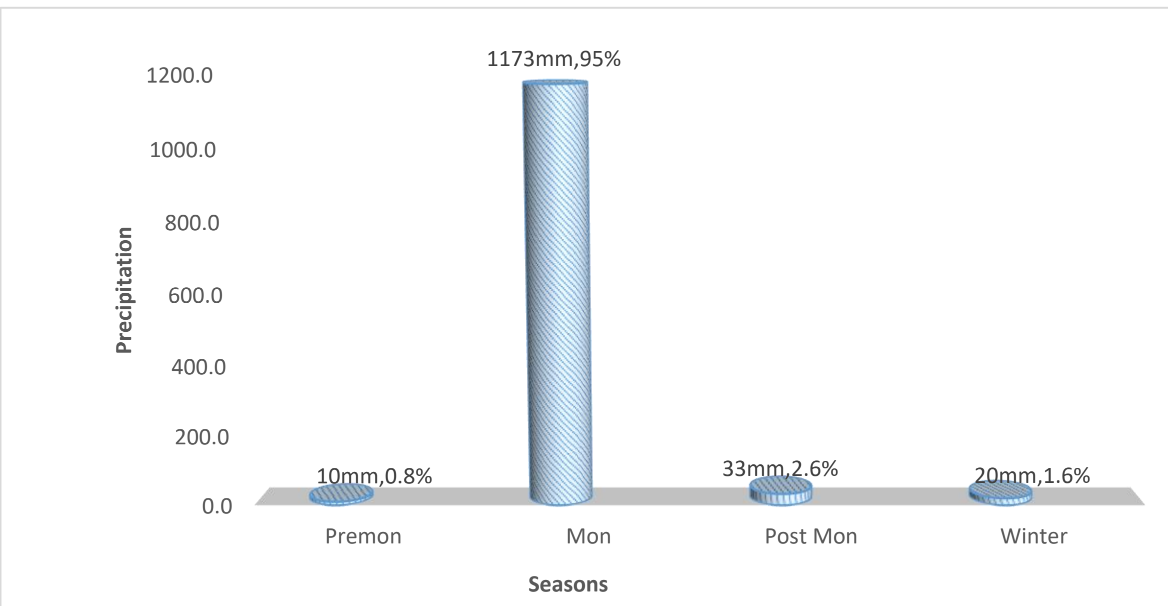


Figure 4.1: Seasonal precipitation contribution

All precipitation records were used in this study, were tested by the double-mass curve technique to ensure that any trends detected are due to meteorological causes and not to changes in gauge location, in exposure, or in observational methods.

4.1.2. Rainfall Trend Analysis at Station Level

4.1.2.1. Annual trend

The magnitude of the trend in the rainfall series, as estimated using the Sen Estimator, is given in Table 4.1. The Annual rainfall over Gyaraspur and Kurwai stations of Bina basin showed insignificant decreasing and Begumganj and Gairatganj stations showed the insignificant increasing trend at 95% level of confidence.

Using a linear regression model as shown in Table 4.2, the rate of change is defined by the slope of regression line which in this case is about -8.9745 mm/year and -9.7972mm/year annual decreasing over Begumganj and Gairatganj stations respectively. The annual increasing trend was indicated at Gyaraspur (8.0984mm/year) and Kurwai (3.0704mm/year).

4.1.2.2. Seasonal trend

Pre-monsoon rainfall of Begumganj, Gairatganj, and Gyaraspur indicates no trend while pre-monsoon rainfall of Kurwai was showed an insignificant increasing trend as shown in Table 4.1. Monsoon rainfall of Begumganj,Gairatganj and Kurwai have experienced insignificant decreasing trend whereas Gyaraspur observed the insignificant increasing trend. Post-monsoon and winter rainfall of all the stations were not indicated any trend.

Table 4.1: Sen Estimator of slope (mm/year) for annual and seasonal rainfall

Stations	Begumganj		Gairatganj		Gyaraspur		Kurwai	
Seasons	MK	Sens-Slope	MK	Sens-Slope	MK	Sens-Slope	MK	Sens-Slope
Pre-Monsoon	-0.80	0.00	-0.52	0.00	0.65	0.00	0.82	2.25
Monsoon	-0.96	-7.10	-0.39	-2.48	0.73	8.73	-0.20	-2.44
Post-Monsoon	-0.21	0.00	0.20	0.00	0.51	0.00	0.92	0.00
Winter	-0.41	0.00	-0.03	0.00	-0.60	0.00	-0.80	0.00
Annual	-0.68	-4.49	-0.68	-4.73	0.73	12.33	0.11	0.94

On the other hand, by means of a linear regression model, monsoon season rainfall of Begumganj and Gairatganj experienced -9.008 and -9.8508 mm/year declining trend respectively. Stations Gyaraspur (7.8524mm/year) and Kurwai (3.1859 mm/year) experienced rising trend as shown in Table 4.2. During pre-monsoon season rainfall at all stations indicated non-significant trend whereas post-monsoon season rainfall indicated a slight decreasing trend. Similarly during winter season all stations except Kurwai, have depicted with the slight increasing trend as shown in Table 4.2. Appendix I presents the estimated regression slope in seasonal basis for the stations in Bina basin.

Table 4.2: Regression slope (mm/year) for Seasonal and Annual rainfall

Sr.no	Stations Seasons	Begumganj (Slope)	Gairatganj (Slope)	Gyaraspur (Slope)	Kurwai (Slope)
1	Pre-monsoon	-0.23	-0.56	-0.04	-0.20
2	Monsoon	-9.01	-9.85	7.85	3.19
3	Post-monsoon	0.00	0.20	0.50	1.48
4	Winter	0.16	0.26	0.05	-0.54
5	Annual	-8.97	-9.80	8.10	3.07

A description of the applied statistical test result is given in Table 4.2. Statistically, significant trends are not found for rainfall on the annual and seasonal basis, even though there are negative and positive trends for the period of 1986-2008 record for all rain gauge stations of Bina basin, viz. Begumganj, Gairatganj, Gyaraspur, and Kurwai. Kumar et al. (2010) from trend analysis of rainfall data of 135 years (1871– 2005) have also suggested that no significant trend for annual, seasonal and monthly rainfall on an all-India basis.

Trends in rainfall for Ram Ganga basin

The magnitude of the seasonal and annual trend in the time series as determined using the Sen's estimator is given in Table 4.3. The annual rainfall indicates falling trend in all station only one station namely Lansdowne is found significant at 95% confidence level with maximum decrease (-23.814 mm/year).

Seasonal analysis of rainfall trends during pre-monsoon, monsoon and winter season shows that falling trend at Lansdowne with maximum magnitude of (-3.110 mm/year), (-19.327 mm/year), (-

2.262 mm/year), respectively and found significant at 95% confidence level and during post monsoon season one station namely Naula sowing significantly decreasing trend at 95% confidence level with maximum decrease (-0.309 mm/year) and remaining majority of the station indicate falling trend as shown in Table 4.3.

Table 4.3: Seasonal and annual trends in rainfall of different stations in Ramganga basin

Season	Station	Z statistic	S	Sen Estimator	Linear regresion	Trend
Annual	Kalagarh	-0.12	-11	-1.133	2.0049	Falling
	Marchulla	-0.17	-16	-1.192	0.7974	Falling
	Naula	0.23	21	0.814	-0.0747	Rising
	Chaukutiya	-1.15	-100	-4.923	-5.1137	Falling
	Ranikhet	-0.78	-68	-2.136	-2.1076	Falling
	Lansdowne	**-3.79**	-326	**-23.814**	-23.7360	**Falling**
Pre monsoon (Mar - May)	Kalagarh	-0.26	-23	-0.192	-0.2268	Falling
	Marchulla	-1.64	-142	-1.424	-1.9187	Falling
	Naula	-1.50	-130	-1.555	-1.7891	Falling
	Chaukutiya	-1.67	-144	-2.680	-2.2995	Falling
	Ranikhet	-0.59	-52	-0.736	-0.7213	Falling
	Lansdowne	**-3.30**	-284	**-3.110**	-3.0606	**Falling**
Monsoon (Jun - Sept)	Kalagarh	-0.10	-9	0.262	1.8194	Rising
	Marchulla	0.17	16	0.986	2.9022	Rising
	Naula	1.32	114	2.695	2.0007	Rising
	Chaukutiya	-0.13	-12	-0.743	-1.6460	Falling
	Ranikhet	-0.90	-78	-2.088	-1.7106	Falling
	Lansdowne	**-3.25**	-280	**-19.327**	-18.2940	**Falling**
Post Monsoon (Oct - Nov)	Kalagarh	-0.42	-37	-0.026	0.3420	Falling
	Marchulla	-0.87	-75	-0.082	-0.1280	Falling
	Naula	**-2.05**	-176	**-0.309**	-0.4687	**Falling**
	Chaukutiya	-0.70	-61	-0.246	-0.1074	Falling
	Ranikhet	-0.26	-23	0.000	-0.1700	Falling
	Lansdowne	-1.65	-141	-0.354	-0.7702	Falling
Winter (Dec - Feb)	Kalagarh	-0.61	-53	-0.523	-0.2890	Falling
	Marchulla	-0.80	-70	-0.881	-0.7430	Falling
	Naula	-0.23	-21	-0.171	-0.2498	Falling
	Chaukutiya	-1.43	-124	-1.442	-1.5307	Falling
	Ranikhet	0.22	20	0.281	0.0277	Rising
	Lansdowne	**-2.32**	-200	**-2.262**	-1.9374	**Falling**

4.1.4 Spatial analysis of rainfall data

The Spatial interpolation technique (**Singh and Chowdhury, 1986; Lebel et al, 1987**) is employed to determine the spatial pattern of meteorological variable using ArcGIS 10.1. The geographical information system (GIS) tool is widely used in the processing of spatially distributed hydrological modelling (**Maidment, 1991; Eldho et al, 2006; Jat et al, 2009**). In recent time, GIS interpolation methods has been widely used to show the spatial distribution of climate variable and it provides the layout and drawing tools essential to present the outcomes visually. Thus in present study spatial distribution of temporal trend in annual and seasonal precipitation as detected by the Mann–Kendall statistics method to each station in the Ramganga basin, temporal trends of annual and seasonal precipitation are tested at the $\alpha = 0.05$ level of significance. These temporal trends are then interpolated by using the IDW (Inverse Distance Weighting) method to show their spatial distributions. The spatial distributions of temporal trend in annual and seasonal precipitation are shown in Fig. 4.2 and 4.3. It is seen that the results are non-significantly change in precipitation in most parts of the Ramganga basin at $\alpha = 0.05$ level of significance. The trend of annual rainfall series indicated that only single station namely Lansdowne is found to be significantly change in decreasing trend at 95 % significant level, although rest of remaining station sowed there is no change significantly. Seasonal analysis of rainfall indicates one station namely Lansdowne has significantly change with decreasing trend during all season at $\alpha = 0.05$ level of significance. During post monsoon and Winter season two station namely Naula and Lansdowne respectively sowing significant decreasing trend at $\alpha = 0.05$ level of significance and remaining station sowing non-significant change during all season.

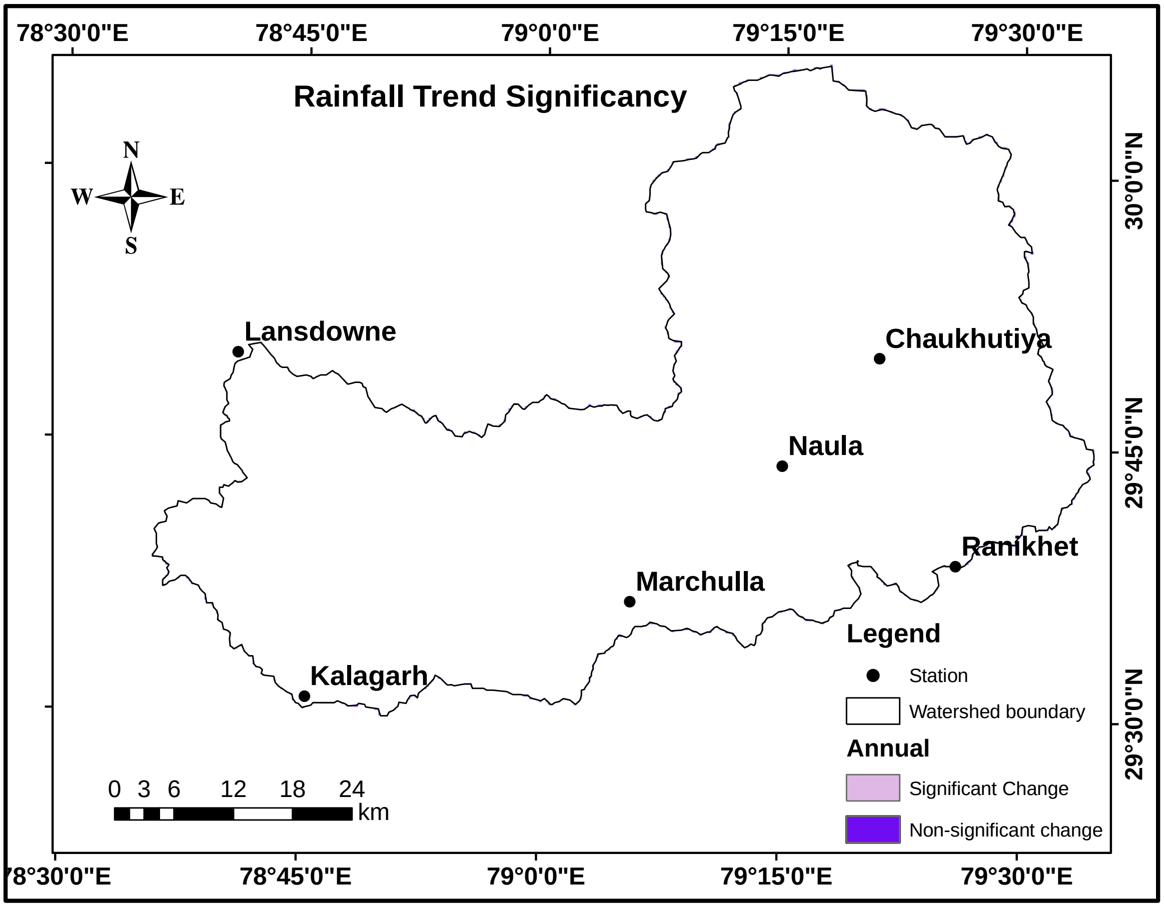


Fig. 4.2: Spatial distribution of the temporal trends of annual precipitation

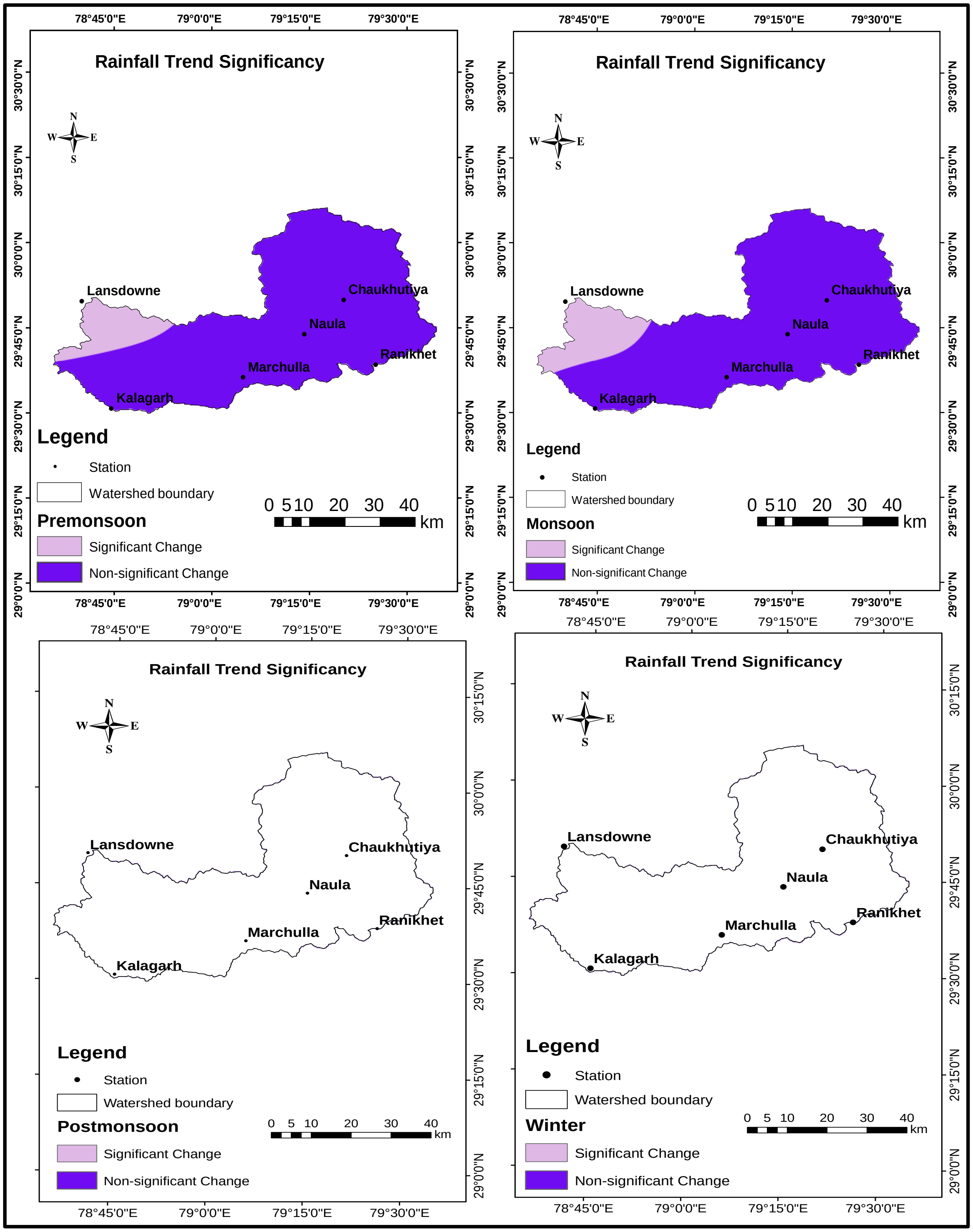


Fig. 4.3: Spatial distribution of the temporal trends of seasonal precipitation

Trends in Rainfall for Chaliyar Basin

Annual Trend

According to parametric approach, the annual rainfall indicates rising trend in Ambalavayal ,Kalladi and Nilambur station increasing at the rate of 18.72 mm/year, 57.18 mm/year and 2.57 mm/year respectively, while Manjeri indicates falling trend decreasing at the rate of 21.57 mm/year.Result obtained from non parametric approach, no significant trend is observed in any of the station (as per Z statistic of Mann Kendall), but still precipitation increases at the rate of 19.5 mm/year & 54.33 mm/year in Ambalavayal & Kalladi stations & decreases at the rate of 17.38 mm/year & 0.335 mm/year in Nilambur and Manjeri (as per sen's estimator

Seasonal Trend

From table 4.4, Seasonal trend for all the four stations by parametric method (linear regression) is described by the following table in which the magnitude of regression slope or 'm' denotes the rate of increase or decrease of seasonal precipitation in mm/year while the sign of 'm' denotes the nature of trend i.e. falling or rising.

Whereas the seasonal trend for all the four stations by non parametric method (Mann Kendall & Sen's estimator) is described by the table 4.5 in which the value of Z statistic denotes the significance of trend i.e., whether the trend is significant or not. If the value of z does not lie within the range 1.96<z<1.96 at 95% significance, then the trend is significant, else the trend is not significant & the magitude of Sen slope denote the rate of increase or decrease in vseasonal or annual precipitation in the units of mm/year while the sign of sen slope denotesthe nature of trend i.e. falling or rising.

Table 4.4: Seasonal trends in rainfall of different stations in Chaliyar basin Season Station trend Magnitude

Season	Station	trend	Magnitude
Premonsoon (Mar - May)	Ambalavayal	Rising	11.06
	Kalladi	Rising	5.785
	Manjeri	falling	-4.291
	Nilambur	Rising	2.142
South west Monsoon (Jun - Sept)	Ambalavayal	Rising	3.651
	Kalladi	Rising	55.94
	Manjeri	Falling	-12.52
	Nilambur	Rising	6.957
North east Monsoon (Oct - Nov)	Ambalavayal	Rising	5.864
	Kalladi	falling	-2.529
	Manjeri	falling	-3.091
	Nilambur	falling	-3.886
Winter (Dec - Feb)	Ambalavayal	falling	-1.850
	Kalladi	falling	-2.018
	Manjeri	falling	-1.670
	Nilambur	falling	-2.631

Table 1.5: SEN estimator of slop (mm/year) & Mann Kendall Zstatistics for significance of trend

Station	Premonsoon		South west Monsoon		North east Monsoon		Winter		Annual	
	Z statistic	Sen slope	Z statistic	Sen slope	Z statistic	Sen slope	Z statistic	Sen slope	Z statistic	Sen slope
Ambalavayal	1.36	13.892	0.08	1.25	1.14	7.9	-0.87	-1	0.76	19.5
Kalladi	0.63	3.05	1.05	53.357	0.28	3.013	-.74	-1.188	1.33	56.827
Manjeri	-1.21	-2.5	-0.42	-12.992	-0.84	-4.667	-0..68	-0..222	-0.77	-17.38
Nilambur	0.14	0.36	-0.14	-0.278	-0.49	-2.869	-1.84	-1.086	0	-0.335

Trends in Rainfall for Dhadhar Basin

Annual Trend

At Annual Scale

From Table 4.6 it is revealed that at annual scale there is a decreasing trend at majority of the stations whereas stations Amreli (0.352 mm/yr), Bhavnagar (0.205 mm/yr) and Kachchh (0.122 mm/yr) indicated increasing non-significant trends at 95% of confidence level. Among all the 11 stations, Amreli shows the maximum (0.352 mm/yr) rate of rising trend while Dohad (0.76 mm/yr) shows the maximum rate of falling trend in the rainfall during these 102 years.

4.2 At seasonal scale

From Table 4.6, during Pre-monsoon season non-significant increasing trend were seen at Anand, Bharuch Kachchh and Vadodara whereas decreasing trend were seen at remaining stations. In the monsoon season, all the stations show decreasing non-significant trend in rainfall except Amreli and Bhavnagar. It is clear from the table 3 that all the 11 stations show increasing (non-significant) trend in rainfall during the post monsoon season. However, during the winter season all of the stations show a decreasing trend in rainfall during these 102 years. Moreover, rainfall at Amreli (-0.009 mm/yr), Anand (-0.017 mm/yr) and Kheda (-0.022 mm/yr) are found to be significant at 95% confidence interval. Also, Amreli (0.288 mm/yr) and Dohad (0.751 mm/yr) stations show maximum rate of rising and falling trend in the rainfall over this period of time.

Table 4.6: Sen estimator of slope (mm/year) for seasonal and annual rainfall.

Station	**Pre-monsoon (Mar-May)**		**Monsoon (June-Sept)**		**Post-monsoon (Oct-Nov)**		**Winter (Dec-Feb)**		**Annual**	
	Z statistics	**Sen Slope**	**Z statistics**	**Sen Slope**	**Z statistics**	**Sen Slope**	**Z statistics**	**Sen Slope**	**Z statistics**	**Sen Slope**
Ahmedabad	-1.02	-0.012	-0.5	-0.313	1.47	0.035	-1.69	-0.008	-0.27	-0.163
Amreli	-0.73	-0.004	0.35	0.288	1.46	0.037	-3.13	**-0.009**	0.36	0.352
Anand	0.38	0.002	-0.68	-0.566	1.62	0.046	-2.23	**-0.017**	-0.44	-0.358
Banas Kantha	-0.44	-0.345	-0.73	-0.53	2	0.019	-0.77	-0.004	-0.24	-0.206
Bharuch	1.61	0.011	-0.38	-0.354	1.48	0.074	-0.34	-0.005	-0.15	-0.142
Bhavnagar	-1.21	-0.015	0.1	0.104	1.48	0.07	-0.66	-0.007	0.23	0.205
Dohad	-0.31	-0.006	-0.75	-0.751	1.11	0.035	-1.46	-0.01	-0.76	-0.766
Gandhinagar	-0.38	0	-0.17	-0.159	1.77	0.021	-1.38	-0.007	-0.02	-0.012

Kachchh	0.24	0.001	-0.18	-0.08	1.45	0.032	-1.09	-0.009	0.21	0.122
Kheda	-0.42	-0.001	-0.87	-0.638	1.53	0.033	-2.26	**-0.022**	-0.79	-0.645
Vadodara	1.25	0.011	-0.78	-0.698	1.63	0.079	-1.85	-0.014	-0.67	-0.607

Drought Characterization

The SPI has been applied in this study for the four watershed to quantify monthly precipitation deficit anomalies on multiple time scale. The extreme and severe events observed at different time scales for Ramganga, Bina,

Year	Month	3_month	Drought	6_month	Drought	9_month	Drought	12_month	Drought
1981	10	-2.49	Extreme	-1.8	Severe	-1.79	Severe	-1.56	Severe
1985	4	-2.04	Extreme	-0.32	Normal	-1.67	Severe	-1.49	Moderate
1989	5	-2.33	Extreme	-1.96	Severe	-1.77	Severe	-0.29	Normal
1989	6	-2.41	Extreme	-2.3	Extreme	-2.39	Extreme	-0.83	Normal
1989	7	-2.13	Extreme	-2.59	Extreme	-2.3	Extreme	-1.24	Moderate
1999	4	-2	Extreme	-1.54	Severe	0.81	Normal	1.49	Normal
2006	2	-2.14	Extreme	0.84	Normal	0.18	Normal	-0.13	Normal
2006	11	-2.47	Extreme	-1.86	Severe	-1.12	Moderate	-1.47	Moderate

2008	2	-2.57	Extreme	-0.3	Normal	-1.04	Moderate	-0.76	Normal
2008	3	-3.01	Extreme	-2.14	Extreme	-1.51	Severe	-1.34	Moderate
2009	2	-2.89	Extreme	-0.99	Normal	-0.56	Normal	-0.69	Normal
2009	3	-2.13	Extreme	-2.61	Extreme	-0.53	Normal	-0.67	Normal
2009	7	-2.59	Extreme	-2.75	Extreme	-2.98	Extreme	-2.56	Extreme
2009	8	-2.94	Extreme	-2.53	Extreme	-2.95	Extreme	-2.46	Extreme
2012	6	-2.12	Extreme	-2.28	Extreme	-2.41	Extreme	-0.74	Normal
2013	5	-2.72	Extreme	-0.81	Normal	-0.57	Normal	-0.29	Normal
2014	6	-2.05	Extreme	-1.25	Moderate	-1.41	Moderate	-0.92	Normal
2014	10	-2.37	Extreme	-1.77	Severe	-1.47	Moderate	-1.49	Moderate

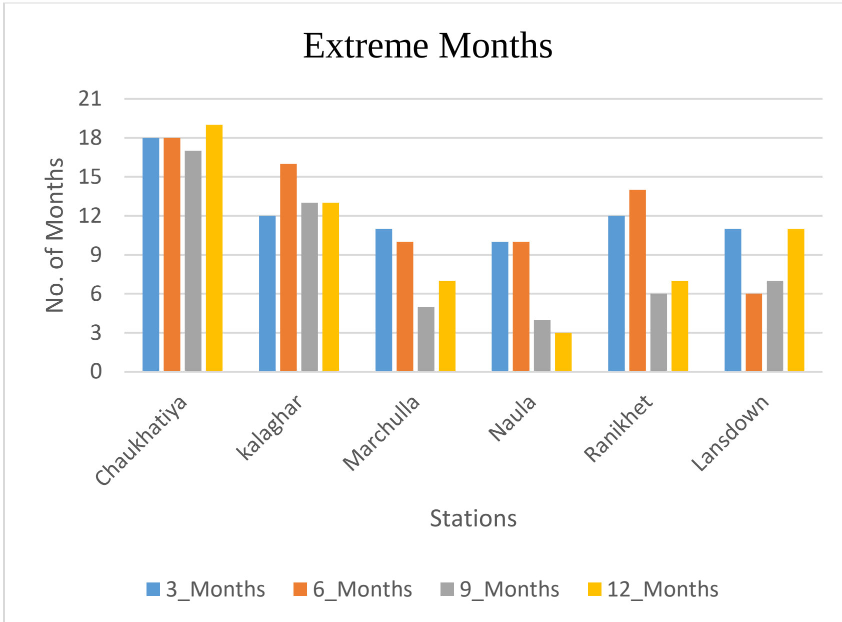


Figure: 4.4: Drought at different time scale for Ramganga basin

Bina basisn

The results identified the extreme and severe drought periods which had been experienced in the meteorological stations of Bina basin . In Begumganj meteorological station, 2001, 2004 and 2007 on the scale of 6 months and 2001/2002, 2004 and 2007 on the scale of 12 months were the years which severe drought was experienced and the extreme drought years were, 2002 and 2008 on the scale of 6 months and 2008 on the scale of 12 months as shown in Table 4.4.

The SPI for the Begumganj station indicating the severe and extreme drought periods are given in the table

Severe and Extreme Drought periods for 6-month time scale		Severe and Extreme Drought periods for 12-month time scale	
Time	6 month SPI	Time	12 month SPI
Feb-01	-1.93	Jul-02	-1.81
Jul-02	-2.66	Jun-05	-1.73
Dec-04	-1.98	Sep-07	-1.55

Jun-06	-1.6	Oct-07	-1.53
Aug-07	-1.8	Nov-07	-1.62
Sep-07	-1.52	Dec-07	-1.62
Oct-07	-1.54	Jan-08	-1.84
Nov-07	-1.57	Feb-08	-1.92
Dec-07	-1.62	Mar-08	-1.92
Jan-08	-1.96	Apr-08	-1.92
Jun-08	-1.71	May-08	-1.91
Aug-08	-2.03	Jun-08	-2.1
Sep-08	-1.95	Jul-08	-1.73
Oct-08	-1.94	Aug-08	-1.78
Nov-08	-1.97	Sep-08	-1.99
Dec-08	-1.6	Oct-08	-1.94
		Nov-08	-2
		Dec-08	-2

Dhadhar basin

The SPI for the Vadodara indicating the severe and extreme drought periods are given in the table

Year	Month	3_month	Drought	6_month	Drought	9_month	Drought	12_month	Drought
1911	8	-2.23	Extreme	-2.26	Extreme	-2.27	Extreme	-2.39	Extreme
1911	9	-2.94	Extreme	-2.22	Extreme	-2.18	Extreme	-1.83	Severe
1915	9	-2.03	Extreme	-1.89	Severe	-1.84	Severe	-1.89	Severe
1918	8	-2.25	Extreme	-2.2	Extreme	-2.24	Extreme	-0.25	Normal
1918	9	-2.08	Extreme	-2.51	Extreme	-2.53	Extreme	-2.23	Extreme
1918	11	-2.18	Extreme	-2.69	Extreme	-2.64	Extreme	-2.7	Extreme
1923	6	-3.01	Extreme	-2.48	Extreme	-2.1	Extreme	-0.66	Normal
1925	10	-2.44	Extreme	-0.99	Normal	-1	Moderate	-1.07	Moderate
1947	6	-2.51	Extreme	-2.62	Extreme	-1.16	Moderate	-0.17	Normal
1951	11	-2.02	Extreme	-1.71	Severe	-1.76	Severe	-1.81	Severe
1952	11	-2.33	Extreme	-0.55	Normal	-0.59	Normal	-0.62	Normal
1965	6	-2.77	Extreme	-2.7	Extreme	-3.05	Extreme	0.04	Normal

1968	7	-2.4	Extreme	-2.4	Extreme	-2.41	Extreme	-1.44	Moderate
1974	8	-2.76	Extreme	-2.33	Extreme	-2.36	Extreme	-0.86	Normal
1987	7	-2.39	Extreme	-2.38	Extreme	-2.38	Extreme	-2.38	Extreme

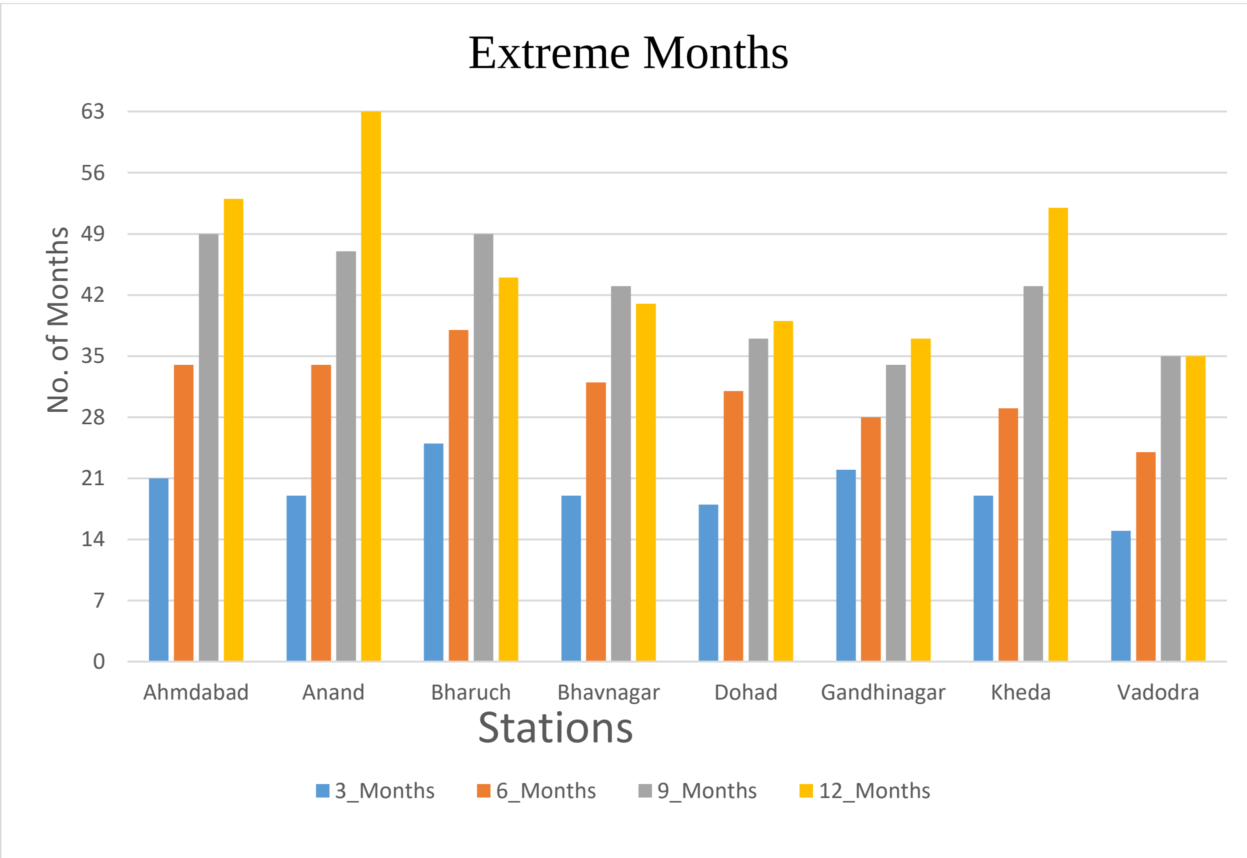
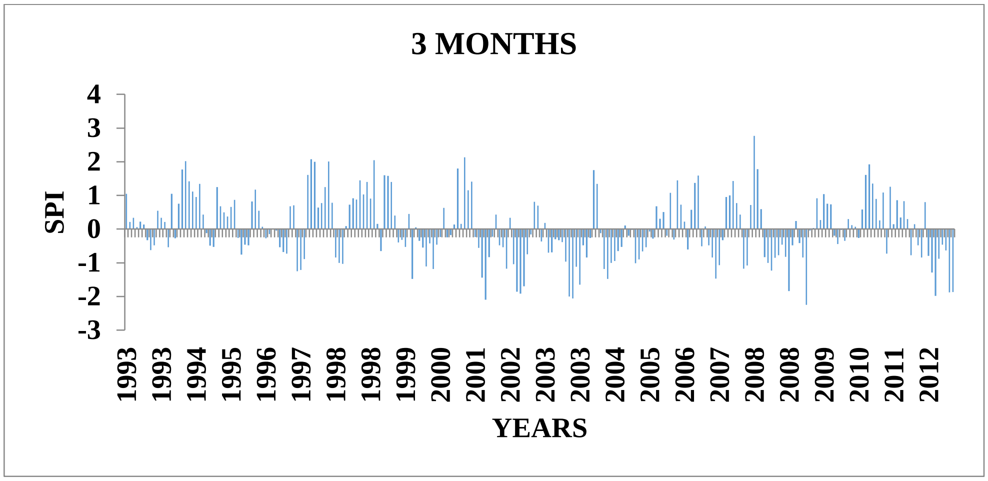


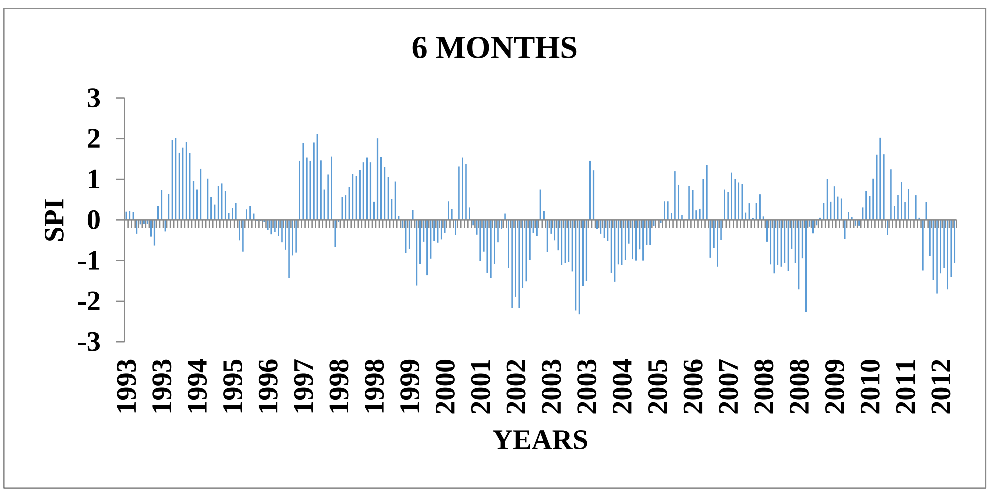
Figure: 4.5: Drought at different time scale for Dhdhar basin

Chaliyar Basin

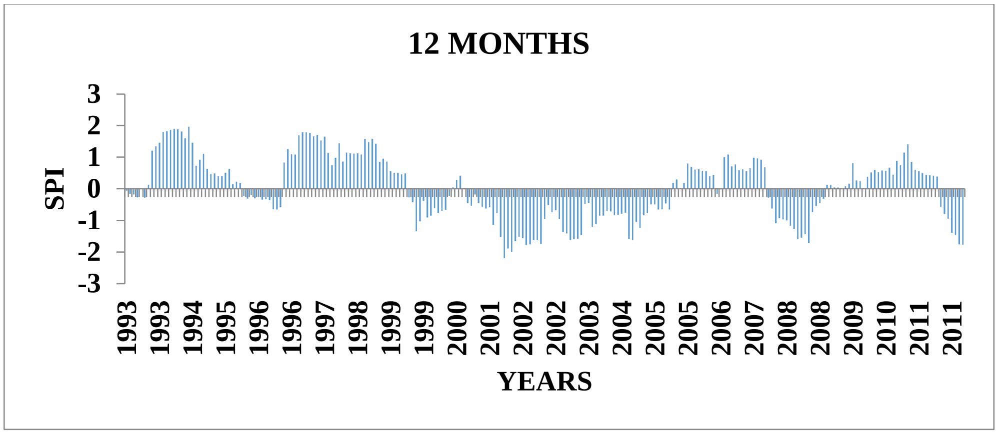
Drought analysis was performed using Standardized Precipitation Index (SPI) on both short-term (3 and 6 months) & long-term (12 months) time scales at all the four rain gauge stations (Ambalavayal, Kalladi, Manjeri & Nilambur) of Chaliyar river basin. Time series plots for all stations on different time scales showed fluctuations representing wide range of weather & drought events ranging from extremely drought to extremely wet events



(a) 3 Months Timescale



(b) 6 Months Timescale



(c) 12 Months Timescale

Figure: 4.6 SPIs time series on timescale of 3, 6 and 12 months for Manjeri

Hydrological Modelling

BINA BASIN SWAT Model

Bina catchment has an average curve number of 83.3 as presented in the Table 4.10, higher curve number causes higher run-off potential. Curve number is governed by land use, hydrological soil group, hydrologic conditions, and antecedent moisture conditions which depend on the average slope of the basin.

Table 4.10

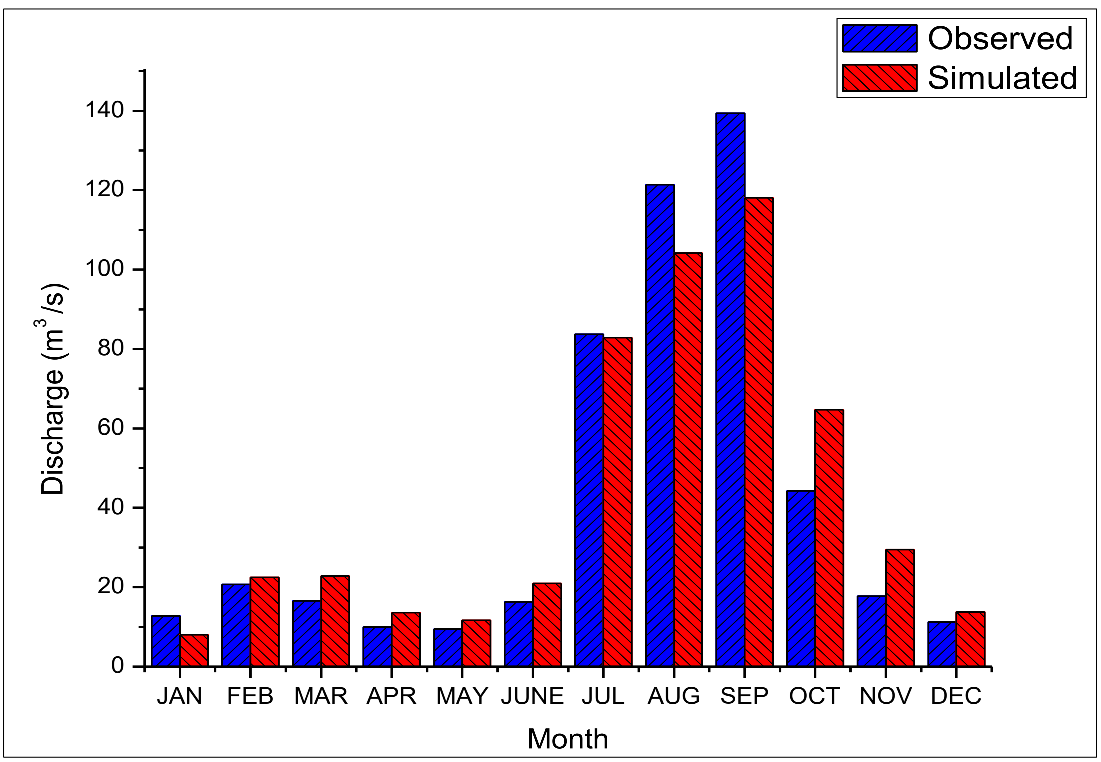
Sr.no	Hydrological parameters	Value(mm)
1	Precipitation	1210.2
2	Surface runoff	225.8
3	Lateral flow	0.62
4	Groundwater	12.51
5	Revaporation from shallow aquifer	0.82
6	Recharge to deep aquifer	0.7
7	Total aquifer recharge	14.04
8	Total water yield	237.92
9	Percolation to shallow aquifer	13.13
10	Actual Evapotranspiration	978.9
11	Potential evapotranspiration	2256.1
12	Transmission Losses	1
13	Average curve number	83.33

The global sensitivity of model parameters has been estimated using Latin hypercube regression systems. The most sensitive parameters observed after global sensitivity analysis for daily and monthly calibration in SUFI-2 are shown in Table 4.12 and 4.13 respectively. These Tables show r_SOL_BD.sol (Moist bulk density), v__ALPHA_BF.gw (base flow alfa factor) and r_CN2.mgt (curve number) for a daily basis and r__SOL_ AWC.sol (soil available water capacity), r_SOL_Z.sol (Depth from the soil surface to bottom of the layer) and r_CN2.mgt (curve number) on a monthly basis are most sensitive parameters of the model. It was experienced that the stream flow simulations process was not affected by parameters which are relatively insensitive compared to sensitive parameters and changes in their range had not caused significant changes in the model result

Ram Ganga Basin

Flow calibration and validation by SUFI-2

Comparative results between the observed and simulation flow discharge values for the calibration and validation periods indicated a good agreement between the observed and simulated flows using SUFI-2 algorithm (Fig. 4.7). Four statistics measures, namely, NSE, R^2, P-factor, and R-factor, were used to quantify the achieved calibration levels, and the overall performance of the model was subsequently evaluated. The results of simulated stream flow along the uncertainty band and observed data are presented in Fig. 4.8. The calibration [2003-2005 (a)] and validation [2006-2008 (b)] periods show acceptable NSEs (0.78) at calibration and (.76) at validation for the study area. According to the literature (**Moriasi et al., Benaman et al., 2005**), a model simulation can be evaluated as satisfactory if R^2 is greater than 0.6. In this case, the results agreed reasonably well with these values with R^2 (.78) (Fig. 4.8). The P-factor and R-factor ranged between 49% to 90% and 0.54 to 0.81 respectively during calibration and obtain 90% and 1.06 during validation (Fig. 4.9)



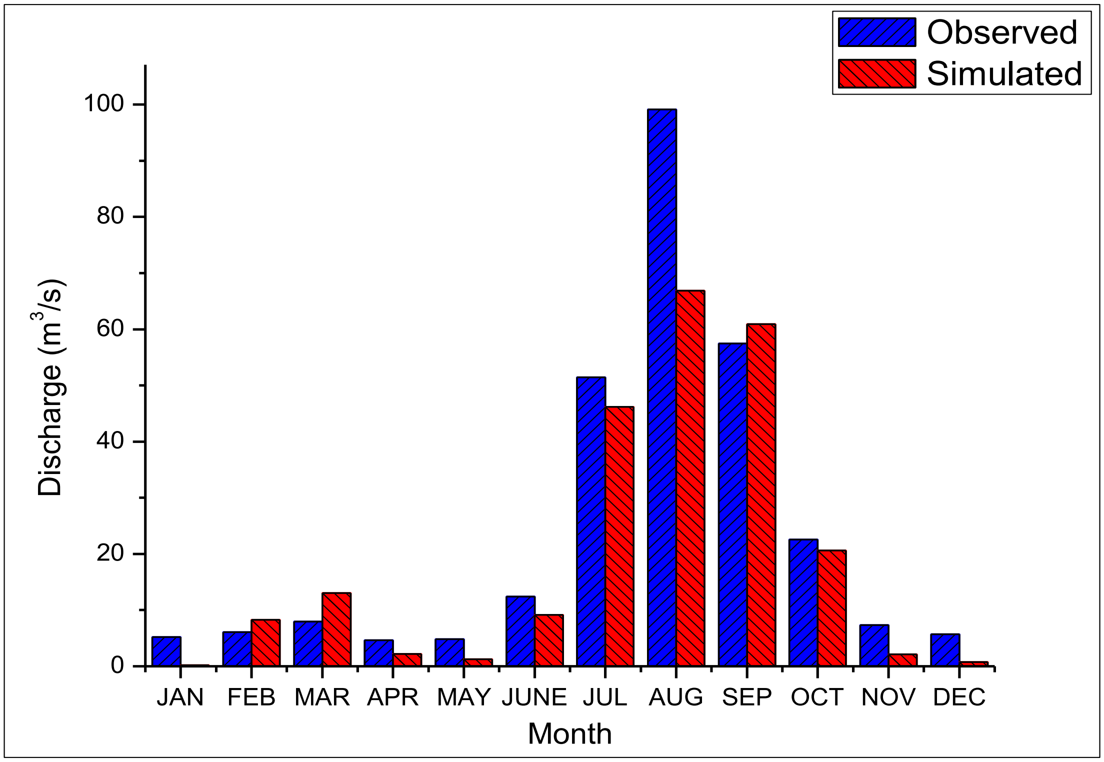


Fig 4.7: Comparison of observed and simulated flow discharge at Calibration (a) and Validation (b) period

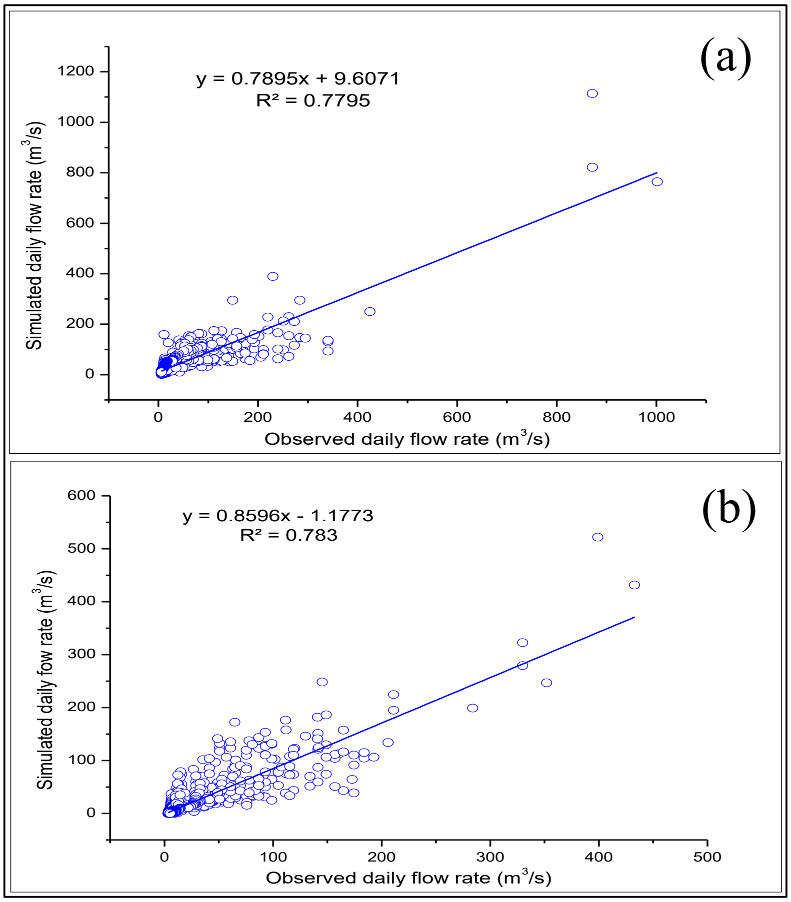


Fig. 4.8: Observation versus simulation flow rate during calibration (a) and validation (b) period

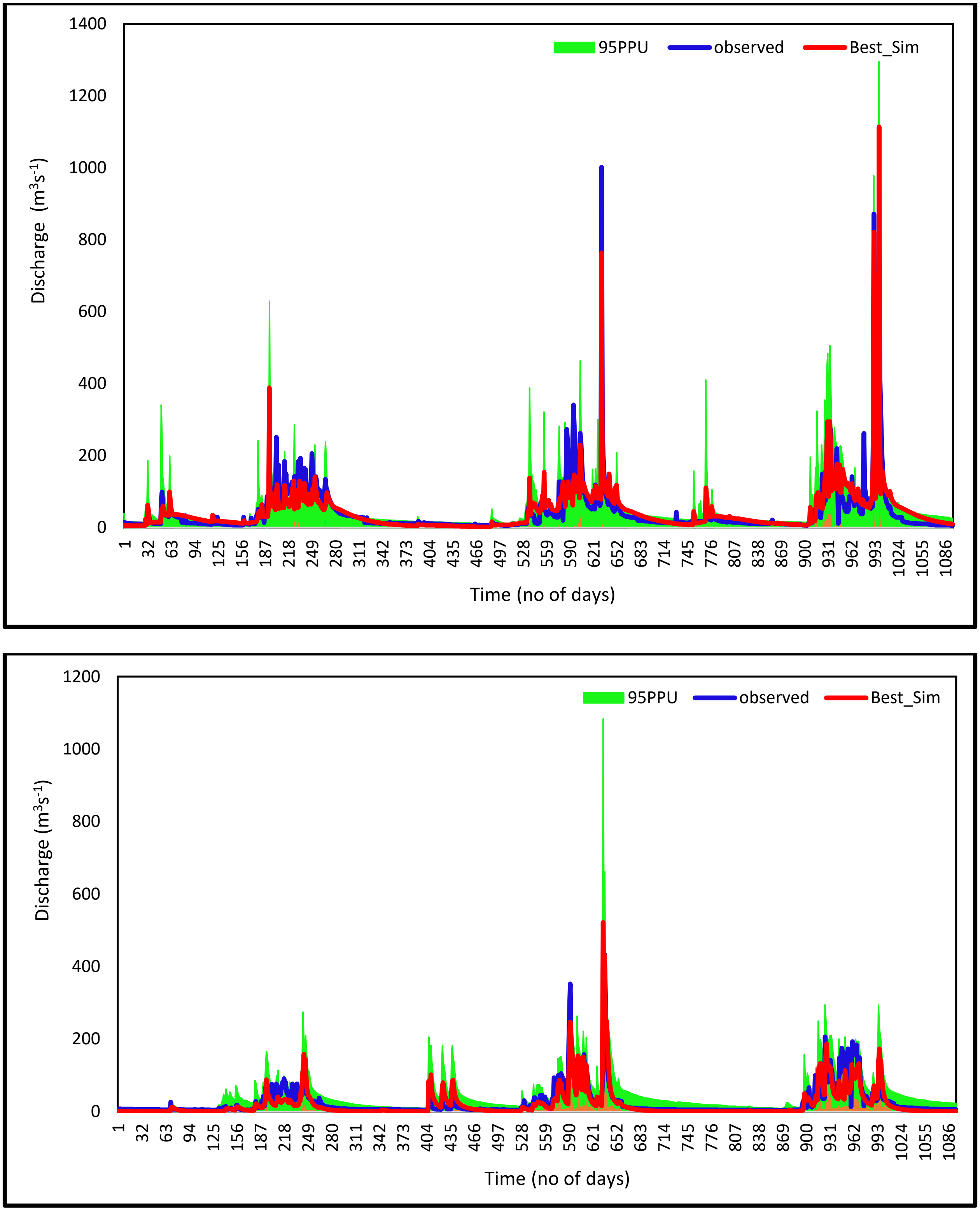


Fig. 4.9: Illustration of full SWAT-CUP output showing Calibration (a) and validation (b), the observed, the best simulation, and the 95% prediction uncertainty (95PPU)

Chaliyar Basin- SWAT model run

Calibration Results

Once the the swat model run with good accuracy aand sensitive parameters were recognized the model was calibrated for the inflow data of chaliyar basin for the period of 2003-2007. During the calibration numerous iterations was run to find the most favorable range of parameters until the observed and simulated flows appropriately matches to each other. These optimum values of simulated flow shows the performance and the accuracy of the model. After the results it was seen that the observed and simulated values of the calibrated model matched reasonably well which is being shown in figure 4.10. The time series plot of the measured monthly data simulated during the calibration period is given in figure 4.11. Various parameters showing the accuracy of Swat model are as follows.

- $R^2 = 0.77$
- NSE = 0.75
- P Factor = 0.21
- R Factor = 0.13

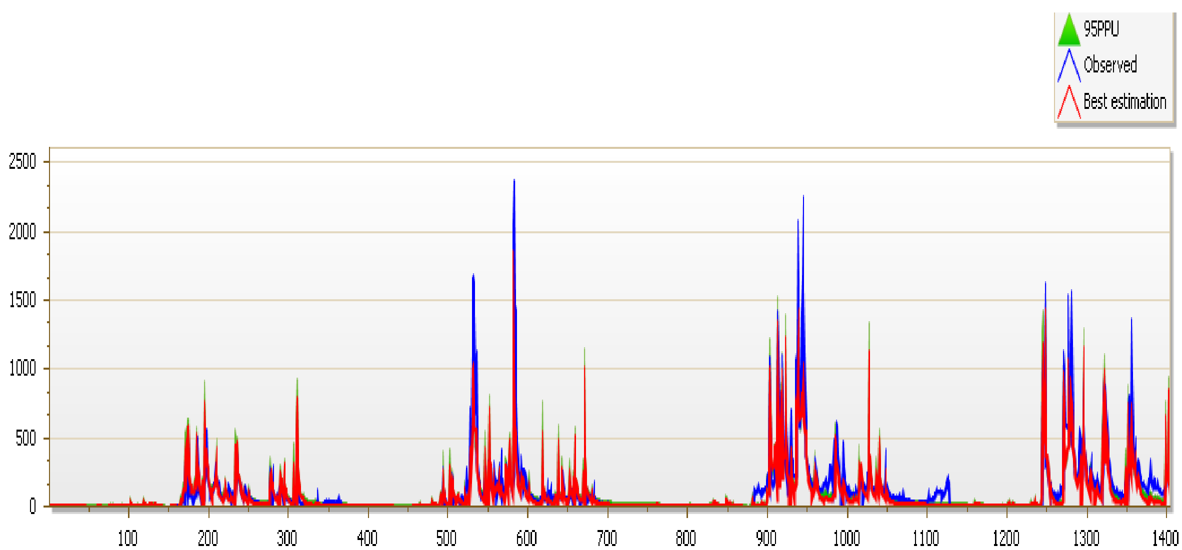


Figure4.10: Comparison of observed and simulated daily runoff Hydrograph during calibration

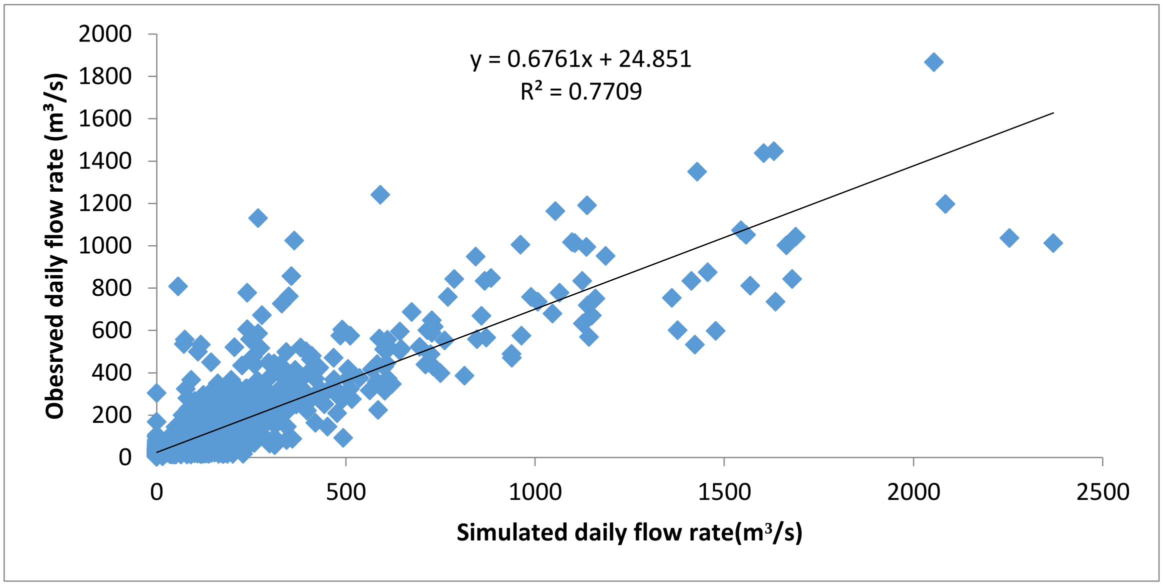


Figure 4.11: Observation versus simulated flow rate during calibration period

Validation

The validation of the results is done by four year inflow data ofchaliyar basin starting from 2008 to 2011. The comparison of observed and simulated flow is given in fig.4.12 and the time series plot of the monthly simulated data during the validation period of 1996-1999 is given in fig. 4.13 The parameters that shows the accuracy of the model is given as.

- $R^2 = 0.77$
- NSE = 0.73
- P Factor = 0.13
- R Factor = 0.12

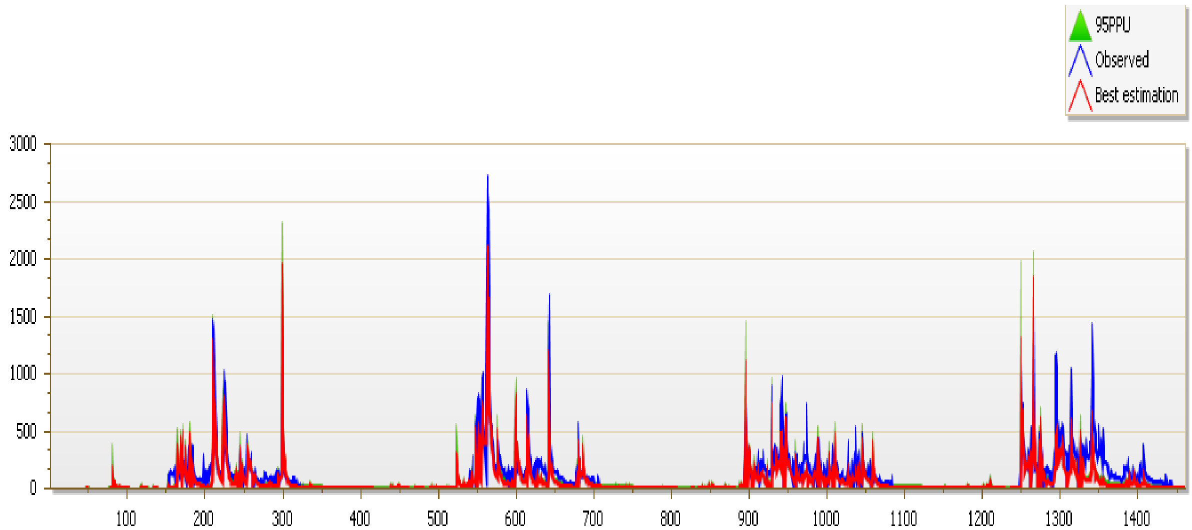


Figure 4.12: Comparison of observed and simulated daily runoff Hydrograph during Validation

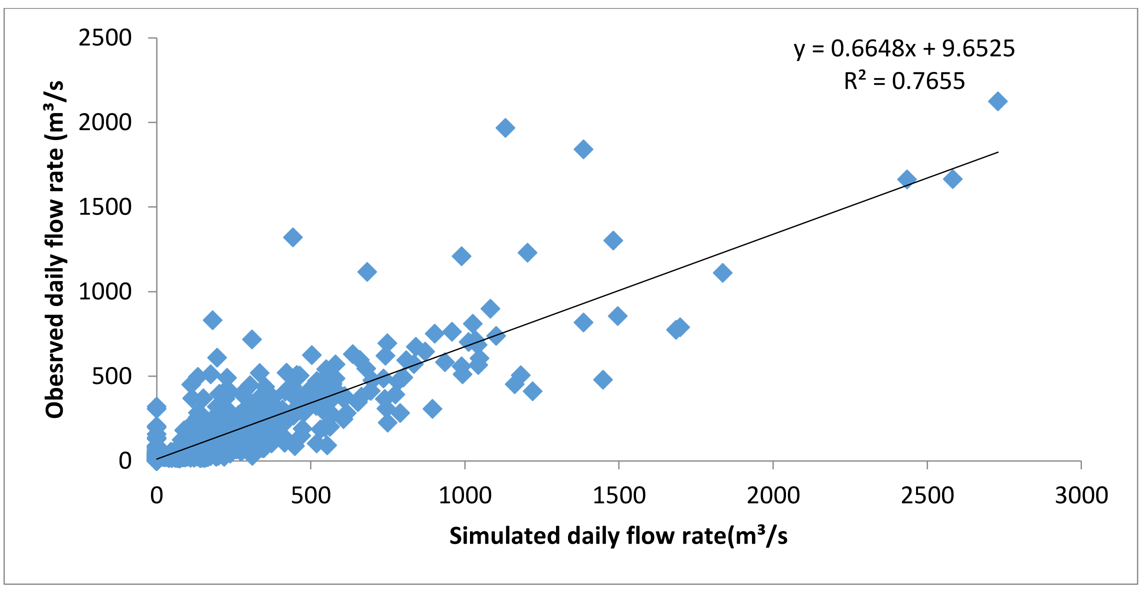


Figure 4.13: Observation versus simulated flow rate during calibration period

Dhadhar Basin-SWAT Model

Daily calibration hydrograph, presented in Fig. 4.14, shows that almost all the time occurrence of peak discharge in both observed and simulated hydrograph coincide. Hence the SWAT simulation can be considered good. This fact is supported by the statistical parameters presented for daily calibration column in Table 4.11, i.e. p-factor is 0.79, r-factor is 0.25, R2 is 0.86 and NSE is 0.86 which indicate the performance rating is to be ‘very good’.

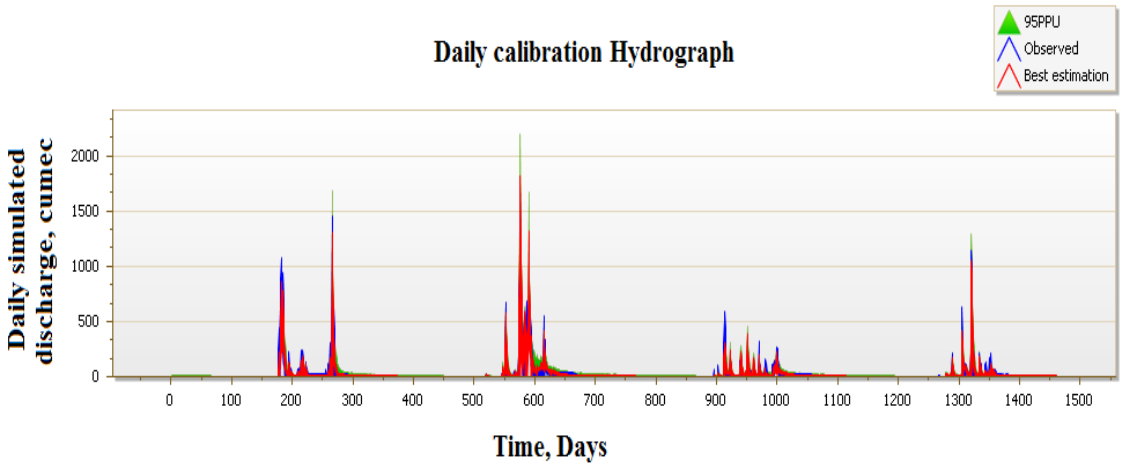


Fig.4.14: Daily calibration hydrograph of Dhadhar basin

Table 4.11: Daily and monthly objective functions

Objective variable	Daily		Monthly	
	Calibration	Validation	Calibration	Validation
p-factor	0.79	0.66	0.71	0.47
r-factor	0.25	0.23	0.28	0.32
R^2	0.86	0.73	0.95	0.85
NSE	0.86	0.72	0.93	0.83

The time-step data of the observed and simulated flows on the daily and monthly basis for the period 2005-2008 for calibration and 2009-2011 for validation were plotted for visual comparison to explore the similarity of the peak values resulting from SUFI-2 uncertainty techniques.

Daily calibration hydrograph, presented in Fig. 4.15, shows that almost all the time occurrence of peak discharge in both observed and simulated hydrograph coincide. Hence the SWAT simulation can be considered good. This fact is supported by the statistical parameters presented for daily calibration column in Table 4.11, i.e. p-factor is 0.79, r-factor is 0.25, R^2 is 0.86 and NSE is 0.86 which indicate the performance rating is to be 'very good'.

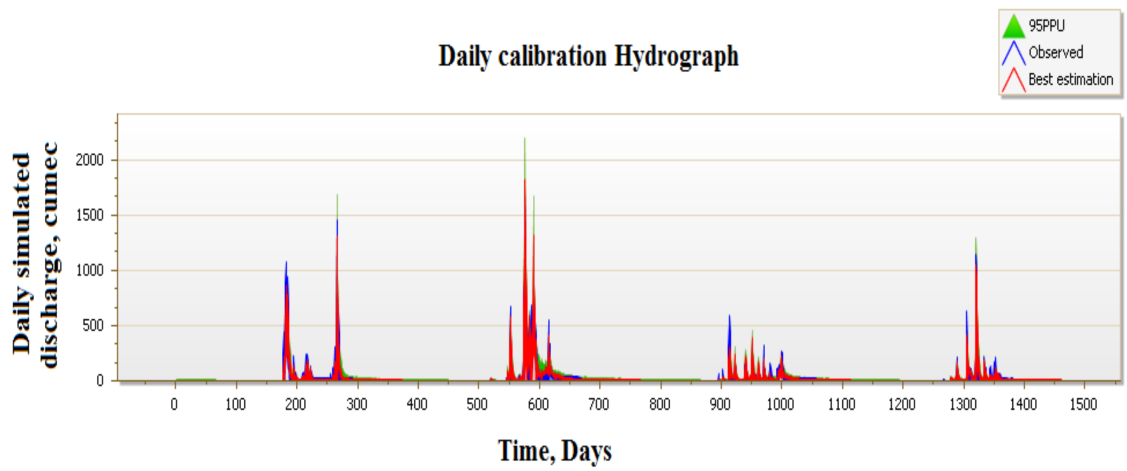


Fig.4.15: Daily calibration hydrograph of Dhadhar basin

In daily validation hydrograph, demonstrated in Fig. 4.16, the peak discharge of both simulated and observed hydrograph match. The SWAT simulation can be viewed as good hence. This known simple truth is supported by the statistical parameters presented for daily calibration column in Table 4.11, i.e. p-factor is 0.66, r-factor is 0.23, R^2 is 0.73 and NSE is 0.72 which also indicate the performance rating is to be 'very good'.

Comparison of observed and simulated discharge is shown as a scatter plot in Fig. 4.17. The R^2 value of the best fit line was calculated to be 0.86, which suggests that the line describes 86% of variance in the dataset.

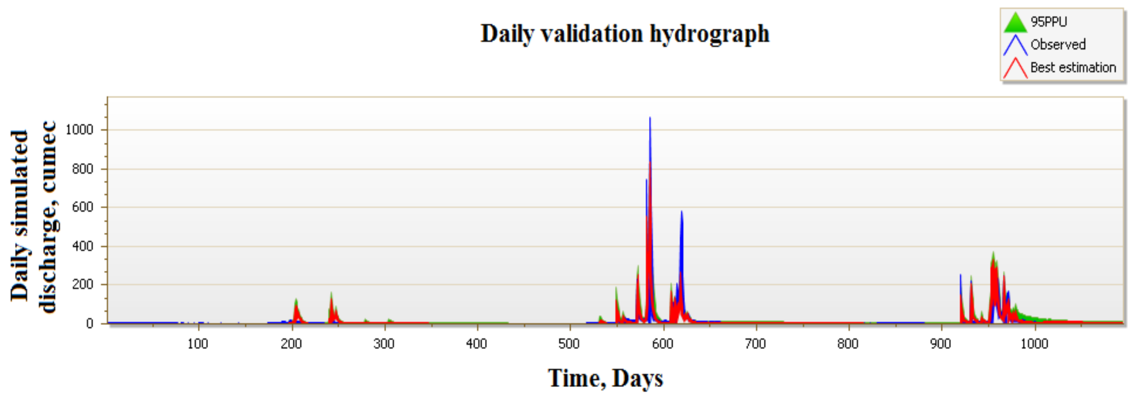


Fig. 4.16: Daily validation hydrograph of Dhadhar basin

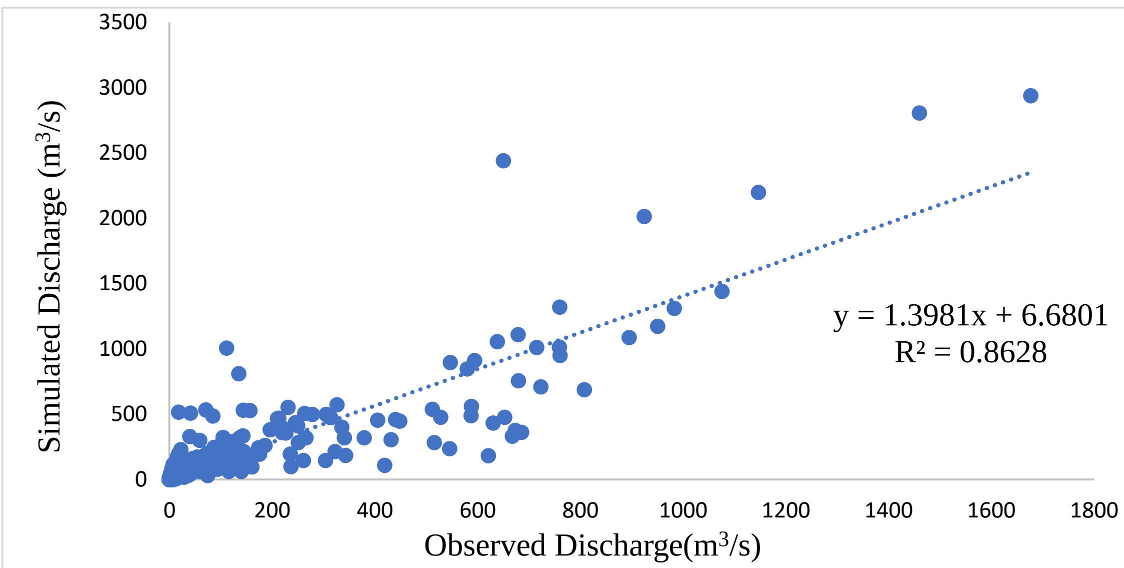


Fig. 4.17: Daily scatterplot showing observed vs simulated discharge for Dhadhar basin

Dhadhar basin has an average curve number of 80.81 as presented in the Table 4.12. Higher curve number causes higher runoff potential. Curve number is governed by land use, hydrological soil group, hydrologic conditions, and antecedent moisture conditions which depend on the average slope of the basin. The high curve number value supports the fact that the basin has more clay soil and converts more than 50% of the rainfall into runoff as suggested by the values in Table 4.12. Flow processes of the basin is clearly described by Fig. 4.7.

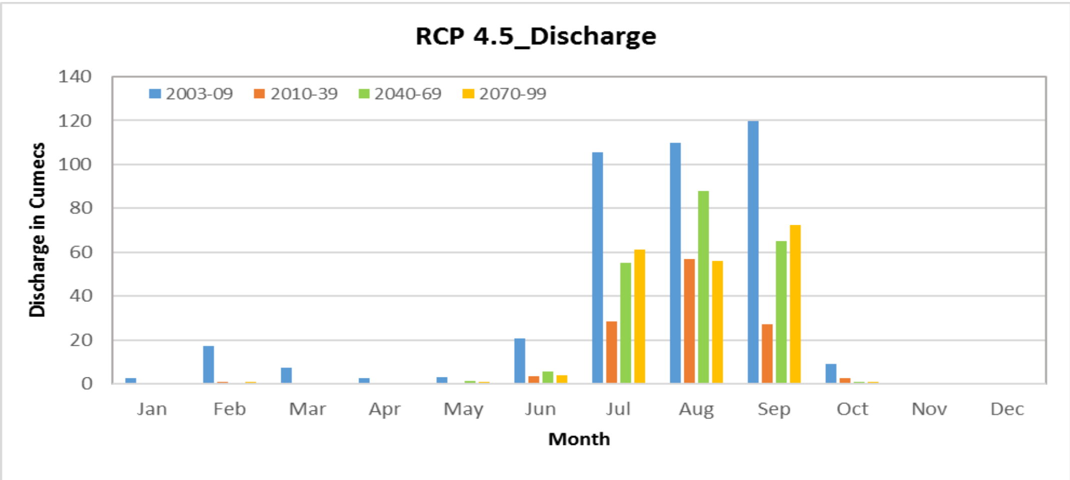
Table 4.12: Hydrological parameters for Dhadhar basin

Hydrological parameters	Value, mm
Precipitation	1026.2
Surface runoff	526.05
Lateral flow	2.83
Return flow	203.56
Revaporation from shallow aquifer	48.08
Recharge to deep aquifer	13.25
Total water yield	745.73
Percolation to shallow aquifer	264.97
Actual evapotranspiration	232.3
Average curve number	80.81

Climate Change

The present study is envisaged on the assessment of hydrological changes in different watersheds in India under changing environment. Four different watersheds located in different climatic regions namely Dhadhar river basin (Gujarat), Ramganga up to Kalagarh (Uttarakhand), Bina River basin (M.P) and Chaliyar river basin (Kerala) were selected. The impact of climate change on the streamflow under RCP scenarios 4.5 and 8.5 for these basin are described as:

Ram Ganga: Simulated flow will reduce for all the future scenarios for RC 4.5 and RCP 8.5 for the basin. However, comparatively period of 2040-69 will have more average flows then 2010-39 and 2070-99.



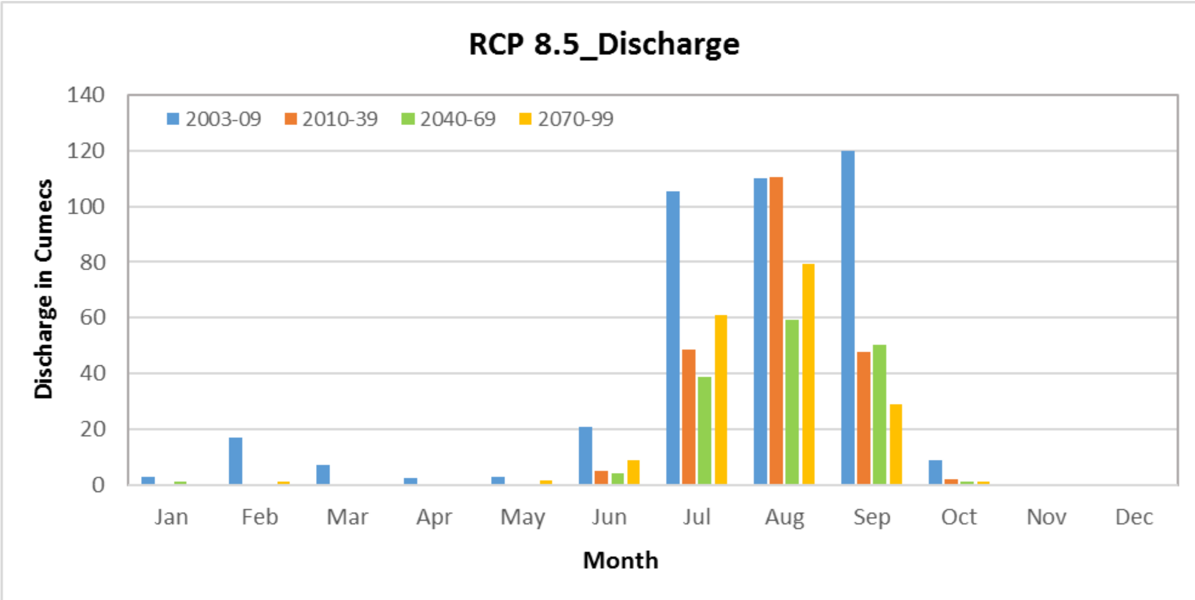
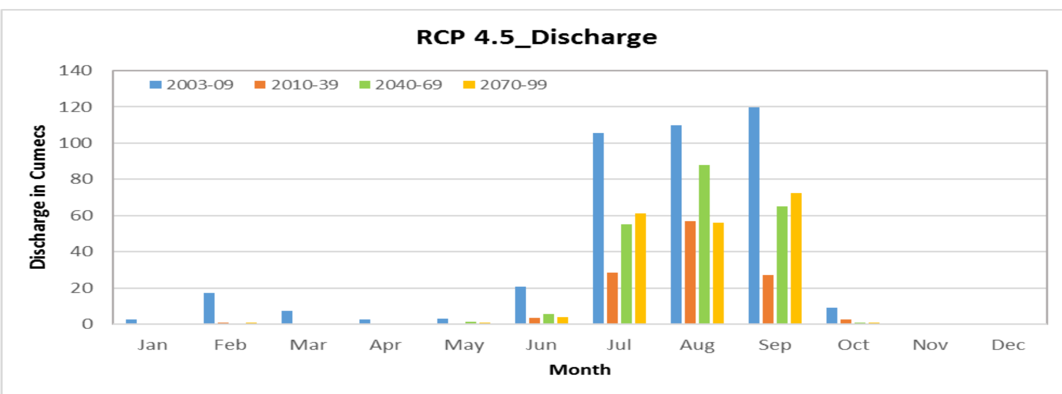


Figure 4.18: streamflow under RCP scenarios 4.5 and 8.5 for Ramganga basin

Bina: simulated runoff will be increasing in period 2040- 2070 and decreasing during 2010-2039 while almost same during 2071-2099 (RCP4.5) and decreasing runoffs under RCP8.5 scenarios



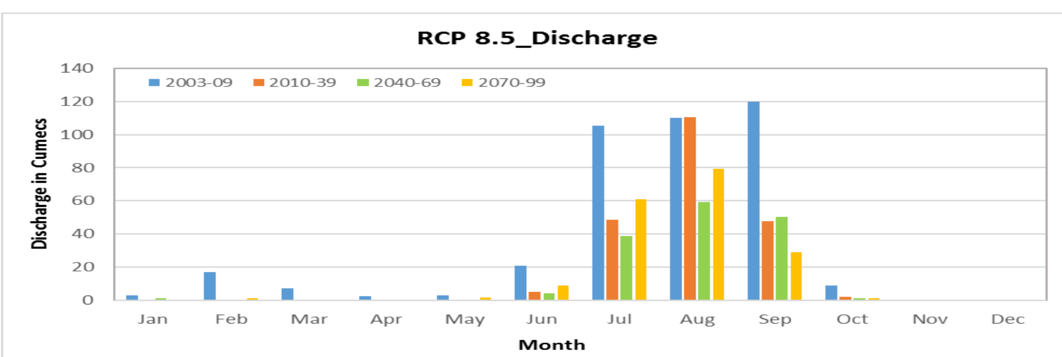
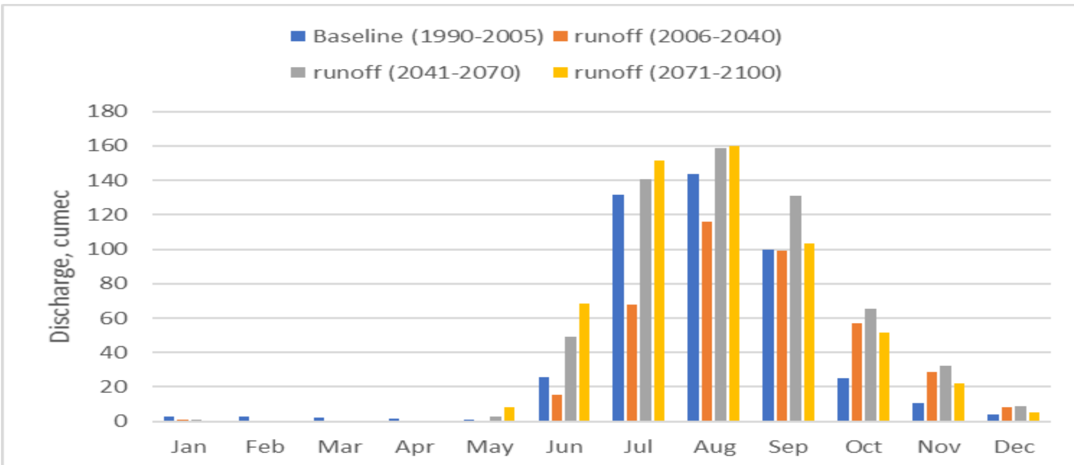


Figure 4.19: streamflow under RCP scenarios 4.5 and 8.5 for Bina basin

Dhadhar: Simulated runoff will be increasing in all periods with highest during 2014-2070 (RCP4.5) and 2006-2040 (RCP8.5)



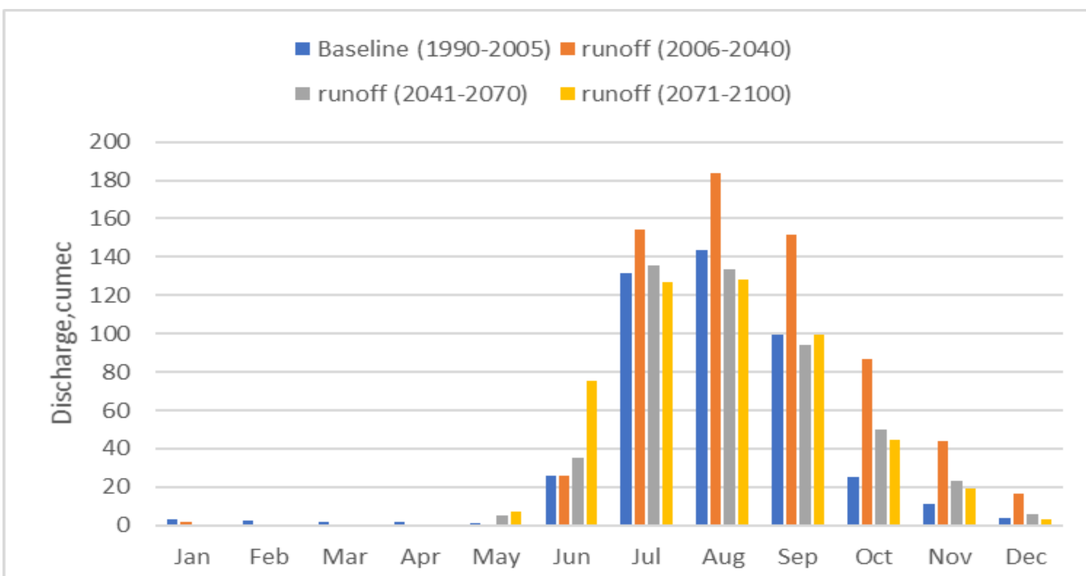
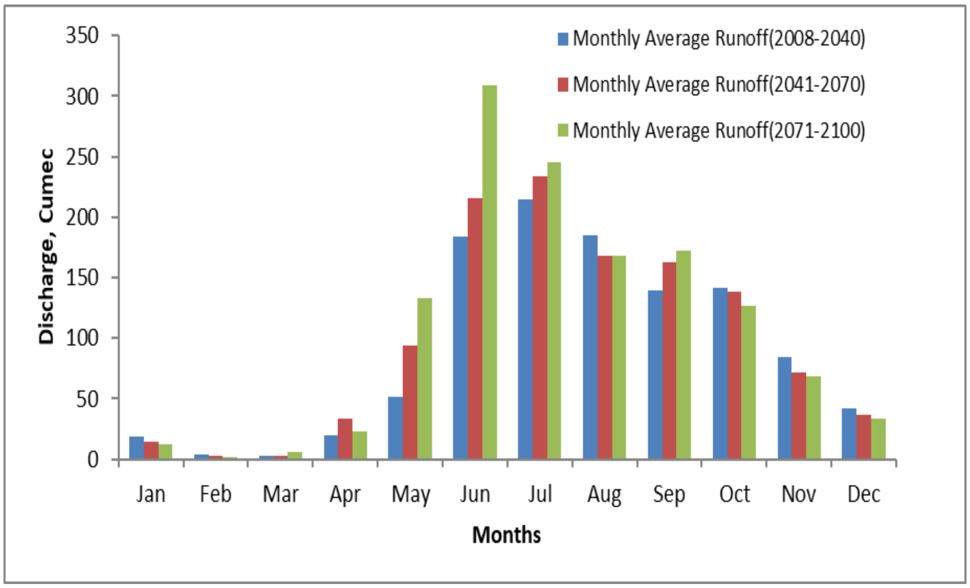


Figure 4.20: streamflow under RCP scenarios 4.5 and 8.5 for Dhadhar basin

Chaliyar: Simulated runoff is observed to be increasing in all periods with highest during 2071-2100 (RCP 4.5) and 2041-2070 (RCP8.5).



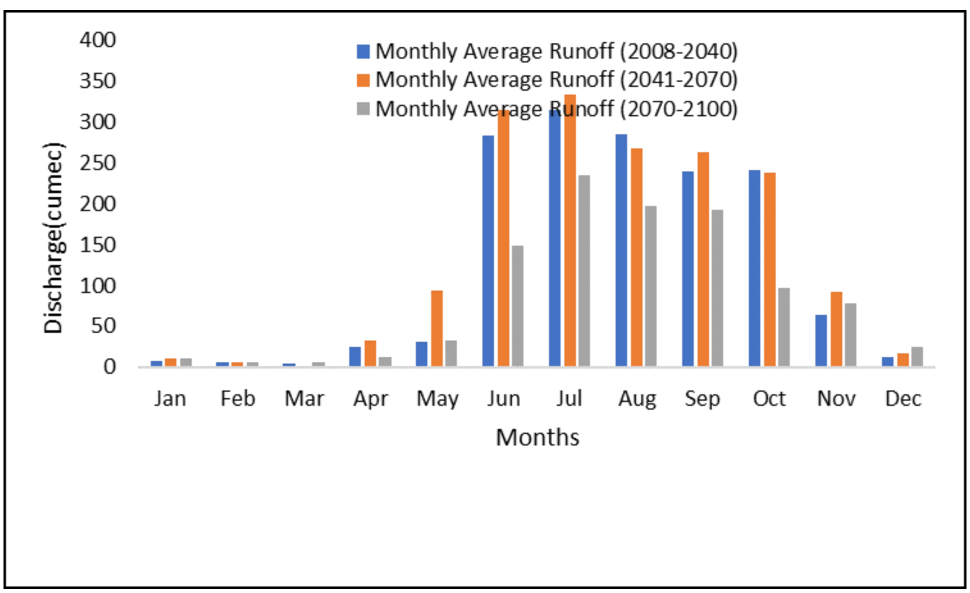


Figure 4.21: streamflow under RCP scenarios 4.5 and 8.5 for Chaliyar basin

Transformation of rainfall and temperature regimes is leading to the changes in the streamflow in these river basins. As a next step, the development of effective climate change management responses will likely to involve local-level strategies of water Conservation practices including rainwater harvesting; renovation of traditional water bodies; watershed development activities namely soil and water conservation, check dams, trench etc. along with intensive forestation. Moreover, drought resistant crops with efficient methods of irrigation with irrigation scheduling need to be practiced to cope with changing climate.

Hence, hydrological modeling integrating climate change scenarios at basin scale will be helpful to analyze, understand, and explore solutions for sustainable water management, in order to support decision makers and operational water managers and provide useful suggestions for IWRM.

The inter-comparison of water resources variability in selected basins and suggestions for IWRM are given in Table 4.13

Table: 4.13: suggestions for IWRM are given in Table 4.13

Basin	Trend	Drought	Scenarios under RCP's
Ram Ganga	Annual: The annual rainfall indicates falling trend in all station only one station namely Lansdowne is found significant at 95% confidence level with maximum decrease (-23.814 mm/year). Seasonal: Seasonal analysis of rainfall trends during pre-monsoon, monsoon and winter season shows that falling trend at Lansdowne with maximum magnitude of (-3.110 mm/year), (-19.327 mm/year), (-2.262 mm/year), respectively and found significant at 95% confidence level	Extreme and severe events observed at different time scales	Average simulated flow will reduce for all the future scenarios for RC 4.5 and Rcp 8.5 for the basin. However, comparatively period of 2040-69 will have more average flows then 2010-39 and 2070-99.
Bina	Monsoon rainfall of Begumganj,Gairatganj and Kurwai have experienced insignificant decreasing trend whereas Gyaraspur observed the insignificant increasing trend. Overall, incresing trend in raifall is seen at Gyraspur station	Extreme and severe events observed at different time scales	Runoff will be increasing in Period 2040- 2070 and decreasing during 2010-2039 while almost same during 2071-2099 (RCP4.5) and decreasing runoffs under RCP8.5 scenarios
Dhadhar	Annual: decreasing trend at majority of the stations whereas station Bhavnagar (0.205 mm/yr) indicated increasing non-significant trends at 95% of confidence level.Seasonal : In the monsoon season, all the stations show	Extreme and severe events observed at different time scales	Dhadhar: Runoff will be increasing in all periods with highest during 2014-2070 (RCP4.5) and 2006-2040 (RCP8.5)

	decreasing non-significant trend in rainfall except Bhavnagar.		
Chaliyar	Annual: rainfall indicates rising trend at Ambalavayal, Kalladi and Nilambur stations increasing at the rate of 18.72 mm/year, 57.18 mm/year and 2.57 mm/year respectively, while Manjeri indicates falling trend decreasing at the rate of 21.57 mm/year. Monsoon rainfall increases at the two stations Ambalavayal and Kalladi and decreases at the other two stations	Extreme and severe events observed at different time scales	Simulated runoff flow is observed to be increasing in all periods with highest during 2071-2100 (RCP 4.5) and 2041-2070 (RCP8.5)

CHAPTER 5

SUMMARY AND CONCLUSIONS

Hydrological modelling is of foremost importance for appropriate planning, designing and decision-making activities of water resources. A simple, logistic and systematic modeling of Rainfall-Runoff is an important & challenging issue in recent changing environments to properly manage water resources for socio economic development of the society in the region. Rainfall-Runoff for a basin is an important hydrological study as these results are required in the most hydrological analysis for the purpose of water resources planning, development & management. In the present study, a lumped conceptual model of SWAT model has been used. Four different watersheds located in different climatic regions namely Dhadhar river basin (Gujarat), Ramganga up to Kalagarh (Uttarakhand), Bina River basin (M.P) and Chaliyar river basin (Kerala) have been selected for the present study.

The remote sensing and GIS are the promising tools for providing spatio-temporal inputs for rainfall runoff studies

Bina Basin

- The rainfall trend analysis conducted at the station and basin level at monthly, seasonal and annual scales using non-parametric trend test (Mann-Kendall tests) were showed an increasing and decreasing trends for the period of 1986-2008, even
- Drought analysis results using standard precipitation index in different timescales viz. SPI 6 and SPI 12 in rain gauge stations of Bina basin viz. Begumganj, Gairatganj, Gyaraspur, and Kurwai showed fluctuations of the extremely drought and wet events.
- SWAT-CUP advance calibration and uncertainty analysis tool have been used for automatic calibration/uncertainty analysis, validation, and sensitivity analysis of stream-flow measurements on the daily and monthly basis for the period 1989–1996 using SUFI-2 techniques.
- The coefficient of determination (R2) for the daily and monthly runoff was obtained as 0.66 and 0.96 respectively for the calibration period and 0.65 and 0.72 respectively for the validation period.
- The model gives satisfactory result in Bina basin

- SWAT is a fair model for simulation and calibration for discharge in Bina river basin.
- MIKE11-NAM other hydrological model satisfactory and reliable results were obtained with efficiency index, the coefficient of determination and water balance error as 0.87, 0.87 and-8.63% respectively.
- The capability of the model was revealed by a good match of simulated data with the observed data and a good overall agreement of the shape of the hydrograph with respect to timing, rate, and volume.

Ram Ganga Basin

- Annual, pre monsoon, and monsoon season of Kalagarh station showed falling trend in T_{max}, T_{min}, and T_{avg} during winter and post monsoon season whereas T_{max} indicated rising trends.
- Relative humidity indicated increasing trend at seasonal scale whereas decreasing trend has been observed at annual scale which insignificant at 95% confidence level. Average discharge also indicated falling trend at annual and seasonal scale.
- Hydrological model NAM and SWAT developed for the Ramganga basin have been found suitable for rainfall runoff processes with high degree of accuracy with coefficient of determination 0.77 and 0.78 during validation period respectively.
- The model was seen performing well to simulate runoff in good agreement with observed runoff in terms of timing, rate, volume and shape of hydrograph.
- The rainfall runoff model thus developed seems to be capable of predicting runoff for extended time period in Ramganga basin and other sub basin of similar characteristics.
- The NAM model was found sensible to parameters like, C_{QOF}, L_{max} and C_{K1K2}. The coefficient of overland flow (C_{QOF}) was found as the important parameter for modelling as it was seen affecting water balance error and peak flows both.
- Similarly, SWAT model also suitable for the study area to simulate the runoff. Parameters namely CN, available water capacity, soil depth, soil evaporation compensation factor and threshold depth of water in the shallow aquifer (GWQ_MN) were found to be the most sensitive parameters for the Ramganga basin.
- In runoff calculation both the model overestimates the runoff. The error for overestimation was within the limit of calibration for low to medium rainfall (daily). Comparison between

both the model based on coefficient of determination are respond approximately same as NAM model showed 0.77 and SWAT model showed 0.78 during validation period.

- Thus, both NAM and SWAT model could be the important tool in water resources planning and management to generate runoff and other components of hydrological cycle.

Dhadhar Basin

- Dhadhar basin consist of agriculture, barren land, forest, settlement, and water body which cover 59.51%, 30.76%, 4.47%, 3.17% and 2.1% respectively. Soil of the catchment includes clay, loam, sandy loam and clay loam covering an area of 59.69%, 21.4%, 16.1% and 2.81% respectively. Maximum elevation of this basin is found to be 750 m.
- The basin has been delineated into 19 sub-basins and further classified into 140 Hydrological response units (HRUs). Dhadhar basin has an average curve number of 80.81.
- Sensitivity analysis shows that for daily flow Manning's roughness coefficient for channel flow and for monthly flow SCS curve number are the most sensitive parameters. Coefficient of determination (R2) was found to be 0.86 and 0.73 for daily calibration and validation and 0.95 and 0.85 for monthly calibration and validation period respectively for SWAT model.
- Similarly, NSE was found to be 0.86 and 0.72 for daily calibration and validation period and 0.93 and 0.83 for monthly calibration and validation period respectively.
- From this study it has been concluded that The SWAT model accurately simulates runoff from the watersheds on daily and monthly basis and can successfully be used to apply for estimating the runoff from the similar watersheds.

Chaliyar Basin

- The rainfall trend analysis conducted at four different stations in the basin at monthly, seasonal and annual scales using non-parametric tests (Mann Kendall & Sen slope) showed an increasing and decreasing trends for the period of 1991 to 2011, even though statically insignificant at 95 % level of confidence .
- On the other hand Parametric test (Regression analysis) identified some negative and positive trend for all the four stations at seasonal and annual scale.
- Model have been applied for modelling of stream flow for Chaliyar river basin, Kerala, India with a basin area of 2013 km2.

- The model yielded satisfactory and reliable results with coefficient of determination and Nash-Sutcliffe Efficiency 0.77 & .75 % respectively for calibration and for validation these value are .77 & .73 respectively .
- A good match of simulated data with the observed data and a good overall agreement of the shape of the hydrograph with respect to timing, rate and volume revealed the capability of the model.

Suggestions for IWRM

Transformation of rainfall and temperature regimes is leading to the changes in the streamflow in these river basins. As a next step, the development of effective climate change management responses will likely to involve local-level strategies of water Conservation practices including rainwater harvesting; renovation of traditional water bodies; watershed development activities namely soil and water conservation, check dams, trench etc. along with intensive forestation. Moreover, drought resistant crops with efficient methods of irrigation with irrigation scheduling need to be practiced to cope with changing climate.

Hence, hydrological modeling integrating climate change scenarios at basin scale will be helpful to analyze, understand, and explore solutions for sustainable water management, in order to support decision makers and operational water managers and provide useful suggestions for IWRM.

The suggestion that may help to manage the water resources in the study area are

- Water Conservation practices: Rain water harvesting under the changing scenarios may be practiced to tire the rain water
- Renovation of traditional water bodies, Desilting etc
- Watershed Development: Soil and water conservation measures and structures namely check dams, trench etc. may be helpful to conserve the water
- Water Supply scheme to be taken up
- Drought resistant crops with efficient methods/Scheduling of irrigation to be practiced Intensive Forestation

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