

**INVESTIGATING THE APPLICABILITY OF MIKE MODELS FOR  
EVALUATING DIFFERENT WATER AVAILABILITY AND  
ALLOCATION SCENARIOS UNDER CLIMATE CHANGE  
SITUATIONS**

by

Miss. Mandave Vidya Ramchandra

(Reg. No. 2013/05)

**DOCTOR OF PHILOSOPHY  
(AGRICULTURAL ENGINEERING)**



**DEPARTMENT OF IRRIGATION AND DRAINAGE ENGINEERING**

**DR. ANNASAHEB SHINDE COLLEGE OF AGRICULTURAL ENGINEERING AND  
TECHNOLOGY, FACULTY OF AGRICULTURAL ENGINEERING**

**MAHATMA PHULE KRISHI VIDYAPEETH, RAHURI - 413 722  
DIST. AHMEDNAGAR, MAHARASHTRA, INDIA**

**2020**

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**MAHATMA PHULE KRISHI VIDYAPEETH, RAHURI - 413 722,  
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**2020**

## CANDIDATE'S DECLARATION

I hereby declare that this thesis or part  
thereof has not been submitted  
by me or other person to any  
other University or Institute  
for a Degree or  
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The assistance and help received during the course of this investigation has been duly acknowledged.

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**(D. D. Pawar)**

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## LIST OF ABBREVIATIONS AND SYMBOLS

%	:	Per cent
@	:	At the rate
Agri.	:	Agriculture
Agril.	:	Agricultural
ANN	:	Artificial Neural Network
ASAE	:	American Society of Agricultural Engineering
BF	:	Baseflow
CC	:	Climate Change scenario
CCA	:	Culturable Command Area
cm	:	Centimeter
DEM	:	Digital Elevation Model
Dept.	:	Department
DHI	:	Danish Hydraulic Institute
Diff.	:	Difference
Dist.	:	District
DSS-IWM	:	Decision Support System- Irrigation Water Management
EI (NS)	:	Efficiency Index (Nash Sutcliffe)
Engg.	:	Engineering
Eq.	:	Equation
<i>et al.</i>	:	And others
ETc	:	Crop evapotranspiration
etc.	:	Etcetera
ETo	:	Reference crop evapotranspiration
FAO	:	Food Agriculture Organization
FC	:	Field capacity
Fig.	:	Figure
GDP	:	Gross Domestic Product
GIS	:	Geographical Information System
GWR	:	Groundwater Recharge
Ha	:	Hectare
HD	:	Hydrodynamic
h	:	Hour
i.e.	:	That is
IDE	:	Irrigation and Drainage Engineering
IF	:	Interflow

IMOS	:	Irrigation Management and Optimization System
IRMOS	:	Irrigation Management and Optimization System
IWAM	:	Integrated Water Allocation Model
IWPM	:	Irrigation Water Planning Model
Kc	:	Crop coefficient
Kg	:	Kilogram
Kg/ha	:	Kilogram per hectare
Km/hr	:	Kilo meter per hour
Km <sup>2</sup>	:	Square Kilometer
Ky	:	Yield Response Factor
LAV	:	Level-Area-Volume
LBC	:	Left Bank Canal
m	:	Meter
M. S.	:	Maharashtra State
MCM	:	Million Cubic Meter
mm	:	Millimeter
MPKV	:	Mahatma Phule Krishi Vidyapeeth
NA	:	Not Available
NAM	:	Nedbør-Afstrømnings-Model
NDVI	:	Normalized Difference Vegetative Index
NIR	:	Near Infrared
NSE	:	Nash Sutcliffe Efficiency
OF	:	Overland Flow
P.joga	:	Pimpalgaonjoga
Q	:	Runoff
Q-Obs	:	Observed Runoff
Q-Sim	:	Simulated Runoff
r	:	Correlation Coefficient
R <sup>2</sup>	:	Coefficient of determination
RBC	:	Right Bank Canal
RH	:	Relative humidity
RMSE	:	Root mean square error
RR	:	Rainfall-Runoff
Rs.	:	Rupees
s	:	Second
Sci.	:	Science
Soc.	:	Society
SRTM	:	Shuttle Radar Topography Mission

SWAB-CRYB	:	<b>Soil Water Balance-Crop Yield Benefit model</b>
TRMM	:	Tropical Rainfall Measuring Mission
<i>viz.</i>	:	Namely
WBE	:	Water Balance Error

## ABSTRACT

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**“Investigating the Applicability of MIKE Models for Evaluating Different Water Availability and Allocation Scenarios under Climate Change Situations”**

by

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in

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Increasing food demand for population and growing industrialization create pressure on the available water resources. As agriculture consumes more than 80% of surface and groundwater resources, it is necessary to utilize the water efficiently for agriculture and overcome the water scarcity problems for sustainable production. Hence, optimum utilization of the available surface and ground water is a need. Assessment of surface water availability in reservoir is, therefore, important for water authorities and farmers to plan irrigation water management and water allocation. Water availability and water allocation both are influenced due to climate vulnerability and climate change situations. Considering the importance of assessment and allocation of water, the study was conducted to investigate the applicability of suit of MIKE models: MIKE 11 NAM, MIKE HYDRO Basin and MIKE Zero climate change module for assessing water availability and water allocation scenarios under climate change situations in Ghod complex sub catchments of Maharashtra. Ghod and Kukadi river are main source of water for irrigating the vulnerable areas of Pune, Ahmednagar and Solapur districts.

The water availability study was undertaken in Ghod complex sub catchments viz. Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon by using MIKE 11 NAM rainfall- runoff model. The model was manually calibrated by interchanging the range of different nine model parameters for the period of year 2002-2009 and validated for the year 2010-2011. The model was evaluated by using graphical and statistical performance measures, and results indicated the evaluation parameters such as coefficient of determination ( $R^2$ ), correlation coefficient ( $r$ ), Nash Sutcliffe Efficiency Index (EI) and water balance error (WBE) between observed and simulated runoff were in permissible limits. These calibrated and validated model were used to forecast the water availability for the year 2013 for all the catchments. Artificial Neural Network (ANN) 4-10-1 model forecasted rainfall of different stations was used to forecast the water

availability for the year 2013. MIKE 11 NAM rainfall runoff model was found suitable to forecast water availability using forecasted series of runoff.

The water allocation scenarios were studied by using MIKE HYDRO Basin model for Ghod command area by considering three different cropping patterns: multi-crop, major-crops and Sugarcane only, on the basis of area allocation from 150 km<sup>2</sup> to 415 km<sup>2</sup> with the increment of 50 km<sup>2</sup>. In base scenario, the irrigation water demand and deficit were estimated for the period of year 2002-2009. In this, multi-crop cropping pattern provided better results with minimum deficit to fulfill the irrigation water demand of Ghod command area up to 250 km<sup>2</sup>. Water allocation scenarios were generated for the given three different cropping patterns under increasing irrigation water demand in base scenario by 25% and 40%. In all scenarios, it was found that, as the area increased, irrigation water demand and deficit were found increased. In forecasted water allocation scenarios, during the year 2020, 2050 and 2080 the irrigation water demand and deficit were found increased approximately by 3%, 10-15% and 20-25% respectively, than baseline scenario for all the three cropping patterns. Also, MIKE HYDRO Basin model and SWAB-CRYB simulation models were compared for estimation of crop yield using similar crop database and MIKE HYDRO Basin model simulated more yield as compared to SWAB-CRYB model.

Water availability and water allocations were studied using MIKE Zero climate change functionality tool. GCM model, CNRM: CM3 in combination with three emission scenarios SRB1, SRA1B and SRB2 were used to study water availability in 2020's, 2050's and 2080's. CNRM: CM3- SRA1B combination was found suitable in statistical evaluation to estimate water availability for all the catchments. Water availability was found to be increased by 3.45 to 5.87 %, 11.34 to 17% and 5.94 to 23.36% in the year 2020's, 2050's and 2080's respectively, for all the catchments. This increased water availability was considered for studying effect of climate change on water allocation for three different cropping patterns in 2020's, 2050's and 2080's. Irrigation water demand and deficit were found to be increased in 2020's, 2050's and 2080's than base scenario. Multi-crop cropping pattern was found suitable to fulfill the water demand of 250 km<sup>2</sup> of command area during 2020's and 2050's, and 200 km<sup>2</sup> of command area during 2080's. Under climate change situation, with the increased water demand condition, the increased water availability was found sufficient to irrigate 50% of Ghod command area using multi-crop cropping pattern.

Thus, the present research contributes all the water management and planning in catchment and command area for historical and futuristic climate change situations. The hydrological model like MIKE models provided a platform to study the water availability and water allocation under Ghod complex sub catchments and Ghod command area.

## 1. INTRODUCTION

The water resources around the world are under increasing pressure due to rapid population and economic growth, aggravated by a lack of coordinated management and governance (UNESCO, 2003). Increasing population, growing urbanization, and rapid industrialization combined with the need for raising agricultural production generates competing claims for water. The total volume of water on earth is estimated at 1.386 billion km<sup>3</sup> with 97.5% being salt water and 2.5% being fresh water. Only 0.3% of fresh water is available in liquid form on the surface. Out of the freshwater available on the Earth, much more is stored as groundwater and little is available in rivers and lakes. The total volume of water in the rivers on earth is estimated as 2120 km<sup>3</sup> or 2% of the total fresh water on earth (Gleick, 1993). Rivers and basins are often compared not according to their static volume but their flow of water or surface runoff.

India being a large country with different climatic regimes and the characteristics of the water cycle differs from one region to other which are reflecting on the water availability. Sustainable development and efficient management of water is an increasingly complex challenge in India now-a-days. India having 2.4% of the world's total area, contributing around 16% of the world's total population; but has only 4% of the total available fresh water. To feed the constantly growing population of India, it is necessary to increase the area under irrigation as the productivity of irrigated agriculture is two to three times more than the productivity of rain fed agriculture (Anonymous, 2013). This clearly indicates the need for water resource development, conservation, and optimum use in India.

India comprises around 20 major river basin with several tributaries. The total water resource potential, which occurs as a natural runoff in these rivers, is estimated to be about 1869 BCM (EnviStats-India, 2018). Many of these rivers are perennial while some are seasonal. More than 50% of water resources of India is located in various tributaries of these river systems. Apart from the water available in various rivers of the country, the groundwater is also an important source for drinking, irrigation, industrial uses, etc. It accounts for about 80% of the domestic water requirement and more than 45% of the total irrigation in the country. According to the planning commission of India and National Commission for Integrated Water Resources Development, the water requirement for irrigation purpose alone would be 1191 BCM by the year 2050.

Maharashtra state has geographical area about 30.8 Mha and cultivable area about 24.6 Mha, from which only 16.2 % is at present irrigated. Out of this, about 50 % area is irrigated by groundwater through wells and remaining by surface water stored in large to small reservoirs. There are five major

river basins in Maharashtra viz. Krishna, Godavari, Tapi, Narmada and western flowing rivers in Konkan region. According to MWRRA (2018), the estimated average annual water availability of water resources consists of 164 km<sup>3</sup> of surface water and 20.5 km<sup>3</sup> of subsurface water. 45% of the state water resources are available from the west flowing rivers of Konkan region which are mainly monsoon specific rivers. On full development and optimum utilization of all available water resources, it is possible to increase the irrigation potential of Maharashtra up to 30 % of the total cultivable area. Pune, Ahmednagar and Solapur are three leading districts in western Maharashtra by many ways. Considering Maharashtra state Ahmednagar district produces more than half of sugar production of the total production, and Shrigonda Tahsil is leading in it. Pune is an industrial, commercial center and most important end market for agriculture. Ghod and Kukadi rivers are main source of water in these districts. All the water availed from rainfall in both of these river is collected in seven reservoirs viz. Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon. These seven reservoirs are contributing major part of water resources in Upper Bhima river basin. Therefore, the present study was conducted for the assessment of water availability and water allocation under these river basin.

The land and water which are the major inputs for agriculture production are the limited resources. Due to rapid urbanization and industrialization, the share of these resources to agriculture is reducing day by day. Water is a very critical input for the plant growth and crop production. Hence, we do not have any option other than to produce more food grain from these limited water resources. Therefore, we have to produce maximum output from the limited water resources and for this, efficient management of limited water resources is necessary.

Thus, managing limited water resources is a major challenge in the changing environmental and demand conditions. The relative increase in demand of water for various purposes brought about by the population growth, agricultural and economic development combined with increasing population of water supplies, have raised serious problems. Water can now no longer be taken for granted.

Water is required not only in different sectors but also within specified sector, and required for different purposes. Additionally, these requirements vary with space and time. Assessment of water availability in the catchments can be done by studying rainfall-runoff relations. Estimation of runoff is an essential component in the management of water resources. Runoff is one of the major component of hydrologic cycle. The hydrologic system consists of inflows, outflows and storages which makes water balance. Water balance studies need to be carried out to assess the available quantity of water in a given basin. There is also necessity to formulate and evaluate different water allocation scenarios for different water availability and demand conditions.

The allocation of water resources in river basin is one of the critical issues. Most of the past work reported in the literature are either area specific or based solely on economic criteria for allocation of water or environmental needs using optimization and simulation techniques. Conflicts often arise when different water users (including the environment) compete for a limited water supply. In order to achieve sustainable development and a secure society, institutions and methodologies for water allocation should be reformed, especially for regions having water resources shortages (Juiping *et al.*, 2012). An integrated analysis at the watershed scale would be valuable, where individual water related sectors, such as, agriculture, municipal and industrial water supply are brought together in framework (Bangash *et al.*, 2012). Water allocation should consider three key principles: equity, efficiency and sustainability (UNESCAP, 2000). Equity means that water resources within a river basin should be fairly shared by all of the stakeholders. Efficiency concerns the economic use of water resources with respect to minimizing costs and maximizing benefits. Under sustainability, water is utilized economically both now and in the future such that the environment is not harmed. However, it is not easy to fulfill all three of the principles or goals for a water allocation problem at the basin scale.

As long as water demand remains small compared to its availability, all users can coexist without conflicts and as such the problem of water allocation does not arise. But this is not the case with the increase in demand, the conflicts between users intensify and increase in frequency and its impacts on water resources become noticeable. Thus, to avoid the present as well as future conflicts between the competing demands, researchers and scientists have given increased emphasis in developing tools and techniques for improved management of the water resources. The development and application of mathematical models, which provide a good insight into the intricacies of various problems related to proper water allocation, is therefore necessary.

Water is involved in all the components of climate system such as atmosphere, hydrosphere, cryosphere, land surface and biosphere. Some observational records and climate projections provide evidence that, water resources are vulnerable and have potential, to be strongly impacted by climate change with wide- ranging consequences, for human societies and ecosystem. Therefore, climate change affect water through a number of mechanisms. Climate warming is observed over the past several decades. It is consistently associated with changes in number of components of the hydrological cycle such as: changing precipitation pattern, intensity and extremes, widespread melting of snow and ice, increasing atmospheric vapor, increasing evaporation and temperature, changing soil moisture and runoff (ADB, 2010). Hence there is need to study the impact of climate change on water resources, which influences the water availability, demand patterns and thereof water allocation scenarios.

Mathematical models provide the opportunity for the well-structured basin-wide analyses of water availability, water allocation and climate change effect on both and offer a framework for a coordinated planning and management. Basin-scale models have been widely used to assess performance of water resources systems. They use hydrologic input data and simulate the behavior of various hydrologic, water quality, economic or other variables under a fixed set of water allocation policies. A distinguishing feature of these simulation modeling is the ability to assess water resources system responses to extremes, non-equilibrium conditions and thereby to identify the system components more prone to failure.

There are several modelling tools available for water resource management viz. MIKE models, RIBASIM (RIver BASin SIMulation), Arc-SWAT (Soil and Water Assessment Tool), HEC (Hydrologic Engineering Center's) models etc. Some of these models for e.g. ARC SWAT and HEC are in free domain. However, MIKE suit of models have the capabilities to analyze the allocation of water for different crops.

The MIKE 11 NAM Rainfall-Runoff model is a hydrological model that simulates the rainfall-runoff processes occurring at the catchment scale. It is one of the rainfall-runoff models widely used for rainfall-runoff modelling. It is a conceptual representation of the land phase of the hydrological cycle simulates water through four storages viz. surface storage, root zone storage, groundwater storage and snow storage. The rainfall runoff model used to assess water availability in study area. MIKE HYDRO Basin model is a new interface of MIKE BASIN model which is one of the important models used for modeling of river basin for optimizing and utilizing the river water potential. It is a mathematical representation of the river basin encompassing the configuration of the main rivers and their tributaries, the hydrology of the basin in space and time, existing as well as potential major schemes and their various demands on water. In this study the models is used to study different water allocation scenarios. MIKE HYDRO Basin model and Soil Water Balance and Crop Yield Benefit (SWAB-CRYB) model (Gorantiwar, 1995, Gorantiwar and Smout, 2003) estimates crop yield using same data.

Forecasting of water availability and water demand are useful for better planning and management in the river basin. Artificial Neural Network (ANN) model capable of identifying nonlinear relationship between input and output data sets, which may be too difficult to represent by conventional. It is most promising and capable of forecasting rainfall and evapotranspiration which is used to forecast water availability and water demand.

Also, MIKE software makes it possible to generate climate change scenarios for a large number of the models available within the MIKE Zero suit. The MIKE Zero Climate Change functionality is based on the work reported by the Intergovernmental Panel for Climate Change (IPCC) in the Fourth

Assessment Report (AR4) and more recent research results on global sea level rise. As climate is showing the greater variability than ever and forth coming 'climate change', it is necessary to evaluate water availability water allocation under different scenarios of climate variability and climate change. Hence, MIKE Zero Climate Change functionality tool is used to study climate variability under different climate change scenarios. As MIKE suit of models provides a platform for evaluating different water availability and water allocation scenarios under climate change situation, it is proposed therefore to investigate the applicability of these models.

The present study is therefore undertaken to calibrate and validate MIKE 11 NAM, MIKE HYDRO Basin and MIKE Zero Climate Change functionality models for the river basin data of Upper Bhima basin and evaluate different water availability and water allocation scenarios under climate change situations with following specific objectives:

1. To simulate water availability in Ghod complex sub catchment of Upper-Bhima basin using MIKE 11 RR model for historical and synthetically generated series of rainfall
2. To simulate water demand in Ghod complex sub catchment for different cropping patterns using MIKE HYDRO BASIN model for historical and synthetically generated series of climatological variables influencing evapotranspiration
3. To compare the SWAB-CRYB model with MIKE HYDRO BASIN model for estimation of yield of different crops
4. To evaluate the effect of different water allocation scenarios for different water availability and demand
5. To study the influence of climate variability and climate change on water allocation pattern in Ghod complex sub catchment

## 2. REVIEW OF LITERATURE

Hydrological modeling is one of the tools that can be used to provide the means to quantitatively extrapolate or predict hydrologic response which is helpful in decision making concerning a particular hydrological problem. During last decades, various models and software were developed in the domain of water resources, which have shown tremendous progress and established the potential of using different technologies for water allocation. Several models and software have been developed for applications in water resources that have contributed in enhancing the efficiency of water use.

The water is scarce commodity and hence need to be used and allocated optimally. Therefore, this study was also aimed at allocation of the available water. The main focus of the study was on the calibration of MIKE 11 NAM model for water availability, MIKE HYDRO Basin model for water allocation and MIKE Zero climate change tool for studying the future water availability and water allocation in the selected area. In this chapter the reviews of the earlier research work pertaining to water allocation using different models and software, effect of different water allocation scenarios for different water availability, simulation of water availability and different water allocation models, for allocation water resources are presented. The results of previous studies are reviewed in following categories.

1. Rainfall-Runoff modeling
2. MIKE 11 NAM model
3. Application of ANN technique
  - a. ANN for forecasting of rainfall
  - b. ANN for forecasting of ETr
4. Water allocation modeling
5. MIKE HYDRO Basin model
6. SWAB-CRYB model
7. Climate Change scenarios

### 2.1 Rainfall-Runoff modeling

Hydrological cycle is a complex phenomenon that imitates to the natural system. Hydrological models are mathematical models, used to solve this complex phenomenon into simple form. Rainfall-runoff models are hydrological models, particularly effective tools to predict the responses of a basin with a given amount of rainfall. This section reviews the different previous studies reported on this aspect.

Pathak *et al.*, (1989) developed a Modified Soil Conservation Services runoff model to predict runoff volume from small watershed which was based on the modified soil conservation services curve

number technique and on a soil moisture accounting procedure. This model was tested with data from three Vertisol watershed at ICRISAT center, Patancheru, India. The model simulated daily monthly and annual runoff volume accurately. In 1978 which was a high rainfall year, the model simulated an annual runoff of 270 mm compared with a measured runoff of 264 mm for watershed BW1. The error was 2.3%. In a normal rainfall year, e.g. 1980, its performance accuracy was also quite high (% error = 3.5). Coefficient of determination ( $R^2$ ) and Root Mean Square Error (RMSE) for Vertisol watershed BW2 (1976-82) were found to be 0.992, 0.985, 0.983 and 5.2, 3.1, 1.6 for annual, monthly and daily runoff respectively. About 10-15 runoff events and daily soil moisture data were sufficient to estimate the parameters of the model.

Chew and McMahon (1994) used MODHYDROLOG model to 28 catchments in Australia for estimation of runoff from rainfall and potential evapotranspiration data. Four simulations were carried out for each catchment, with the simulations differing in the numbers of model parameters optimized in the model calibration. The study indicated that the use of nine model parameters is sufficient to give adequate estimates of streamflow, and the use of five parameters sufficient in temperate catchments and in applications where only approximate estimates of runoff are required.

Todini (1996) described ARNO, a semi-distributed conceptual rainfall-runoff model which is used in land-surface-atmosphere process research and as an operational flood forecasting tool on several catchments in different parts of the world. The model incorporates the concepts of a spatial probability distribution of soil moisture capacity and of dynamically varying saturated contributing areas. The main phenomena in model includes soil water balance, on the basis of present soil moisture content, rainfall, runoff, evapotranspiration, drainage and percolation; water losses through evapotranspiration, evaluated on the basis of the air temperature data and the soil moisture content; snow accumulation and/or melt, based upon the energy balance of the snow cover (when present) as a function of the air temperature and precipitation data; groundwater flow represented by means of a multiple linear reservoir-type model; overland and channel flow routing represented with linear parabolic models. Geomorphological data such as average catchment elevation, catchment surface area and length of stream, as well as parameters including celerity and diffusivity, thermal gradient, and parameters characterizing the spatial distribution of soil moisture storage must be provided to apply the model to a catchment. Rainfall and air temperature inputs are provided to the model as area averages by means of weights generally based upon Thiessen polygons. In the case of temperature, the calculation of the average temperature over a sub-basin takes into account the effects of a thermal gradient with elevation. ARNO model performance indicated good predictive stability. Explained variance and determination coefficient were obtained during calibration and validation were 0.888, 0.880 and 0.853, 0.851. ARNO model, showed high flexibility by achieving fairly good calibrations in a variety

of different climate and geomorphological conditions, with a noticeable stability of results, in which the drop in performance between calibration and validation periods was always very small.

Zhang (1995) presented a physically-based distributed rainfall-runoff model, called DBS (Distributed Basin Simulator). He demonstrated the applications of a DBS to two river basins of vastly different characteristics. The first river basin, the Arno river basin, was located in central Italy, against three streamflow gauges at different parts of river Channel. Both rain gauge and meteorological radar data were used as rainfall input. The second river basin, the Souhegan river basin, was located in New England, only radar data was used as a rainfall input to the model. It was found from the calibration that the model did well in the two vastly different basins, with two different rainfall measuring methods. According to author a physically-based distributed rainfall-runoff model combined with spatially distributed Digital Elevation Model (DEM), and real time radar rainfall data could be a very useful for real time flood forecasting.

Shoemaker *et al.*, (1997) showed that hydrological models, especially simple rainfall-runoff models, are widely used in understanding and quantifying the impacts of land-use changes, and to provide information that can be used in land-use decision making. These hydrologic models available are varying in nature, complexity, and purpose.

Liden and Harlin (2000) studied conceptual rainfall runoff modelling performance in different climates. The HBV-96 model (Hydrologiska Byråns Vattenbalansavdelning) was applied on four catchments located in Europe, Africa and South America. Manual, automatic and Monte Carlo techniques were used for model calibration and parameter analyses. It was found that the magnitude of the water balance components had a significant influence on model performance. Performance decreased and demands of calibration period length increased with increased catchment dryness primarily because of a neater water balance and higher climatic variability in drier areas. The model applications in the four climatically different catchments displayed a large degree of equifinality where manual, automated search and Monte Carlo calibration methods yielded equally good results but with different parameter combinations.

Campling *et al.*, (2002) applied semi-distributed, topographically based hydrological model, TOPMODEL, to simulate continuously the runoff hydrograph of a medium-sized (379 km<sup>2</sup>), in a humid tropical catchment. The objectives were to relate hydrological responses to runoff generation mechanisms operating in the catchment and to estimate the uncertainty associated with runoff prediction. Field observations indicated that water tables were not parallel to the surface topography, particularly at the start of the wet season. A reference topographic index  $\lambda_{REF}$  was therefore introduced into the TOPMODEL structure to increase the weighting of local storage deficits in upland areas. The model adaptation had the effect of deepening water tables with distance from the river channel. The

Generalized Likelihood Uncertainty Estimation (GLUE) framework was used to assess the performance of the model with randomly selected parameter sets, and to set simulation confidence limits. The model simulated well the fast subsurface and overland flow events superimposed on the seasonal rise and fall of the baseflow. The top ranked parameter sets achieved modelling efficiencies of 0.943 and 0.849 in 1994 and 1995 respectively. The GLUE analysis showed that the exponential decay parameter  $m$ , controlling the baseflow and the local storage deficit, was the most sensitive parameter. There was increased uncertainty in the simulations of storm events during the early and late phases of the season, which was due to a combination of: errors in detecting the rainfall depths for convectional rainfall events; the treatment of rainfall as a catchment areal value and the strong seasonality in runoff response in the humid tropics.

Xu *et al.*, (2002) applied a distributed rainfall-runoff model to simulate both infiltration excess flow and saturation excess flow in arid and semi-arid regions. The land surface was represented by a DEM, from which the stream network was generated by using Arc/View GIS. Elevation data was also used to integrate topographic effects on air temperature, precipitation, and wind speed. Streamflow was routed from cell to cell. Both Hortonian and Dunne runoff generation mechanisms within each grid cell were dynamically coupled via a surface runoff parameterization with a feedback loop; therefore was defined as Coupled Hortonian and Dunne Flow (CHDF) hydrologic model for simplicity in the study. The CHDF model was characterized by a storm flow component representing the surface water balance coupling both infiltration excess flow and saturation excess flow. Other components such as subsurface flow, groundwater flow, drainage flow and evapotranspiration were also used. The model was applied in the arid and mountainous Wei River basin, the largest sub-basin of the Yellow River in China. It was tested on a daily time scale by using available field data. The result showed that the CHDF model was able to adequately simulate the water budgets of the catchment on a daily time scale.

Moore (2007) developed Probability Distributed Model (PDM), as a toolkit of model functions that together constitute a lumped rainfall-runoff model capable of representing a variety of catchment-scale hydrological behaviors. PDM is a fairly general conceptual rainfall-runoff model which transforms rainfall and potential evaporation data to flow at the catchment outlet. Typical state variables are the water content in the surface and groundwater storage and of probability distributed soil storage. For real-time forecasting applications, the PDM is complemented by updating methods based on error prediction and state correction approaches. The ARMA noise models were used as the basis of the error-predictor technique available as an alternative method of updating the PDM forecast.

Moretti and Montanari (2007) described spatially distributed grid based AFFDEF a rainfall-runoff model that was released into the public domain via the World Wide Web. The model, performs

continuous time simulations of river flows at any time step and at any location in the catchment. It does not, however, account for snowmelt. Conceptual and physically based schemes are employed for simulating the rainfall runoff transformation. AFFDEF's main strength is its computational efficiency, which allows the model to perform long simulation runs (e.g. thousands of years at hourly time step). In the Reno River Basin of Italy AFFDEF model was used to study the reliability of the model when it was calibrated using data sets of increasing length. Overall, the results indicated that the best out-of-sample performances are obtained by calibrating the model with minimum periods of three months.

Herron and Croke (2009) presented a version of the IHACRES rainfall-runoff model, in which the CMD module for calculating effective rainfall was coupled to explore the impacts of historical groundwater extractions on streamflow. The model was applied to the Coxs Creek catchment, in Australia. An analysis of the input rainfall time-series generated using a standard weighted Thissen polygon approach, revealed mismatches between observed streamflow events and the occurrence of rainfall, which imposed major limits on model performance. The challenge was to develop a simple lumped rainfall-runoff model that has the potential to improve system understanding and allow for meaningful exploration of alternate climate, groundwater extraction and land use change scenarios, given a situation of poor data catchments in many parts of Australia.

Jukic and Denic-Jukic (2009) proposed a conceptual rainfall-runoff model for the estimation of groundwater balance components including the influences of time-variant catchment boundaries and inter-catchment groundwater flows. The proposed methodology was applied to the Jadro Spring located near the city of Split in Croatia. The rainfall-runoff model was divided in two sub-models. The sub-models based on the moisture balance of soil cover and epikarst production store calculated effective rainfalls. The sub-model based on the groundwater balance of vadose and phreatic zone calculated groundwater recharges. The difference between the effective rainfalls and the groundwater recharges represented the contribution of epikarst zone and non-conservative and time-variant components to the groundwater balance. The calculated groundwater balance showed that the Jadro Spring aquifer contains a significant storage capacity in the vadose and phreatic zones. During the year, the aquifer may accumulate up to 140 MCM. The average catchment area of 396 km<sup>2</sup> was estimated by using the average monthly effective rainfalls and the average monthly groundwater recharges.

Birsan (2013) introduced a spatially distributed rainfall-runoff model TOPKAPI (**TOP**ographic **K**inematic **AP**proximation and **I**ntegration) which was widely used for continuous modelling of floods. The model used three non-linear reservoir differential equations for the drainage in the soil, the overland flow on saturated or impervious soil, and the channel flow along the drainage network, respectively. The geometry of the catchment was described by a lattice of cells-the pixels of the DEM

and their slope-over which the equations are integrated to lead to a cascade of non-linear reservoirs. The parameterization relies on the digital thematic maps of soil, geology and land use. The model was applied on the upper river basin of Somesul Mare, upstream Beclean (4328 km<sup>2</sup>) for the 2000-2006 intervals: the years 2000-2002 were used for calibration, the model being validated for the 2003-2006 period. The soil and the landuse maps were reclassified with respect to hydrological properties (e.g., soil depth, soil texture, surface roughness, canopy interception). For the time-dependent input, precipitation and temperature from eight meteorological stations had been used. The trial-and-error calibration-based on visually matching the modeled streamflow with the observed one-managed to reproduce the behavior of the catchment while keeping the parameters within their physically meaningful values.

Gad (2013) in his research developed a useful GIS-based automated **Semi-DIS**tributed **T**ime-**A**rea model (SDISTA) which was intended for engineering applications in semi-arid regions. SDISTA was a simple rainfall-runoff model that reconsiders the time-area technique using an improved approach that deals with each grid cell as a completely independent hydrologic unit. Travel times through the grid cells were estimated using a spatially varied grid-based Manning's formula that relates the hydraulic radius at each grid cell to the characteristics of its upstream catchment area and excess rainfall depth. SDISTA was tested in the research on cases from semi-arid regions including Sinai Peninsula. The results showed that SDISTA can be as accurate as HEC-1/HEC-HMS using a very dense network. SDISTA was fully automated and requires minimum effort from the user. SDISTA had ability to automatically delineate and simulate any number of catchment areas simultaneously on digital elevation models.

Narasayya *et al.*, (2013) studied a framework for continuous time scale Rainfall-Runoff modelling that integrates several years precipitation, GIS knowledge, and a hydrological model for Burhanpur watershed (about 8527 km<sup>2</sup>) covered in inter-states of Madhya Pradesh and Maharashtra (India). The model consists of a Rainfall-Runoff model (ArcSWAT) that converts precipitation excess to overland flow and channel runoff. The Scenario-1 was created by assigning same threshold value of 5% for landuse/10 for soil/ and 10% for slope definition. The results obtained in Scenario-1 revealed that the surface runoff of 42.61 mm was the maximum in the month of August and maximum lateral runoff in the month of July. The Scenario-2 was created by assigning different threshold values as 10% for landuse/ 20% for soil/ 10% for slope definition. The result obtained in Scenario 2 revealed that surface runoff of 16.83 mm was highest in the month of August and the lateral runoff of 96.82mm was maximum in the month of August. This study showed that the ArcSWAT model is a capable tool for simulating hydrologic components in Burhanpur Watershed.

Rusli *et al.*, (2015) studied the **H**ydrologiska **B**yråns **V**attenbalansavedling (HBV) model by applying to the Jiangwan Catchment, whose geological features include lots of cracks and gaps, simulations under various schemes were developed: short, medium-length, and long temporal calibrations. With medium-length temporal calibration, manual optimization delivers the best simulation results, with NSE, RE, RMSE, and the high flow ratio being 0.563 6, 0.122 3, 0.978 8, and 0.854 7, respectively and calibration using average parameter values delivers NSE, RE, RMSE, and the high flow ratio of 0.481 1, 0.467 6, 1.021 0, and 2.784 0, respectively. Similar behavior is found with long temporal calibration, when NSE, RE, RMSE, and the high flow ratio using manual optimization are 0.525 3, 0.069 2, 1.058 0, and 0.980 0, respectively, as compared with 0.490 3, 0.224 8, 1.096 2, and 0.547 9, respectively, using average parameter values. This study showed that selection of longer periods of temporal calibration in hydrological analysis delivers better simulation in general for water balance analysis.

Vaze *et al.*, (2015) studied the application of six commonly used lumped conceptual rainfall-runoff models to estimate daily runoff across the water resources region of southeast Australia. The daily climate data set and the daily modelled runoff were available from 1895 to 2008 at 0.05° grid resolution across the region. Daily streamflow data from 232 catchments (50 to 2000 km<sup>2</sup>) were used for this study. Six lumped conceptual daily rainfall-runoff models were used: AWBM (Boughton, 2004), IHACRES (Croke *et al.*, 2006), Sacramento (Burnash *et al.*, 1973), SIMHYD (Chiew *et al.*, 2002), SMARG (Goswami *et al.*, 2002) and GR4J (Perrin *et al.*, 2003). The number of parameters calibrated were six for AWBM, seven for IHACRES, 14 for Sacramento, six for SIMHYD, eight for SMARG and four for GR4J. The model parameters were optimized to maximize the NSE-bias objective function, which was a weighted combination of daily Nash-Sutcliffe (Nash and Sutcliffe, 1970) efficiency and a logarithmic function of bias. The modelling exercise indicated that the rainfall-runoff models can generally be calibrated to reproduce the daily observed streamflow (for 232 catchments in the high runoff generation areas), and the regionalization results indicated that the use of optimized parameter values from a gauged catchment nearby modelled runoff reasonably well in the ungauged areas.

The rainfall-runoff models reviewed in this section and summarized in the Table 2.1 shows that these models are conceptual, distributed, semi-distributed, physical based, timescale models. The rainfall-runoff models were used for flood forecasting, water balance studies, gap filling of records, assessment of water availability etc. There were number of rainfall-runoff models found in literature in which MIKE 11 NAM is one of the conceptual, lumped, commercially used rainfall-runoff model. MIKE 11 NAM model is used here to study the rainfall-runoff processes in the catchments as it

simulates water from mutually inter related forms of storages namely overland flow, interflow and base flow. The model is used to obtain historical and futuristic water availability for the catchments.

**Table 2.1 Summary of studies on rainfall-runoff modeling**

<b>Year</b>	<b>Name of Researcher</b>	<b>Study Area</b>	<b>Model used</b>	<b>Remark</b>
1989	P. Pathak, K. B. Laryea, and R. Sudi	Vertisol watershed at ICRISAT center, Patancheru, India	Modified Soil Conservation Services runoff model	A runoff model based on modified Soil Conservation Services curve number technique and on soil moisture accounting procedure was developed for small watersheds in semi-arid tropics. The main outputs were daily runoff volume and soil moisture. About 10-15 events and daily soil moisture data was sufficient to estimate the parameters of soil.
1994	F. Chew and T. Mohan	Australia	MODHYDROLOG	MODHYDROLOG is physically based daily time step based rainfall-runoff model. The study indicated that the use of nine (or fewer) model parameters were sufficient to give adequate estimates of streamflow, and the use of five parameters may be sufficient in temperate catchments and in applications where only approximate estimates of runoff are required.
1995	E. Todini	Arno River basin, Tuscany	ARNO	ARNO model semi-distributed conceptual rainfall runoff model incorporates the concepts of a spatial probability distribution of soil moisture capacity and of dynamically varying saturated contributing areas.
1995	Y. Zhand	Arno River basin and Souhegan river basin Italy	DBS (Distributed Basin Simulator)	DBS is physically based distributed runoff model combined with DEM data and real time radar rainfall data which was used to derive prestorm water table depth and hydrograph in the Arno river basin.
2000	R. Liden and J. Harlin	Europe, Africa and South America	HBV-96	HBV-96 is conceptual rainfall-runoff model was applied on four catchments with manual, automatic and Monte Carlo techniques were used for calibration and parameter analysis.
2002	P. Campling, A. Gobin, K. Beven and J. Feyen	Ebonyi river headwater catchment, Nigeria	TOPMODEL	TOPMODEL is a semi-distributed, topographically based hydrological model used as a continuous hydrograph simulator. Topographic index approach was for calculating runoff in the catchments.

2002	Z. X. Xu, K. Takeuchi and H. Ishidaira	Wei River basin, China	Coupled Hortonian and Dunne Flow (CHDF) hydrologic model	Streamflow was routed from cell to cell. The model was able to adequately simulate the water budgets of the catchment on a daily time scale.
2007	R. Moore	Thames basin, London	Probability Distributed Model (PDM)	General conceptual rainfall-runoff model which transforms rainfall and potential evaporation data to flow at the catchment outlet.
2007	G. Moretti and A. Montanari	Reno River Basin in Italy	AFFDEF	AFDEF is spatially distributed (grid based), continuous simulation rainfall runoff model. The model was applied to three river basin and proved to be robust and efficient, even though it was calculated with limited historical data.
2009	N. Herron and B. Croke	Coxs Creek catchment, in Australia	IHACRES	An analysis of the input rainfall time-series generated using a standard weighted Thissen polygon approach, revealed mismatches between observed streamflow events and the occurrence of rainfall, which imposed major limits on model performance.
2009	D. Jukic and V. Denic Jukic	Jadro Spring, Split in Croatia	Karst	The rainfall-runoff model was divided in two sub-models which calculated effective rainfall and groundwater recharge.
2013	M. V. Birsan	Upper river basin of Somesul Mare, Rome	TOPKAPI (TOPographic Kinematic APproximation and Integration)	TOPKAPI is a spatially-distributed physically-based hydrological model with a simple parameterization, which simulates the rainfall-runoff transformation using precipitation and temperature time series.
2013	M. A. Gad	Sinai Peninsula	Semi-Distributed Time-Area model (SDISTA)	SDISTA can be as accurate as HEC-1/HEC-HMS using a very dense network.

2013	K. Narasayya, U. Roman, B. Meena, S. Sreekanth and S. Ali	Burhanpur watershed Madhya Pradesh and Maharashtra (India).	ArcSWAT	SWAT is physically based continuous time model to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, landuse and management conditions over a large period of time. In the study, runoff was 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.
2015	S. R. Rusli, D. Yudianto and J. Liu	Jiangwan Catchment	Hydrologiska Byrans Vattenbalansavdelning (HBV) model	Selection of longer periods of temporal calibration in hydrological analysis delivers better simulation in general for water balance analysis.
2015	J. Vaze, F. H. S. Chiew, J. M. Perraud, N. Viney, D. Post, J. Teng, B. Wang, J. Lerat and M. Goswami	Southeast Australia.	AWBM, IHACRES Sacramento SIMHYD SMARG GR4J	A daily rainfall, PET and streamflow data set compiled for the important water resources region of southeast Australia, and the application of six lumped conceptual rainfall-runoff models to estimate daily runoff across the region. A little difference between model results was found because of different parameters of model.

## 2.2 MIKE 11 NAM model

MIKE 11 NAM model is a hydrological model that simulates rainfall-runoff processes occurring at catchment scale. The MIKE 11 NAM model can be characterized as deterministic, lumped, conceptual model with moderate input data requirement. For the present study MIKE 11 NAM model is used to simulate the water availability in selected sub catchments. This section provides the brief reviews of the MIKE 11 NAM /MIKE 11 rainfall-runoff model.

Hossain *et al.*, (1994) studied the detailed calibration and verification of MIKE11-NAM rainfall runoff model parameters for one of the catchments in the North-West region of Bangladesh. The performance of the model illustrated that in the calibration period the model correlates with observed discharge and in the verification period of the model gives acceptable compliance with the observed discharge. The parameters that have more influence were surface storage capacity ( $U_{max}$ ), time constant for interflow (CKIF), time constant for baseflow (CKBF), infiltration factor (Ko-inf) and maximum depth of groundwater causing baseflow (GWLBFo). It was observed that if the field storage due to rainfall exceeds the surface storage capacity (i.e.,  $U > U_{max}$ ), then all water flows as an overland flow and causes sudden increases in the peaks values of the model result. Verification result from April 1989 to March 1990 revealed that observed discharge was a bit less than the model simulated discharge. The performance of the model illustrates that in the calibration period the model correlates nicely with observed discharge and in the verification period the model gives acceptable compliance with observed discharge.

Shamsudin and Hashim (2002) estimated the rainfall runoff discharges of Sungai Layang watershed using MIKE 11 NAM model. The calibration and validation procedures were carried out to provide a satisfactory estimation. The runoff discharges were simulated based on the daily rainfall for a 12-year period (1988-2000) based on the available rainfall and evaporation data. The simulated peak flow occurred in 1992 and 1995 with approximate values of 20.94 m<sup>3</sup>/s and 18.93 m<sup>3</sup>/s respectively. The optimum values of the model parameters obtained during the calibration procedure were presented. Satisfactory and reliable results were obtained with their Efficiency Index (EI) and RMSE of 0.75 and 0.08 respectively.

Jin and Webb (2003) used MIKE 11 hydraulic and hydrologic model for Topanga Creek watershed of Southern California. The study involved identifying the existing conditions, testing alternative solutions, recommending the preferred alternative, and refining the alternative for future planning actions of environmental review, permitting and funding applications. For hydraulic calibration and verification, water depths predicted and measured at various locations were compared. The results showed relatively good agreement. These visual correlations were considered sufficient to conclude

that the hydrology and hydraulic model can be used with confidence to model alternatives and make relative comparisons of their performance.

Khu *et al.*, (2004) used new approach in rainfall- runoff modeling, developed meta-models using artificial neural network (ANN) in coupling with genetic algorithm. This new approach tested in the calibration of a popular rainfall-runoff model, MIKE11 NAM, applied to the Treggevaede catchment in Denmark. Both the calibration and verification results for single objective calibration indicated that the proposed method was able to achieve the same or better calibration performance compared to published studies using traditional population-based search methods and yet required only about 40% of the simulation runs on average.

Hayat (2007) studied hydro-meteorological model MIKE 11 for pre-alerts and warnings from flash floods in local stream known as Lai Nullah. Simulation from the MIKE11 model predicted that water level may rise to pre-alert warning level. The flood Warning System for lai Nullah Basin is highly robust in term of real-time monitoring of storm precipitation intensities (10 min, 30 min, 60 min) and combining runoff and point rainfall recorded data to simulate stream flow and accumulation forecasts every 10 minutes for both meteorological and hydrological purposes. As such the system is a useful tool for flash flood mitigation purposes.

Keskin *et al.*, (2007) calibrated and validated MIKE 11 model to simulate the runoff from snowmelt in a semi-distributed manner. The model was applied to Yuvacik Basin in the eastern part of Marmara Region of Turkey to simulate the rain/snowmelt runoff for the period in between the years 2001 and 2006. Several tries during the model simulations showed that the most effective parameters were  $L_{max}$ ,  $U_{max}$ , CKOF and CKIF which also define the base flow in the basin. Nash and Sutcliffe model efficiency (NSE) statistical criteria and coefficient of determination ( $R^2$ ) were used for the model performance evaluation and model efficiencies found higher than 0.7 at least for half of the events. The performance of the hydrological model shows that the simulated streamflow reflects the variation in temperature and precipitation as well as the moisture interaction between the surface, subsurface and the groundwater storages. Statistical analysis revealed that the model quantitatively matches the historical data.

DHI (2008) constructed DHI's MIKE BASIN model for the mainstem McKenzie River and major tributaries. NAM models were constructed for each of the 25 (later expanded to 30) NAM catchments in order to predict hourly and daily inflows. NAM rainfall-runoff models were calibrated by LCOG for two tributary catchments within the model where long-term USGS gage data was available: Mohawk River and Lookout Creek. Once these models were calibrated, the NAM parameters determined for these two catchments were transferred to the models of the remaining catchments and

the results from all of the NAM models were then imported into the MIKE BASIN model. The second and final phase of the calibration of the model was then accomplished by DHI by comparing the simulated and observed hydrographs at the main-stem McKenzie River gages and computing reach gains/losses. Coefficient of determination ( $R^2$ ) for Mohawk River and Lookout Creek was found to be 0.79 and 0.913 respectively. Annual water budget information found in a literature search was compared to the water budget calculated from the calibrated model.

Kamel (2008) developed a one-dimensional unsteady flow hydraulic model MIKE 11 from the Danish Hydraulic Institute (DHI) for the simulation of flow in the Euphrates River in Iraq. In the study, the hydraulic model used flow and stage hydrographs in a time series format from field measurements. The approach for this model leads to unsteady flow simulations along stream channel reach. The stream length used for this model was 1.6 km. The study focused on the development of a MIKE 11 model based on surveyed, stream cross-section data. The results of the study explained that the model gave a good simulation of the flow according to a comparison between the estimated and observed stage hydrograph. Also, the comparison between this model and the Uday model that was used for the same river explains that the MIKE 11 model give better simulation.

Lan Anh *et al.*, (2008) compared three lumped conceptual rainfall-runoff models: NAM (DHI), FEH (UK), and TVM (a simplified model was developed by the author). Statistical analyses revealed that for the NAM model results overestimation is apparent to the flows smaller than  $6.7 \text{ m}^3/\text{s}$  and underestimation is observed for the flows above that threshold. Although the NAM model tends to underestimate the peaks, there are more of the intermediate flows than the peaks, thus, the amount of water from overestimation of the intermediate flows compensated for underestimation of the peaks is larger than required. Although both models, the NAM and TVM, underestimated the peaks but the TVM modelled results were much closer to the observation. RMSE values of the TVM model are smaller than those of the NAM model, for instance, the value of 0.97 for flow maxima from the TVM model is compared to 5.2 from the NAM model.

Makungo *et al.*, (2010) studied rainfall runoff modelling approach for ungauged catchments. Efficient calibration and verification was achieved by using two models Mike 11 NAM and the AWBM (Australian Water Balance Model). The two model results were compared in order to deduce the model which simulates hydrological processes of the Mutshedzi River SQC (sub-quatarnary catchments) better. The performance of Mike 11 NAM and the AWBM rainfall-runoff models were assessed using measures of goodness of fit between the simulated and observed runoff including RMSE, E, R, OWBE and PBIAS. The Mike 11 NAM and AWBM rainfall-runoff models performances were good and comparable though the AWBM performance was relatively better than

that of the Mike 11 NAM. It was therefore decided to use both models in the simulation of the streamflow hydrograph for Nzhelele River SQC and compare the results. The streamflow hydrograph for the Nzhelele River SQC simulated from both the models is comparable and correlates well with the areal rainfall for the Nzhelele River SQC from upstream to Siloam Village.

Roelevink *et al.*, (2010) described a forecasting system developed in cooperation with the National Institute for Hydrology and Meteorology (NIHM) and the East Aegean River Basin Directorate (EARBD) for the rivers Maritsa and Tundzha. The flood forecasting system (using MIKE-Flood Watch) uses the combined calibrated hydrological (MIKE11-NAM) and hydraulic models (MIKE11-HD) and produces forecasted water levels and alerts at predefined control points. A data assimilation routine is used to update calculated water levels and discharges at the inflow points with the observed data. The difference between the calculated and measured series during the hindcast period is used to correct the water levels during forecast period. A Data Exchange Tool (DET) disseminates relevant information between the databases of NIHM and the EARBD, the flood forecasting system and a website that shows forecast bulletins.

Giang and Phuong (2010) introduced a method to calibrate and verify the parameters of hydrological models with the interrupted (event) data. The method was applied to calibrate and verify MIKE-NAM model parameters with the case study of Ben Hai river basin. The method was the combination of auto-calibration and trial-and error methods. The results showed the good agreements of the hydrograph shape and total flow volume between simulation and observation for all four calibration events. The peak flow simulation was quite good for event 2004 and 2007 and acceptable for event 2005. The calibrated parameters were afterward verified using data from 1999 flood event. The good agreement of the verification results indicate that the parameters are consistent, predictive and can be applied for different purposes such as flood forecast, water resources planning and management.

Galkate *et al.*, (2011) described the application of NAM model, to investigate its performance, efficiency and suitability in Bina river basin of Madhya Pradesh. The model was found suitable for Bina basin in simulating hydrological response of the basin to the rainfall and predicting daily runoff with high degree of accuracy. The coefficient of determinations for the model calibration and validation were 0.796 and 0.609 respectively indicating good agreement between the observed and simulated runoff in terms of timing, rate and volume and shape of hydrograph. The model was found efficient with Efficiency Index 81% and found capable of predicting runoff for extended time period in Bina basin. The MIKE 11 NAM model was found sensible to parameters like, *CQOF*, *Lmax* and *CKIK2*. The coefficient of overland flow (*CQOF*) was found as the important parameter in modeling as it was seen significantly affecting peaks and low flows both. The difference in the total observed

and simulated flows was 0.3% which was reasonable indicating good match between observed and simulated runoff.

Odiyo *et al.*, (2012) conducted rainfall runoff modelling to estimate the flows that Latonyanda River contribute to Luvuvhu River downstream of Albasini Dam. Calibration and verification runs of Mike 11 NAM rainfall–runoff model were carried out using data for periods of 4 and 2 years, respectively. The observed and the simulated runoff showed similar trends and measures of performances for both calibration and verification runs fell within acceptable ranges. The pairs of values obtained for  $R^2$ , RMSE, OWBE and PBIAS for calibration and verification were 0.86 and 0.73, 0.21 and 0.2, 2.1 and 1.3, and 4.1 and 3.4, respectively. The mean and maximum daily flow contributions from the Latonyanda River are 0.91 and 49  $m^3/s$  respectively. The estimation of these ungauged flows makes it possible to plan and manage the water requirements for the downstream users.

Sharma (2012) studied the rainfall runoff modelling using MIKE 11 NAM for the Bina river basin up to the Rahatgarh gauge discharge site contributing about 1180  $km^2$  area. Calibration of the model was done for the period of three years from 1990 to 1992. During calibration, the default model parameters were kept same and model was run in auto-calibration mode. The model then resulted in obtaining set of model parameters for the calibration period. The coefficient of determination for the model calibration was observed to be 0.805 and water balance error was -0.1% which indicated the good agreement between the observed and simulated runoff in terms of timing, rate and volume. For the model validation, model was run without auto-calibration mode using calibrated model parameters for remaining period from the year 1993 to 1994 and statistics of the output were compared with the calibration results. The coefficient of determination for the validation period of the model was observed as 0.608 and water balance error was -0.7%. The efficiency index obtained during the calibration was 81%.

Amir *et al.*, (2013) estimated the rainfall runoff discharges for the large Fitzroy Basin by using a conceptual rainfall runoff model, the MIKE 11 NAM, considering the multi-objective calibration. The MIKE 11 NAM model performance was evaluated by the statistical method, Index of Agreement (IA). IA value varied from 0 to 1 with 1 signifying the perfect agreement between simulated and observed values and 0 indicates no agreement at all. Efficiency Index (EI) was another hydrological model assessor 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. The statistical and hydrology specific indicators IA and EI values obtained in between 0.864 to 0.951 and 0.934 to 0.961. The automatic calibration yielded  $R^2$  values between 0.82 to .91 and %WBL (water balance

error) maximum up to 8.4% which is admissible. A reasonably good calibration was achieved which shows the ability of the model to predict stream flow. The optimum model parameter values represent the runoff coefficient for a particular sub-catchment.

Hafezparast *et al.*, (2013) used MIKE 11 NAM model to estimate the daily runoff to the Sarisoo River catchment for a twelve-year time period. Auto-calibration yielded %WBL and  $R^2$  values of 0.0 % and 0.74 respectively. The model's results were significantly improved by the use of additional groundwater parameters. Furthermore, the model was also validated for the period of 1<sup>st</sup> September 2007 to 29<sup>th</sup> February 2008 and satisfactorily predicted the Sarisoo River discharges. Prediction of daily and monthly discharges for the four years which were missed in the historical time series of observed discharge in 2000-2003 and 2006-2007 years was done. The results showed that the simulated peak flows were occurring in the February months of 2003, 2006 and 2007 with approximate values of 6.32, 9.35 and 6.13  $m^3/s$  respectively. Average, minimum and maximum discharges in gap years are calculated to be 0.99, 0.11 and 6.32  $m^3/s$  and 2.52, 1.73 and 6.14  $m^3/s$  for the periods of Oct 2000 to Sep 2003 and Oct 2006 to Sep 2007, respectively. The monthly discharges including mean, minimum and maximum flows were calculated based on the simulated daily discharges for the 1996-2008 years to assess water resources management aspects. When comparing the output of the Nam model for the calculated daily discharges with observed data that was a significant correlation found ( $R^2=0.74$ ) in the calibration stage. However the monthly averages of mean, minimum and maximum flows are about 10%, 33% and 2% respectively less than the daily computed Nash–Sutcliffe coefficients in the 12 years period.

Lafdani *et al.*, (2013) studied the comparison of performance of BFGS-ANN model, Conjugate ANN model and conceptual hydrological MIKE11-NAM model for simulating rainfall runoff. Artificial neural networks and MIKE11-NAM models were applied to simulate runoff discharge in Qaleh Shahrokh basin located in Iran. In training (calibration) period, BFGS-ANN and Conjugate ANN models performed with RMSE= 0.65, 1.25 ( $m^3 /s$ ),  $R^2= 0.98, 0.86$  and EI= 0.92, 0.87 respectively better than MIKE 11-NAM model with RMSE= 3.41 ( $m^3 /s$ ),  $R^2= 0.71$  and EI= 0.7. Also BFGS-ANN results were better than Conjugate ANN model. However, in the testing (verification) period, BFGS-ANN model, with highest correlation coefficient and EI (0.92, 0.9) and lowest RMSE (2.01  $m^3 /s$ ), was the best model in runoff simulation. In the testing (verification) period, Conjugate ANN model also had a higher capability in runoff simulation with correlation coefficient equal to 0.84 and RMSE equal to 2.87 ( $m^3 /s$ ) compared with MIKE11- NAM model ( $R^2= 0.69$ , RMSE = 3.53  $m^3 /s$ , EI= 0.88). The results obtained from this study show that the BFGS-based ANN model and Conjugate ANN model produce the best performance in daily runoff simulation. In addition, MIKE11-NAM model represents the reasonable and promising.

Ngoc *et al.*, (2013) studied optimization of two hydrological models using Genetic Algorithm (GA). The GA optimization search was combined into the parameter calibration of two hydrological models (GA–NAM and GA–Tank). The GA optimization in study concurrently adjusted eighteen of the Tank Model parameters and ten NAM Model parameters to improve modeling efficiency. According to the calibration results of the GA–NAM Model, the error indicators R,  $E_2$ , and MSE were 0.86, 0.72, and 0.28, respectively, in 1995 and 0.93, 0.86, and 0.14, respectively, in 2000, showing that all error indicators were lower in 2000 than in 1995. In particular, max.RE and RE of peak flow values were 19.07 and 8.96%, respectively, in 2000 and lower than the 1995 values (34.80 and 9.34%, respectively). These results demonstrated that the simulated discharge of the GA–NAM model was more appropriate and accurate in 2000 than in 1995, hence the calibrated parameters produced in 2000 were selected for validation. In a comparison of the two hydrological models, calibration and validation results were similar and showed good correlation between simulated and observed flows, with increased accuracy and convenience. Although error indicators showed that performance was slightly higher in the GA–Tank model than in the GA–NAM model. In the validation, the error indicators  $R = 0.91$ ,  $E_2 = 0.82$ , and  $MSE = 0.18$  were obtained in 1998 and 2001, showing that the calibrated parameters in 2000 ( $R = 0.93$ ,  $E_2 = 0.86$ , and  $MSE = 0.14$ ) provided a versatile model, although the accuracy was slightly lower. The volume errors in the 2 validated years, 1998 and 2001, were -5.41 and -1.32%, respectively, and were less than the volume error in 2000 (-8.64%). Hence concluded that the calibrated parameters obtained in 2000 provided stabilizing and versatile forecasts for the NAM model.

Ghule (2014) calibrated MIKE 11 NAM model and MIKE HYDRO Basin model for Ghod intermediate catchment. Runoff of Ghod intermediate catchment was required in MIKE 11 NAM model to compare it with the simulated runoff. Hence catchment routing was needed to calculate the intermediate flow of the Ghod catchment. Routing was done in MIKE HYDRO Basin model. Linear reservoir routing method was used for routing and delay parameters/ travel time of 36 hr, 70 hr and 10 hr were fixed for Dimbhe, Wadaj and Yedgaon reservoir respectively. Routing was performed for long period from 1st June 1992 to 31<sup>st</sup> December, 2009. The  $R^2$  obtained for values of the calibration parameters from calibration of model was found to be 0.864. Chi-square test was used for testing the goodness of fit at 5 % significance level to synthetically generate the weekly rainfall and evaporation. The simulations were performed in MIKE HYDRO Basin model by giving priority first to domestic water user and second to irrigation water user. The simulation was performed using historical and forecasted water availability which was calculated by calibrated MIKE 11 NAM model. In base scenario no water deficit was observed for irrigation water user, however 0.1 MCM and 0.41 MCM deficits were observed for second (25 % increase) and third (40 % increase) scenarios in Ghod sub

catchment. For domestic water user no water deficit was obtained in base scenario; 0.003 MCM and 0.016 MCM deficits were observed for second (25 % increase) and third (40 % increase) scenarios respectively. In forecasted water allocation scenarios, water deficits of 0.32 MCM, 1.48 MCM and 2.45 MCM were observed in base scenario, second (25 % increase) and third (40 % increase) scenarios respectively for irrigation water user. For domestic water user deficits of 0.005 MCM, 0.036 MCM and 0.063 MCM were observed for second (25 % increase) and third (40 % increase) scenarios respectively.

Butler *et al.*, (2014) investigated the application of high resolution remote sensing, coupled with the commercially available product, MIKE 11, to monitor watershed land use and its impact on water quality. Remote sensing proved to be an extremely useful tool in the identification of sources of fecal bacteria contamination, as well as the detection of land use change over time. Validation of the MIKE 11 model produced very good agreement ( $R^2 = 0.88$ ,  $E = 0.85$ ) between predicted and observed river flows, while model calibration of *E. coli* concentrations showed fair agreement ( $R^2 = 0.51$  and  $E = 0.38$ ) between predicted and observed values. A proper evaluation of the MIKE 11 model was constrained due to limited water sampling. However, the model was very effective in predicting times of high contamination for use in the integrated forecasting framework, especially during substantial precipitation events.

Khan *et al.*, (2014) used rainfall-runoff model for a part catchment of river Dhunn using NAM module of MIKE BASIN. Integration of both MIKE BASIN and NAM allows the computation of time series data of runoff based on time series data of evaporation and precipitation. Applying graphical and numerical performance measures in calibration process, NAM parameters are estimated using data of three years. The best values found for Nash-Sutcliffe is 0.62 and correlation coefficient is 0.713. Forest, meadow and urban scenarios for the given catchment have been used to study the changes in surface runoff for three years' time period. Peak runoff values are considerably low in forest scenario due to more infiltration. In meadow scenario, peak runoff values are approximately similar to the measured values as 60 percent of actual land is meadow. In case of urban scenario, high peak runoff values are obtained but runoff values are not dramatically changed due to small catchment area.

Singh *et al.*, (2014) studied the rainfall-runoff modeling using MIKE 11 NAM model in Vinayakpur intercepted catchment in Chhattisgarh state. The model was calibrated using measured stream flow data for the period 2001 to 2004 and then validated from the period of 2005 to 2007. The calibration and validation procedures were carried out to provide a satisfactory estimation. The simulated runoff occurred maximum in August ( $1681.63 \text{ m}^3/\text{s}$ ) and minimum in April ( $84.14 \text{ m}^3/\text{s}$ ). The outputs of the calibrated model were used in water resources management model viz., MIKE basin as they normally

work based on monthly flows with a large time horizon. The optimum values of nine NAM model parameters obtained during calibration procedure were used for simulation. The reliability of MIKE 11 NAM was evaluated based on Nash-Sutcliffe coefficient, correlation coefficient ( $r$ ) and root mean square error (RMSE). The  $R^2$  value for model calibration and validation were observed to be 0.79 and 0.75, respectively.

Vansteenkiste *et al.*, (2014) were applied five hydrological models with different spatial resolutions and process descriptions to a medium sized catchment in Belgium in order to assess the accuracy and differences of simulated hydrological variables, including peak and low flow extremes and quick and slow runoff sub flows. The models varied from the lumped conceptual NAM, PDM and VHM models over the intermediate detailed and distributed WetSpa model to the highly detailed and fully distributed MIKE SHE model. The calibration data covered the period from September 2002 to the end of 2005 which covers a wide range of meteorological and hydrological conditions, including a very wet winter with several high peak flows and flooding (December 2002–January 2003) and a very dry summer (2005). The validation was then carried out for another 3 year period (January 2006 to December 2008). All simulations were carried out with a warming up period from January to August 2002. For the calibration period, NSE values obtained were high for all models ( $>0.70$ ) with the VHM model having the lowest efficiency (0.71). For the validation period, the model performance was less good for VHM (NSE = 0.57) and the distributed models (NSE between 0.6 and 0.7), whereas they were as high as 0.75 and 0.74 for the PDM and NAM models respectively. The  $R^2$  of simulated versus observed total runoff flows did not differ much for the five models. The  $R^2$  values are high and vary between 0.8 and 0.9 for all models.

Loliyana and Patel (2015) studied the a lumped conceptual hydrological model, NAM (MIKE11), is calibrated while optimizing the runoff simulations on the basis of minimization of percentage water balance (% WBL) and root mean square error (RMSE) using measured stream flow data of eight years from 1991 to 1998 for Yerli catchment (area = 15,701 km<sup>2</sup>) of upper Tapi basin, Maharashtra in Western India. The simulated results demonstrated that calibrated model is able to simulate hydrographs satisfactorily for Yerli (NSE = 0.86–0.88,  $r$  = 0.93–0.96, EI = 1.05–1.12) as well as Gopalkheda sub-catchments (NSE = 0.76–0.92 and  $r$  = 0.88–0.96, EI = 0.89–0.91) at monthly time scale. The model also performs reasonably well in simulating the annual hydrographs at daily time scale. The performance of the model at Gopalkheda gauging station is relatively better than Yerli gauging station in terms of its performance prediction of daily, monthly flows and flow duration curve due to existence of better homogeneity in the smaller catchment (Gopalkheda) and, hence, better applicability of lumped hydrological model. The performance of calibrated NAM model for independent data at Yerli and Gopalkheda gauging stations indicates that the model can be used for

prediction of water yield while planning water conservation scheme within the catchment, and prediction of flooding conditions in the catchment.

Amrit *et al.*, (2016) used the MIKE 11 NAM for the estimation of natural ground water recharge in the Andhiyarkhore intermediate catchment in Chhatisgarh state. Thirteen years data (1995 to 2007) of rainfall, runoff and evaporation was used for modelling. The model was calibrated for the period of 1995 to 2003 and validated for the period of 2004 to 2007. The pairs of values obtained for coefficient of determination, correlation coefficient, Nash–Sutcliffe coefficient and water balance error during calibration and validation were 0.5 and 0.56, 0.75 and 0.71, 0.56 and 0.5 and 0.7% and 0.3%, respectively. The groundwater recharge in the basin was maximum in the year 2003 (350.7 mm) and minimum in the year of 2006 (69.5 mm). The average recharge estimated in the basin is 40311.7 ha-m.

Balan *et al.*, (2016) performed simulation of flash flood alternatively with MIKE 11 NAM and MIKE 11 UHM model using radar precipitation as input data. Between the 11<sup>th</sup> and 13<sup>th</sup> of September 2013 large quantities of rainfall occurred in the upper catchment of river Geru. The precipitations have generated a flash flood with three peaks, with the maximum discharges of 118.00 m<sup>3</sup>/s recorded on 12th of September 2013. The discharge hydrographs simulated with MIKE 11 were compared to discharge measured at hydrometric station. This method led to a complex discharge hydrograph with two major peaks of 118.37 m<sup>3</sup>/s, respectively 40.99 m<sup>3</sup>/s and a total volume of 6611577 m<sup>3</sup>. The correlation coefficient was found to be 0.819.

Tiwari *et al.*, (2016) studied the utilization of MIKE11 NAM Rainfall runoff model to explore its execution, proficiency and appropriateness in Shipra river basin in Madhya Pradesh, India. The input data utilized by the model was weighted precipitation, Potential evapotranspiration and observed runoff. The total time series of 11 years duration from 1996 to 2006 was used in this study. The model calibration was done for the time frame from 1996 to 2001 and validated for the years 2002 to 2006. The dependability and performance of the NAM model was assessed based on Accuracy criteria Coefficient of determination ( $R^2$ ). The coefficient of determination  $R^2$  value for calibration and validation period was observed 0.720 and 0.502 respectively. The Nash–Sutcliffe Efficiency (EI) for calibration and validation is 76% and 85% respectively. The NAM model was found appropriate for simulation and prediction of daily runoff with good degree of accuracy.

The reviews on MIKE 11 NAM rainfall-runoff models described above and summarized in Table 2.6 show that the model was used on different catchments for different purpose. MIKE 11 NAM model found to have capability to simulate runoff using limited input data and can be couple with MIKE HYDRO Basin water allocation model properly. Different reviews showed the best calibration and

validation results based on graphical and statistical evaluation. This proves the capability of model to simulate the water availability. Therefore, in present study MIKE 11 NAM model was used for estimating runoff and thereby simulating water availability of Ghod complex sub catchments.

**Table 2.2 Summary of studies on MIKE 11 NAM model**

Year	Name of Researcher	Study Area	Calibration	Validation	Results/Findings
1994	S. Hossain, M. Hoque and S. Ahmed	North-West region of Bangladesh	1990	April 1986 to March 1990 and from April to October 1991	Validation revealed that observed discharge was less than the model simulated discharge. The parameters that have more influence are Umax, CKIF, CKBF, Ko-inf and GWLBFo. Comparison of rainfall and model simulated discharge indicates that in the hydrological year 1989 field data measured were 20 to 30 percent lower than the actual value.
2002	S. Shamsudin and N. Hashim,	Sungai Layang watershed	October 1999 – September 2000	Jun 1998 – July 1998 Simulation-1988-2000	The rainfall discharges was successfully modeled using MIKE11-NAM during this study. The simulated peak flow discharges occurred in 1992 and 1995 with approximated values of 20.94 m <sup>3</sup> /s and 18.93 m <sup>3</sup> /s respectively.
2003	W. Jin and C. Webb	Topanga Creek watershed of Southern California	1997-2001	Not reported	Water depths predicted and measured at various locations were compared, showed relatively good agreement.
2004	S. T. Khu, D. Savik, Y. Liu and H. Madsen	Danish Tryggevælde Catchment,, Denmark	1984-1988	1979-1983	A novel evolutionary-based meta-model, using genetic algorithm and radial basis function neural network with dynamic updating, for hydrological model calibration was proposed.
2007	A. Hayat	National Weather Forecasting Centre Islamabad	Not reported	Not reported	MIKE11-RR Unit Hydrograph model (UHM) was used for flash flood runoff mitigation
2007	F. Keskin, A. Sensoy and A. Sorman	Yuvacık Basin, Turkey	2001- 2006	Not reported	Snow-water equivalent (SWE) used to simulate the runoff from snowmelt in a semi-distributed manner. NSE and R <sup>2</sup> were found greater than 0.7. Comparison of the results from simulation and observation indicated that the model can reproduce well the observed inflow starting time, peak and the time base. Statistical analysis revealed that the model quantitatively matches the historical data.
2008	DHI	Mohawk River and Lookout Creek	October 1, 2002 - January 1, 2006	Not reported	A minimum of 3 years including periods of above-average precipitation is recommended for calibration, with longer periods resulting in a more reliable model.

2008	N. Lan Anh, P. Willems, J. Boxall and A. Saul.	Bradford catchment	June 2000- June 2001	January 1999 – January 2004	NAM was compared with event-based model FEH and continuous model TVM. The NAM model has an advantage over the FEH model by being able to simulate data continuously although in case of the Bradford catchment it does not handle the intermediate flows well which makes the volume of water balance increases significantly due to overestimation of the intermediate flows.
2010	R. Makungo, J. Odiyo, J. Ndiritu and B. Mwaka.	Mutshedzi River	April 22, 1994 - April 22, 1997	April 23, 1997 – March 06, 1999	The computed inflow time series was considered reasonable although 6.8% of the inflows were negative. The negative flows summed up to only 7.3% of the sum of the positive flows. 90% of the negative flows were less than 10% of the mean flow. All the negative flows were therefore converted to zero flows. The performance of Mike 11 NAM and the AWBM rainfall-runoff models were assessed using RMSE, E, R, OWBE and PBIAS.
2010	A. Roelevink, J. Udo, G. Koshinchanov and S. Balabanova,	NIHM and EARBD for the rivers Maritsa and Tundzha.	Not reported	Not reported	The flood forecasting system (using MIKE-Flood Watch) used the combined calibrated hydrological (MIKE11-NAM) and hydraulic models (MIKE11-HD) and produced forecasted water levels and alerts at predefined control points.
2010	N. T. Giang and T. A. Phuong.	Ben Hai river basin	Four flood events of 2004, 2005, 2007 and 2009.	One flood event of 1999	The peak flow simulation was good for event 2004 and 2007 and acceptable for event 2005. The good agreement of the verification results indicate that the parameters are consistent, predictive and can be applied for different purposes such as flood forecast, water resources planning and management.
2011	R. V. Galkate, R. K. Jaiswal, T. Thomas and T. R. Nayak,	Bina river basin of Madhya Pradesh	1990 to 1992	1993 to 1994	During the calibration period of three years, out of total rainfall of 3490.5 mm, the simulated discharge was 1840 mm, overland flow formed was 1043.1 mm, the water contributed as inter flow and base flow were 76 and 721.6 mm respectively and remaining 728.2 mm of water was contributed to the ground water recharge.
2012	J. O. Odiyo, J. I. Phangisa and R. Makungo	Luvuvhu River downstream of Albasini Dam	Oct. 24, 2002 to Oct. 24, 2006	Oct. 25, 2006 to Oct. 24, 2008	The observed and the simulated runoff for the upper LRSQC correlated well except for under-prediction of peak events and a few low flows, in addition to a few over predictions that can be explained in terms of inherent uncertainty in the model and the data. Illegal irrigation abstractions could be responsible for over predictions as they reduce the observed values. The measures of performances for both calibration and verification runs fell within acceptable ranges.

2013	Md. S. I. I. Amir, M. K. Khan, Md. G. Rasul, R. H. Sharma and F. Akram	Fitzroy Basin	January 1, 2007 to January 31, 2011	January 1, 1987 to December 31, 1991.	During calibration index of agreement and efficiency of index values obtained in between 0.864 to .951 and 0.934 to 0.961 similarly that for validation 0.849 to 0.927 and 0.821 to 0.846.
2013	M.Hafezparast, S. Araghinejad, S. Fatemi and H. Bressers,	Sarisoo River catchment	October 10, 2003 to March 31, 2006	September 1, 2007 to February 29, 2008	Average, minimum and maximum discharges in gap years are calculated to be 0.99, 0.11 and 6.32 m <sup>3</sup> /s and 2.52, 1.73 and 6.14 m <sup>3</sup> /s for the periods of Oct 2000 to Sep 2003 and Oct 2006 to Sep 2007, respectively. The results showed that the simulated peak flows were occurring in the February months of 2003, 2006 and 2007 with approximate values of 6.32, 9.35 and 6.13 m <sup>3</sup> /s respectively.
2013	T. A. Ngoc, K. Hiramatsu and M. Harada.	Dau Tieng River watershed in Tay Ninh Province	1995 and 2000	1998 and 2001	The GA–NAM model showed good correlation between the observed and simulated flow hydrographs in the validation as well as in the calibration. Results demonstrated the simulated discharge of the GA–NAM model was more appropriate and accurate in 2000 than in 1995, hence the calibrated parameters produced in 2000 were selected for validation.
2014	P. S. Ghule	Ghod catchment	June 1, 2001 to December 31, 2005	June 1, 2014 to December 31, 2014	R <sup>2</sup> =0.864 was obtained which showed good fit between observed and simulated runoff. Linear reservoir routing method was used for routing and delay parameters/ travel time of 36 hr, 70 hr and 10 hr were fixed for Dimbhe, Wadaj and Yedgaon reservoir respectively. Routing was performed for long period from 1st June 1992 to 31st December, 2009.
2014	S. Butler, T. Webster, A. Redden, J. Rand, N. Crowell and W. Livingstone	Moose River catchment	August 1 to December 31, 2010	April 1 to July 31, 2010	A mean observed discharge for the validation period was 0.63 m <sup>3</sup> /s, compared with a mean simulated discharge of 0.53 m <sup>3</sup> /s. The model captured peak discharge values within 1–4 h of observed flows. A 6 June 2010 rain event yielded observed flows of 6.4 m <sup>3</sup> /s, compared with simulated flows of 6.7 m <sup>3</sup> /s. Similarly, a 15 July 2010 rain event produced observed flows of 3.7 m <sup>3</sup> /s, compared with simulated flows of 4.1 m <sup>3</sup> /s.
2014	M. Khan, B. Mujtaba R. Masood and T. Ali.	Dhunn River	January 1, 2003 to December 31, 2005.	Not reported	Manual and automatic calibrations of 9 NAM parameters have been done for three years which shows satisfactory similarity between observed and measured discharges.

2014	A. Singh, S. Singh, A. Nema, G. Singh and A. Gangwar	Vinayakpur intercepted catchment Chhattisgarh	2001 to 2004	2005 to 2007	The simulated minimum and maximum runoff for a seven year period (2001-2007) show that the annual runoff varies between 68.6 mm to 611.6 mm. The simulated runoff was maximum for the month of August (1681.63 m <sup>3</sup> /s) and minimum for the month of April (84.14 m <sup>3</sup> /s).
2014	T. Vansteenkiste, M. Tavakoli, N. Steenbergen, F. Smedt, O. Batelaan, F. Pereira and P. Willems	Belgium	September 2002 to the end of 2005	January 2006 to December 2008	The NAM mode tends to underestimate the quick flow changes when interflow is incorporated in the analysis. The NAM conceptualization of interflow underestimates the interflow peaks in winter.
2015	V. D. Loliyana and P. L. Patel	Purna River catchment of upper Tapi basin, Maharashtra	1991–1998	2001to2004 for Yerli, and 1991– 1998 and 2001–2004 for Gopalkheda	The parameters Lmax plays dominant role in affecting the runoff volume while CQOF governs the peak flow. The parameter Umax, representing surface water storage, affects the water balance moderately within the catchment. On the other hand, routing parameter CK1,2 for interflow and overland flow affects the peak of flood hydrograph at the outlet of catchment.
2016	K. Amrit, S. Singh and R. Singh.	Andhiyarkhore intermediate catchment in Chhatisgarh	1995 to 2003	2004 to 2007	The groundwater recharge in the basin was estimated using calibration and validation of MIKE 11 NAM model.
2016	I. Balan, L. Crenganis and F. Corduneanu.	Geru River	2013	Not reported	NAM leads to a discharge hydrograph with a longer total time and a form coefficient almost equal to the one of the measured hydrograph. The simulated hydrograph overlaps the measured hydrograph. The value of the second peak (41 m <sup>3</sup> /s) is closer to the second peak of the measured hydrograph (75.30 m <sup>3</sup> /s).
2016	H. L.Tiwari, A. Balvanshi and D. Chouhan	Shipra river basin in Madhya Pradesh, India.	1996 to 2001	2002 to 2006	The model was found suitable for Shipra basin in simulating hydrological response of the basin to the rainfall and predicting daily runoff with good degree of accuracy.

## **2.3 Artificial Neural Network (ANN) model**

An Artificial Neural Network (ANN) is a flexible mathematical structure which is capable of identifying complex nonlinear relationships between input and output data sets. Artificial neural network models compute complex nonlinear problems, which may be difficult to represent by conventional mathematical equations. ANN models have been found useful and efficient, particularly in problems for which the characteristics of the processes are difficult to describe using physical equations. The conventional model requires many input parameters and variables, some of which cannot be obtained easily from the field and may vary from site to site even within the same geographical region. Artificial neural network has found successful applications in the areas of science, engineering, industry, business, economics and agriculture. In hydrology, the ANN models have been satisfactorily applied for the prediction of nonlinear hydrologic processes such as rainfall, runoff, stream flow, and water quality since the 1990s (ASCE, 2000). A number of researchers have investigated the potential of artificial neural networks in modeling the rainfall-runoff process as well as the rainfall process by which the effect of variability of future climate can also be studied. In present study ANN model is used to forecast rainfall and evapotranspiration which further used for the forecasting of water availability and water demand.

### **2.3.1 Application of ANN technique for forecasting of rainfall time series**

A number of alternatives for forecasting of rainfall time series have been explored in recent years, which are capable of modeling non-linear processes, including simple regression, multiple linear regressions and artificial neural networks. In recent years, the applications of artificial neural network (ANN) techniques in hydrological modeling have received increasing attention. The ANN has the capability to identify complex nonlinear relationships between input and output data sets without the necessity of understanding the nature of the phenomena and without making any underlying assumptions regarding linearity or normality (Abudu *et al.*, 2011). In case of rainfall, the ANNs were used for its forecasting either from its previous and current values or in combination with the previous and current values of other variables like evaporation, temperature and humidity etc. The important studies/works related to application of ANNs for rainfall forecasting are described in this section.

Sahai *et al.*, (2000) applied the ANN technique with error- back-propagation algorithm to predict Indian Summer Monsoon Rainfall (ISMR) on monthly and seasonal time scales. The ANN technique was applied to the five-time series of June, July, August, September monthly means and seasonal mean (June + July + August + September) rainfall from 1871 to 1994 based on Parthasarathy data set. The previous five years' values from all the five time-series were used to train the ANN to predict for the next year. Various statistic indices were calculated to examine the performance of the models and

according to authors the models could be used as a forecasting tool on seasonal and monthly time scales.

Toth *et al.*, (2000) forecasted the short-term rainfall obtained with different time-series analysis techniques using past rainfall depths as the only input. They applied ANN for forecasting storm rainfall of the Sieve River basin, Italy for the period of 1992 to 1996 with lead times varying from 1 to 6 hr. In the split-sampling method, applications of ANN architectures with a number of input nodes ranging from 2 to 24 were tested. For each input layer dimension, the number of hidden nodes was progressively increased from 2 to 8 nodes. The performance of ANN architectures, considering all the lead-times was improved as the number of input nodes increased with modest additional gain for more than 15-18 nodes. The networks tested in the adaptive calibration were of extremely parsimonious (both number of input node and hidden node ranging from 2 to 5). The optimal network complexity for adaptively calibrated neural networks corresponded to numbers of input and hidden nodes equal to 3. The result showed that the ANN performed the best in the improvement of the runoff forecasting accuracy when the predicted rainfall was used as inputs of the rainfall runoff model.

Luk *et al.*, (2001) studied the performance of three alternative ANNs, namely multilayer feed forward neural network (MLFN), partial recurrent neural network and time delay neural network (TDNN). Rainfall amounts during 15 minute intervals at the 16 rain gauges were obtained from January 1991 to September 1996. During this period, 34 storms occurred with daily rainfall total greater than 20mm, with 1749 rainfall amounts at each site. The 34 storm events were divided into three data sets: first, training set-16 storms with a total of 748 rainfall periods (each of 15 minutes), second, monitoring set-eight storms with a total of 376 rainfall periods, and third validation set-ten storms with a total of 625 rainfall periods. The maximum epoch for training was set at 1000. During training, the networks were checked at every 100 epochs. Training was stopped when the error in monitoring data reached its lowest value or the training reached the maximum epoch, whichever came first. A sigmoidal activation function was adopted for the hidden nodes, whereas a linear activation function was used for the output nodes. The normalized mean squared error (NMSE) was chosen as the performance indicator. During the development of the ANN model various network configuration were attempted in order to determine the effect of two key variables which were the lag of network and number of hidden nodes. For the multilayer feed forward neural network, networks with lags 1, 2, 3, and 4 were attempted. In addition, the numbers of hidden nodes tried were 2, 4, 8, 16, 24, 32, 64 and 128. Networks with two layers of hidden nodes were also attempted. For the Elman network the order of lag was fixed at 1. The numbers of context unit tried were 2, 4, 8, 16, 24, 32 and 64. For time delay neural network, networks with 2, 3 and 4 input were attempted. The result showed that the normalized mean squared errors in the validation samples for all networks were in the range of 0.63 to 0.67 with

small difference. They found that all alternative networks reasonably forecasted rainfall one-time step (15 min) ahead for 16 gauges concurrently. In addition to this authors also observed that, for each type of network there existed an optimal complexity which was a function of the number of hidden nodes and the lag of the network.

Kumarsiri and Sonnadara (2006) applied the ANN technique for short term and long term rainfall forecasting using feed-forward back-propagation architecture for Colombo, Sri Lanka. Input/output of each neuron was normalized within the range of 0 to 1. The log-sigmoid activation function was used to increase the training efficiency of the model. The network performance was analyzed using the prediction success rate and root mean square errors (RMSE). For short term forecasting, an attempt was made at forecasting the rainfall occurrence of the next day i.e. one-day-ahead model. The network was trained for a period of 9 years from 1994 to 2002. A total data set of 3284 input/output pairs using the error back-propagation algorithm was used. The result showed that the ANN 10-6-1 neural network architecture showed best potential within a short training and testing period. For one-month-ahead model the network was trained for 50 years from 1949 to 1998 and testing was done for period of 1999 to 2003. For one-year-ahead forecast model, the network was trained for a period of 105 years, from 1869 to 1973 using the error back-propagation algorithm and was tested for a separate data set of 30 years from 1974 to 2003. The percentage error was introduced for analyzing the one-year-ahead network model. The results showed that the 10-6-1 network architecture of one-day-ahead network model was successful in forecasting the rainfall occurrence of the next day with a success rate of 74.25 per cent. When the model was extended for multiple days ahead, the success rate of the network decreased and root mean square errors increased with the number of days. Seven days was the limit up to where reasonable predictions could be made. The one-month-ahead network was reasonably successful in forecasting the next month's rainfall depth category with a success rate of 58.33% within a  $\pm 50$  mm error limit. Extension for multiple months into the future produced the same result as above. The success rate dropped to 41% within 6 months into the future and the one-year-ahead network was highly successful in forecasting the annual rainfall depth of the next year, with a success rate of 76.67 per cent within a  $\pm 100$ mm error limit. When the values for droughts in 2001 and 1995-96 were ignored the rate increased to 83.33%. The network performance dropped rapidly when multiple year ahead predictions were made. Hence, according to authors this model ideally should not be used beyond the second year into the future.

Surajit and Manojit (2007) developed an ANN model to predict the average rainfall over India during summer-monsoon. The months of June, July, and August were identified as the summer-monsoon months in India. The data of three months June, July and August corresponding to the years 1871-1999 were used for model development. The 75 per cent of the available data was used as training set

and remaining 25 per cent as test set. The model was trained up to 50 epochs. The learning rate 0.4 and momentum 0.9 were kept constant throughout out the training process. Least mean squared error was chosen as the stopping criteria for the learning or training procedure. Multilayer perceptron with two hidden layers, each hidden layer containing 2 nodes were used to train the model. Performance of the model was evaluated through computation of overall prediction error (PE). The performance of the neural network model was compared with conventional persistence forecast. The result showed that the prediction error was small i.e. 10.2% of overall prediction error which was yielded by the perceptron model i.e. ANN model. It was found that in 87.5% test cases the prediction error was less than 20%. Thus, there was a high prediction yield. The performance of the neural network model was compared with conventional persistence forecast. It was found that the prediction error in case of persistence forecast was 18.3%. Therefore, neural network in the form of multilayer perceptron was found to be best in the prediction of monsoon rainfall over India.

Hung *et al.*, (2009) developed an artificial neural network technique for forecasting rainfall. Historical rainfall data was collected from 104 stations of the Bangkok Metropolitan Administration (BMA) and Thai Meteorological Department (TMD) rain gauge networks for the period from 1991 to 2005. The period from 1 January 1997 to 31 December 1999 was selected to train ANN models, and the data of the year 2003 were used as a testing set which was used for the final evaluation of the model performance. The feed forward neural network model with hyperbolic tangent transfer function was used to train with different network types and tested with different inputs. Preliminary tests showed that a generalized feed forward ANN model achieved the best generalization of rainfall especially, the use of a combination of meteorological parameters such as relative humidity, air pressure, wet bulb temperature and cloudiness. The rainfall at the point of forecasting and rainfall at the surrounding stations as an input data were used in ANN model to apply with continuous data containing rainy and non-rainy periods. Additionally, forecast by ANN model were compared to the convenient approach namely simple persistent method. The performances of the selected model were evaluated using efficiency index, root mean square error, correlation coefficient. Results revealed that ANN forecasts had superiority over the ones obtained by the persistent model. Rainfall forecasts for Bangkok from 1 to 3 h ahead were highly satisfactory. Sensitivity analysis indicated that the most important input parameter besides rainfall itself was the wet bulb temperature in forecasting rainfall.

Vamsidhar *et al.*, (2010) examined the back propagation neural network model for predicting the rainfall based on humidity, dew point and pressure. The meteorological data from the period 1901-2000 were used for development of the neural network model. Datasets were divided into two parts, two-third of the data was used for training and one-third of data was used for testing the models. The numbers of training and testing patterns were 250 and 120 respectively. Using trial and error procedure

the neural network architecture of 3:7:1 model (input node: hidden node: output node) was found to be the best for prediction of rainfall. They obtained 99.79 per cent of accuracy in the training and 94.28 per cent of accuracy in testing.

Geeta and Selvaraj (2011) predicted the monthly rainfall for Chennai, Tamilnadu using back propagation neural network model. 32 years of monthly mean data from 1978 to 2009 of meteorological parameters such as wind speed, mean temperature, relative humidity and aerosol values in the area were used to develop the ANN model. Air mean temperature, relative humidity, wind speed and aerosol values were given as input to the model. Monthly rainfall data were selected to be the desired output data for training and testing of the models. From input layer to hidden layer, the logistic sigmoid function was used as the activation function. Learning parameter 0.3 and momentum 0.5 were kept constant throughout the training of models. Performance of the model was measured with the least training error. They found that the ANN (4-9- 1) neural network architecture generated a good forecast with the prediction error of the model at 9.96 per cent only. The actual rainfall amount almost coincided with the predicted amount except in the sharp peak values. Authors also concluded that when more input values were considered then even the peak values can be predicted accurately.

Abdulkadir *et al.*, (2012) developed ANN model to forecast monthly rainfall for Ilorin, Nigeria using observed rainfall records. The neural network was trained with sixty years (from 1952 to 2011) monthly historical rainfall data collected from Nigerian Metrological Agency (NiMET) in Ilorin. ANN model was designed to run a real time task in which the input to model was a consecutive data of the rainfall. ANN model was trained using the data format of the form in the rainfall data at the present time as an output and subsequent data series as an input to the ANN model. The neural network model was trained with three-layer feed-forward model with backpropagation neural network (BPNN) learning algorithms. Nonlinear log sigmoid transfer function was used. The network training of the rainfall data was automated in “ALYUDA Neuro Intelligence forecaster” software with total of seven hundred twenty (720) rainfall data points. Performance was measured with help of correlation coefficient. The findings of the study showed that the trained network yielded 76 percent and 87 per cent of good forecast for the training and testing data sets respectively. The 88 percent correlation coefficient was obtained which showed that the network was fit to be used for the subsequent quantitative prediction of rainfall in Ilorin. Authors concluded that forecasting using ANN is a very versatile tool in water resources management modeling.

Deshpande (2012) compared the multilayer perceptron neural network for multi-step ahead (1, 5, 10, 20) prediction of rainfall with the Jordon Elmann Neural Network (JENN), Self-organized feature

map (SOFM) and Recurrent neural network (RNN) for Yavatmal district of Maharashtra. Rainfall time series was split into three data set viz., training, testing and cross validation. Sixty per cent samples as training, 25 per cent samples as testing, and 15 per cent samples were used as cross validation. The performance measures such as mean square error (MSE) and normalized mean square error (NMSE) on testing as well as training data set were used for various networks. The optimum parameters of neural network were decided on the test data set and training dataset. The numbers of trials were carried by changing various parameters like number of possessing elements, number of neuron in hidden layers, number of iterations, transfer function learning rule for which the network gave minimum mean square error. The proposed model was trained with different error criteria and the best combination network was then trained and tested for different transfer functions such as tanh, sigmoid, linear and sigmoid. The numbers of epochs were varied from 1000 to 20000 in the step 2000. The proposed multilayer perceptron neural network model was trained for the best combinations for training and testing exemplars and it was experimented for 1000 to 20000 iterations for getting an optimum result for each multi step ( $k=1, 5, 10, 20$ ) of rainfall time series. It was found that the performance of the selected model was optimal for 22 neurons in the hidden layer with regard to the mean square error and normalized mean square error for the testing data sets. Comparison of Jordan Elman neural network and multilayer perceptron neural network for rainfall time series prediction for  $k=10$  was  $MSE=0.062007$ ,  $NMSE=0.781608$ , and for 20 step ahead;  $MSE=0.064779$ ,  $NMSE=0.828212$ . Initially he found that for small step ahead values, the Jordan Elman Network gave good results, but for the larger step ahead values, the performance of multilayer network was better than all the other networks.

Srivastava and Tripathi (2012) compared artificial neural network and nonlinear regression models for prediction of Indian summer monsoon rainfall. The 140 years' monthly rainfall data (from 1871 to 2010) of all-India rainfall of 30 meteorological subdivisions were obtained from the Indian Meteorological Department (IMD) Pune. All the data points were taken serially month wise and year wise in an array of 1680 data points. All data points were split into the training and testing data sets. The starting 1631 data points for the training and for validation last 48 values have been chosen for the testing. Non-linear regression models of 2<sup>nd</sup> order were made for forecasting the rainfall. The training and testing data were the same as that for the ANN model for non-linear regression models. The training was done using the back propagation algorithm, neuron in the hidden layer were used as  $n=6, 7, 8$ . The training was stopped after every 10 cycles or epochs and the cross-validation was done. The results of the performance evaluation of the ANN model showed that the correlation coefficient was better when neuron in the hidden layer was 6 (0.76) than the neuron in the hidden layer 5 (0.75). Also, the RMSE for 6 neurons in the hidden layer (0.1071) was better than the RMSE for 5 neurons

in the hidden layer (0.1084). For regression model it was found that the correlation coefficient was better for second order (0.74) than first order (0.73). Also, the RMSE for second order (0.1081) was better than the RMSE for first order (0.1090). From the above performance of statically measures, authors concluded that a simple ANN model with 6 neurons in the single hidden layer was successful in modeling the dynamical relationship in the all India rainfall pattern. They found that a good correlation coefficient was obtained along with an RMSE which was below the standard deviation of the observed data.

Kumar and Yadav (2013) examined the suitability of ANN model for rainfall forecasting in Varanasi district of Uttar Pradesh. Five years' monthly rainfall, maximum temperature, minimum temperature and relative humidity data from period of 2003 to 2007 were used. Feed forward neural network was applied to the monthly rainfall and model was trained with the Levenberg-Marquardt back Propagation algorithm. Regression coefficient was measured for the performance of developed neural network model. The neuron in the hidden layer in neural network architecture varied from 15 to 40. The findings of this study revealed that, regression coefficient varied from 0.659 to 0.964. At 20 neurons in the hidden layer the regression coefficient was found to be maximum i.e. 0.964 in years 2006 with the lowest learning rate 0.00000001

AL-Suhaili and Karim (2014) used artificial neural network model to predict missing monthly precipitation data of one station from the eight weather stations of Sulaimani Governorate, Iraq. The monthly precipitation data of these stations of eight years from 2004-2011 were collected from moderate of Agro-meteorological Center-General Directorate of Agricultural, Ministry of Agriculture, KRG. Many trials were adopted for the selection of the number of the hidden nodes in the hidden layer. All ANN models with hyperbolic tangent as an activation functions for the hidden and output layers with learning rate of 0.4 and momentum term of 0.9, but with different data set subdivision were used for training, testing and holdout data sub-sets, and different number of hidden nodes in the hidden layer were used. Eight models were developed, one for each station for prediction. The trial that exhibited the highest correlation coefficient between the predicted and the measured monthly precipitation was selected. The findings of this study concluded that the ANN model can provide a good prediction model for predicting the monthly precipitation values for eight weather stations in the Sulaimani Governorate with correlation coefficient ranged 0.9 to 0.972.

Popale (2016) developed the stochastic models and artificial neural network models for generating and forecasting rainfall. He compared the forecasts of rainfall obtained from stochastic and artificial neural network models. ARIMA class and ANN technique were used to forecast and generate weekly rainfall sequences and compared to investigate their performance and suggested the appropriate

models for forecasting and generation of weekly rainfall. The ANN model 4-10-1 architecture trained with resilient back propagation algorithm *trainrp* using cascade feed forward back propagation, non-linear activation function i.e. a log-sigmoidal for the hidden layer and linear transfer function in output layer, single hidden layer with 10 number of neurons in the hidden layer, having small learning rate i.e. 0.1 and 0.9 as a momentum constant was found best for forecasting rainfall. The model includes input of weekly rainfall of same week of previous two years and rainfall of two preceding weeks of same year. The ANN model 4-10-1 found best in terms of values of R,  $R^2$ , RMSE and MAE of 0.875, 0.766, 1.09 and 4.24 respectively.

The studies reviewed in this section and summarized in Table 2.3 indicated that ANN is important tool to forecast rainfall. For forecasting of water availability, forecasted rainfall plays an important role. Hence, in present study already, developed ANN model 4-10-1 by Popale (2016) was used for forecasting of rainfall of different station. This forecasted rainfall was then used to forecast runoff and thereof water availability for different catchments under Ghod complex sub basin.

**Table 2.3 Summary of studies on application of ANN technique for forecasting of rainfall time series**

Year	Name of authors	Location/ Place	Length of data used	Input variable used	Variable simulated (output)	Type of Network & Algorithm	Activation function used in		Results/Findings
							Input	Output	
2000	A.K.Sahai, M.K.Soman and Satyan	India	Time series of June, July, August, September, monthly and seasonal rainfall data from 1871 to 1994	5 years values of rainfall from all the five time-series were used as an input to train the ANN to predict for the next year	Monthly and seasonal rainfall data	Artificial neural network (ANN) model trained with error-back-propagation algorithm	Not available	Not available	It was found that the ANN models could be used as a forecasting tool on seasonal and monthly time scales. It is also observed by various researchers that with the passage of time the relationships between various predictors and Indian monsoon are changing, leading to changes in monsoon predictability.
2000	E. Toth, A. Brath and A. Montanari	Sieve River basin, Italy	The rainfall data of 192 to 1996 of Sieve river basin, Italy were used.	Past rainfall depths	Rainfall	Artificial neural networks (ANN) model	Not available	Not available	The optimal network complexity for adaptively calibrated neural networks seems to correspond to numbers of input and hidden nodes equal to 3. The result showed that the ANN performed the best in the improvement of the runoff forecasting accuracy when the predicted rainfall was used as inputs of the rainfall run-off model.
2001	C. K. Luk, J. E. Ball and A. Sharma	The Upper Psrramatta river catchment, Sydney, Australia	The 34 storm events data of Upper Psrramatta river catchment were used.	Rainfall of different lags	Rainfall	Multilayer feed forward neural network (MLFN), Partial recurrent neural	Sigmoid	Linear	The result showed that the normalized mean squared errors in the validation samples for all networks were in the range of 0.63 to 0.67 with small difference. They found that all alternative networks reasonably forecasted rainfall one time step (15 min) ahead for 16

						network and Time delay neural network (TDNN)			gauges concurrently. In addition to this authors also observed that, for each type of network there existed an optimal complexity which was a function of the number of hidden nodes and the lag of the network.
2006	A. D. Kumarasiri and D. U. J. Sonnadara.	Colombo, Sri Lanka.	For one-month-ahead model 50 years rainfall data from 1949 to 2003 and for one-year-ahead forecast model, 105 years data from 1869 to 2003 and for short term forecasting the nine years rainfall data from 1994 to 2002 were used.	Rainfall	Rainfall	Feed-forward back-propagation architecture, One-day-ahead ANN model, one-year-ahead forecast model was trained with error back propagation architecture	Log-sigmoid	Log-sigmoid	The results showed that the 10-6-1 network architecture of one-day-ahead network model was successful in forecasting the rainfall occurrence of the next day with a success rate of 74.25%. The One-Month-Ahead network was reasonably successful in forecasting the next month's rainfall depth category with a success rate of 58.33% within a $\pm 50$ mm error limit. One-Year-Ahead network is highly successful in forecasting the annual rainfall depth of the next year, with a success rate of 76.67% within a $\pm 100$ mm error limit.
2009	N. Q. Hung, M. S. Babel, S. Weesakul and N. K. Tripathi	Bangkok, Thailand	Four years of hourly data from 75 rain gauge stations in	The rainfall at the point of forecasting and rainfall at the surrounding	Rainfall	Feed forward neural network model	Hyperbolic tangent	Hyperbolic tangent	Results were highly satisfactory for rainfall forecast 1 to 3 hr ahead. Sensitivity analysis indicated that the most important input parameter

			the area of Bangkok, Thailand	stations were used as an input.					beside rainfall itself is the wet bulb temperature in forecasting rainfall.
2010	E. Vamsidhar, K. V.S.R.P.Varma, P. S. Rao, R. satapati	Not available	A monthly rainfall data in the period of 1901-2000	Humidity, dew point and pressure as an input.	Rainfall	Backpropagation neural network type	Not available	Not available	The architecture of neural network 3-7-1 showed the accuracy 99.79 %, in the training dataset and 94.28% for testing data set. The corresponding mean square error for each data type was 0.210 for training and 5.82 for testing data set. According to the authors, the backpropagation neural network was acceptably accurate and can be used for predicting the rainfall.
2011	G. Geetha and R. S. Selvaraju	Chennai, Tamilnadu	32 years of monthly mean data from 1978 to 2009 of meteorological parameters such as wind speed, mean temperature, relative humidity and aerosol values were used.	Air mean temperature, relative humidity, wind speed and aerosol values	Monthly rainfall	Back Propagation neural network (BPNN) was used	Logistic sigmoid function	Logistic sigmoid function	They found that the ANN (4-9-1) neural network architecture generated a good forecast with the prediction error of the model at 9.96 per cent only. The actual rainfall amount almost coincided with the predicted amount except in the sharp peak values. Authors also concluded that when more input values were considered then even the peak values can be predicted accurately.
2012	T. S. Abdulkadir, A. W. Salami	Ilorin, Nigeria.	Sixty years from 1952 to 2011	A consecutive data of the rainfall	Rainfall	ANN model	Not available	Not available	The findings of the study showed that the trained network yielded 76 per cent and 87 per cent of good

	and A. G. Kareem		monthly historical rainfall data was used.						forecast for the training and testing data sets respectively. The 88 percent correlation coefficient was obtained which showed that the network was fit to be used for the subsequent quantitative prediction of rainfall in Ilorin
2012	R. R. Deshpande	Yavatmal district of Maharashtra.	Data length not available	Rainfall	Rainfall	Jordan Elmann Neural Network (JENN), Self-organized feature map (SOFM) and Recurrent neural network (RNN)	Combination of Tanh, sigmoid, and sigmoid transfer function were used.	Not available	It was found that the performance of the selected model was optimal for 22 neurons in the hidden layer with regard to the mean square error and normalized mean square error for the testing data sets. Initially, the Jordan Elman Network was giving good results, but as soon as we go for the larger step ahead values then the performance of multilayer network was better than all the other networks.
2012	Srivastava and Tripathi	Indian summer monsoon rainfall	The 140 years monthly rainfall data from 1871 to 2010 of all-India rainfall of 30 meteorological subdivisions	Not available	Rainfall	Artificial neural network and nonlinear regression models	Not available	Not available	The results of the ANN model showed that the correlation coefficient was better when neuron in the hidden layer was 6 (0.76) than the neuron in the hidden layer 5 (0.75). A simple ANN model with 6 neurons in the single hidden layer was successful in modeling the dynamical relationship in the all India rainfall pattern.

2013	Rajankumar and Yadav	Varanasi district of Uttar Pradesh	Five years monthly rainfall, maximum temperature, minimum temperature and relative humidity data from period of 2003 to 2007 were used	Not available	Rainfall	Feed forward neural network with Levenberg-Marquardt back Propagation algorithm was used. The neuron in the hidden layer in neural network architecture varied from 15 to 40.	Not available	Not available	The findings of this study revealed that, regression coefficient varied from 0.659 to 0.964. At 20 neurons in the hidden layer the regression coefficient was found to be maximum i.e. 0.964 in years 2006 with the lowest learning rate 0.00000001.
2014	AL-Suhaili and Karim	Sulaimani Governorate, Iraq	Monthly precipitation data of 8 stations of 8 years from 2004-2011	Rainfall data of seven weather stations	Rainfall	ANN model	Hyperbolic tangent	Hyperbolic tangent	ANN model can provide a good prediction models for predicting the monthly precipitation values for eight weather stations with correlation coefficient ranged 0.9 to 0.972.
2016	P. G. Popale	Rahuri India	Daily rainfall data of 30-31 years converted into weekly data for two stations	Rainfall	Rainfall	Cascade feed foreword trained with resilient back propagation algorithm ( <i>trainrp</i> )	Logsigmoid	Linear	The ANN model-C having network architecture of 4-10-1, network type of cascade feed foreword trained with resilient back propagation algorithm ( <i>trainrp</i> ) exhibited the best performance criteria among all the models for forecasting of weekly rainfall.

### 2.3.2 Application of ANN technique for forecasting of evapotranspiration series

Evapotranspiration is a complex and nonlinear phenomenon because it depends on several interacting climatological factors, such as temperature, humidity, wind speed, radiation, type and growth stage of the crop, etc. Artificial neural networks (ANN) are effective tools to model nonlinear systems. Artificial neural network models compute complex nonlinear problems, which may be difficult to represent by conventional mathematical equations. These models are well suited to situations, where the relationships between the input variable and the output are not explicit. The advantage of the artificial neural network approach in estimating evapotranspiration is that it eliminates the need for identifying a reference crop and it requires only limited climatic data.

Jain *et al.*, (2008) developed models for estimating evapotranspiration using Artificial Neural Networks and their physical interpretation. Estimation of evapotranspiration (ET) requires knowledge of the values of many climatic variables, some of which require special equipment and careful observations. Although ET is an important component of water balance, the data required for its accurate estimation are commonly available only at widely spaced measurement stations. The major objective of this study was to estimate ET using an artificial neural network (ANN) technique and to examine if a trained neural network with limited input variables can estimate ET efficiently. The results indicated that even with limited climatic variables an ANN can estimate ET accurately. The paper also outlines a procedure to evaluate the effects of input variables on the output variable using the weight connections of ANN models. Such an analysis performed on the ANN-ET models developed was able to explain the reasons for the ANN's potential in estimating the ET effectively from limited climatic data.

Gorkalanderas *et al.*, (2009) studied the forecasting ability of ANN models for weekly evapotranspiration in Alava region of Basque Country (Northern Spain). Daily values of 28 years for the period of 1975 to 2003 of evapotranspiration were calculated by locally calibrated Hargreaves-Samani equation which was grouped in weekly evapotranspiration time series. The weekly evapotranspiration data from 1975 to 1998 were used for model development and data from 1999 to 2003 were used for testing or validation of model. Ten multilayer perceptron and two radial basis function neural network were formulated for training and cross validation of the network architecture. Supervised training process was executed using three different minimization algorithms namely back propagation, Levenberg-Marquardt and quick propagation with a maximum 70,000 iterations. Performance of ANN model was tested using mean absolute difference and root mean square difference. Findings of this study revealed that the ANN (6-4-1) of MLP model trained with back propagation algorithm having six neurons in the input layer and four neurons in the hidden layer

showed lowest root mean square difference value (i.e. 2.459 mm per week) for total period of 1999-2003 and 3.405 mm per week, for the irrigation period (May-September). ANN (6-4-1) also showed the lowest value of mean absolute difference for the total period of 1999-2003 (i.e. 1.783) and for the irrigation period May to September it was 2.057.

Ariapour and Zavareh (2010) estimated daily evaporation using of Artificial Neural Networks for Borujerd Meteorological Station, Iran. In order to estimate the evaporation, direct measurement methods or physical and empirical models can be used. Using direct methods require installing meteorological stations and instruments for measuring evaporation. Installing such instruments in various areas requires specific facilities and cost which is impossible to be specified. Pan evaporation is one of the most popular instruments for direct measuring. In this research, by using daily temperature, relative humidity, wind velocity, sunshine hours, and evaporation data in meteorological station and neural network model, daily evaporation is estimated. Network training using daily data takes three years and network testing takes one year in which data is standardize for training and testing the model. In this model, a feed forward multiple layer network with a hidden layer and sigmoid function is used. The results showed the suitable capability and acceptable accuracy of artificial neural networks in estimating of daily evaporation. Best model for estimation of evaporation is ANN (5-4-1), it has MSE 0.006716 and  $R^2$  0.725398. Artificial neural networking is one of the best methods for estimation of evaporation. This method can be used in any area with only maximum and minimum data for estimation of evaporation.

Chowdhary and Shrivastava (2010) estimated reference crop evapotranspiration using artificial neural networks. Improved water management requires accurate scheduling of irrigation, which in turn requires an accurate estimation of crop evapotranspiration. Crop coefficients are used to estimate crop evapotranspiration from weather based reference crop evapotranspiration. Reference crop evapotranspiration is an important quantity for computing the irrigation demands for various crops. Monthly reference crop evapotranspiration is estimated by FAO Penman-Monteith method and irrigation requirements for the system are estimated based on the methodology suggested in FAO 24. Artificial Neural Network approach is found appropriate for the modeling of reference evapotranspiration for MRP command area. This study explores the potential of feed forward neural network (FFNN) for estimation and forecasting of monthly ETo values in MRP command area.

Diamantopoulou *et al.*, (2011) evaluated performance of artificial neural networks in estimating reference evapotranspiration with minimal meteorological data. Detailed meteorological data required for the equation of FAO-56 Penman-Monteith (P-M) method which was adopted by Food and Agriculture Organization (FAO) as a standard method in estimating reference crop evapotranspiration

(ETo) are not often available, especially in developing countries. The Hargreaves equation (HG) has been successfully used in some locations to estimate ETo where sufficient data are not available to use the P-M method. This paper investigates the potential of two Artificial Neural Network (ANN) architectures, the multilayer perceptron architecture, in which a Back Propagation Algorithm (BPANN) is used, and the Cascade Correlation Architecture (CCANN), in which Kalman's learning rule is embedded in modeling the daily ETo with minimal meteorological data. An overview of the features of ANNs and traditional methods such as P-M and HG is presented, and the advantages and limitations of each method are discussed. Daily meteorological data from three automatic weather stations located in Greece were used to optimize and test the different models. The exponent value of the HG equation was locally optimized, and an adjusted HGadj equation was used. The comparisons were based on error statistical techniques using P-M daily ETo values as reference. According to the results obtained, it was found that taking into account only the mean, maximum and minimum air temperatures, the selected ANN models markedly improved the daily ETo estimates and provided unbiased predictions and systematically better accuracy compared with the HGadj equation. The results also show that the CCANN model performed better than the BPANN model at all stations.

Kumar and Tiwari (2012) estimated evaporation using Artificial Neural Networks and adaptive Neuro-Fuzzy inference system techniques. Accurate estimation of potential evaporation has been of a great as its importance is obvious in many water resources applications such as management of hydrologic, hydraulic and agricultural systems. Although there are empirical formulas available for Evaporation estimation, but their performances are not all satisfactory due to the complicated nature of the evaporation process and the data availability. For this purpose, artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models were developed to forecast monthly potential evaporation in Pantnagar, U.S. Nagar (India) based on four explanatory climatic factors. Observations of relative humidity, solar radiation, temperature, wind speed and evaporation for the past 19 years and 8 months (total 236 months) have been used to train and test the developed models. Results revealed that the models were able to well learn the events they were trained to recognize. Moreover, they were capable of effectively generalizing their training by predicting evaporation for sets of unseen cases. These encouraging results were supported by high values of coefficient of correlation and low mean square errors. It has been found that ANN and ANFIS techniques have good performances (for the test data set, correlation coefficient for ANN is 0.9236 and root mean square error is 0.9863 and for ANFIS correlation coefficient is 0.9562 and root mean square error is 1.2812. Between ANN and ANFIS, ANFIS model is slightly better as the difference is small. Although ANN and ANFIS techniques seem to be powerful, their data input selection process was done by trial and error method.

Khoshhal and Mokarram (2012) developed model for prediction of evapotranspiration using MLP Neural Network. Artificial neural networks in recent decades, and studies for modeling complex systems and nonlinear features have shown ability very high. In this study multi-layer perceptron networks (MLP) were used for estimating reference crop evapotranspiration. By using meteorological data from 2000 to 2010 at the stations of Eghlid plain in Iran was calculated the average values of evapotranspiration was estimated using the Penman-Monteith (PM) equation. Then using these values as the output target, different networks with different structures were defined and taught. Finally, the network was evaluated to estimate evapotranspiration. By comparing the results of the ten networks, it was determined that MODEL 10 in the estimation of reference crop evapotranspiration is relatively more accurate than others.

Ojha and Bhakar (2012) investigated the utility of artificial neural networks (ANNs) for comparison of daily reference evapotranspiration (ET<sub>o</sub>) estimated by Penman-Monteith (PM) method and that of estimated by ANNs during growing season of wheat crop. Feed forward network has been used for prediction of ET<sub>o</sub> using resilient back-propagation method. For the purpose of the study, daily meteorological observations such as minimum and maximum temperature, minimum and maximum relative humidity, wind speed and solar radiation for the period of November 21, 1997 to March 2, 1998 were used as input and ET<sub>o</sub> estimated by Penman -Monteith method for growing season of wheat crop as output. The comparisons were made between ET<sub>o</sub> estimated by using ANNs and PM method. The correlation coefficient between actual and predicted ET<sub>o</sub> during training of ET<sub>o</sub> for growing season of wheat crop was found to be 0.990 which was found to be significant at 5 % level. The networks were also used for computation of crop evapotranspiration (ET<sub>c</sub>). During training of ET<sub>c</sub>, crop coefficient values estimated by quadratic method have been taken as input to the network along with meteorological parameters and ET<sub>c</sub> estimated using crop coefficient approach and that of measured by lysimeter as output separately. The crop evapotranspiration estimated by ANNs were compared with ET<sub>c</sub> estimated by crop coefficient approach and that of evapotranspiration measured by lysimeter. The correlation coefficients during training of ET<sub>c</sub> of wheat crop were found to be 0.994 and 0.915 respectively which were also found significant at 5 % level. Based on these comparisons, it was concluded that the ANN models is suitable for prediction of ET<sub>o</sub> and ET<sub>c</sub>.

Chauhan and Shrivastava (2012) investigated potential of artificial neural networks (ANNs) for estimation of reference crop evapotranspiration with climatic data required for Penman-Monteith (P-M) method, to test artificial neural networks (ANNs) for estimating reference crop evapotranspiration (ET<sub>o</sub>) with limited climatic data (ET<sub>o</sub>) and compared the performance of ANNs with P-M method. The ANNs are trained to estimate ET<sub>o</sub> from weekly climate data as input and the Penman-Monteith (PM) method as output. The networks, using varied input combinations of climatic variables have

been trained using three backpropagation learning algorithms namely quasi-Newton algorithm, Levenberg-Marquardt algorithm and Backpropagation with variable learning rate. Firstly, the networks were trained with weekly climate data (maximum and minimum temperature, maximum and minimum relative humidity, wind speed, and sunshine hours) as input and the P-M estimate as output. Then the networks, using varied input combinations of climatic variables were trained using the same training algorithms as mentioned above. For each class of inputs, the best ANN architecture for estimation of ETo was selected on the basis of statistical parameters like square estimates of error (SEE) and model efficiency. The analyses suggested the ETo can be computed from limited climate data using the ANN approach in Mahanadi Reservoir Project (MRP) command area. Further based on the results obtained, it can also be concluded that ANN performed well when the input (first) layer receives the input variables consisting of all quantities that can influence the output.

Meshram *et al.*, (2015) predicted one month ahead the reference evapotranspiration using artificial neural network for Akola station. Climatic parameters for 35 years (1977-2011) were used and ETo was estimated by using standard Penman-Monteith method which was further used for development and validation of the ANN models as the observed data on ETo was not available. The ANN models were developed using different input combinations. The models learned to predict one month ahead ETo (i.e. ETo, t+1) for Akola using Levenberg-Marquardt learning method. The ANN model with architecture of 4-12-1 (four, twelve and one neuron(s) in the input, hidden, and output layers, respectively) was found to be the best amongst all the models with minimum standard error (SE) of estimates of  $0.74 \text{ mm day}^{-1}$  and correlation co-efficient of 0.9260. The ANN4 model had given better performance with mean absolute error of estimates (MAE) and root mean square error (RMSE) of 0.20 and  $0.27 \text{ mm day}^{-1}$ , respectively, mean absolute relative error (MARE) of 5.7 per cent and model efficiency of 0.9745.

Sharma and Regulwar (2016) estimated evapotranspiration using an artificial neural network (ANN) technique for Jayakwadi reservoir. The evapotranspiration was calculated with the help of conventional methods using Blaney Criddle Method, Modified Penman Method, and Thornthwaite Method and also with the help of Artificial Neural Network with target value of each method. The ANN model 5-5-1 was used with the different training and testing layers. The ETo values were also predicted with help of ANN model for three different methods. The results of predicted value by ANN and calculated value of conventional methods were compared. From conventional method, it was observed that Thornthwaite method had great accuracy for calculating evapotranspiration with comparison of ANN for same method. The Thornthwaite method showed the successful application by using ANN with highest regression value  $R = 0.99753$ .

Abdullahi and Elkiran (2017) studied the future impact of climate change on reference evapotranspiration in for Girne and Larnaca regions of Cyprus for the next 3 decades (2017 – 2050) using artificial neural network. CROPWAT 8.0 software was used to compute past ETo while Artificial Neural Network (ANN) was used to predict for the future. A three-layer network trained by FFBP (Feed Forward Back Propagation) and LM (Levenberg-Marquardt) optimization algorithm was used. Two approaches were adopted for the study; in the first approach, the input parameters remained static while changing the number of hidden neurons; in the second approach, the inputs varied from 2 to 6 parameters and the hidden neurons doubled the inputs. The results disclosed that ANN can efficiently predict future ETo in the regions even with limited climate parameters, but the performance significantly increased by adding more inputs, as  $R^2$  difference from 0.8959 to 0.9997 and 0.8633 to 0.9996 in the regions were observed.

Bhagat and Popale (2017) estimated reference evapotranspiration using ANN model and compared the performance of ANNs with the conventional method Penman-Monteith model. Artificial neural network (ANN) with feed forward backpropagation (BP) network having training function (TRAINLM), adaption learning function (LEARNINGDM), performance function (MSE) and transfer function (TANSIG) was used for estimating ETo for growing season of pomegranate. The study was done for estimation of weekly and daily ETo by Penman Monteith method and ANN technique. On daily basis using ANN model, the best results were occurred during training of ETr for growing season of pomegranate at 11 neurons in hidden layer and 85 epoch/iteration having minimum MSE of 0.00093 and maximum coefficient of correlation as 0.9998. The results revealed that, coefficient of correlation and mean square error between weekly and daily reference evapotranspiration (ETr) estimated using Penman-Monteith method and ANN estimated ETr, for growing season of the pomegranate is 0.986 and 0.008618; and 0.999 and 0.00093, respectively.

Kishore and Pushpalatha (2017) studied two models, ARIMA and ANN for forecasting of evapotranspiration for irrigation scheduling in the area of Kanchipuram, India. The results of the two models were compared over a 5-year time period. The model was trained on data from 1991-1996 and it was tested by predicting the values from 1997-2002. The parameters including 4 number of inputs from previous data, 2 input delays, 1 feedback delay, and 1 hidden layers were trained on the Levenberg-Marquardt (LM) algorithm. It adjusts the bias values according to the target time series data. The network was trained for 100 epochs but the network converged at 10 epochs and MSE was 0.00401. The predicted results were compared against the data set and the accuracy was measured for each year. Overall accuracy of ANN model was found to be better over ARIMA model. Mean absolute error of ARIMA and ANN were found as 0.317 and 0.0282, respectively.

**Table 2.4 Summary of studies on application of ANN technique for forecasting of evapotranspiration time series**

Year	Name of authors	Location/Place	Length of data used	Input variable used	Variable simulated (output)	Type of Network & Algorithm	Activation function used in		Results/Findings
							Input	Output	
2008	S.K. Jain, P.C. Nayak and K.P. Sudheer.	India	2 years (1990 and 1991)	2 years climatic data was used to compute ETo and used to train ANN models	ETo	A standard back propagation algorithm	Sigmoid	Sigmoid	ETo estimated using the FAO recommended Penman–Monteith method. The results of the study indicated that the ANN can estimate ETo accurately even if data for only these two variables are available. An ANN model whose input consists of temperature and humidity or temperature, humidity and wind speed cannot provide a good estimate of ETo because the major predictor variable (radiation) is not present in the input vector.
2009	M.D. Gorkalanderas, A.O. Barredo and J.J. Lopez.	Spain	1975 to 2003	weekly evapotranspiration data from	ETo	back propagation, Levenberg-Marquardt and quick propagation	Not available	Not available	ANN (6-4-1) showed the lowest value of mean absolute difference for the total period of 1999-2003 (i.e. 1.783) and for the irrigation period May to September it was 2.057.
2010	A.Ariapour and M.N. Zavareh	Iran	1993-2001	daily temp., relative humidity, wind velocity, sunshine hrs, evaporation	daily evaporation	feed forward multiple layer network	Sigmoid	Sigmoid	Best model for estimation of evaporation was found to be ANN (5-4-1) with MSE=0.006716 and R <sup>2</sup> =0.725398.
2010	Chowdhary A. and R. K. Shrivastava.	India	NA	Crop coefficients, weather data	Monthly ETo	feed forward neural network	Sigmoid	Sigmoid	Monthly reference evapotranspiration was estimated by FAO Penman-Monteith method and irrigation requirements for the system were estimated based on the methodology suggested in FAO 24.

2011	M.J Diamantopoulou, P. E. Georgiou and D. M. Papamichail.	Greece	1994-1998	daily mean, maximum and minimum air temperature (oC) and the daily extraterrestrial radiation	Daily ETo	backpropagation algorithm and cascade correlation architecture	NA	NA	The cascade correlation architecture model (CCANN) performed better than backpropagation algorithm model (BPANN).
2012	J. Khoshhal and M. Mokarram	Iran	2002-2010	meteorological data	ETo	multi-layer perceptron networks (MLP)	Sigmoid	nonlinear regression vector	Multilayer perceptron network includes three-layers of neurons (input, hidden and output). Comparison was made with Penman-Monteith (PM) and 10 models produced by multi-layer perceptron networks (MLP).
2012	S. Ojha, and S. R. Bhakar	India	1997-1998	Min. and max. temperature, min. and max. relative humidity, wind speed and solar radiation	Daily ETo	Feed forward network and resilient back-propagation method	NA	NA	Daily reference evapotranspiration (ETo) estimated by artificial neural networks (ANNs) was compared with Penman-Monteith (PM) method.
2015	R.V Meshram et. al,	India	1977-2011	ETo	Daily ETo	Levenberg-Marquardt learning method.	linear sigmoid	linear transfer	The ANN model with architecture of 4-12-1 (four, twelve and one neuron(s) in the input, hidden, and output layers, respectively) was found to be the best amongst all the models. Standard error (SE) of estimates of 0.74 mm day <sup>-1</sup> and correlation co-efficient of 0.9260.
2017	J. Abdullahi, and G. Elkiran	Cyprus	2017-2050	Tmax, Tmin, Relative humidity, Wind speed	ETo	Feed Forward Back Propagation Levenberg-Marquardt	Sigmoid	Sigmoid	The results obtained emphasized the potentiality of black box modelling of ANN in determining effectively the nonlinear correlation between ETo and Climate variables in the regions.

2017	V. Kishore, and M. Pushpalatha	India	1991-2007	ETo	ETo	Multilayer feed forward network and Lavenberg marquardt	NA	NA	Overall accuracy of ANN model was found to be better over ARIMA model. Mean absolute error of ARIMA and ANN were found as 0.317 and 0.0282 respectively.
2017	A. D. Bhagat and P.G. Popale	India	1983-2007	ETo	Daily ETo	Back propagation Feed forward Network	sigmoid	sigmoid	ANN model 6-11-1 was found to be best with MSE=0.0093 and Correlation coefficient= 0.998

The studies reviewed in this section and summarized in Table 2.4 indicated that, forecasting of evapotranspiration can be done successfully with ANN model. In present study ANN model 6-11-1 architecture by Bhagat and Popale (2017) was used for forecasting of ETo. This forecasted ETo was then used to simulate forecasted water demand using MIKE HYDRO Basin model for the Ghod command area.

## **2.4 Water allocation modelling**

Water allocation models are computer applications that contain data about the river-basin hydrology and active water rights in the system, capturing the essential statistical characteristics of the hydrologic system and accounting for the probable range of its future hydrology. This study uses a water allocation model to allocate the water for the selected sub-catchment. In past, several methodologies and models have been developed to optimally utilize the water resources and allocate those to different crops. This section reviews these models and results of their applications.

Gulati and Murty (1979) developed a model for optimal distribution of water in the canal command areas. Water production functions in the form of polynomial expressions were developed from existing experimental information. Using the production functions, water distribution was indicated in order to obtain maximum returns. The values of the actual ET obtained from the ET model under different irrigation treatments. An analysis of the available data shows that crop yield obtained under different irrigation treatments is related more closely with the actual evapotranspiration values than with the actual water applied or seasonal water utilized. Second degree polynomial functions were found to represent satisfactorily the crop yield and actual evapotranspiration relations. It was observed that the present pattern of water releases is not in accordance with the evapotranspiration requirements of the cropping pattern and better returns could be obtained by suitably modifying the canal water releases.

Joshi *et al.*, (1995) developed CROSOWAT: A decision tool for irrigation schedule to predict the soil moisture content over the root zone depth as a function of time and to estimate the irrigation water requirements in humid basins under various management options. An implicit finite difference model for transient one dimensional flow, backed up by routines for computing various components of the field hydrological cycle such as evapotranspiration, effective rainfall, surface runoff, capillary rise, etc. is proposed. The model was applied to simulate the soil moisture conditions for a complete crop season of red cabbage (*Bramica oleraceaL. cultivar Rode Herfst*) grown on the 3 ha experimental field having sticky clay at Geestmerambacht, the Netherlands. It was proved to be a very useful tool for predicting the status of soil moisture content throughout the root zone depth over a growing period.

Gorantiwar and Smout (1995) formulated water allocation model to generate the irrigation schedule and estimate corresponding crop yield and net benefits, and to allocate area and water to different crop-soil combinations for maximizing the total net benefits for fixed depth or variable depth approach. The rotational water schedules followed in some of the irrigation schemes in arid and semi-arid regions of India are based on 'fixed depth-fixed interval' approach. According to authors, with multi crop soil nature of these irrigation schemes and variation in response of different crops to different water applied during their crop growth period, the fixed depth approach needs to be changed, especially when water is limited. The variable depth approach based on deficit irrigation was introduced and compared with fixed depth for obtaining net benefits and allocation of area and water to two crops grown on four different soils. It was found that the adoption of variable depth can increase the benefits to the extent of 18 to 20%.

Diaz *et al.*, (1997) introduced AQUARIUS, a state-of-the-art computer model devoted to the temporal and spatial allocation of water among competing uses in a river basin. The model was driven by an economic efficiency operational criterion requiring the reallocation of stream flows until the net marginal return in all water uses is equal. The water allocation problem solved by Aquarius, involving a set of exponential/linear/constant demand functions, requires a complex nonlinear objective function. Aquarius was conceived to simulate the allocation of water using any time interval (days, weeks, months). Aquarius can be used in a full deterministic optimization mode, for general planning purposes, or in a quasi-simulation mode, with restricted foresight capabilities.

Amir and Fisher (1999) introduced an optimizing linear model for analyzing agricultural production under various water quantities, qualities, timing, prices and pricing policies. "Agricultural sub-model" or AGSM model was designed to serve as a decision-making tool for planners of agricultural production on district and national levels. The output solutions provide the optimal mix of water consuming activities to maximize the net income of the agricultural production of the districts and the water demands under various prices. It also provides the user with procedures to carry out 'if then' sensitivity and scenario analyses and to generate optimal water demand curves. The model provided a quantitative tool for analyzing water policies on a national level, especially where national authorities control water.

Babel *et al.*, (2005) developed a simple interactive integrated water allocation model (IWAM), which can assist the planners and decision makers in optimal allocation of limited water from a storage reservoir to different user sectors, considering socio-economic, environmental and technical aspects. IWAM comprised three modules viz. a reservoir operation module (ROM), an economic analysis module (EAM) and a water allocation module (WAM). The model can optimize the water allocation with any of two different objectives or two objectives together. The two individual objectives included

in the model are the maximization of satisfaction and the maximization of net economic benefit by the demand sectors. Weighting technique (WT) or simultaneous compromise constraint (SICCON) technique was used to convert the multi-objective decision-making problem into a single objective function. The suitability of the model was demonstrated with various cases and conditions using a hypothetical example.

Hussain *et al.*, (2009) used Water Evaluation And Planning Model (WEAP) for optimizing the water allocation system at Jordan valley. The model was tested and adopted for the current status of the valley. Future scenarios were considered in running the model and testing the water demand/supply system. Running the model using the actual data shows that the water qualities will not sufficient to cover all the purposes for irrigation at the Jordan Valley. Around 70% of the actual water demand was met with the available resources. This will be reflected on scaling down the production of agricultural sector. For the domestic uses in Amman, the anticipated quantities that could be pumped were 90 MCM/year. The current supply is 45 MCM/year which is around 50% of the planned figures. From the purely technical aspects (quantity and quality), adaptation of supplying the system with 50 MCM of fresh water from the Unity Dam proved to be the best scenario.

Dogra *et al.*, (2011) studied optimal allocation of available water in a middle Himalayan watershed by using a linear programming model for maximizing production from crops and livestock. Present and future water availability under different environmental scenarios at various locations in the watershed was considered. Rice Equivalent Production from the watershed was found to improve by 207% (to 919 tonnes) and Rice Equivalent Yield by 58% (to 4427 Kg/ha) through optimal allocation of available water resource. Occurrence of drought of 60% intensity would limit production to 737 tonnes. Environmental degradation by 2025 would though reduce production marginally, the surplus water available within the watershed would, however, decrease significantly during January to March.

George *et al.*, (2011) developed an integrated modelling framework for water resources planning and management. The modelling approach was based on integrating a network allocation model (REALM) and a social Cost Benefit economic model, to evaluate the physical and economic outcomes from alternative water allocation policies in a river basin or sub-basin. From a hydrological perspective, surface and groundwater models were first applied to assess surface and groundwater resource availability. Then an allocation model was applied to reconcile the calculated surface and groundwater resources. From an economic perspective initially the value of water allocated to different uses in each demand center within the system was estimated. These values were then placed in a social Cost Benefit Analysis to assess the economic consequences of different allocation scenarios over time and space. The framework was applied to the Musi sub-basin located in the Krishna Basin, India. It was found that the average value of water to different agricultural zones is very low and amongst crops varies

greatly. The return to domestic users was estimated to be \$US 1.1/m<sup>3</sup>, industrial use at \$US 0.21/m<sup>3</sup> and power generation at \$US 0.07/KW. The social Cost Benefit analysis suggest that the total net present value from the system has been calculated at \$US 6113 million over the period from 2008 to 2031 for the baseline scenario.

Bakker *et al.*, (2013) developed a model that forecasts the water demand for the next 48 h with 15-min time steps. The model uses measured water demand and static calendar data as single input to calculate the forecast. For six water distribution areas, the performance of the model was examined. The results showed that MAPE of the model varied between 1.44 and 5.12% for the 24-h forecast, and between 3.35 and 10.44% for the 15-min time step forecasts. The error had a strong relation with the average water demand in the area: The error increased as the average water demand in the area decreased. The model has enhanced functionality compared to existing models with respect to the small time step (15-min), the fully adaptive functionality, the number of discerned water demand patterns and the mechanism to detect and forecast sprinkle demand without using weather input.

Berhe *et al.*, (2013) studied the MODSIM-based water allocation modeling for Awash River Basin, Ethiopia. This study was conducted to analyze the water balance of the Awash Basin under different levels of irrigation development and also determine the water allocation in the Upper, Middle and Lower Valleys in the basin. Awash Basin includes Koka Dam and two reservoirs namely, Kesem and Tendaho. The modeling runs were done for simulating mean annual flows for the year 2018, 2028 and 2038 in three reservoirs Koka, Kesem and Tendaho, using their elevation–area–capacity curves. Conditional rules of target storage levels were set to have four hydrological states which were classified as Dry, 25% Deficit, 50% Deficit and Wet. Four scenarios were set: Scenario I- present withdrawal rate in the basin; Scenario II - Scenario I plus downstream Tendaho Dam operational; Scenario III - Scenario II plus expansion of middle valley farms and Kesem Dam operational; and Scenario IV -Scenario III plus additional expansion in the middle valley. Analysis of flow records within the basin was done for a period of 1963–2003. The results of MODSIM model depict that there will be incremental release from Koka Dam from 2.8% to 5.7% in years 2018 and 2038, respectively. Due to increased diversions in Scenario III when compared to Scenario I, losses in to Gedebeessa Swamp will significantly decrease by an average of 27.6%. In the year 2038, owing to less capacity of upstream reservoirs due to sedimentation, water will be lost in the swamp complex causing slight decrease of inflow to Tendaho Dam.

Dai and Li (2013) developed a multistage irrigation water allocation (MIWA) model for agricultural water management and cropland use planning in response to such complexities. The model was applied for planning agricultural activities in Zhangweinan River Basin in association with multiple crops and multiple periods. The developed model has been applied to optimizing irrigation targets as

well as allocating the limited water resources from the Yuecheng Reservoir to multiple crops in multiple subareas over a multistage context. The model dealing with complex irrigation problem through pre-defined cropping pattern selection and real-time dynamic water allocation.

**Table 2.5 Summary of studies on water allocation modelling**

Year	Name of Researcher	Study area/ Location	Model used/ developed	Results/ Findings
1979	H. S. Gulati, V. V. N. Murty.	Bhakra Irrigation system, India	Not reported	The amount of water allocated increases with the increase in the given amount of water availability. It was a maximum for wheat and a minimum for barley. An analysis of the available data shows that crop yield obtained under different irrigation treatments is related more closely with the actual evapotranspiration values than with the actual water applied or seasonal water utilized.
1995	M. B. Joshi, J. S. R. Murthy M. M. Shah.	Geestmerambacht Netherlands	CROSOWAT	Useful tool for predicting the status of soil moisture content throughout the root zone depth over a growing period. The results prove that estimation of ER is very important in simulating soil moisture conditions.
1995	S. D. Gorantiwar I. K. Smout	India	SWAB-CRYB	Simulates various processes such as evapotranspiration, root growth, soil moisture, crop yield and net benefits in response to different applications of water with minimum data.
1997	G. E. Diaz, T. C. Brown and O. Sveinsson.	Colorado, U.S.	AQUARIUS	Simulates the allocation of water using any time interval (days, weeks, months). The temporal and spatial allocation of flows among competing water uses in a river basin.
1999	I. Amir, F. M. Fisher.	Israel	AGSM	A decision support tool for planning agricultural production on district and national levels under various water quantities, qualities and prices.
2005.	M. S. Babel, A. D. Gupta D. K. Nayak.	Thailand	IWAM	A user-friendly tool and is capable of allocating water among six sectors with objectives of maximizing satisfaction, maximizing net economic return (NER) or maximizing both satisfaction and NER.
2009	I. Hussein R. Al Weshah.	Jordan Valley	WEAP	Future scenarios were considered in running the model and testing the water demand/supply system. From the purely technical aspects (quantity and quality), adaptation of supplying the system with 50

				MCM of fresh water from the Unity Dam proved to be the best scenario.
2011	P. Dogra, V. N. Sharda, P.R. Ojasvi., S. O. Prasher R. M. Patel.	Tehri-Garhwal, Uttaranchal	LP model	A linear programming model for maximizing production from crops and livestock, after meeting the present and future demands of human and environmental flows, was analyzed. Present and future water availability under different environmental scenarios at various locations in the watershed was considered.
2011	B. George, Malanoa, B. Davidsonb, et. al	Musi sub-basin Krishna Basin, India	REALM	A hydro-economic modelling framework which accounts for the interactions between hydrology, water allocation and economic processes.
2013	M. Bakker, J. H. G. Vreeburg, K. M. Schagen L. C. Rietveld.	Netherlands	Water demand forecasting model	The model uses measured water demand and static calendar data as single input to calculate the forecast.
2013	F. T. Berhe, A. M. Melesse, D. Hailu Y. Sileshi.	Awash River Basin, Ethiopia	MODSIM- based water allocation modeling	The modeling runs were done for three reservoir elevation–area– capacity curves which the Koka, Kesem and Tendaho dams expected to have at year 2018, 2028 and 2038. Conditional rules of target storage levels were set to have four hydrological states which were classified as Dry, 25% Deficit, 50% Deficit and Wet.
2013	Z. Y. Dai, Y. P. Li.	Zhangweinan River Basin, China	MIWA	The developed model was applied to optimizing irrigation targets as well as allocating the limited water resources to multiple crops in multiple subareas over a multistage context.

The studies reviewed in this section and summarized in Table 2.5 shows that water allocation is important issue and several methodologies and tools have been developed and investigated. Therefore, in this study, it was decided to evaluate different water allocation scenarios in context of different water availability and demand using MIKE HYDRO Basin model.

## 2.5 MIKE HYDRO Basin model

MIKE HYDRO model is the common Graphical User Interface (GUI) framework for water resources products of MIKE by DHI. It has been applied to various water resources projects. This section provides the brief review of the important applications. Earlier, MIKE HYDRO Basin model was known with name of MIKE BASIN, hence most of the reviews found with name of MIKE BASIN model.

Jha and Gupta (2003) described the application of a basin scale simulation model, MIKE BASIN, to the Mun river basin located in northeastern Thailand. Monthly simulation was carried out based on the water availability and utilization using hydrological data from 1965 through 1997. Climatic analysis was found to be high seasonal variation: wet season water availability is more than six times dry season availability. Event-based reliability calculations of irrigation and water supply systems of the basin indicated that the existing level of demand has reasonable wet season water availability, but limited dry season availability. Moreover, sensitivity analysis found 80 percent reliable cropping intensity in wet season and only 12 percent in dry season.

Ireson *et al.*, (2006) studied the coupling of a strategic scale water resources management simulation model (MIKE-Basin) and a finite difference groundwater model (ASM), as a tool to support decision making in data scarce environments. The models were applied in a particularly data scarce region, the Vrbas River basin, in Republic Srpska (RS) in Bosnia and Herzegovina (BiH). The water quality modelling capabilities of Mike BASIN for point source pollution were successfully demonstrated. There was need for more data in order to calibrate the parameters, and thus decrease the associated uncertainty. It was suggested that a study should be carried out to identify all pollution sources in the catchment, and incorporate these into the GIS. The issue of model integration was addressed so that the results from both the groundwater and surface water models could be processed and presented in the GIS software.

DHI (2008) developed a model using DHI's MIKE BASIN model for the main stem McKenzie River and major tributaries. Model construction was a collaborative effort between EWEB, LCOG, and DHI and took place between December 2006 and April 2008. The calibrated MIKE BASIN model from 1/1/2000 – 10/1/2006 provided a powerful means of simulating water availability under existing conditions and considered as a valuable tool for running operational scenarios involving changes in water use and/or water availability. The model can be used to address various hydrologic questions posed by EWEB and its partners at the basin-scale now and into the foreseeable future as well as it can provide a foundation for modelling water quality constituents at the basin scale and the development of more detailed-scale water quality and hydrodynamic models during subsequent modelling phases.

Leemhuis *et al.*, (2009) developed a Volta Basin Water Allocation System (VBWAS), a decision support tool that allows assessing the impact of infrastructure development in the basin on the availability of current and future water resources, with the given current or future climate conditions. The spatial corresponding specific discharge time series (mm) simulated with the joint modeling application MM5/WASIM-ETH was fed as specific discharge (mm) for each hydro-economic catchment of the Mike Basin model. VB-WAS is a joint modeling approach that combines the river

basin management model Mike Basin (Danish Institute of Hydrology, 2003), which allows fast simulations of water allocation using a network approach, and the 1-way coupling simulation results of the MM5/ WASIM-ETH climate hydrological joint modeling approach, providing spatial and temporal distributed input for water supply. The simulation results of the spatially distributed and process based hydrological model WASIM-ETH accounted for the physical discharge variability of the Volta basin.

Jensen *et al.*, (2009) designed an operational decision support system to forecast and optimize reservoir operations in both the short-term and long-term. The system has been established for the 20,000 km<sup>2</sup> Mantaro river basin located in the high Andes with altitudes ranging from 3500 to nearly 6000 m.a.s.l. The two main power stations at Tablachaca have a combined capacity of more than 1000 MW that supplies 30% of Peru's electrical energy. The methodologies used for the integrating short-term and long-term forecasting were presented together with their application to the optimal operation of reservoirs. The system used several modelling capabilities of MIKE BASIN: rainfall-runoff, reservoir operation, hydropower production, and river flow routing. The continually updated runoff and flow forecasts enter the optimization, which applied the Model Predictive Control principle for MIKE BASIN as the core simulation model. For each optimization, a non-linear program algorithm was used to find the best release strategy.

Bangash *et al.*, (2012) studied the River Francolí watershed assessments to support and inform region-wide planning efforts from the perspective of water protection, climate change and water allocation. In his study, a hydrological model of the Francolí River watershed was developed for use as a tool for watershed planning, water resource assessment, and ultimately, water allocation purposes using hydrological data from 2002 to 2006 inclusive. DHI's MIKE BASIN model was used for the application. Due to the unavailability of required catchment runoff data, the NAM rainfall-runoff model was used to calculate runoff of all the sub-watersheds. Water availability and water demand were compared by analyzing the hydrological condition of the basin. The results reveal a potential pressure on the availability of groundwater and surface water in the lower part of River Francolí as was expected by the IPCC for Mediterranean river basins. The combined ArcGIS/ MIKE BASIN models appear as a useful tool to assess the hydrological cycle and to better understand water allocation to different sectors in the Francolí River watershed.

Jaiswal *et al.*, (2013) studied the application of simulation software "MIKE BASIN" (2009) for optimum utilization of water resources of MRP Complex. Mahanadi Reservoir Project (MRP) Complex is a multipurpose multi-reservoir system. There are three possible ways of supplying water from the two upstream reservoirs to the Ravishankar reservoir. These three ways of supplying water has been simulated in MIKE BASIN and designated as three models. The simulation was run for

twenty-one years (1975 to 1995) historical data. To check the efficiency of models the annual deficit between demand and supply was computed for each model. The results of these three models have been compared with the results of earlier reported optimization model. The total deficit for twenty-one years was found minimum in the first model hence considered as the efficient model. First Model was then run for recent data (1996-2008). The total deficit in Model-I was 689.547 Mm<sup>3</sup> which was very close to 679.3 Mm<sup>3</sup>, the total deficit in PGM model. The accuracy of Model-I was found to be 98.5%.

Kaiglova and Langhammer (2014) studied the applicability of the MIKE Basin model for simulating the efficiency of scenarios for reducing water pollution. The model was tested on the Olsava River Basin (520 km<sup>2</sup>) which is a typical rural region with a heterogeneous mix of pollution sources with variable topography and land use. The study proved that the model can be calibrated successfully using even the limited amount of data typically available in rural basins. The scenarios of pollution reduction were based on implementation and intensification of municipal wastewater treatment and conversion of arable land on fields under the risk of soil erosion to permanent grassland. The application of simulation results of these scenarios with proposed measures proved decreasing concentrations in downstream monitoring stations.

The studies reviewed in this section and summarized in Table 2.6 indicated that, MIKE HYDRO Basin model is used for a large variety of applications concerning allocation, management and planning aspects of water resources within a river basin. MIKE HYDRO Basin model has the large adaptability and ability to model and evaluate different water allocation scenarios. Therefore, in this study the MIKE HYDRO Basin model was used for assessing the irrigation water demand and different water allocation scenarios in Ghod command area.

**Table 2.6 Summary of studies on MIKE HYDRO Basin model**

Year	Name of Researcher	Study area/ Location	Results/ Findings
2003	M. K. Jha and A. D. Gupta	Mun river basin Thailand	The total irrigation water demand was found to be 93 percent and the remaining is covered by other sectors. The irrigation is the major concern in the basin and the water usage for domestic, municipal, and industrial purposes does not have a significant impact on the overall water balance of the basin. The system performance was analyzed by changing the irrigation efficiencies to 35 percent and 55 percent. There was not much difference between the water availability and water demand on an annual basis. The comparison of demand and supply showed minor shortages. This indicates that demand should not be increased

2006	A. Ireson, C. Makropoulos and C. Maksimovic.	Vrbas River basin in Republic Srpska (RS) in Bosnia and Herzegovina	Mike BASIN model was used to check capability of model for water quality assessment for point source pollution.
2008	DHI	McKenzie River and major tributaries	The calibrated MIKE BASIN model from 1/1/2000 – 10/1/2006 provided a powerful means of simulating water availability under existing conditions and provides a valuable tool for running operational scenarios involving changes in water use and/or water availability.
2009	C. Leemhuis, G. Jung., R. Kasei and J. Liebe.	Volta basin, West Africa	Volta Basin Water Allocation System which combines VB-WAS and Mike Basin model. The simulated water level of the historical small and medium scale reservoir Scenario A for the time slice 1992–2000 indicates an overall minor impact, Whereas Scenario B showed a more considerable impact compared to the simulated water level of the baseline simulation.
2009	R. A. Jensen, A. Lasarte and M. B. Butts.	Mantaro Basin, Peru.	MIKE BASIN used for rainfall-runoff, reservoir operation, hydropower production, and river flow routing. The methodologies used for the integrating short-term and long-term forecasting together with their application to the optimal operation of reservoirs.
2012	R. F. Bangash, A. Passuello, M. Hammond and M. Schuhmacher.	Francoli River, Spain	Water availability and water demand were compared by analyzing the hydrological condition of the basin.
2013	S. K. Jaiswal, M. K. Verma and M. Gupta.	MRP Complex. Mahanadi Reservoir Project (MRP) Complex	Three models MIKE BASIN were developed possible ways of supplying water compared with the results of another optimization model. The total deficit in Model- I was 689.547 Mm <sup>3</sup> which was very close to 679.3 Mm <sup>3</sup> , the total deficit in PGM model. The accuracy of Model- I was found to be 98.5%
2014	J. Kaiglova and J. Langhammer	Olsava River Basin	The model can be calibrated successfully using even the limited amount of data typically available in rural basins. MIKE Basin model was used for simulating the efficiency of scenarios for reducing water pollution.

## 2.6 SWAB-CRYB model

Optimal irrigation water management relies on accurate knowledge of plant water consumption, water flows and soil moisture dynamics throughout the growing season. The Soil Water Balance-Crop Yield Benefits (SWAB-CRYB) simulation model enables the estimation of soil moisture in the root zone, actual evapotranspiration, return flow to groundwater due to irrigation, crop yield and net benefits. Crop yield is the function of actual evapotranspiration from the plant. In this section different reviews on SWAB-CRYB model (Gorantiwar, 1995) are presented.

Gorantiwar (1995) developed Soil Water Balance-Crop Yield Benefits (SWAB-CRYB) simulation model that simulates various processes such as evapotranspiration, root growth, soil moisture, crop yield and net benefits in response to different applications of water with minimum data. He applied the model to Nazare Medium Irrigation Project, Maharashtra and evaluated actual and several formulated irrigation strategies. The model was found to have potential in management of land and water resources in command area. He further modified SWAB-CRYB to SWABGRAPH to include graphical representation of outputs.

Godase (2001) chose the Mula irrigation project which was situated at Baragaon Nandur in Rahuri taluka of Ahmednagar district, Maharashtra for suggesting the alternate crop plans using remote sensing and GIS. The SWAB-CRYB simulation model (Gorantiwar, 1995) was used to evaluate the different irrigation strategies and to develop the alternate crop plans. It was observed that for alternate schedules of 100 mm and 75 mm level per irrigation, average irrigation water depth and the average rise in ground water table were 258 mm and 105 mm, respectively. While that of 75 mm application of water, there was slight reduction in yield of sugarcane and other crop yields remained maximum. From the above results, he suggested that 100 mm and 75 mm application depths seem to be optimum as there was not much difference in deep percolation. The application of 100 mm water depth gave maximum crop yield.

Dagade (2003) selected the Nazare medium irrigation project which is situated in Pune district, Maharashtra for evaluation of SWAB-CRYB model. Data generated from remote sensing and GIS and collected from other sources, were used in the simulation model SWABGRAPH for evaluating the existing irrigation schedule and some derived irrigation strategies. Irrigations were released in four rotations to different crops grown on different soils in the different units of command area. The crop yield and net benefits were estimated for each crop grown on each type of soil in each unit and finally the net benefits for each unit and for entire command area were estimated. Results showed that the net benefits estimated in I-21-70 (i.e. irrigation 68 interval of 21 days and depth of 70 mm) is 240 % more than those estimated for existing strategy and 35 % more than those estimated for I-14-70.

Gorantiwar and Smout (2003) formulated the water allocation simulation model to generate the irrigation schedule and estimate corresponding crop yield and net benefits, and to allocate area and water to different crop soil combinations for maximizing the total net benefits for fixed depth or variable depth approach. The rotational water schedules followed in some of the irrigation schemes in arid and semi-arid regions of India are based on 'fixed depth fixed interval' approach. According to authors, with multi crop-soil nature of these irrigation schemes and variation in response to different crops to different water applied during their crop growth period, the fixed depth approach needs to be changed, especially when water is limited. The variable depth approach based on deficit irrigation was

introduced and compared with fixed depth for obtaining net benefits and allocation of area and water to two crops grown on four different soils. It was found that variable depth approach can increase benefits up to of 18 – 20 % extent.

Sawant and Patil (2008) evaluated operating policies using SWAB-CRYB simulation model. Sina Medium Irrigation Project situated at village Nimgaon Gangarda in Karjat taluka of Ahmednagar District, Maharashtra was selected for evaluation of irrigation policies. It was found that with the application of 100 mm irrigation depth at an interval of 21 days in rabi, 14 days in summer, 28 days in Kharif, there was slight reduction in yield of wheat, gram and Rabi Jowar when grown on clay and silt clay loam soil; however there was moderate reduction in yields of these crops when grown on clay loam and considerable reduction in yield when these crops were grown on silty loam soil. The reductions in yield for the above mentioned irrigation policy for onion and sugarcane were considerable when grown on clay, silty clay loam and clay loam soils and major reduction in yields were obtained when these crops were grown on silt loam soils for the reason stated above. The results obtained for application of different depths of water to wheat when grown on silty clay loam soil indicated that for achieving maximum yield and benefits, 100 mm depth of irrigation per application was the most suitable.

Yawatkar (2008) developed DSS (modSWAB-CRYB) based on SWAB-CRYB for irrigation water management based on NDVI. The model simulating the movement of water in the crop root zone and crop yield are useful for this purpose. The SWABCRYB is one such simulation model. In which, transpiration, the important process in simulation of crop yield is separated from evapotranspiration based on crop coefficient ( $K_c$ ). In this study the focus was to separate transpiration based on leaf area index (LAI) and normalized difference vegetation index (NDVI). The developed DSS (modSWAB-CRYB) was applied to wheat and maize to evaluate different irrigation strategies, to study the response of soils and irrigation strategies on crop yield and compare the results obtained with separation based on  $K_c$ , LAI and NDVI. The results indicated that the % reduction in yield of wheat and maize is more in loamy sand soil as compared to clay loam and clayey soil due to low water holding capacity of loamy sand soil (0.05m/m) compared to clay loam (0.20 m/m) and clayey soils (0.18m/m).

Palkar (2011) developed the NDVI based decision support system for irrigation water management by using SWAB-CRYB simulation model that makes use of NDVI for separation of evaporation and transpiration from evapotranspiration. He related the crop coefficients to NDVI to introduce NDVI in the simulation process.

Kadam (2014) developed the decision support system (DSS) based on SWAB-CRYB and modSWAB-CRYB simulation models and spatial decision support system (SDSS) by integrating decision support system with GIS for irrigation water management at the farm level. The NDVI values

were introduced in the DSS to estimate crop coefficient using Kc-NDVI relationships developed during the field study. The developed DSS was applied to three crops *viz.* sorghum, chickpea and wheat. Four soils *viz.* clay, clay loam, silty clay loam and silty loam were considered. Fourteen irrigation strategies were developed by considering three approaches: fixed date fixed depth, fixed date variable depth and variable date variable depth. The DSS was applied for knowing the influence of different irrigation strategies on yield and total benefits of crop when grown on specific soil and influence of different irrigation strategies in terms of applying different depths at different levels on yield and net benefits.

The simulation model- SWAB-CRYB reviewed in this section and summarized in Table 2.5, show that, model uses crop data, soil data, climate data, irrigation strategies etc. to estimate crop yield for different crops. MIKE HYDRO Basin model also estimates crop yield using same input data. In present study crop yield estimated by using both models SWAB-CRYB and MIKE HYDRO Basin were compared.

**Table 2.7 Summary of studies on SWAB-CRYB Model**

Year	Name of Researcher	Study area/ Location	Results/ Findings
1995	S. D. Gorantiwar and I. K. Smout.	Nazare Medium Irrigation Project, Maharashtra	Developed Soil Water Balance-Crop Yield Benefits (SWAB-CRYB) simulation model that simulates various processes such as evapotranspiration, root growth, soil moisture, crop yield and net benefits in response to different applications of water with minimum data
2001	Y. R. Godase,	Mula irrigation project	Model evaluated for different irrigation depths 75 and 100mm. the application depth 100mm water depth gave maximum crop yield.
2003	S. J. Dagade,	Nazare medium irrigation project, Pune	Crop yield and net benefits were estimated for each crop grown on each type of soil in each unit using SWAB-CRYB model. The net benefits estimated in I-21-70 (i.e. irrigation interval of 21 days and depth of 70 mm) is 240 % more than those estimated for existing strategy and 35 % more than those estimated for I-14-70.
2003	S. D. Gorantiwar and I. K. Smout		Introduced variable depth approach based on deficit irrigation and compared with fixed depth for obtaining net benefits and allocation of area. Variable depth approach can increase benefits to extent of 18 – 20 %.
2008	S. A. Sawant and S. D. Patil.	Sina Medium Irrigation Project, Ahmednagar	With the application of 100 mm irrigation depth at an interval of 21 days in rabi, 14 days in summer, 28 days in Kharif, there was slight reduction in yield of wheat, gram and Rabi Jowar when grown on clay and silt clay loam soil

2008	A. P. Yawatkar,	Rahuri	Developed a DSS modSWAB-CRYB based on SWAB-CRYB. The % reduction in yield of wheat and maize is more in loamy sand soil as compared to clay loam and clayey soil due to low water holding capacity of loamy sand soil (0.05 m/m) compared to clay loam (0.20 m/m) and clayey soils (0.18 m/m).
2011	H. M. Palkar	Rahuri	Developed the NDVI based decision support system for irrigation water management by using SWAB-CRYB simulation model and estimated yield and net benefits.
2014	S. A. Kadam	Rahuri	Developed the decision support system (DSS) based on SWAB-CRYB simulation model and spatial decision support system (SDSS) by integrating decision support system with GIS to estimate yield, net benefits and % reduction in yield under different irrigation strategies.

## 2.7 Climate change scenarios

Water availability in river basin is mainly governed by rainfall and runoff. Rainfall and temperatures are both found to be influenced by climate changes as per the predictions from different GCMs emission scenarios. This section presents the reviews on climate change effect on runoff and thereby on water availability.

Andersen *et al.*, (2006) applied The Mike 11–TRANS modelling system to the lowland Gjern river basin in Denmark to assess climate-change impacts on hydrology and nitrogen retention processes in watercourses, lakes and riparian wetlands. Climate-change was predicted by the ECHAM4/OPYC General Circulation Model (IPCC A2 scenario) dynamically downscaled by the Danish HIRHAM regional climate model (25 km grid) for two time slices: 1961–1990 (control) and 2071–2100 (scenario). HIRHAM predicted an increase in mean annual precipitation of 47mm (5%) and an increase in mean annual air temperature of 3.2°C (43%). The HIRHAM predictions were used as external forcing to the rainfall-runoff model NAM, which was set up and run for 6 sub catchments within and for the entire, Gjern river basin. Mean annual runoff from the river basin was increased 27mm (7.5%,  $p < 0.05$ ) when compared with the scenario to the control. Larger changes, however, were found regarding the extremes; runoff during the wettest year in the 30-year period increased by 58mm (12.3%). The seasonal pattern was expected to change with significantly higher runoff during winter. Summer runoff was expected to increase in predominantly groundwater fed streams and decrease in streams with a low base-flow index. The modelled change in the seasonal hydrological pattern was found to be most pronounced in first- or second-order streams draining loamy catchments, which currently have a low base-flow during the summer period. Reductions of 40–70% in summer runoff was predicted for this stream type. The analysis with the NAM–MIKE 11–TRANS model-chain was the first attempt in Denmark of dynamic and semi-distributed modelling of climate-change impacts on hydrology, nitrogen loss and nitrogen retention.

Elsaesser *et al.*, (2006) applied the NAM rainfall runoff model to a range of catchments in Ireland. Model was calibrated on a medium sized catchment of the river Main in Northern Ireland and a range of climate change scenarios were tested and compared against a reference scenario. In the UKCIP02 scenario (HADRM3 –SRES-A1FI) the 2041 to 2070 future simulation was used taking the high emissions scenario, whereas the RCA-F scenario was based on moderately increasing greenhouse gas emission (ECHAM4 SRES-B2) and the period was 2021 to 2060. These climate change predictions were applied to a well calibrated hydrological model and the difference in total water balance, seasonal runoff and percentile flows were assessed. The water balance for the two UKCIP02 scenarios for the 2050s period compared against the reference data from the period of 1993-2002. In C4i scenario valid for the 2040s period, the total amount of discharge has risen by 16% compared to a total increase in rainfall of only 12%. The application of the NAM model, illustrated that the model is capable of modelling the changes in rainfall runoff due to moderate climate change scenarios.

Anandhi *et al.*, (2008) presents a methodology to downscale monthly precipitation to river basin scale in Indian context for special report of emission scenarios (SRES) using Support Vector Machine (SVM). They extracted probable predictor variables from the National Center for Environmental Prediction (NCEP) reanalysis data set for the period of 1971–2000 and the simulations from the third generation Canadian general circulation model (CGCM3) for SRES emission scenarios A1B, A2, B1 and COMMIT for the period of 1971–2100. The effectiveness of the model was demonstrated through application to downscale precipitation in the catchment of Malaprabha reservoir from simulations of the third generation CGCM3 for four IPCC scenarios namely SRES A1B, A2, B1 and COMMIT. The projected increase in precipitation was high for A2 scenario, whereas it was least for COMMIT scenario. The results of validation clearly indicated that the model is a feasible choice for downscaling precipitation to river basin scale.

Jeppesen and Kronvang (2009) discussed the impact of global warming on runoff and transport of Phosphorus to lakes. Climate change projections by the ECHAM4/OPYC General Circulation Model (IPCC A2 scenario) were dynamically downscaled by the Danish HIRHAM regional climate model (25 km grid) for two time periods: 1961 to 1990 (control) and 2071 to 2100 (scenario). The IPCC A2 climate emission scenario was used for the periods 1961 to 1990 (the control period) and 2071 to 2100 (the scenario period) as input to the hydrological NAM model. Daily climate data were simulated for a 25 × 25 km grid covering the entire Denmark. HIRHAM daily model simulations were transformed as input to the hydrological model (NAM) using a three-step procedure. Auto-calibration of the NAM model was performed using daily discharge data for the period of 1989 to 1996, and the NAM model was validated via daily observations for the period of 1997 to 2004. The calibration results of the NAM model such as coefficient of determination ( $R^2$ ) were found above 0.7 for the calibration period

and above 0.6 in the validation period in all 10 streams. The water balance error was very low in the calibration period (-14.8 to 3.4%) but increased in the validation period from -20.9 to 14.4%. The NAM-calculated changes in annual mean runoff between the control and the scenario period showed an increase of 7 to 78 mm/yr or 9 to 34% for the 10 streams. A much stronger seasonal change in runoff was observed in all 10 streams. Monthly runoff generally increases in winter (December–March) and decreases in the late summer (August–October). The modeled reduction in monthly runoff during the summer was most extreme and lasted for a longer period in streams draining loamy catchments.

Alam *et al.*, (2012) studied the combined effect of urbanization and climate change on catchment runoff on the city of Turnhout, Belgium. A lumped conceptual hydrological model NAM was developed for generating runoff from the catchment. The CCI-HYDR perturbation tool, developed by Katholieke Universiteit Leuven, was applied to generate time series of future rainfall and evapotranspiration. The time series of urban runoff were obtained from the correlation between rainfall and urban runoff under both current and climate change (A1B, A2, B1 and B2) scenarios. The average increase in peak runoff from the catchment was 36% due to the impact of urbanization in the region. On the other hand, the individual impact of climate change ‘high’ scenario on peak runoff from the catchment showed also a quite significant influence with an average increase in peak runoff by 23% and an average reduction of relatively lower peak runoff with lower return periods by 19% as compared to the current condition without considering the impact of urbanization. Finally, the combined impact of urbanization and climate change showed a very significant intensification of the peak runoff with an average increase in the peak runoff by 56% as compared to the current condition where no impacts were considered.

Butts *et al.*, (2013) illustrated a modelling framework to support climate adaptation on a regional scale has been developed by DHI and the UK Met Office for the project adapting to climate change induced water stress in the Nile River Basin. This project was launched in March 2010 as a partnership between the United Nations Environment Programme (UNEP) and the Nile Basin Initiative (NBI), sponsored by the Swedish International Development Cooperation Agency (SIDA), for assessing climate change impacts and adaptation potential for floods and droughts within the basin. The MIKE HYDRO model was developed and calibrated against available discharge data within the period 1960 to 1980. Model was then run using bias-corrected values for rainfall and PET over the same period. All other factors such as the operation and operation strategies of the reservoirs, the extractions for irrigation, etc. were kept fixed. The flow projections developed indicate reductions in the flows for the near future (2020-2049). For the far future (2070-2099) both increasing and decreasing trends were seen. The framework incorporates the state of the art Perturbed Physics Ensemble approach for climate change modelling

and appropriate hydrological modelling using MIKE HYDRO. As a result the framework can provide an assessment of climate change impacts, an indication of the uncertainties and can be used for regional scale adaptation.

Dlamini *et al.*, (2017) modelled Potential impacts of climate change on the streamflow of the Bernam River Basin in Malaysia. The results were assessed using ten Global Climate Models (GCMs) under three Representative Concentration on Pathways (RCP4.5, RCP6.0 and RCP8.5). The downscaled rainfall and temperature outputs from the interface were used as inputs to the validated SWAT model to explore the responses of the Bernam streamflow in the future years. The average changes under RCP4.5, 6.0 and 8.5 were  $-1.5\%$ ,  $-2.8\%$  and  $-4.3\%$ , respectively, during the dry season. Generally, all future periods showed a decreasing trend in streamflow during this season, with a significant decrease ( $-6.6\%$ ) occurring in the late century (2080s) of the RCP8.5 scenarios. The wet season, on the other hand, had predicted to receive more rainfall with average changes of  $4.4\%$ ,  $5.0\%$  and  $9.4\%$  for RCP4.5, 6.0 and 8.5, respectively. The maximum increase ( $11.4\%$ ) was predicted to occur in the 2080s under the worst-case scenario (RCP8.5). For most scenarios, the streamflow showed a decreasing trend during January, February and March (with the exception of April and May) and in June, July and August. The increase during April and May represents the Southwest Monsoon rainfall that usually comes during these months, although, to a limited extent. The greatest flow decrease was  $12.3\%$  in the 2050s (RCP4.5),  $14.4\%$  (RCP6.0) and  $24.8\%$  (RCP8.5) during the 2080s period. The remaining months of the wet season (September, October, November and December) showed an increasing trend in streamflow following the Northeast Monsoon rainfall during these months. The overall future annual streamflow projections showed a slight increase of  $2.5\%$  and  $4.4\%$  in the 2020s under RCP4.5 and RCP6.0, respectively, with almost no change in the other periods (2050s and 2080s), while the changes under RCP8.5 were between  $3.1\%$ ,  $0.5\%$  and  $1.3\%$  for the 2020s, 2050s and 2080s, respectively.

It is now widely recognized within the climate community that assessments of climate change should be based on multiple model projections or ensembles (Collins and Knight, 2007; Buontempo *et al.*, 2011). This is motivated by the inherent uncertainty in climate projections. Different Global Circulation Models (GCM's) project different responses to climate change (Giorgi and Francisco, 2000) and there is no methodology for determining which is correct (Butts *et al.*, 2013). The prevailing view is that no single "true" model can be found. Results from multiple global climate models, multiple parameterizations of the same model (Murphy *et al.*, 2004; Stainforth *et al.*, 2005) and multiple GCM-RCM combinations (Christensen *et al.*; 2007, Hewitt, 2005) are now available and represent the current state of the art in terms of climate change assessment.

The reviews stated above and summarized in Table 2.8 on different climate models in combination with MIKE Model revealed that, the model is capable of modelling the changes in rainfall runoff and thereof water availability. Also futuristic series of water availability can be used to study the effect of climate change on water allocation patterns.

## **2.8 Epilogue**

Several studies have been conducted in worldwide on rainfall-runoff simulations using different hydrological models including HBV, HEC-HMS, MODHYDROLOG, Arc-SWAT etc. These models simulate runoff in catchments, study water balance, and provide flood forecasting and prediction of runoff. But this study required forecasting of long term water availability and predicting the changes for which the well calibrated and validated hydrological models are required. MIKE 11, one of the commercial models, is used in this study for rainfall-runoff modelling. Different reviews on MIKE 11 NAM model proved its capability to simulate the water availability. However, forecasting of runoff using forecasted rainfall data was not performed in previous studies and hence found to be the research gap. Therefore, synthetically generated series of rainfall for one year by using ANN model was proposed to forecast the one-year runoff. This kind of studies can help in predicting water availability, flood forecasting and managing water resources appropriately.

Climate change effect on water resources is difficult to envisage. But using GCM model availed data on forecasted rainfall and other parameters may help to explain future water status. MIKE model provides facility through climate change functionality tool to use already well set NAM model for forecasting runoff using different combination of GCM model and CO<sub>2</sub> emission scenarios. There are few previous researches found on predicting long term change on water availability. Therefore, the futuristic water availability change is proposed to be investigated in this study.

Another important aspect of water resources management is allocation of water for irrigation users. Hence, water allocation study is proposed using MIKE Hydro Basin model for different allocation basis. Several studies have been found on water allocation studies but in this research, three different cropping patterns are required to be tested for incremental area condition and also by considering futuristic water availability. This new vision will provide opportunities to good water management practices, in present and also in future, for both catchment and command areas.

**Table 2.8 Summary of studies on climate change scenarios**

Year	Name of Researcher	Study area	Rainfall Runoff model	GCM model and emission scenario	Downscaling technique	Results/ Findings
2006	H. E. Andersen, B. Kronvang, S. E. Larsen, C. C. Hoffmann, T. S. Jensen, and E. K. Rasmussen.	Gjern river basin, Denmark	NAM	ECHAM4/OPYC General Circulation Model (IPCC A2 scenario)	Danish HIRHAM regional climate model (25 km grid)	Increase in Mean annual runoff by 27mm than control scenario. Reductions of 40–70% in summer runoff for first- or second-order streams draining loamy catchments
2006	B. Elsaesser, A. K. Bell and G. Glasgow	Main river, Northern Ireland	NAM	HADRM3 ECHAM4	SRES-A1FI SRES-B2	Increase in extreme rainfall resulted in overall greater discharge. Total amount of discharge has risen by 16% compared to a total increase in rainfall of only 12%.
2008	A. Anandhi, V. V. Srinivas, R. S.Nanjundiah and D. N. Kumar	Malaprabha reservoir	Not used	CGCM3	A1B, A2, B1 and COMMIT	Precipitation was high for A2 scenario, whereas least for COMMIT scenario. CGCM3 model a feasible choice for downscaling precipitation to river basin scale.
2009	E. Jeppesen and B. Kronvang	Denmark	NAM	ECHAM4/OPYC	IPCC A2	Annual mean runoff increased by 7 to 78 mm yr <sup>-1</sup> or 9 to 34%.
2012	M. S. Alam and P.Willems	Turnhout, Belgium	NAM		A1B, A2, B1 and B2	An average increase of peak runoff by 23% for higher return periods, while an average decrease of relatively lower peak runoff by 19% for lower return periods as compared to the current conditions.
2013	M. B. Butts, C. Buontempo, J. K. Lorup, K.Williams, C. Mathison, N.D. Riegels, O.Z Jessen	Nile River Basin	MIKE HYDRO And NAM	Bias correction method used for rainfall and potential ET	Not used	Reductions in the flows for 2020-2049 and both increasing and decreasing trends for 2070-2099.

2017	Md. R. K. Dlamini Md R. Kamal Md. Amin Bin, Md. Soom, Md. S.F. Bin Md. A. Fikri Bin Abdullah and L. S. Hin	Bernam River Basin Malaysia	SWAT	RCP4.5, RCP6.0 and RCP8.5	Not reported	The overall future annual streamflow projections showed a slight increase of 2.5% and 4.4% in the 2020s under RCP 4.5 and RCP6.0, respectively, with almost no change in the other periods (2050s and 2080s), while the changes under RCP8.5 were between 3.1%, 0.5% and 1.3% for the 2020s, 2050s and 2080s, respectively.
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### 3. MATERIALS AND METHODS

This chapter describes the study area including data used for study and the methodologies that were adopted for the assessment of water availability, forecasting of runoff, assessing irrigation water demand and deficit, scenarios for water allocation using different cropping patterns, estimation of crop yield by using different simulation models and their comparison, effect of climate change on precipitation, evaporation and temperature and there of water availability for future scenarios, effect of climate change on water allocation scenarios etc. The different models that were used to fulfill the objectives of study includes MIKE 11 NAM rainfall-runoff model, MIKE Hydro Basin model, MIKE Zero climate change model, SWAB-CRYB model and Artificial Neural Network (ANN) model.

#### 3.1 Study area description

The detail description of the study area is discussed in this section. The Ghod complex sub catchment which includes seven reservoirs as Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon were selected for assessment of water availability, water demand, water allocation scenarios, crop yield and climate change impact on water availability by using different models such as MIKE 11 NAM model, MIKE HYDRO Basin model, MIKE Zero climate change functionality tool and SWAB-CRYB model.

##### 3.1.1 Ghod complex sub catchments location

In western Maharashtra the main sources available for irrigating the scarcity affected areas of Pune, Ahmednagar and Solapur districts are the Ghod and the Kukadi rivers. Ghod and Kukadi River are the main tributaries of Bhima River and located in the Upper Bhima catchment. Hence, the study was conducted for the Ghod catchment which is commonly known to be Ghod complex sub catchment of Upper Bhima basin. This catchment includes seven reservoirs as Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon.

The river Meena is a left bank tributary of the Ghod and joins it near the village Shingve, situated about 16 km east of the village Manchar on Pune-Nasik road. The river valley opens in to a wide valley near Nirgudsar village and the Wadaj dam is located on River Meena near village Wadaj in Junner Tehsil of Pune district. Pimpalgaonjoge Dam on the Ar River was mainly intended to feed the Yedgaon dam and to a certain extent firm up the irrigation on the existing Bandhara at Netwad on the Pushpawati River. Pushpawati and Ar rivers meet Kukadi River upstream of Yedgaon. Manikdoh dam is situated on river Kukadi. Dimbhe dam is located in the reach of the Ghod river between the towns of Ambegaon and Ghodegaon. The geodetic location of all dam site and site specifications along with raingauge stations are shown in Figure 3.1 and given in Table 3.1.

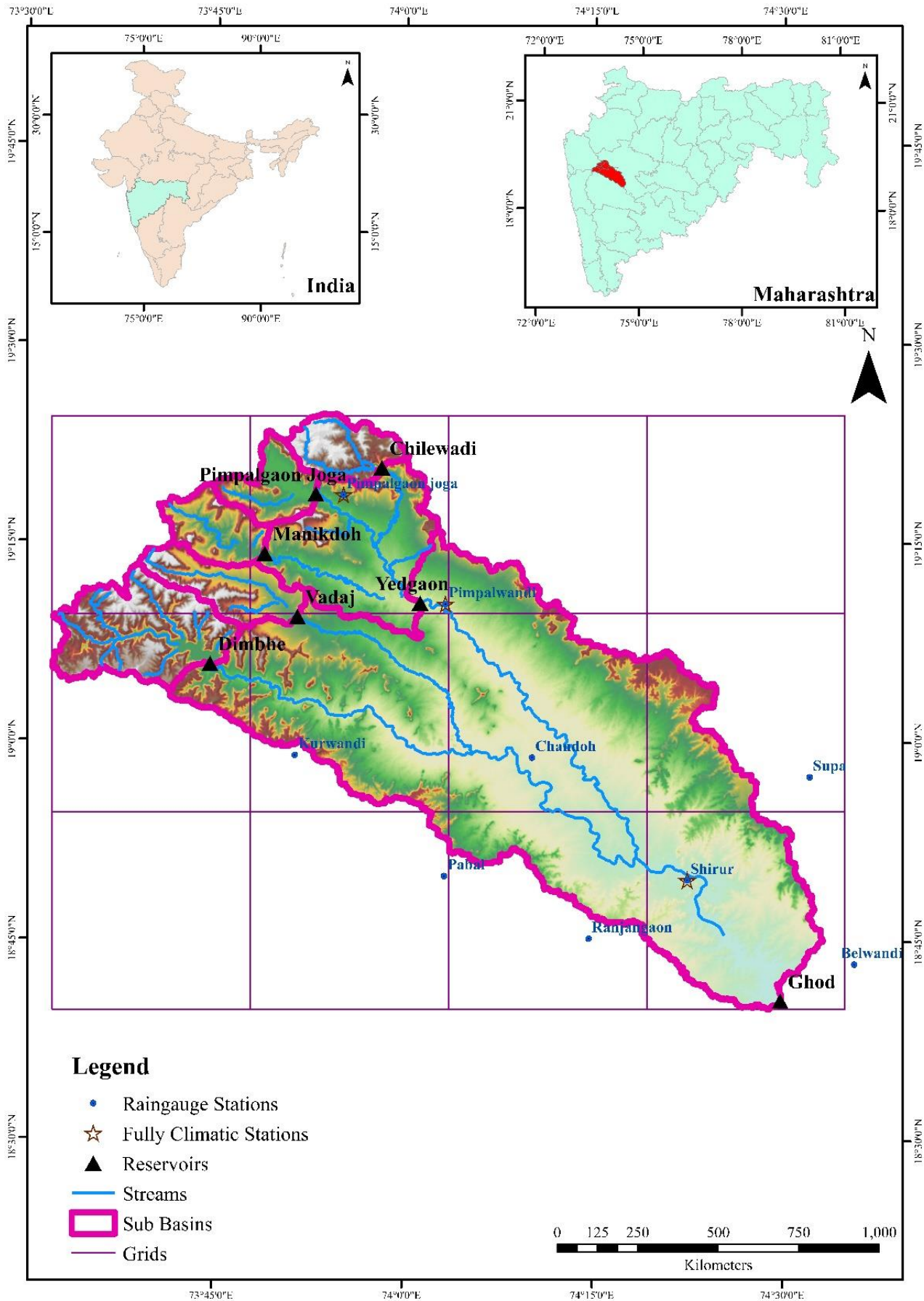


Figure 3.1 Details of Ghod complex sub catchments

**Table 3.1 Site specifications of reservoirs**

Sr. No.	Reservoir name	Latitude	Longitude	Altitude (m)	Catchment Area (km <sup>2</sup> )
1.	Chilewadi	19.34 °N	73.96 °E	715	104
2.	Dimbhe	19.09 °N	73.74 °E	690	273
3.	Ghod	18.67 °N	74.49 °E	545	2551
4.	Manikdoh	19.23 °N	73.81 °E	690	106
5.	Pimpalgaonjoga	19.31 °N	73.88 °E	686	98
6.	Wadaj	19.15 °N	73.85 °E	714	134
7.	Yedgaon	19.17 °N	74.02 °E	640	366
<b>Total area</b>					<b>3632 km<sup>2</sup></b>

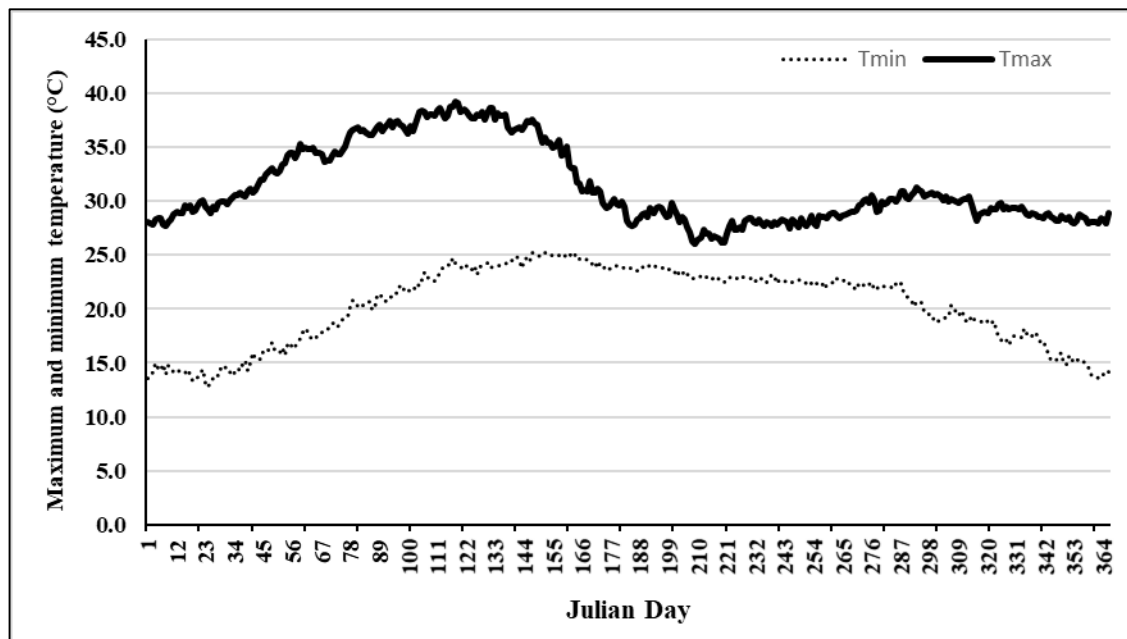
### 3.1.2 Climate in the study area

Climatically the study area falls under the semi-arid and sub-tropical zone with average annual rainfall of 605.5 mm. The annual average values of all the weather parameters during the period of year 2000-2012 are given in Table 3.2. The maximum temperature in the study area varied from 21.5°C to 42°C with an average value of 31.37°C. The minimum temperature in the study area varied from 7.75°C to 28.75°C with an average value of 20.34°C. The relative humidity varied from 12.5 to 96% with an average value of 58.56%. The sunshine hours are in-between 4.40 to 9.10 h/day with average value of 7.12 h/day. The wind speed varied from 1.06 to 4.48 km/h with average value of 5.67 km/h. The pan evaporation varied from 1.2 to 13.6 mm. The average pan evaporation during the crop growth cycle was 5.7 mm.

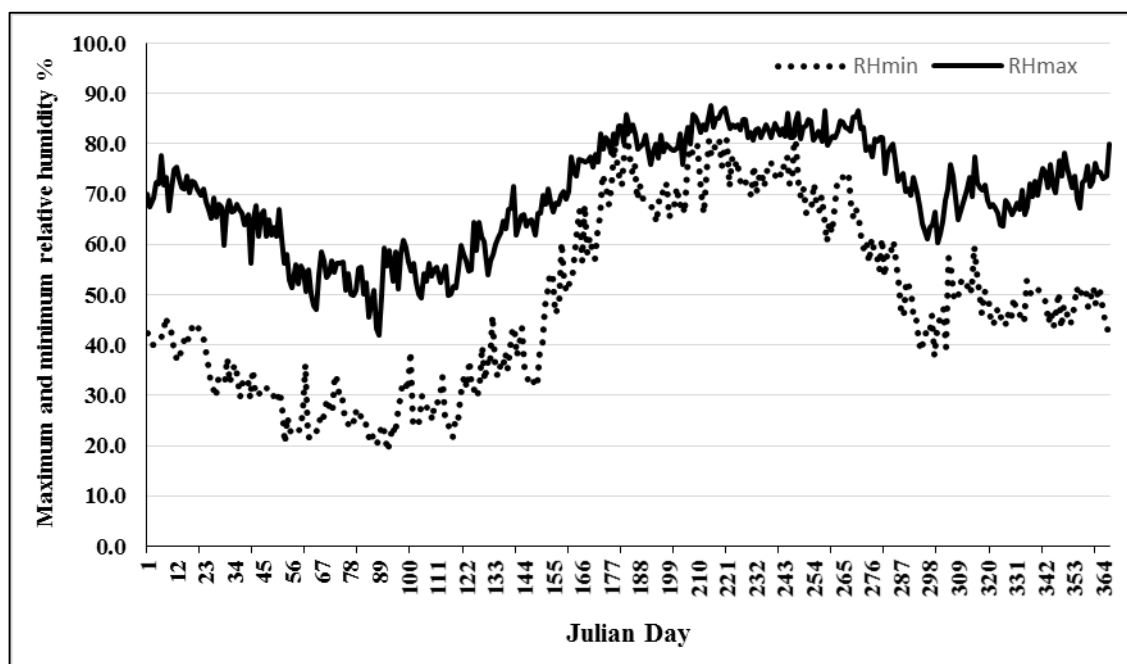
**Table 3.2 Average annual weather parameters during the period of 2000-2012**

Year	Relative Humidity %	Min. Temp. °C	Max. Temp. °C	Evaporation mm	Sunshine Hours h/day	Wind Speed km/h
<b>2000</b>	59.34	20.74	31.74	5.25	6.29	5.24
<b>2001</b>	64.88	19.43	31.47	4.86	6.50	4.85
<b>2002</b>	59.04	20.40	31.23	5.79	7.08	6.32
<b>2003</b>	52.93	20.64	32.04	6.29	7.64	6.29
<b>2004</b>	59.80	20.30	31.12	5.70	6.99	6.24
<b>2005</b>	60.21	20.31	31.12	5.66	6.94	4.87
<b>2006</b>	60.19	20.36	31.13	5.73	6.92	6.36
<b>2007</b>	59.78	20.36	31.17	5.66	6.91	4.96
<b>2008</b>	59.84	20.31	31.18	5.75	6.94	5.87
<b>2009</b>	59.12	20.44	31.28	5.73	6.93	5.26
<b>2010</b>	58.89	20.39	31.20	5.81	7.01	4.87
<b>2011</b>	57.55	20.26	31.14	6.00	7.18	6.36
<b>2012</b>	52.92	20.34	31.19	6.20	7.53	6.2

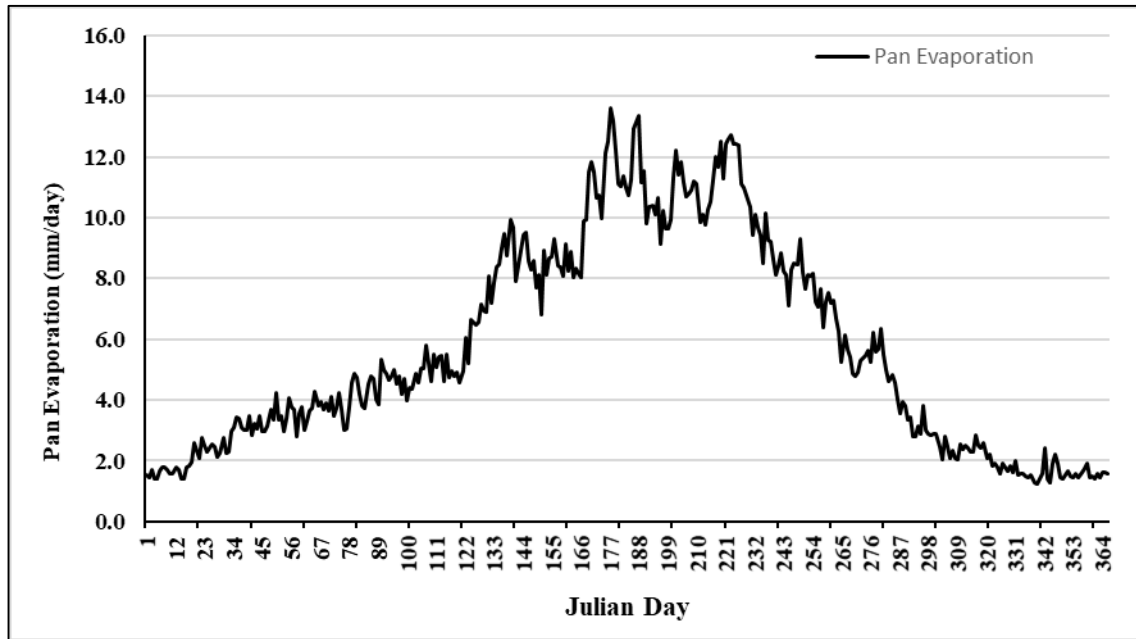
The variation in the daily average of maximum and minimum temperature, relative humidity, wind speed, sunshine hours and pan evaporation during the period of 2000-2012 are presented in Figures 3.2, 3.3, 3.4, 3.5 and 3.6.



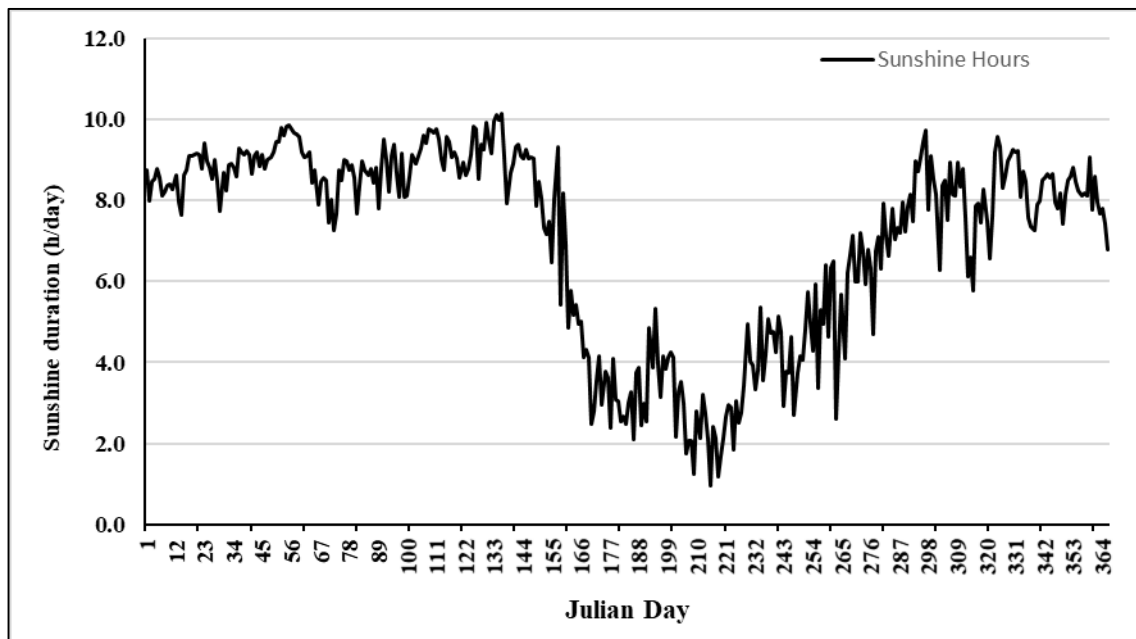
**Figure 3.2 Daily average of maximum and minimum temperature during the period of year 2000-2012**



**Figure 3.3 Daily average of maximum and minimum relative humidity during the period of year 2000-2012**



**Figure 3.4 Daily average of pan evaporation during the period of year 2000-2012**



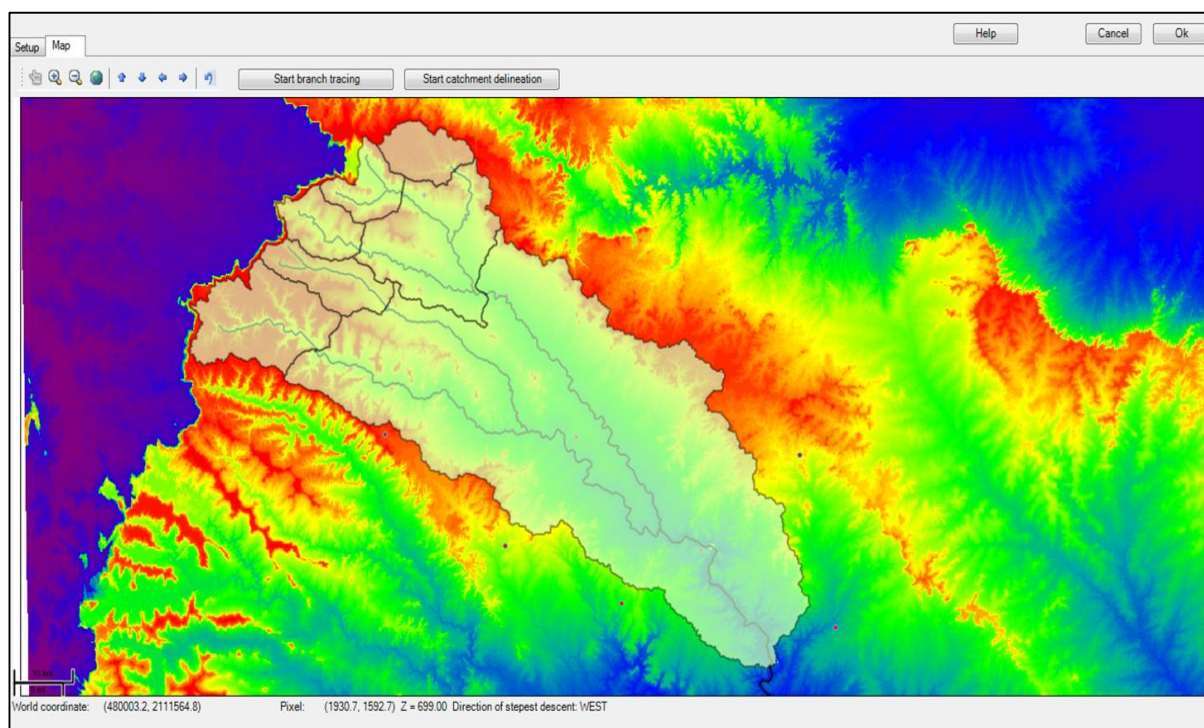
**Figure 3.5 Daily average of wind speed during the period of year 2000-2012**

### 3.1.3 Data requirement for the study

The necessary data used for carrying out the research work is as follows.

**Climatological data:** Climatological data such as rainfall, evaporation, maximum and minimum temperature, wind speed, relative humidity and bright sunshine hours were collected from State Data Storage Center, Hydrology Project (Surface Water), Jal Vigyan Bhavan, Nasik. The daily rainfall data of Belwandi, Chandoh, Kurwandi, Pabal, Pimpalwandi, Ranjangaon, Shirur and Supa rainguage stations was collected for the period of 1982 to 2012.

**SRTM data:** Digital Elevation Model (cell size 90 m x 90 m) was downloaded from website (<http://srtm.csi.cgiar.org/>). The DEM was transformed in ASCII file format. Shape files of raingauge stations, reservoirs and Ghod catchment were prepared by using Arc-GIS tool. Extraction of study area was done in Arc GIS and it was further processed in MIKE HYDRO Basin for catchment delineation. The delineated catchment is presented in Figure 3.6.



**Figure 3.6 Window showing catchment delineation of Ghod complex sub catchments by using DEM in MIKE HYDRO Basin model**

**Daily water balance data:** Daily water balance data for the period of 1997 to 2014 was obtained from Kukadi Irrigation Division I and II, Narayangaon, Pune for the seven reservoirs *viz.* Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod. Data includes daily water level, lake content, spill over spillways, different releases from dam such as irrigation use, domestic use etc. The sample data of daily water balance is given at Appendix-H.

**TRMM grid rainfall data:** Grids were formed in Arc-GIS for whole study area and the daily rainfall data for each grid was downloaded from TRMM website for the period of 1998 to 2014. The grid coordinates and sample data of gridded 3 hourly rainfalls is given at Appendix-E. This rainfall data was used for calibration of MIKE 11 RR model.

**Crop data:** Data of crop coefficient values ( $K_c$ ), crop length according to crop growth stages, root depth, maximum height of crop, depletion fraction, crop yield response factor ( $K_y$ ) and potential yield were collected from literature and FAO 56 manual (Allen et al., 1998). Common crops grown in the catchment are Soybean, Jowar, Groundnut, Tur, Bajara, Maize, Sugarcane, Wheat, Gram, Cotton and

Sunflower. The crop data used for simulation of irrigation water demand and yield using MIKE HYDRO Basin model for three different cropping patterns are given in Appendix- F and Appendix- G.

**Soil data:** Soil properties such as bulk density, particle density, porosity, field capacity and permanent wilting point etc. were obtained from literature.

### 3.2 MIKE Models

Hydrological models such as MIKE 11, MIKE HYDRO Basin, MIKE Zero climate change model were used to accomplish the objective of simulating water availability, water demand of different cropping pattern and study climate change effect on it. Prior to the simulation by MIKE models, data sets were prepared by preprocessing the raw data.

#### **Input data handling and pre-processing for MIKE models**

MIKE models operates with 'dfs0' types of data files. The 'dfs0' data files (time series) consist of series of individual values or scalars. Each time step in the series can be different. The time series data files of rainfall, potential evaporation, specific runoff, climate data, irrigation and non-irrigation demand, water supply fraction, Level-Area-Volume (LAV), flow control level, characteristic levels of reservoirs were prepared for running the simulation. This information was stored as 'dfs0' (time series) data files.

### 3.3 Water availability assessment using MIKE 11 NAM Rainfall-Runoff model

Rainfall-runoff estimation for a catchment is having vital importance in most of the hydrologic analysis for water resources planning. The modelling of hydrological processes is an important activity for water resources management. A rainfall-runoff model is a mathematical representation describing the rainfall-runoff relations of a catchment area, drainage basin or watershed. MIKE 11 is a professional engineering software package for the simulation of flows, water quality and sediment transport in estuaries, rivers, irrigation systems, channels and other water bodies. The MIKE 11 Rainfall-Runoff model is a hydrological model that simulates the rainfall-runoff processes occurring at the catchment scale.

Six different types of "Rainfall-Runoff models" are available:

**NAM:** A lumped, conceptual rainfall-runoff model, simulating the overland-flow, inter- flow, and base-flow components as a function of the moisture contents in four storages.

**UHM:** The Unit Hydrograph Module includes different loss models and the SCS method for estimating storm runoff.

**SMAP:** A monthly Soil Moisture Accounting Model.

**Urban:** Two different model runoff computation concepts are available in the Rainfall Runoff Module for fast urban runoff: A) Time/area Method and B) Non-linear Reservoir (kinematic wave) Method

**FEH:** Flood Estimation Handbook. A method for flood estimation in the UK.

**DRiFt (Discharge River Forecast):** A semi-distributed event model based on a geomorphologic approach.

The MIKE 11 NAM model was used to study the rainfall runoff processes in seven catchments Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon of Ghod complex sub catchment.

### **3.3.1 MIKE 11 NAM model**

MIKE 11 NAM model is one of widely used rainfall-runoff models present in the MIKE 11 model for rainfall-runoff modelling.

NAM is the abbreviation of the Danish "Nedbør-Afstrømnings-Model", meaning rainfall-runoff-model. This model was originally developed by the Department of Hydrodynamics and Water Resources at the Technical University of Denmark. MIKE 11 NAM model represents various components of the rainfall-runoff process by continuously accounting for the water content in four different and mutually interrelated storages. Each storage represents different physical elements of the catchment. MIKE 11 NAM model can be used for either continuous hydrological modelling over a range of flows or for simulating single events.

The MIKE 11 NAM model can be characterized as a deterministic, lumped, conceptual model with moderate input data requirements. The MIKE 11 NAM model is a well-proven engineering tool that has been applied to a number of catchments around the world, representing many different hydrological regimes and climatic conditions.

#### **3.3.1.1 Model Structure**

MIKE 11 NAM model is a conceptual model, based on physical structures and equations as shown in Figure 3.7. As MIKE 11 NAM model is a lumped model, it treats each catchment as a single unit. Therefore, parameters and variables represent average values for the entire catchment. Some of the model parameters can be evaluated from physical catchment data, but the final parameter estimation must be performed by calibration against time series of hydrological observations.

MIKE 11 NAM model simulates the rainfall-runoff process by continuously accounting for the water content in four different and mutually interrelated storages that represent different physical elements of the catchment. These storages are viz. snow storage, surface storage, lower root zone storage and groundwater storage.

Based on the meteorological input data MIKE 11 NAM model estimates catchment runoff. The resulting catchment runoff is split conceptually into overland flow, interflow and baseflow components.

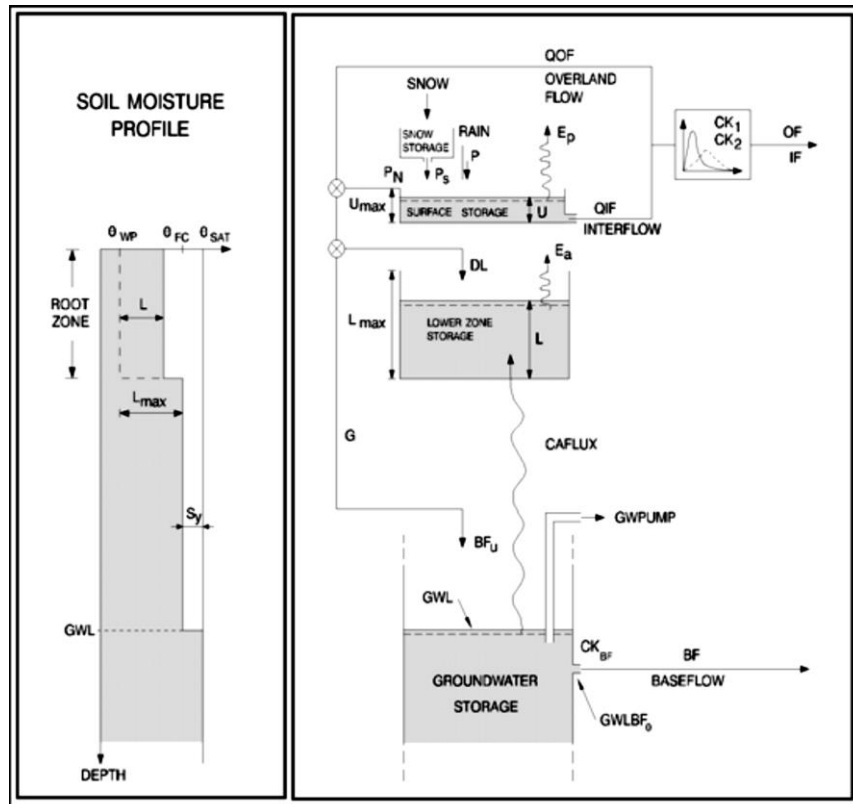


Figure 3.7 MIKE 11 NAM model structure (Source: MIKE 11\_Reference Manual, DHI, 2013)

### 3.3.1.2 Modelling components

MIKE 11 NAM model includes different components which represents surface storage, root zone storage, evapotranspiration, overland flow, interflow, baseflow, groundwater recharge etc.

#### 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 as surface storage.  $U_{max}$  denotes the upper limit of the amount of water in the surface storage.

#### 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.  $L_{max}$  denotes the upper limit of the amount of water in root zone storage.

#### 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  $E_a$ .  $E_a$  is proportional to the potential evapotranspiration and varies linearly with the relative soil moisture content,  $L/L_{\max}$ , of the lower zone storage and is given by equation (3.1).

$$E_a = (E_p - U) \frac{L}{L_{\max}} \quad (3.1)$$

Where,

$E_a$  = Actual evapotranspiration

$E_p$  = Potential evapotranspiration

$U$  = Moisture content

$L$  = lower root zone storage

$L_{\max}$  = the upper limit of the amount of water in root zone storage.

### 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 ' $P_N$ ' that contributes to overland flow. It is assumed to be proportional to ' $P_N$ ' and to vary linearly with the relative soil moisture content,  $L/L_{\max}$ , of the lower zone storage. The overland flow is estimated using equation 3.2.

$$QOF = CQOF \frac{L/L_{\max} - TOF}{1 - TOF} P_N \quad \dots\dots\text{for } L/L_{\max} > TOF \quad (3.2)$$

$$QOF = 0 \quad \dots\dots\text{for } L/L_{\max} \leq TOF$$

Where,

QOF = Overland flow

CQOF = Overland flow runoff coefficient ( $0 \leq CQOF \leq 1$ )

TOF = Threshold value for overland flow ( $0 \leq TOF \leq 1$ )

### Interflow

The interflow contribution, 'QIF' is proportional to 'U' and varies linearly with the relative moisture content of the lower zone storage and is estimated using equation 3.3.

$$QIF = (CQIF)^{-1} \frac{L/L_{\max} - TIF}{1 - TIF} U \quad \dots\dots\text{for } L/L_{\max} > TIF \quad (3.3)$$

$$QIF = 0 \quad \dots\dots\text{for } L/L_{\max} \leq TIF$$

Where,

QIF = Interflow

CKIF = time constant for interflow

TIF = 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 the same time constant 'CK12'. The overland flow routing is also based on the linear reservoir concept but with a variable time constant 'OF<sub>min</sub>'. The time constant for overland flow and inter flow routing are estimated by using equation 3.4.

$$\begin{aligned}
 CK &= CK12 && \dots\dots \text{for } OF < OF_{min} && (3.4) \\
 CK &= CK12 \left( \frac{OF}{OF_{min}} \right)^{-\beta} && \dots\dots \text{for } OF \geq OF_{min}
 \end{aligned}$$

Where,

CK 1 2 = Time constant for overland flow and inter flow routing

OF = overland flow (mm/hour)

OF<sub>min</sub> = upper limit for linear routing (= 0.4 mm/hour)

β = 0.4

### Groundwater recharge

The amount of infiltrating water 'G' recharging the groundwater storage depends on the soil moisture content in the root zone. The groundwater recharge is estimated using equation 3.5.

$$\begin{aligned}
 G &= (P_N - QOF) \frac{L / L_{max} - TG}{1 - TG} U && \dots\dots \text{for } L / L_{max} > TG && (3.5) \\
 G &= 0 && \dots\dots \text{for } L / L_{max} \leq TG
 \end{aligned}$$

Where,

QOF = Overland flow

PN = Rise in overland flow

TG = 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' and is given by equation (3.6).

$$\Delta L = PN - QOF - G \quad (3.6)$$

Where,

ΔL = Soil moisture content

PN = Rise in overland flow

QOF = Overland flow

G = Infiltrating water

## Baseflow

The baseflow 'BF' from the groundwater storage is calculated as the outflow from a linear reservoir with time constant 'CKBF'. These parameters are described in brief as below;

### 3.3.1.3 Model calibration parameters

MIKE 11 NAM is prepared with nine parameters, representing surface zone, root zone and ground water storage.

#### Maximum water content in surface storage ( $U_{max}$ )

$U_{max}$  (mm) defines the maximum water content in the surface storage. This storage includes the water content in the interception storage (on vegetation), in surface depression storages, and in the uppermost few cm's of the ground.

#### Maximum water content in root zone storage ( $L_{max}$ )

$L_{max}$  (mm) defines the maximum water content in the lower or root zone storage.  $L_{max}$  can be interpreted as the maximum soil moisture content in the root zone available for the vegetative transpiration. ' $L_{max}$ ' can be estimated as,

$$L_{max} = (\text{Field capacity} - \text{Wilting point}) \times \text{Effective root zone depth}$$

$$= \text{Available Water Holding Capacity} \times \text{Effective root zone depth}$$

As the actual evapotranspiration is highly dependent on the water content of the surface and root zone storages, ' $U_{max}$ ' and ' $L_{max}$ ' parameters are to be changed in order to adjust the water balance in the simulations. As a rule,  $U_{max} = 0.1 L_{max}$  can be used unless special catchment characteristics or hydrograph behavior indicate otherwise.

#### Overland flow runoff coefficient (CQOF)

'CQOF' is an important parameter that determines the extent to which excess rainfall flows as overland flow and the magnitude of infiltration. Small values of 'CQOF' are used for a flat catchment having coarse, sandy soils and a large unsaturated zone, whereas large 'CQOF' values are used for catchments having low, permeable soils such as clay or bare rocks.

#### Time constant for interflow (CKIF)

'CKIF' (hours) determines together with ' $U_{max}$ ' the amount of interflow. It is the dominant routing parameter of the interflow because  $CKIF \gg CK12$ .

#### Time constant for routing interflow and overland flow (CK12)

‘CK12’ (hours) determines the shape of hydrograph peaks. The value of ‘CK12’ depends on the size of the catchment and how fast it responds to rainfall.

#### **Root zone threshold value for overland flow (TOF)**

Root zone threshold value for overland flow, ‘TOF’, indicates that no overland flow is generated if the relative moisture content of the lower zone storage,  $L/L_{\max}$ , is less than ‘TOF’. The threshold value varies from catchment to catchment and is larger in semi-arid regions.

#### **Root zone threshold value for interflow (TIF)**

Root zone threshold value for interflow, ‘TIF’, acts as threshold values for generation of interflow.

#### **Baseflow time constant (CKBF)**

The time constant for baseflow, ‘CKBF’ (hours), determines the shape of the simulated hydrograph in dry periods. ‘CKBF’ can be estimated from hydrograph recession analysis. If the recession analysis indicates that the shape of the hydrograph changes to a slower recession after a certain time, additional (lower) groundwater storage can be added to improve the description of the baseflow.

#### **Root zone threshold value for groundwater recharge (TG)**

Root zone threshold value for groundwater recharge, ‘TG’, acts as threshold values for generation of groundwater. It is an important parameter for simulating the rise of the groundwater table in the beginning of a wet season.

The parameters should be within the specified range. The upper and lower bounds of these parameters are given in the Table 3.3.

**Table 3.3 MIKE 11 NAM model calibration parameters and range**

<b>Parameter</b>	<b>Description</b>	<b>Lower limit</b>	<b>Upper limit</b>
$U_{\max}$ (mm)	Maximum water content in the surface storage.	5	35
$L_{\max}$ (mm)	Maximum water content in the root zone storage.	50	350
CQOF (–)	Overland flow runoff coefficient.	0	1
TOF (–)	Root zone threshold value for overland flow	0	0.9
TIF (–)	Root zone threshold value for inter flow	0	0.9
TG (–)	Root zone threshold value for ground water recharge	0	0.9
CK <sub>IF</sub> (h)	Time constant for interflow from the surface storage	500	1000
CK <sub>1,2</sub> (h)	Time constant for overland flow and interflow routing	3	72
CK <sub>BF</sub> (h)	Time constant for routing baseflow	500	5000

### **3.3.2 Data requirements**

The basic input requirements for the MIKE 11 NAM model consist of model calibration parameters, initial conditions, meteorological data and streamflow data for model calibration and validation. The basic meteorological data requirements include rainfall and evaporation data.

### **Rainfall (mm)**

Rainfall is main input parameter for rainfall runoff modelling. The daily rainfall data of Belwandi, Chandoh, Kurwandi, Pabal, Pimpalwandi, Ranjangaon, Shirur and Supa rainguage stations were used for calibration and validation of NAM model. As the rainfall from raingauge stations varies the availability period, the rainfall data was not enough for rainfall-runoff modelling therefore gridded rainfall data was used as input. Grids were formed in Arc GIS for whole catchment area and daily rainfall data for each grid was downloaded from TRMM website ([http://gdata1.sci.gsfc.nasa.gov/daacbin/G3/gui.cgi?instance\\_id=TRMM\\_3-Hourly](http://gdata1.sci.gsfc.nasa.gov/daacbin/G3/gui.cgi?instance_id=TRMM_3-Hourly)) for the period of 1998 to 2014 and sample gridded data is given at Appendix-E.

### **Evaporation (mm)**

Daily evaporation data of three different fully climatic stations (FCS) Pimpalgaonjoga, Pimpalwandi and Shirur obtained from HDUG Nasik, was used in rainfall runoff modelling.

### **Discharge (m<sup>3</sup>/s)**

Observed discharge data at the catchment outlet is required for comparison with the simulated runoff during model calibration and validation. In Ghod complex sub catchments, only one-gauge discharge station data was available i.e., for Shirur station up to year 2001 which is out of calibration and validation period. Therefore, inflows of each reservoir obtained from the water balance data records provided by Kukadi Irrigation Division were used as discharge for rainfall-runoff modelling of these ungauged catchments. De Hamer et al. (2007) and Liebe et al. (2008) used water balance from a reservoir to generate streamflow. De Hammer *et al.* (2007) used the water balance of a reservoir to calibrate a rainfall-runoff model for two small ungauged catchments in Zimbabwe. The inflow was estimated by relating the increase in water level after a rain event and the dimensions of the reservoirs (Makungo, *et al.*, 2010). The negative flows were summed up with positive flows. Very small values of negative flow were ignored.

### **3.3.3 Model calibration conditions**

The final parameter estimation must be performed by calibration against time series of hydrological observations. In the calibration process, the following calibration objectives were taken into account;

1. A good agreement between the average simulated and observed catchment runoff
2. A good overall agreement of the shape of the hydrograph

3. A good agreement of the peak flows with respect to timing, rate and volume
4. A good agreement for low flows.

Both graphical and numerical performance measures were applied in both the calibration and validation process. The graphical evaluation includes comparison of the simulated and observed hydrograph, and comparison of the simulated and observed accumulated runoff. Water balance error is the difference between accumulated observed runoff and accumulated simulated runoff over the observed runoff. The value of water balance error equal to zero means there is a perfect match between accumulated observed runoff and accumulated simulated runoff. A value near to zero is acceptable for hydrological models. The numerical performance measures include the overall water balance error, and a measure of the overall shape of the hydrograph based on the coefficient of determination ( $R^2$ ) and is calculated by using equation (3.7).

$$R^2 = 1 - \frac{\sum_{i=1}^N [Q_{obs,i} - Q_{sim,i}]^2}{\sum_{i=1}^N [Q_{obs,i} - \bar{Q}_{obs}]^2} \quad (3.7)$$

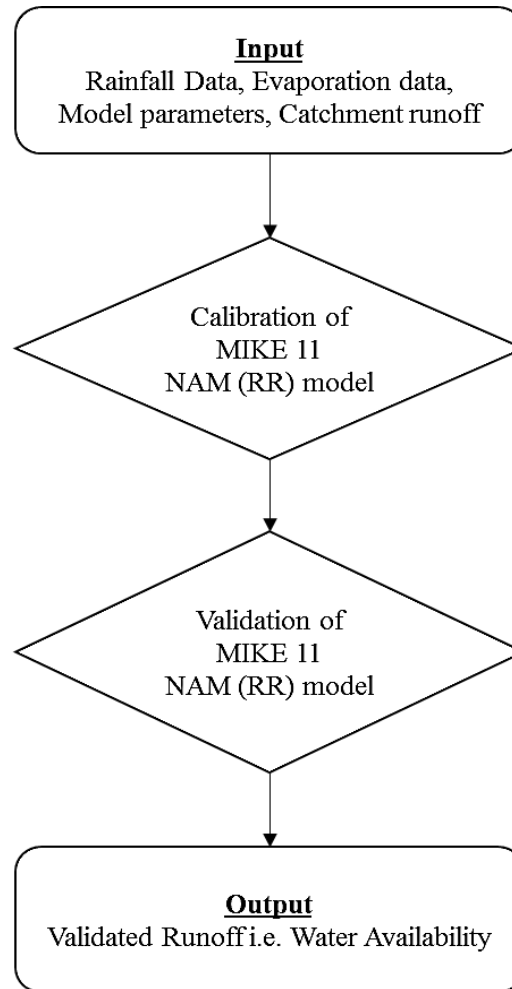
Where,

- $R^2$  = Coefficient of determination
- $Q_{sim,i}$  = Simulated discharge at time  $i$
- $Q_{obs,i}$  = Observed discharge at time  $i$
- $\bar{Q}_{obs}$  = Average observed discharge

The procedure used for calibration and validation of MIKE 11 NAM model with different input data for obtaining water availability of catchments is presented in flowchart at Figure 3.8.

### 3.3.4 Linear reservoir routing

Study area includes two intermediated catchments viz. Yedgaon and Ghod. Spills from upstream catchments added into these intermediate catchments. Specific runoff of the intermediate catchments Yedgaon and Ghod was required in MIKE 11 NAM model for calibration and validation. Hence, catchment routing was needed to calculate the intermediate flow of the Yedgaon and Ghod catchments. The Yedgaon catchment comprises three reservoirs in the upstream i.e. Chilewadi, Pimpalgaonjoga and Manikdoh and Ghod catchment comprises three reservoirs in the upstream i.e. Dimbhe, Wadaj and Yedgaon. To calculate the flow of the intermediate catchment, upstream reservoirs releases were routed using linear reservoir routing method.



**Figure 3.8 Procedure used for calibration and validation of MIKE 11 NAM model**

MIKE HYDRO Basin model was used for routing of flow from reservoirs. The different spills from the upstream reservoirs were used for routing. The spilling data were collected from the Kukadi Irrigation Project Division, Narayangaon, Pune. The delay parameter i.e. time required to travel the spill or flows from upstream reservoir is adjusted by many trial and errors, manually, through matching the peaks of spills of upstream and inflows of downstream reservoir. Then, intermediate flow is estimated by subtracting routed flows from the inflow of downstream reservoir. The intermediate flow calculated from routing procedure in MIKE HYDRO Basin model is then used in the MIKE 11 NAM model to compare it with the simulated runoff. The details of linear reservoir routing method are given below.

In linear reservoir routing flow leaving from the river node is distributed over all time steps. The delay parameter  $K$  (the linear routing time lag), must be specified when linear reservoir routing is selected. The delay parameter  $K$  specifies the observed time for the flow to traverse the river from the selected river node to the next downstream node. For a pulse inflow, outflow peaks after a specified time given by the time lag, and then decays exponentially. The formula used is given by equation 3.8.

$$q_o = (1 - x / ((dt)/K)) \times q_i + x \times s \quad \text{with } x = 1 e^{(-dt/K)} \quad (3.8)$$

Where,

$q_o$  = outflow from the node ( $m^3/s$ )

$dt$  = time step length (time)

$q_i$  = inflow to the node ( $m^3/s$ )

$s$  = storage in the subsurface

$K$  = delay parameter

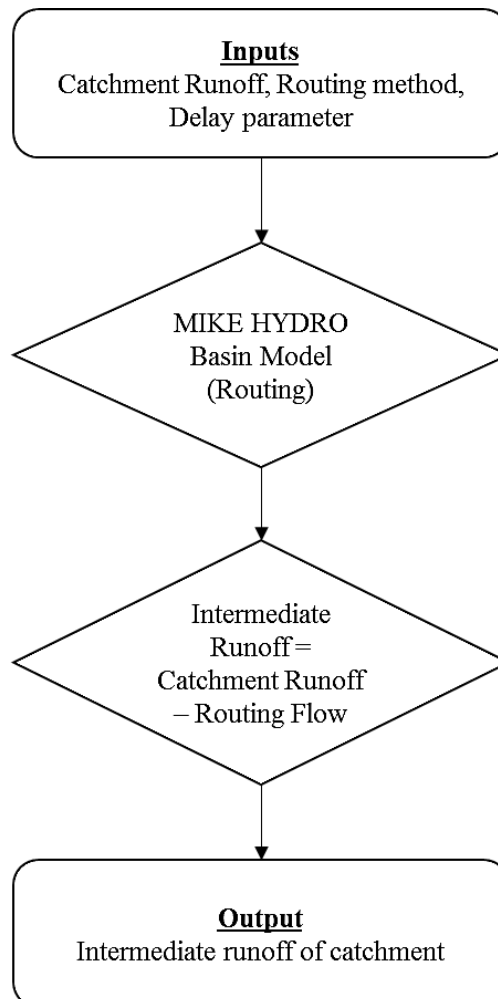
This algorithm includes damping. For a given time step, river storage is updated based on the formula given by equation 3.9.  $\Delta T$  is same as  $dt$ ,  $K$  is as explained previously, and  $T$  is an intermediate result.

$$T = 1.0 - e^{(\Delta T/K)} \quad (3.9)$$

$$\text{Volume}_{\text{outflow}} = (1.0 - T / (\Delta T/K)) \text{Volume}_{\text{inflow}} + T \times \text{Storage}$$

$$\Delta \text{Storage} = \text{Volume}_{\text{Inflow}} - \text{Volume}_{\text{Outflow}}$$

The detailed procedure used for routing flow of intermediate catchments using MIKE HYDRO Basin model is presented in the form of flowchart given in Figure 3.9.



**Figure 3.9 Procedure of routing flow of intermediate catchments using MIKE HYDRO Basin model**

### **3.3.5 MIKE 11 NAM model calibration**

Calibration is a process of standardizing predicted values, using deviations from observed values for a particular area to derive correction factors that can be applied to generate predicted values that are consistent with the observed values. Such empirical corrections are common in modelling and it is understood that every hydrologic model should be tested against observed data, preferably from the watershed under study, to understand the level of reliability of the model (Linsley, 1982). A minimum of 3 years including periods of above-average rainfall is recommended for calibration, with longer periods resulting in a more reliable model (DHI, 2008). Therefore, in the present study seven years' data from 2002-2009 is used for calibration of MIKE 11 NAM model.

The process of model calibration is normally done either manually or by using computer based automatic procedures. The manual calibration procedure is used in this study. In manual calibration parameters are adjusted by trial and error method. In this case, the goodness-of-fit of the calibrated model is basically based on a visual judgment by comparing the simulated and the observed hydrographs.

In the present study, once the NAM model was setup, it was calibrated for seven years' period from 2002 to 2009. During calibration, the model parameters were adjusted on trial and error basis by manual procedure. The model then resulted in obtaining set of model parameters for the calibration period. The model output simulation results during calibration were checked for  $R^2$  (coefficient of determination) value and graphically analyzed for degree of agreement between simulated and observed runoff. The model parameters were again adjusted one by one using trial and error method to obtain best set of model parameters of the NAM model which could simulate runoff with high degree of agreement with observed runoff in term of timings, peaks and total volume. The model parameters thus obtained after refinement of model were then used in validation of the model.

### **3.3.6 MIKE 11 NAM model validation**

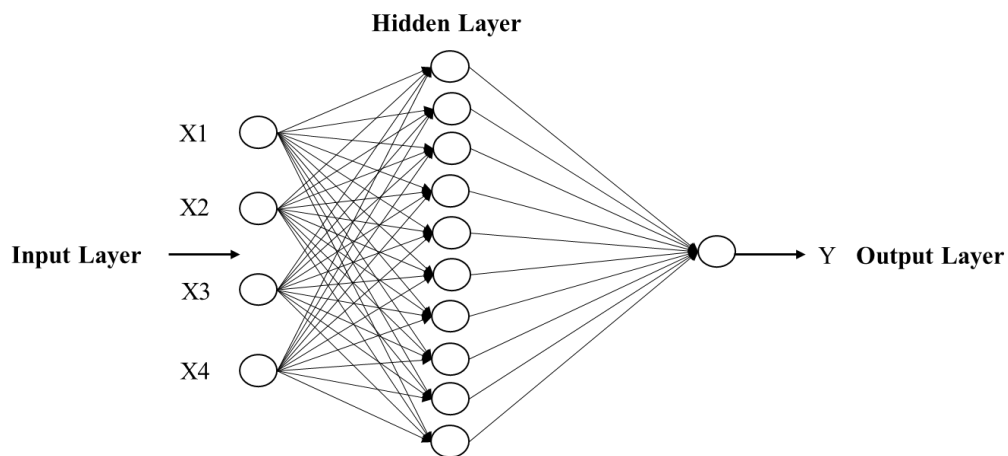
Model validation means judging the performance of the calibrated model over the portion of historical records which have not been used for the calibration. The MIKE 11 NAM model thus calibrated by using the data from 2002 to 2009 was then validated for the period of two years from 2010 to 2011. During validation the set of model parameters obtained during the calibration were used and model was run without auto-calibration mode to simulate runoff. The statistics of the simulated results were analyzed and output of the model were checked to compare the simulated and observed runoff to verify the capability of calibrated model for simulation of the runoff.

### 3.3.7 MIKE 11 NAM model performance criteria

To evaluate the performance of the model, the simulated data were compared with the observed data. The performance can be visually interpreted by plotting the graph of simulated and observed data simultaneously on a single plot. Accuracy of the MIKE 11 NAM model was examined on the basis of statistical evaluation parameters viz. Coefficient of determination ( $R^2$ ), Correlation coefficient ( $r$ ) and Nash and Sutcliffe Efficiency Index (EI).

### 3.4 Rainfall forecasting by using ANN model

Rainfall forecasting is the most important and deciding factor in forecasting water availability. The accurate information about water availability for few periods ahead in time benefits for proper planning and management of water supplies to different users. There are several number of models used in past for the forecasting of rainfall. In this study, Artificial Neural Network commonly known as ANN model is used for forecasting of rainfall of different station in the study area. The ANN model of 4-10-1 network architecture developed by Popale (2016) was used for forecasting of weekly rainfall. The ANN model 4-10-1 architecture was trained with resilient back propagation algorithm *trainrp* using cascade feed forward back propagation, non-linear activation function i.e. a log sigmoidal for the hidden layer and linear transfer function in output layer. The model has single hidden layer with 10 number of neurons in the hidden layer, having small learning rate i.e. 0.1 and 0.9 as a momentum constant. The model includes four neurons in the input layers i.e. rainfall of same week of previous two years 2011 to 2012 and rainfall of two preceding weeks of same year as input to forecast the rainfall of same week of year 2013. The ANN model 4-10-1 architecture is presented in Figure 3.10.

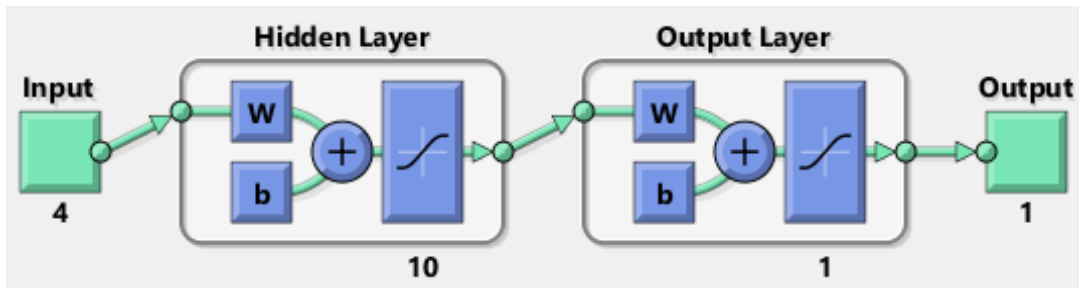


Where,

$X_1, X_2$  = rainfall of same week of previous two year 2011 and 2010

$X_3, X_4$  = rainfall of preceding weeks of 2011 and 2010

$Y$  = Forecasted rainfall for same week



**Figure 3.10 Architecture of ANN model 4-10-1**

Rainfall was forecasted for the year 2013 for the stations Pimpalgaonjoga, Pimpalwandi, Shirur, Kurwandi, Aundhe and Savale. This forecasted rainfall data was then used to simulate the water availability of the year 2013 for all sub catchments of Ghod complex viz. Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod.

### **3.4.1 Simulation of water availability by using forecasted rainfall data**

Already validated MIKE 11 NAM model with set of optimum values of parameters, was used to simulate the runoff for all the sub catchments of Ghod complex using forecasted series of rainfall for the year 2013. This simulated forecasted runoff for the year 2013 was then converted into water availability and compared with observed water availability of each catchment. The results are presented in chapter 4 in section 4.1.8.

### **3.5 Water demand-deficit assessment and water allocation using MIKE-HYDRO Basin model**

MIKE HYDRO Basin model is the common Graphical User Interface (GUI) framework for water resources products of MIKE by DHI. MIKE HYDRO Basin model is a model framework for a large variety of applications concerning allocation, management and planning aspects of water resources within a river basin. Therefore, in this study the MIKE HYDRO Basin model was used for assessing the water allocation in Ghod command area. The Ghod command area is having about 415 km<sup>2</sup> cultivable command area (CCA) and details are given in Figure 3.11.

The methodology adopted for assessing the water allocation in Ghod command area is presented in the form of flowchart given in Figure 3.12 which depicts the different processes involved in MIKE HYDRO Basin model viz. calibration of model, estimation of irrigation water demand, different water allocation scenarios etc.

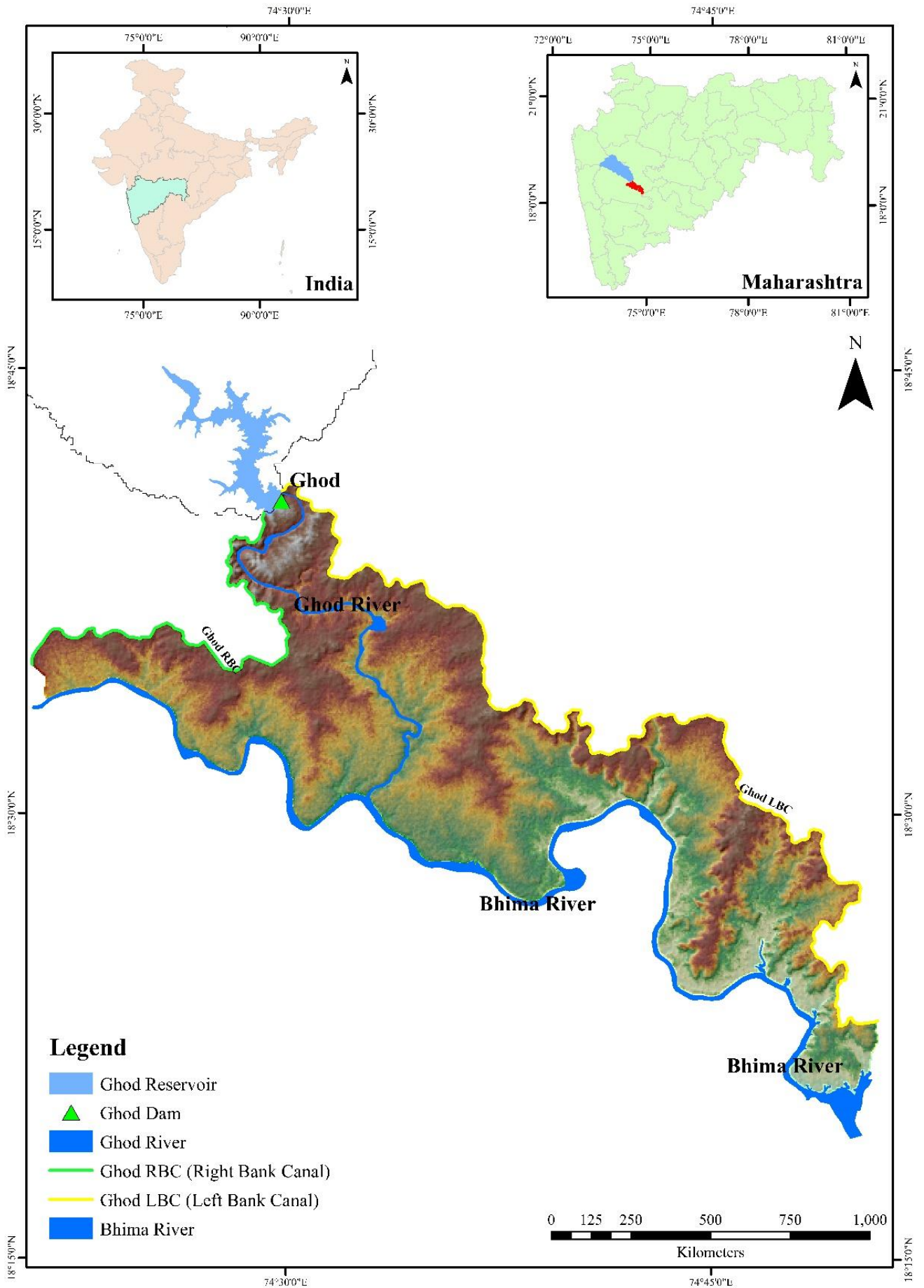
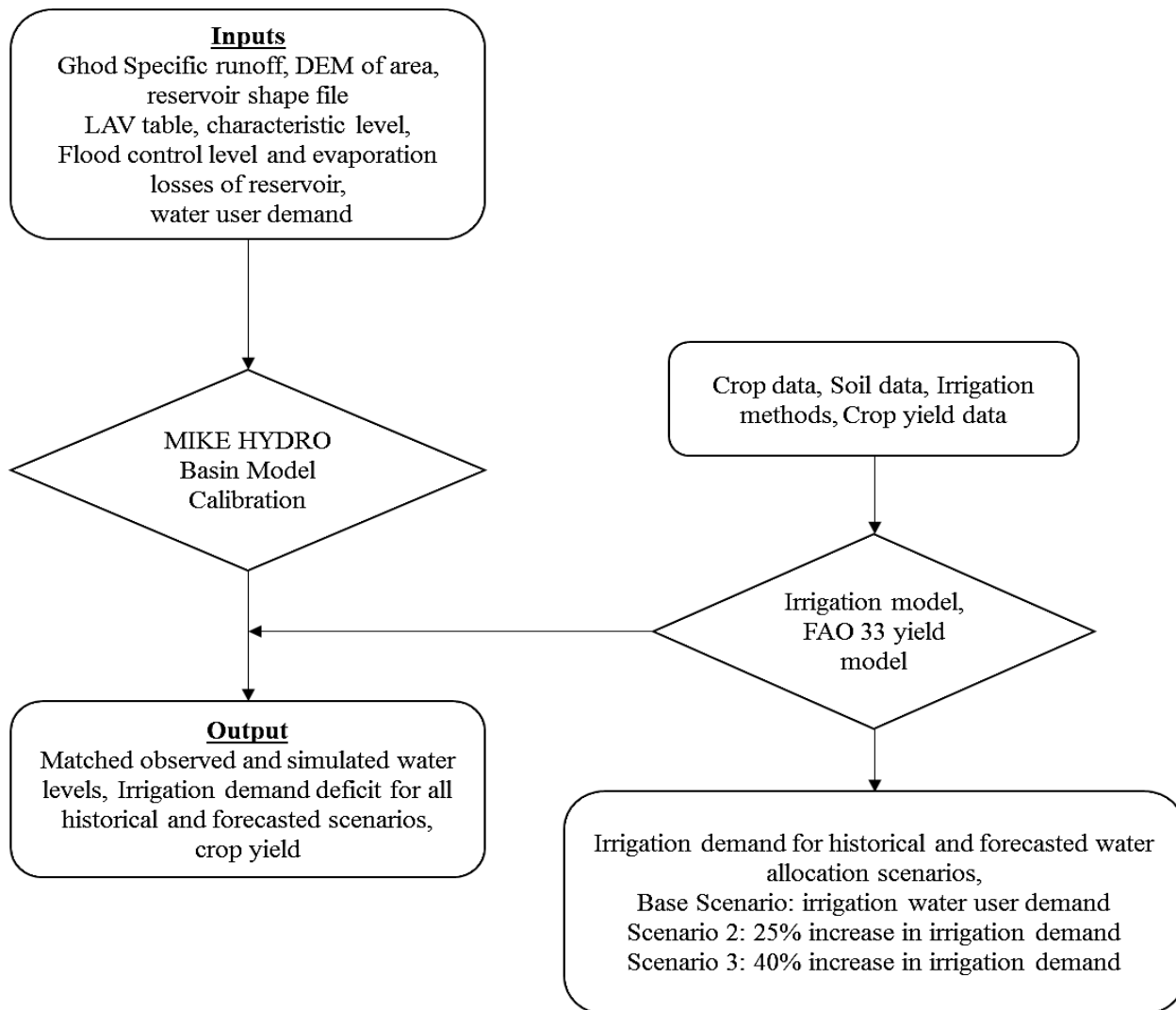


Figure 3.11 Details of Ghod command area



**Figure 3.12 Procedure used for water allocation using MIKE HYDRO Basin model**

### 3.5.1 Input data required for MIKE HYDRO Basin model

Prior to the calibration of MIKE HYDRO Basin model time series of reservoir characteristics, level area volume, different user demands, historical water levels etc. were prepared. River tracing and catchment delineation was done using digital elevation model in MIKE HYDRO Basin model. The different crop data required for simulating irrigation demand is given in Appendix- G.

### 3.5.2 Modeling setup

MIKE HYDRO Basin modelling setup consists of river nodes, river links, catchments, irrigation nodes, water user nodes and reservoir nodes. In addition, water channels lead water to and from water user nodes and irrigation nodes. River nodes and river links are the main elements in the river modelling. River nodes are placed wherever input data should be given or results should be extracted in addition to water extraction points and return flow points. In other words, wherever some changes regarding water amount occur, river links are given between the river nodes, catchment nodes and areas represent inflow to the model. Catchment area properties include inflow time series.

### 3.5.3 Model components

MIKE HYDRO Basin model includes different types of sub models for different purpose such as for crop water requirement there is irrigation tool, for yield estimation, FAO-33 model is provided etc. All these sub-models are described shortly in this section.

#### 3.5.3.1 Irrigation tool

In model, if irrigation type water user is used then the information regarding irrigation needs to be defined. Irrigation water demand is calculated based on Climate model and Deficit distribution methods (DHI, 2013). Climate model includes “Rainfall only model” and “FAO 56 model”. If the “FAO 56 model” is selected climate time series which includes relative humidity, reference crop evapotranspiration, air temperature (min and max), wind speed and sunshine hours, are required. It is also possible to specify observed values for  $ET_o$  in a time series.

The reference ET is calculated according to the FAO 56 method. Standardized Penman-Monteith equation (3.10) is used for calculating crop reference evapotranspiration (Allen *et.al.*, 1998).

$$ET_o = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)} \quad (3.10)$$

Where,

$ET_o$  = Reference crop evapotranspiration ( $\text{mm day}^{-1}$ )

$R_n$  = Net radiation at the crop surface ( $\text{MJ m}^{-2} \text{day}^{-1}$ )

$G$  = Soil heat flux density ( $\text{MJ m}^{-2} \text{day}^{-1}$ )

$T$  = Air temperature at 2 m height ( $^{\circ}\text{C}$ )

$e_s$  = Saturation vapour pressure (kPa)

$e_a$  = Actual vapour pressure (kPa)

$e_s - e_a$  = Saturation vapour pressure deficit (kPa)

$\Delta$  = Slope vapour pressure curve ( $\text{kPa}^{\circ}\text{C}^{-1}$ )

$\gamma$  = Psychrometric constant ( $\text{kPa}^{\circ}\text{C}^{-1}$ )

There are three water distribution options under the MIKE HYDRO Basin model when the irrigation demand exceeds the available water at the sources viz. equal shortage method, by priority and by yield stress. When the available water is more than the demand, then water is distributed as per full irrigation demand.

In present study, “FAO 56 model” is used for the estimation of historical irrigation water demand in combination with equal shortage distribution method whereas for the forecasting of irrigation water demand rainfall “only model” is used.

### 3.5.3.2 Crop model

The crop model is used to specify the parameters for the crops based on FAO-56 guidelines. The following are the parameters required for the crop model.

**Stage length:** Crop stages are divided into an initial, development, mid-season and late season crop stage and the periods are given in number of days.

**Crop coefficient (K<sub>cb</sub>):** Basal crop coefficient (K<sub>cb</sub>) is assigned for each stage. It is the ratio of the crop evapotranspiration (ET<sub>c</sub>) over the reference evapotranspiration (ET<sub>o</sub>) when the soil surface is dry but transpiration is occurring at potential rate.

**Root depth:** Root depth is specified for initial and middle stage. The root depth R determines the maximum depth from which the crop can extract water. The minimum and maximum depth need to be specified. The variation between the initial depth and the maximum depth is determined by the relationship given in equation (3.11).

$$R = \frac{(K_{cb} - K_{cb,ini})}{(K_{cb,mid} - K_{cb,ini})} (R_{max} - R_{min}) + R_{min} \quad (3.11)$$

Where,

K<sub>cb,ini</sub> = Initial basal crop coefficient

K<sub>cb,mid</sub> = Basal crop coefficient in middle stage

R<sub>max</sub> = Maximum root depth (m)

R<sub>min</sub> = Minimum root depth (m)

**Maximum vegetation height:** The vegetation height is assumed to scale with the basal crop coefficients and is calculated by equation (3.12).

$$H = \frac{(K_{cb} - K_{cb,ini})}{(K_{cb,mid} - K_{cb,ini})} H_{max} \quad (3.12)$$

Where,

H = Vegetation height

H<sub>max</sub> = Maximum vegetation height

K<sub>cb,ini</sub> = Initial basal crop coefficient

K<sub>cb,mid</sub> = Basal crop coefficient in middle stage

**Depletion fraction:** Average fraction of total available soil water that can be depleted from the root zone before moisture stress

The information about crop length, K<sub>cb</sub> values according to crop growth stages, root depth of crop, depletion factor and maximum height of crop were collected from FAO manual and presented in

Appendix-G. The three different cropping patterns are used for varying area condition. The cropping pattern used in irrigation user are as follows;

1. Multi-crop cropping pattern

Season	Crops	% Area
<b>Kharif</b>	Jowar	13
	Bajara	5
	Soybean	5
	Groundnut	7
<b>Rabi</b>	Jowar	22
	Wheat	13
	Gram	5
<b>Summer</b>	Sunflower	8
	Cotton	5
	Maize	5
<b>Perennial</b>	Sugarcane	12

2. Major crops cropping pattern

Season	Crops	% Area
<b>Kharif</b>	Bajara	50
<b>Rabi</b>	Jowar	50
<b>Summer</b>	Maize	50
<b>Perennial</b>	Sugarcane	50

3. Sugarcane only cropping pattern = Total Area 100%

The model is closely linked to a yield model and a crop sequence model.

### 3.5.3.3 Crop sequence model

Crop sequence model specifies the crop rotation on a given field i.e., when a crop is planted or sowed. The following are the parameters required in the crop sequence model; Crop type, sowing date for the specific crop type, specify if the crop is irrigated by the irrigation method or by rainfall only, irrigation method.

MIKE-BASIN calculates the accumulated yield according to the irrigation model and the climatic conditions. Crop data used as input for the MIKE HYDRO Basin model for estimation of irrigation water demand is given at Appendix-G.

### 3.5.3.4 FAO-33 Yield model

Attaching a yield model to a crop model allows the conversion of soil water stress into the corresponding yield loss, and hence, to quantify the costs of a soil moisture deficit. The yield model

currently available is the FAO 33 Yield Model (Doorenbos and Kassam, 1979). The following three options are available for the FAO 33 Yield model;

**Calculate yield:** By using this option a yield model is attached to the crop model. The potential yield of crops need to be entered and so the  $K_y$  parameters for the different crop stages.

**Potential yield:** FAO 33 Yield model is based on a potential yield ( $Y_p$ ), which is the crop yield under optimal conditions (no soil moisture stress). This parameter, expressed in [kg/ha], represents the crop production per unit area of cultivated field and it must be entered when the yield model is included.

**Use yield stage length:** The sensitivity of a crop to soil moisture stress depends on the growth stage. A crop will usually be more sensitive to soil moisture stress in early growth stages than in late stages. A yield response factor has to be specified for each of four growth stages. Each stage is assigned a length that may, but does not have to be the same as the growth stages in the crops model to which it is related. The crop yield is calculated as:

$$\frac{Y_a}{Y_p} = \prod_{i=1}^{i=G} \left[ 1 - K_{yi} \left( 1 - \frac{Et_a}{Et_p} \right) \right] \quad (3.13)$$

Where,

$Y_a$  = Actual yield (kg/ha)

$Y_p$  = Potential yield (kg/ha)

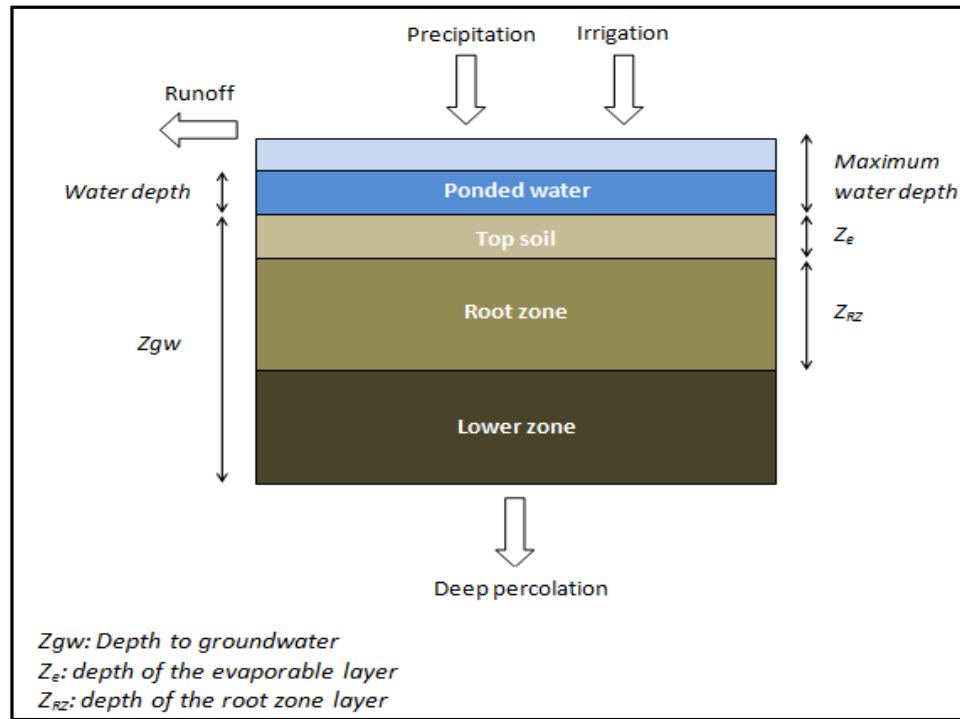
$Et_a$  = Actual transpiration (mm/day)

$Et_p$  = Potential transpiration (mm/day)

Index  $i$  is the  $i^{\text{th}}$  growth stage in a growing season with a total of  $G$  growth periods. The crop yield obtained from MIKE HYDRO Basin model was compared with crop yield obtained from Soil Water Balance and Crop Yield Benefit (SWAB-CRYB) model for different crops sown under Ghod command area.

### 3.5.3.5 Soil model

It is also called as soil water model (Figure 3.13) and keeps track of the water flow between different layers in the soil profile and the time-varying water content in each layer. The soil water model keeps the track of the amount of soil water available for soil evaporation and crop transpiration at any time during the simulation. The soil water content may also be used by the irrigation module to determine the irrigation demand. There are three soil water model types available under MIKE HYDRO Basin model platform viz. FAO 56 soil water model, ZIMsched soil water model and ZIMsched for Rice field soil water model. In present study, FAO 56 soil water model was used which follows the recommendations provided by FAO-56 with use of dual crop coefficient method.



**Figure 3.13 Soil Model in MIKE HYDRO Basin model (Source: MIKE HYDRO\_User Guide, DHI, 2013)**

### 3.5.3.6 Reservoir model

MIKE HYDRO Basin model consists of multiple multi-purpose reservoir systems. Individual reservoirs can simulate the performance of specified operating policies using associated operating rule curves. Reservoirs define the desired storage volumes, water levels and releases at any time as a function of current water level, the time of the year, demand for water, and losses and gains. If reservoirs have a significant surface area compared to the catchment area, in which they are located then extract the reservoir surface area from the catchment area. Rule curve type reservoir is used in this study. Rule curve type reservoir regard as a single physical storage and all users are drawing water from the same storage. Operating rules for each user apply to that same storage and the users compete with each other to fulfill their water demand.

### 3.5.4 Calibration of MIKE HYDRO Basin model

MIKE HYDRO Basin model is a conceptual model framework of river basin model. The calibration of MIKE HYDRO Basin model depends on the precise calibration of MIKE 11 NAM model. The runoff obtained from calibration of MIKE 11 NAM model is used as input for calibration of MIKE HYDRO Basin model. Prior to the calibration of MIKE HYDRO Basin model for Ghod reservoir, the model was set to calibrate and match the water levels with observed water levels for the six reservoirs (Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon) situated at upstream of the Ghod reservoir. The long term water account data of all reservoirs for the period of 2001-2013 was

obtained from Kukadi Irrigation Division 1 and 2, Narayangaon, Pune. An example of the water account data sheet is given in Appendix- H. The initial water level was set to 1<sup>st</sup> October, 2001, which was the actual water level in the model. The model was run for long duration 2001-2012. The calibration of model was done by comparing calibrated and actual water level of all reservoir.

Once the MIKE HYDRO Basin model was calibrated using all the input data required, model is then used to allocate water for different water allocation scenarios. Using the crop data, soil data, climatological variables and reservoir data, crop water demand and deficit for the period of 2002-2013 were calculated for Ghod command area.

### **3.6 Historical water allocation scenarios**

One of the objectives of the study is to evaluate the effect of different water allocation scenarios for different water availability in the selected sub catchment for historical scenario. These scenarios are evaluated in MIKE HYDRO Basin model. The historical water demand data was collected for the Ghod command area from the State Data Storage Center, Hydrology Project, Nasik. The scenarios for 25 % and 40 % increase in the historical water demand were run in MIKE HYDRO Basin model.

#### **3.6.1 Base scenario**

The total irrigation water demand obtained from Irrigation model by using historical dataset of the period 2002 to 2012 for all the sub catchments of Ghod complex is considered as the base scenario.

#### **3.6.2 Scenario 1: 25% increase in irrigation water demand**

MIKE HYDRO model was run by increasing total irrigation demand obtained from the base scenario by 25 %. Keeping other model parameters same as base scenario.

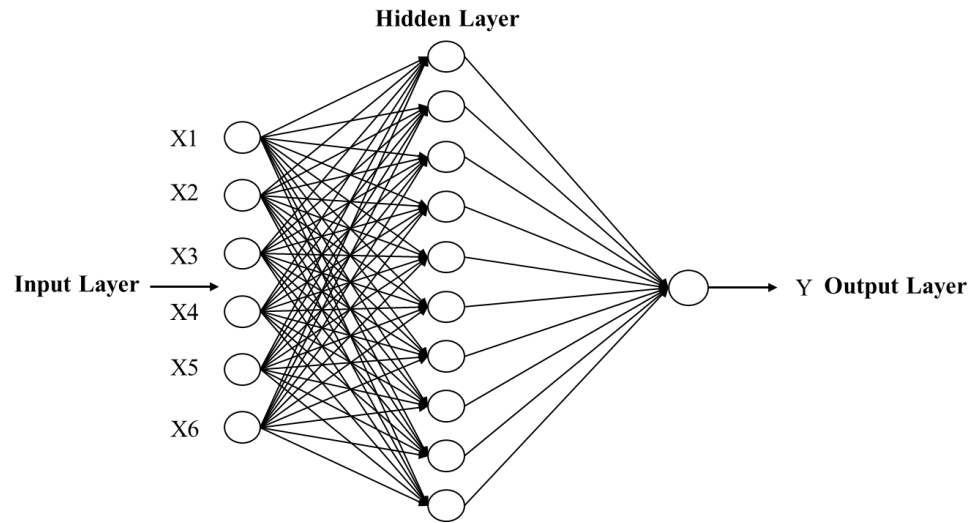
#### **3.6.3 Scenario 2: 40% increase in irrigation water demand**

MIKE HYDRO Model was run by increasing total irrigation demand obtained from the base scenario by 40 %. Keeping other model parameters same as base scenario.

### **3.7 Forecasted water allocation scenarios**

One of the objectives of the study was to evaluate the effect of different water allocation scenarios for the forecasted water availability and demand. The forecasted water availability obtained using forecasted series of rainfall by ANN is used as input to the model. In the MIKE-HYDRO Basin model under the “Climate model” option, choice is there for selection of model between “Rainfall only” and “FAO 56” for the estimation of irrigation water demand. In present study, the “Rainfall only” model is used which is the simplest climate model, requires only a rainfall time series and a reference ET time series as input. As the data of all-weather parameters was not available it was decided to use the “Rainfall only” model for estimation of irrigation water demand. Reference ET time series obtained

by using already developed ANN ETo forecasting model of 6-11-1 network architecture trained with *trainlm* training function using Feed-Forward Back Propagation (FFB) network (Bhagat and Popale, 2017). The ANN model of 6-11-1 network architecture is shown in Figure 3.14.

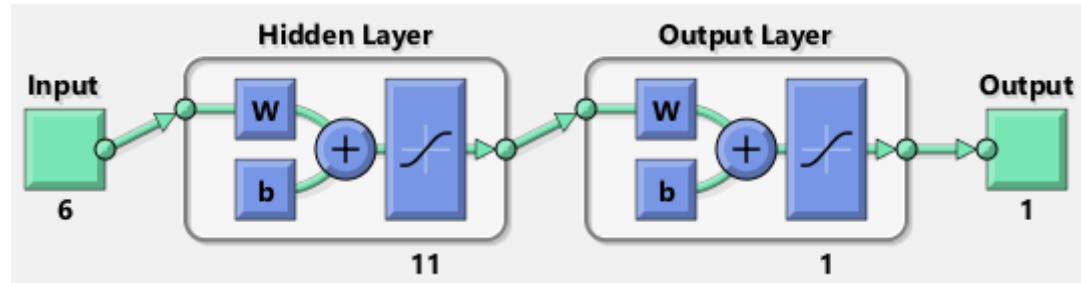


Where,

$X_1, X_2$  and  $X_3$  = ETr of same day of previous three years 2010, 2011 and 2012

$X_4, X_5$  and  $X_6$  = ETr of preceding day of three years 2010, 2011 and 2012

$Y$  = Forecasted ETr of same day for 2013



**Figure 3.14 ANN model 6-11-1 network architecture**

The forecasted rainfall of Shirur station for the year 2013 is used as input to the model. This forecasted irrigation water demand is considered as baseline scenario in forecasted water allocation scenarios.

### 3.7.1 Forecast base scenario

The total irrigation water demand estimated using forecasted water availability in MIKE 11 NAM model, rainfall and ET series obtained by ANN model for year 2013 are considered as the base scenario.

### 3.7.2 Forecast scenario 1: 25% increase in irrigation water demand

MIKE HYDRO model was run by increasing total irrigation demand obtained from the base scenario by 25 %. Keeping other model parameters such as water availability and other releases same as base scenario.

### 3.7.3 Forecast scenario 2: 40% increase in irrigation water demand

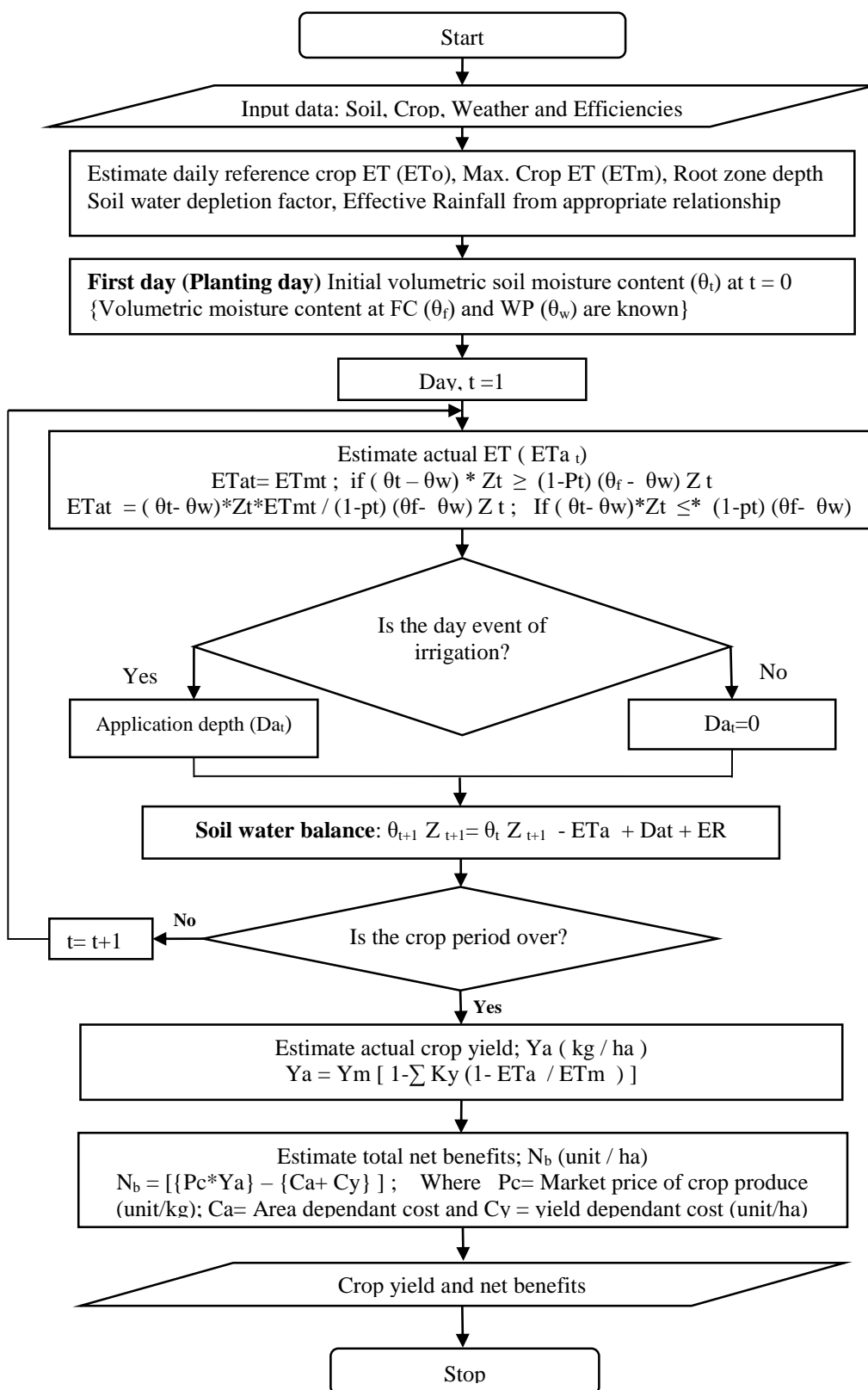
MIKE HYDRO model was run by increasing total irrigation demand obtained from the base scenario by 40 %. Keeping other model parameters such as water availability and other releases same as base scenario.

### 3.8 SWAB-CRYB Simulation model

Crop yield refers to measure the yield of crop or seeds or grains of crop per unit area. SWAB-CRYB model estimates crop yield using different yield response models. SWAB-CRYB is **Soil Water Balance-Crop Yield and Benefits (SWAB-CRYB)** model developed by Gorantiwar (1995) and Gorantiwar and Smout (2003). The model enables the estimation of soil moisture in the root zone, actual evapotranspiration; return flow (deep percolation) to the groundwater due to irrigation, crop yield and net benefits. This model considers the input of water to soil root zone is from effective rainfall and irrigation and output of water from the soil root zone is in the form of evaporation and transpiration (evapotranspiration) and deep percolation. Also in this model, the contribution of moisture to the soil root zone from the groundwater through capillary rise is considered as negligible. The flow is vertical and one-directional. The water added or removed by the process such as precipitation, irrigation, evapotranspiration, percolation, etc. are assumed to occur in the lumped manner at the end of time period. The depth of soil is considered to be homogeneous in its properties. The soil root zone and irrigation water is free from salinity. The different processes involved in SWAB-CRYB model are presented in Figure 3.15.

In present study, SWAB-CRYB model is used to estimates actual yield of different crops under Ghod command area using additive type of crop yield response model proposed by Stewart *et al.*, (1976). Actual yield of different crops is estimated using crop, soil, weather, efficiencies and irrigation data. The sample data used for estimation of actual yield is given in Appendix- G. SWAB- CRYB model embedded in DSS-IWM developed by Kadam (2014) is used for estimation of actual crop yield in this study.

MIKE HYDRO Basin model also having facility to estimate actual crop yield using same dataset provided as input for SWAB-CRYB model. MIKE HYDRO Basin model uses the FAO -33 Crop Yield model to calculate actual crop yield. Hence, MIKE HYDRO Basin model was also used for estimation of actual yield of different crops. Actual crop yield was calculated in MIKE HYDRO Basin model and SWAB-CRYB model using same input data for the period of 11 years from 2002 to 2012. Comparison was made on basis of yearly average yield of different crops that comes under the Ghod command area.

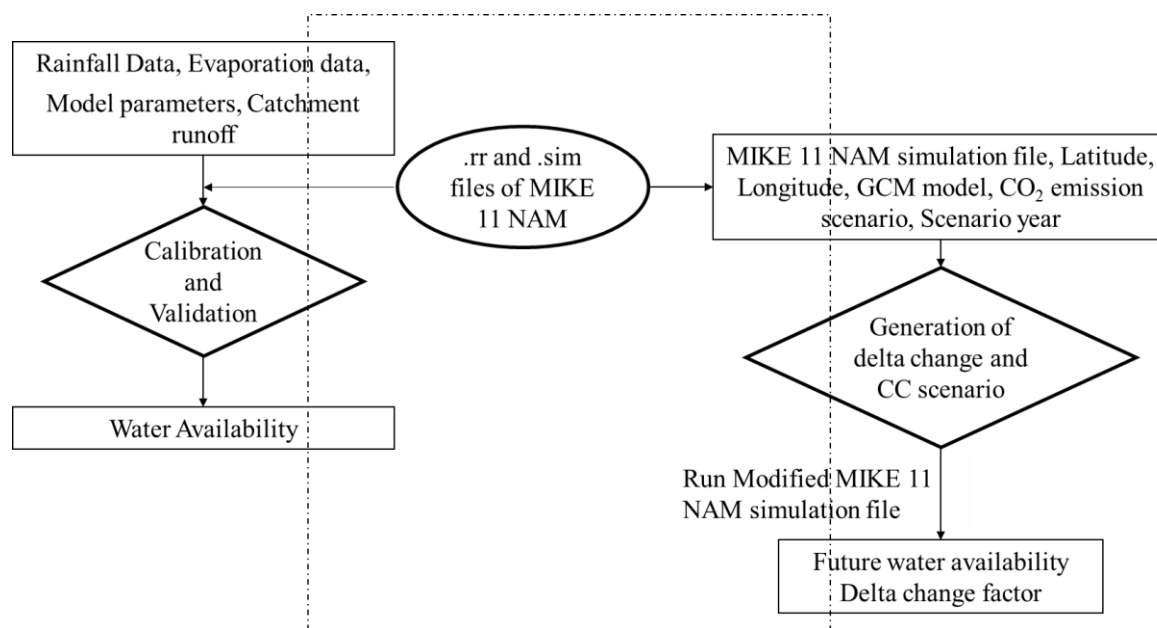


**Figure 3.15 Flowchart of SWAB-CRYB model (Gorantiwar, 1995 Gorantiwar and Smout, 2005 and Kadam, 2014)**

### 3.9 Effect of climate change on water availability

MIKE Zero climate change functionality tool makes it possible to generate climate change scenarios. The functionality is based on the work reported by the Intergovernmental Panel for Climate Change (IPCC) in the Fourth Assessment Report (AR4) and more recent research results on global sea level rise. The climate change projections are taken directly from the IPCC work and other references.

MIKE ZERO Climate Change Module was used to study the impact of climate change on runoff generated by MIKE 11 NAM model. Simulation file of MIKE 11 NAM model which includes all the dataset viz. rainfall, evaporation, model parameters etc. given for estimation of runoff is the main input given to MIKE Zero Climate Change tool for studying the effect of climate change on runoff and thereof water availability in future. Figure 3.16 representing the procedure used for assessing water availability using MIKE 11 NAM and MIKE Zero Climate Change tool.



**Figure 3.16 Procedure used for assessing effect of climate change on water availability using MIKE 11 NAM and MIKE Zero Climate Change tool**

The details of the MIKE Zero Climate Change tool used for assessment of water availability in year 2020's, 2050's and 2080's for the different catchments of Ghod complex viz. Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod are discussed in this section.

#### 3.9.1 Projections of climate variables

Projections of climate variables are constructed based on the delta change factor method. The delta change factors indicate how much a certain variable (e.g. precipitation) will change over time compared to a baseline (reference) period. The MIKE by DHI climate change scenario tool modifies time series of precipitation, temperature and potential evapotranspiration according to the geographic

location and the projection year. The change factors are derived from the climate model projections for various emission scenarios.

### 3.9.2 Global circulation model projections

The work reported in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (Meehl *et al.*, 2007) includes results of a number of so called Global Circulation Models (GCM). Some of the outcomes of the GCMs are predicted future changes for air temperature and precipitation based on a number of emission scenarios.

GCM results reported by IPCC are air temperature and precipitation as well as air temperature and precipitation anomalies that are defined as deviations from the reference values taken as the average over the period 1961-1990. The anomaly predictions are in the form of absolute changes. The data are spatially and temporally varied. The former is covered through the use of gridded values whereas the latter is represented by an average value per month.

Further, the data are a function of the projection year. The data are given as average values for a number of 20-year time spans. The time spans are: 2011-2030, 2046-2065, 2080-2099 and 2180-2199.

Thus, a data set (precipitation, air temperature and anomalies) consists of up to four sets (different projection years) of 12 monthly values per grid point per emission scenario.

#### 3.9.2.1 Emission scenarios

The IPCC has defined a number of emission scenarios that have been used as input to the GCMs. Results of the three most common scenarios SRA1B, SRA2 and SRB1 have been included in the MIKE by DHI software.

**SRA1B:** A future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and rapid introduction of new and more efficient technologies, with the development balanced across energy sources.

**SRA2:** A very heterogeneous world with continuously increasing global population and regionally oriented economic growth that is more fragmented and slower than in other story-lines.

**SRB1:** A convergent world with the same global population as in the SRA1B storyline but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies.

#### 3.9.2.2 Available GCMs and emission scenarios

There are about 55 combinations of GCM and CO<sub>2</sub> emission scenarios. Therefore it was difficult to identify the appropriate combination for the study area. To select the proper GCM model and CO<sub>2</sub>

emission scenarios, all 55 climate change (CC) scenarios were validated over base period of simulation of MIKE 11 NAM model for all the seven sub catchment of Ghod complex. After statistical evaluation based on Nash Sutcliff Efficiency Index and Correlation Coefficient, three best scenarios were selected for the climate change study. The summary of available GCMs, and emission scenarios in MIKE model are presented in Table 3.4.

**Table 3.4 Summary of available GCMs and emission scenario in MIKE model**

Model (GCM)	Acronym	SRA1B	SRA2	SRB1	Agency	Country
BCCR:BCM2	BCM2	✓	✓	✓	Bjerknes Centre for Climate Research (BCCR)	Norway
CCCMA:CGCM 3_1-T47	CGMR	✓			Canadian Centre for Climate Modelling & Analysis	Canada
CCCMA:CGCM 3_1-T63	CGHR	✓		✓	-	-
CNRM:CM3	CNCM3	✓	✓	✓	Centre National de Recherches Météorologiques	France
CONS:ECHO-G	ECHO-G	✓	✓		Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group.	Germany / Korea
CSIRO:MK3	CSMK3	✓	✓	✓	CSIRO Atmospheric Research	Australia
GFDL:CM2	GFCM20	✓	✓	✓	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory	USA
GFDL:CM2_1	GFCM21	✓	✓	✓	-	-
INM:CM3	INCM3	✓	✓	✓	Institute for Numerical Mathematics	Russia
IPSL:CM4	IPCM4	✓	✓	✓	Institut Pierre Simon Laplace	France
LASG:FGOALS-G1_0	FGOALS	✓		✓	-	-
MPIM:ECHAM5	MPEH5	✓	✓	✓	-	-
MRI:CGCM2_3_2	MRCGCM	✓	✓	✓	Meteorological Research Institute	Japan
NASA:GISS-AOM	GIAOM	✓		✓	Goddard Institute for Space Studies (GISS), NASA	USA
NASA:GISS-EH	GIEH	✓			Goddard Institute for Space Studies (GISS), NASA	USA
NASA:GISS-ER	GIER	✓	✓	✓	Goddard Institute for Space Studies (GISS), NASA	USA
NCAR:PCM	NCPCM	✓	✓		-	-
NIES:MIROC3_2-HI	MIHR	✓		✓	-	JAPAN
NIES:MIROC3_2-MED	MIMR	✓	✓	✓	-	JAPAN
UKMO:HADCM3	HADCM3	✓	✓	✓	Hadley Centre for Climate Prediction and Research / Met Office	UK
UKMO:HADGEM1	HADGEM	✓	✓		Hadley Centre for Climate Prediction and Research / Met Office	UK
NCAR:CCSM3	NCCCSM	✓	✓	✓	-	-

As mentioned above, the climate variables that were taken from the GCM projections are air temperature, evapotranspiration and precipitation.

### 3.9.3 Air temperature

The air temperature anomalies are given as gridded delta change values, i.e. the values represent the absolute deviations from the reference values. In the MIKE by DHI software the temperature delta change values are taken at any geo-referenced position represented by a latitude and longitude coordinate set. To achieve this bilinear interpolation is carried out from the gridded values to the specific location. Further, to predict values for any future year (also for years not covered by the 20-year time spans) the data is interpolated linearly between the years.

### 3.9.4 Precipitation

Precipitation amounts may vary drastically within a modelling area. This variation is on a sub-scale that is not reflected in the coarse grid used by the GCMs. To compensate for the sub-scale variation, the delta change values for precipitation have been converted to relative changes within each of the grid cells using equation 3.22. This is done using the absolute change  $\Delta$ precipitation and the absolute precipitation for the future precipitation scenario, i.e.

$$\Delta\text{precipitation}_{\text{relative}} = \frac{\text{precipitation}_{\text{scenario}}}{\text{precipitation}_{\text{scenario}} - \Delta\text{precipitation}} \quad (3.22)$$

If the reference precipitation ( $\text{precipitation}_{\text{scenario}} - \Delta\text{precipitation}$ ) is equal to zero, a relative change is not sensible and then  $\Delta$  precipitation<sub>relative</sub> is set equal to 1. Further, if the reference precipitation is very small, the relative change may become very (unrealistically) large and hence an upper limit on the relative change of 5 is introduced.

### 3.9.5 Potential evapotranspiration

A simple temperature-based method is used to estimate changes in potential evapotranspiration. Potential evapotranspiration (m/s) is calculated using equation 3.23 proposed by Kay and Davies (2008).

$$\text{PE}_T = \begin{cases} \frac{R_e(T + 5)}{\lambda\rho_w 100} & \text{if } (T + 5) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.23)$$

Where

- $\lambda$  = latent heat flux ( $2.45 \cdot 10^6$  J/kg)
- $\rho_w$  = density of water ( $1000$  kg/m<sup>3</sup>)
- $R_e$  = extraterrestrial radiation ( $\text{J/m}^2/\text{s}^1$ )
- $T$  = mean daily air temperature ( $^{\circ}\text{C}$ )

The reference potential evapotranspiration is calculated using the reference temperature. The change in potential evapotranspiration is calculated from the change in temperature using equation 3.24

$$\Delta PE_T = \left\{ \frac{R_e}{\lambda \rho_w 100} \Delta T \right\} \quad (3.24)$$

The relative change is then found equation 3.25

$$PE_{T\text{relative}} = \left\{ \begin{array}{l} \frac{PE_{T\text{scenario}}}{PE_{T\text{scenario}} - \Delta PE_T} \text{ (if } T_{\text{scenario}} - \Delta T + 5 > 0 \text{)} \\ 1 \text{ otherwise} \end{array} \right\} \quad (3.25)$$

Which is equivalent to

$$PE_{T\text{relative}} = \left\{ \begin{array}{l} \frac{\max(T_{\text{scenario}} + 5, 0)}{T_{\text{scenario}} - \Delta T} \text{ (if } T_{\text{scenario}} - \Delta T + 5 > 0 \text{)} \\ 1 \text{ otherwise} \end{array} \right\} \quad (3.26)$$

The relative potential evapotranspiration through this formula is not allowed to become negative. Further, as for relative precipitation changes, an upper limit on the relative change of 5 is introduced.

### 3.9.6 Modifying times series of climate variables

The MIKE by DHI climate change tool will make a copy of an existing setup and modify the time series of climate data according to a given future year, selected GCMs and emission scenario. These time series are then used instead of the original climate time series in the climate change scenario model setup to assess the possible impact of climate change. The time series modification works as follows:

A set of 12 (one for each month) change factors are determined based on latitude and longitude, selected GCMs, projection year and emission scenario.

If the time series is air temperature, the change factors will be added to the individual values within the time series, i.e. the January change factor (in °C) will be added to all values in the time series occurring in January etc. If the time series is precipitation or potential evapotranspiration, the change factors will be multiplied with the individual values within the time series, i.e. the January change factor (dimensionless) will be multiplied with all values in the time series occurring in January etc.

The climate change scenarios were generated for year of 2020's, 2050's and 2080's. Water availability was accessed for the three scenario for 2020's, 2050's and 2080's for all the sub catchments of Ghod complex.

### 3.10 Effect of climate change on water allocation pattern

The effect of climate change on water allocation pattern is studied for the Ghod command area. The procedure for obtaining future water availability is discussed in section 3.9. Under this section futuristically obtained series of runoff, rainfall and evaporation are used to estimate the future

irrigation water demand. The irrigation water demand-deficit for multi-crop, major crops and sugarcane only cropping pattern for the year of 2020's, 2050's and 2080's for Ghod command area under variable area condition are studied. The detail procedure of water demand-deficit assessment and water allocation using MIKE-HYDRO Basin model is discussed in section 3.5.

In the MIKE-HYDRO Basin model under the "Climate model" option, choice is there for selection of model between "Rainfall only" and "FAO 56" for the estimation of irrigation water demand. Here for this study "Rainfall only" model is used which is the simplest climate model, only requiring a rainfall time series and a reference ET time series as input.

Reference ET for future year is calculated using pan evaporation method given by FAO using equation 3.27.

$$ET_O = K_P E_{pan} \quad (3.27)$$

Where,

$ET_O$  = reference evapotranspiration (mm/day)

$K_P$  = pan coefficient,

$E_{pan}$  = pan evaporation (mm/day)

Future  $ET_O$  is calculated using this method and "Rainfall only" model is used for obtaining future irrigation water demand for 2020's, 2050's and 2080's for Ghod command area. Further for the water availability of 2020's, 2050's and 2080's, irrigation water demand-deficit is estimated using MIKE-HYDRO Basin model.

### 3.11 Statistical evaluation

The model evaluation procedure includes calibration and validation. Precise calibration of the hydrological model is essential in the study conditions for accurate simulation results (Pieri *et al.*, 2007). Accuracy is the ability of a measurement to match the actual value of the quantity being measured that is the degree of closeness of measurements of a quantity to that quantities actual value. Accuracy of the model is examined on the basis of statistical evaluation. In order to review the performance of MIKE 11 NAM model Correlation coefficient ( $r$ ) and Nash and Sutcliffe Efficiency Index (EI) statistical criteria were used.

#### 3.11.1 Nash–Sutcliffe coefficient (EI)

The reliability of the MIKE11 NAM was evaluated based on the Efficiency Index (EI) as described by Nash and Sutcliffe (1970). There were several related studies available for model performance evaluation such as by Aitken (1973) and Fleming (1975). The procedure by Nash and Sutcliffe (1970) had been widely used for the detection of systematic errors with respect to long term simulation. The

EI was developed to evaluate the percentage of accuracy or goodness of the simulated values with respect to their observed values. Goodness-of-fit criterion recommended by ASCE Task Committee (1993) is Nash–Sutcliffe coefficient (EI) (Nash and Sutcliffe, 1970) given by equation 3.28.

$$\text{Nash and Sutcliffe Efficiency Index (EI)} = \frac{\sum_{i=1}^n (q_o - \bar{q})^2 - \sum_{i=1}^n (q_o - q_s)^2}{\sum_{i=1}^n (q_o - \bar{q})^2} \quad (3.28)$$

Where,

$q_o$  = Observed runoff

$\bar{q}$  = the mean of observed data

$q_s$  = Simulated runoff

The EI values can vary from  $-\infty$  to 1, with 1 indicating a perfect fit. Table 3.5 shows the performance ratings for Nash–Sutcliffe coefficient.

**Table 3.5 Performance ratings for EI statistics (Moriassi *et al.*, 2007)**

Performance rating	Nash–Sutcliffe coefficient (EI)
Very good	$0.75 < EI \leq 1.00$
Good	$0.65 < EI \leq 0.75$
Satisfactory	$0.50 < EI \leq 0.65$
Unsatisfactory	$EI \leq 0.50$

### 3.11.2 Coefficient of determination ( $R^2$ )

Coefficient of determination ( $R^2$ ) describes the degree of co-linearity between observed and simulated values. Coefficient of determination is a method to evaluate the reliability of the model and describes the proportion of the variance in observed data explained by the model.  $R^2$  ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Santhi *et al.*, 2001).

### 3.11.3 Correlation coefficient (r)

The Pearson product-moment correlation coefficient, also known as r, R, or Pearson's r, is a measure of the strength and direction of the linear relationship between two variables that is defined as the covariance of the variables divided by the product of their standard deviations. The range of r lies between 0 and 1 which describes how much of the observed variable is explained by the simulated variable in Table 3.6. A value of zero means no correlation at all whereas a value of 1 means the dispersion of simulated variable is equal to that of the observed variable. It is given by following equation 3.29,

$$\text{Correlation coefficient (r)} = \frac{\sum_{i=1}^n (q_s - \bar{q})(q_o - \bar{q})}{\sqrt{\sum_{i=1}^n (q_s - \bar{q})^2 (q_o - \bar{q})^2}} \quad (3.29)$$

Where,

$q_o$  = observed runoff (MCM)

$q_s$  = simulated runoff (MCM)

$\bar{q}$  = mean of observed runoff (MCM)

**Table 3.6 Evaluation criteria used for the assessment of the quality of calibration**

Correlation coefficient (r)	Performance rating
$0.20 > r$	Non acceptable agreement
$0.50 > r > 0.20$	Poor agreement
$0.75 > r > 0.50$	Acceptable agreement
$0.90 > r > 0.75$	Good agreement
$0.95 > r > 0.90$	Strong agreement
$0.99 > r > 0.95$	Excellent agreement
$r > 0.99$	Perfect agreement

The objectives of this study were the assessment of historical and futuristic water availability, water allocation, comparison of crop yield and effect of climate change on water availability and water allocation. In this chapter, different models such as, MIKE 11 NAM, MIKE Hydro Basin, SWAB-CRYB, ANN, MIKE Zero climate change etc. used to achieve these objective are explained in detail with the inputs used, methodology adopted, calibration, validation, and different scenarios. The findings obtained using these models are explained thoroughly in the next chapter of ‘Result and Discussion’.

## 4. RESULTS AND DISCUSSION

The present study was carried out with an aim to evaluate different water availability and water allocation scenarios under climate change situations using MIKE Models. The study was conducted to investigate the applicability of MIKE Models for simulation of water availability in Ghod complex sub catchment of Upper-Bhima basin using MIKE 11 RR model for historical and synthetically generated series of rainfall. The purpose of the study was to simulate water demand in Ghod complex sub catchment for different cropping patterns using MIKE HYDRO BASIN model for historical and synthetically generated series of climatological variables influencing evapotranspiration as well as to compare the SWAB-CRYB model with MIKE HYDRO BASIN model for estimation of yield of different crops and thereby evaluate the effect of different water allocation scenarios for different water availability and demand and to study the influence of climate variability and climate change on water allocation pattern in Ghod complex sub catchment. For completion of all the objectives, different MIKE models *viz.* MIKE 11 NAM, MIKE HYDRO Basin, MIKE Zero climate change module were used.

MIKE 11 NAM a conceptual, lumped rainfall- runoff model was used to assess the water availability in the Ghod complex sub catchments Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon. Calibrated and validated model was used to forecast the water availability. ANN 4-10-1 model was used to forecast rainfall of different stations in the study area and used as input for the MIKE 11 NAM model.

MIKE HYDRO Basin model was used for routing of specific runoff of Yedgaon and Ghod catchments and routed runoff is used as observed runoff for calibration and validation of the Yedgaon and Ghod catchments. MIKE HYDRO Basin model was also used to estimate irrigation water demand for the Ghod command area using three different cropping patterns, *viz.* multi-crop, major- crop and sugarcane only cropping patterns. Water allocation scenarios were generated to study water allocation for the three different cropping patterns under increasing irrigation water demand conditions. Forecasted water allocation scenarios were estimated by using forecasted water availability. MIKE Zero climate change module was used to estimate the future water availability and effect of climate change on water allocation. MIKE HYDRO Basin model and SWAB-CRYB models were compared for the estimation of crop yield.

The methodology used for this study by using different MIKE models is discussed in precious chapter and the results obtained for the water availability and water allocation under climate change situations are presented and discussed in this chapter.

## **4.1 Simulation of water availability**

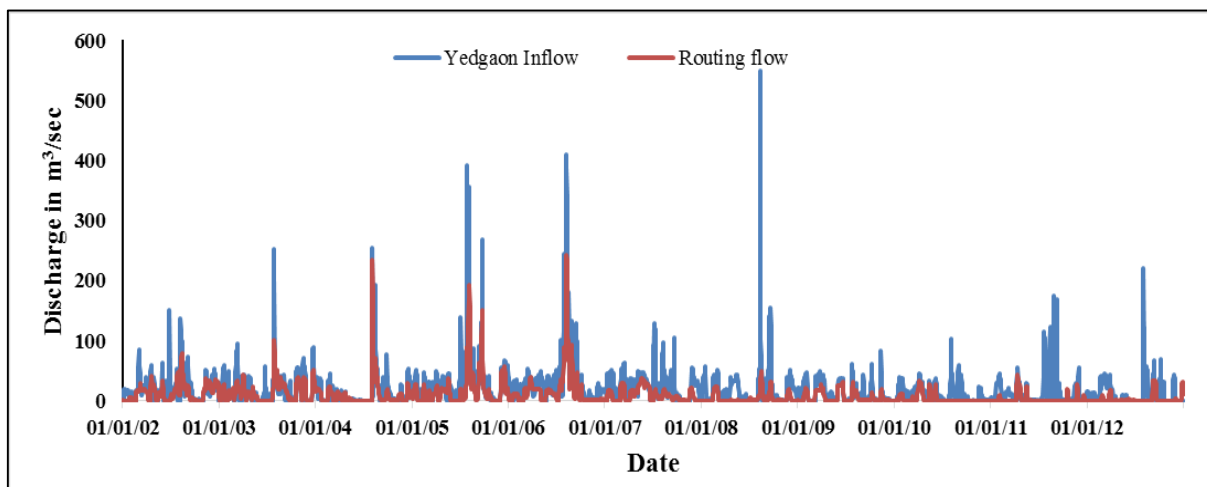
Water availability assessment has vital importance in hydrological studies. The first objective of study was to estimate water availability for historical and synthetically generated series of rainfall using MIKE 11 NAM rainfall runoff model.

In present study MIKE 11 NAM rainfall-runoff model was used to estimate the water availability in Ghod complex sub catchments. Ghod complex sub catchments includes mainly seven catchments, Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon. Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga and Wadaj are separate individual catchments situated at upstream of the study area (Figure 3.1). Section 3.3 describes the procedure that was used for calibration of MIKE 11 NAM model for individual separate catchments. Yedgaon and Ghod are intermediate catchments. Therefore, routing procedure using MIKE HYDRO Basin model described in the section 3.3.4 was used to estimate the intermediate runoff. Section 3.3.6 describes the procedure used for validation of MIKE 11 NAM model. In this section the results of water availability in Ghod complex sub catchment for historical and forecasted series of rainfall are presented.

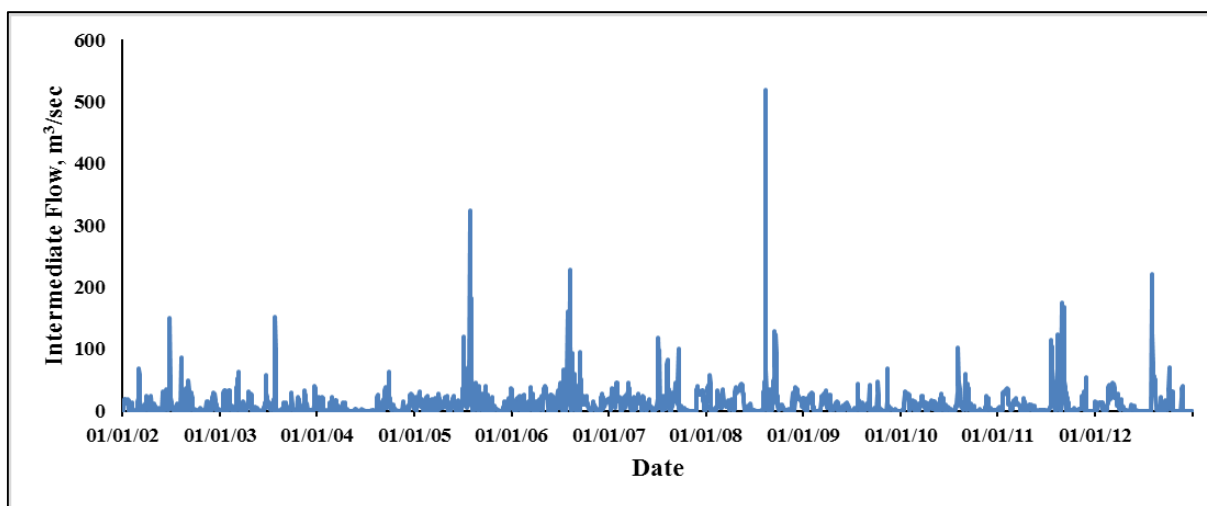
### **4.1.1 Routing flow of intermediate catchments**

The runoff of intermediate catchments was estimated by using linear reservoir routing method in MIKE HYDRO Basin model. The routing model for Yedgaon and Ghod was set separately in MIKE HYDRO Basin model. The catchment wise obtained results are presented here.

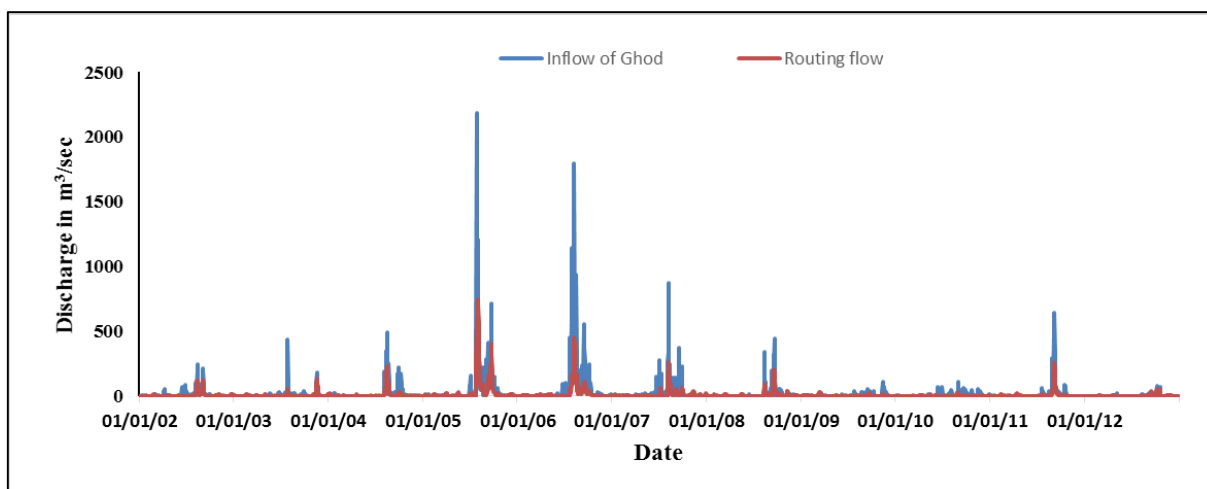
Linear reservoir routing method was used for routing Yedgaon and Ghod reservoir. The delay parameters/ travel time of 48 h, 25 h and 35 h were fixed for Chilewadi, Pimpalgaonjoga and Manikdoh reservoir respectively in Yedgaon reservoir routing. The delay parameters/ travel time of 50 h, 70 h and 25 h were fixed for Dimbhe, Wadaj and Yedgaon reservoir respectively in Ghod reservoir routing. The intermediate runoff timeseries were used as the observed runoff timeseries of the Yedgaon and Ghod intermediate catchment for calibration in MIKE 11 NAM model. The inflow and routed timeseries plot for year 2001 to 2012 are given in Figure 4.1 and 4.3. The intermediate runoff obtained are shown in the Figure 4.2 and 4.4 for Yedgaon and Ghod catchments, respectively. The difference between inflow of reservoir and routed runoff for Yedgaon and Ghod reservoir was observed and presented graphically in Figure 4.1 and 4.3. This difference obtained may be due to loss of water by infiltration and evaporation. Figure 4.2 and 4.4 shows the graph of intermediate flow which is the difference between inflow of reservoir and routed flow for both of reservoir. This intermediate flow of catchments was used as observed runoff for calibration of MIKE 11 NAM model and MIKE HYDRO Basin model.



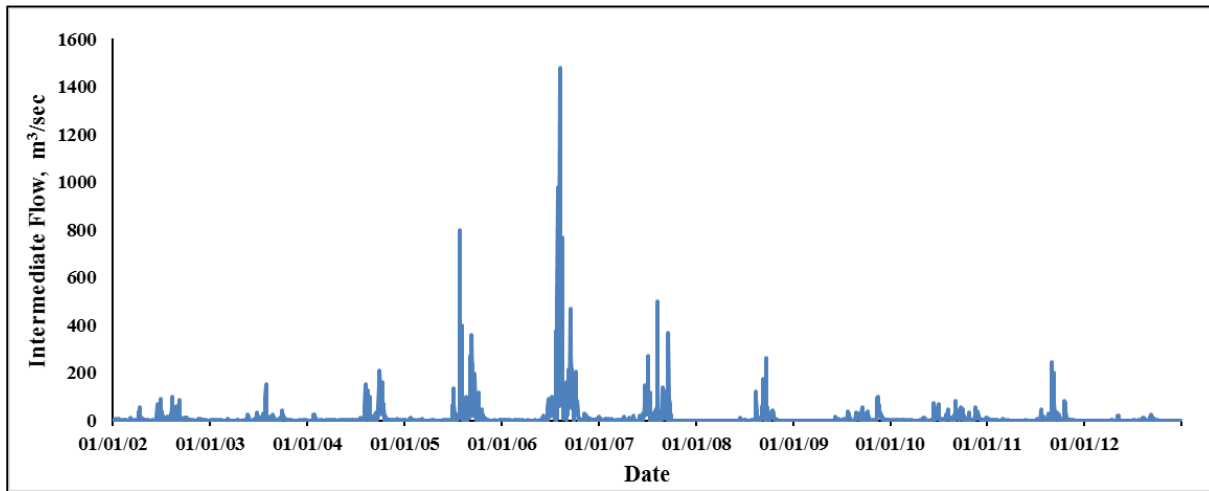
**Figure 4.1** Plot showing graph of inflow and routing flow obtained from routing for Yedgaon catchment



**Figure 4.2** Plot showing graph of intermediate flow obtained from routing for Yedgaon catchment



**Figure 4.3** Plot showing graph of inflow and routing flow obtained from routing for Ghod catchment



**Figure 4.4** Plot showing graph of intermediate flow obtained from routing for Ghod catchment

#### 4.1.2 Calibration of MIKE 11 NAM model

The first stage of the application of the NAM model for rainfall runoff estimation is the calibration process to determine the optimum values of the model parameters. The second stage is the discharge simulation and the prediction of water availability based on the estimated model parameters during the calibration process. The MIKE 11 NAM model was setup by applying the data of daily rainfall time series, evaporation time series, and observed runoff time series for the period from 2002 to 2009 in the seven catchments of Ghod complex. The procedure adopted for the calibration of MIKE 11 NAM model is described in Sections 3.3. The model was first run to simulate the runoff by using the auto calibration mode of MIKE 11 NAM and model parameters were fixed. Model was then calibrated by conducting trials by modifying the model parameters to reduce the error between observed runoff data and simulated runoff data. The model was refined to obtain the best match between observed and simulated runoff. The model parameters were adjusted until a satisfactory fit between simulated runoff contributions (overland flow, inter flow, and base flow) and observed runoff was attained. The values of all the nine parameters obtained during the model calibration and the range of these parameters are shown in Table 4.1.

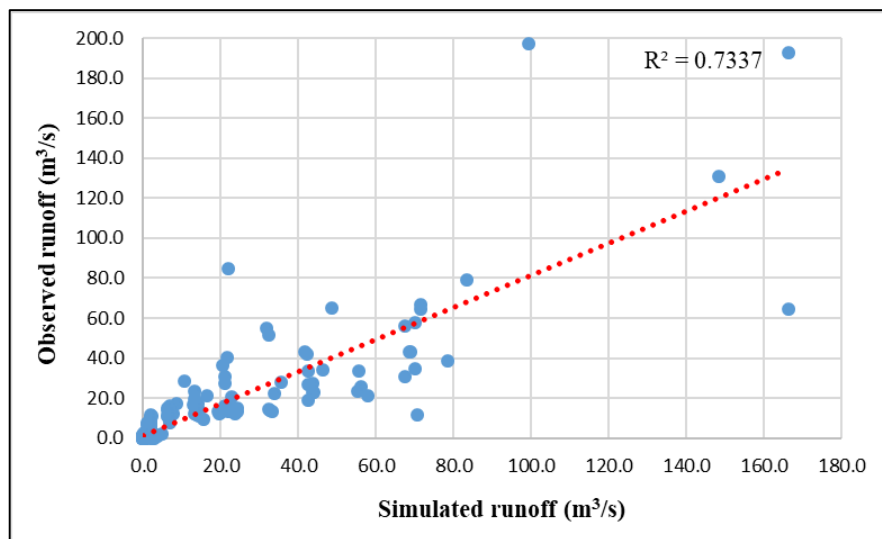
**Table 4.1** Selected model calibration parameters for MIKE 11 NAM model

Parameters	Range	Chilewadi	Dimbhe	Ghod	Manikdoh	Pimpalgaon Joga	Wadaj	Yedgaon
$U_{\max}$ (mm)	5-35	15	15	20	12	14	15	15
$L_{\max}$ (mm)	50-350	160	230	285	130	150	200	200
CQOF	0-1	0.85	0.70	0.80	0.85	0.85	0.80	0.65
$CK_{IF}$ (h)	500-1000	650	600	700	600	650	800	500
$CK_1$ (h)	3-72	15	13	10	18	23	15	18
$CK_2$ (h)	3-72	50	30	50	45	55	40	50

<b>TOF</b>	0-0.9	0.75	0.85	0.30	0.82	0.80	0.80	0.60
<b>TIF</b>	0-0.9	0.65	0.70	0.50	0.70	0.70	0.85	0.70
<b>TG</b>	0-0.9	0.20	0.60	0.70	0.65	0.60	0.70	0.80
<b>CK<sub>BF</sub> (h)</b>	500-5000	1500	2800	3500	2800	1645	2000	3200

#### 4.1.2.1 Calibration of MIKE 11 NAM model for Chilewadi catchment

MIKE 11 NAM model was set for Chilewadi catchment using rainfall data of Pimpalgaonjoga and Pimpalwandi rain gauge stations and evaporation data of Pimpalwandi weather stations for the year 2002-2009. The observed runoff was obtained from inflow data of water account sheets of Chilewadi catchment. After many trial and errors by manual calibration the optimum parameters were obtained for Chilewadi catchment are listed in Table 4.1. The graphs of simulated and observed runoff are shown in Figure 4.6. It was observed that the shapes of the hydrograph of observed and simulated matching well for almost all the runoff events. These graphs indicated the good match between the observed and simulated runoff at Chilewadi catchment with  $R^2$  value of 0.66. The graphs of accumulated observed and accumulated simulated runoff were matches well with minimum water balance error of 0.60 %. From the overall analysis it was concluded that the time of beginning and termination of observed and simulated runoff events were matching, whereas the amplification in peak values of runoff events were matching with moderate accuracy. Nash Sutcliff efficiency index of observed and simulated runoff for Chilewadi catchment was found to be 0.66 and correlation coefficient was obtained to be 0.81. Overall, all the numerical measures values of coefficient of determination, water balance error, Nash Sutcliff efficiency index and correlation coefficient were found within permissible limits for Chilewadi catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in Table 4.2.



**Figure 4.5 Observed values vs simulated values of runoff during calibration period of Chilewadi catchment in the year 2006**

The plot of observed values vs simulated values of runoff during calibration period of Chilewadi catchment in the year 2006 is shown in the Figure 4.5, which depicts the values were found close to 1:1 line with  $R^2$  of 0.74. Similarly, observed values vs simulated values of runoff could be shown on 1:1-line graph for all the catchments in the study area.

#### **4.1.2.2 Calibration of MIKE 11 NAM model for Dimbhe catchment**

MIKE 11 NAM model was set for assessing water availability of Dimbhe catchment using rainfall data of Pimpalgaonjoga, Savale rain gauge stations and Grid 8 data ( $18^{\circ}75'$  to  $19^{\circ}N$  latitude and  $74^{\circ}5'$  to  $75^{\circ}0'E$  longitude) and evaporation data of Pimpalgaonjoga weather station for the year 2002 to 2009. After many trial and errors by manual calibration, the optimum parameters were obtained for Dimbhe catchment which are shown in Table 4.1. The graphs of simulated and observed runoff are shown in Figure 4.7. The coefficient of determination ( $R^2$ ) and water balance error were 0.61 and 0.00 %, respectively obtained in graphical evaluation. While the numerical performance measure, Nash Sutcliff efficiency index and correlation coefficient were found to be 0.60 and 0.79, respectively for Dimbhe catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in Table 4.2.

#### **4.1.2.3 Calibration of MIKE 11 NAM model for Manikdoh catchment**

MIKE 11 NAM model was set for assessing water availability of Manikdoh catchment using rainfall data of Pimpalgaonjoga, Aundhe rain gauge stations and Grid 9 data ( $18^{\circ}5'$  to  $18^{\circ}75' N$  latitude and  $74^{\circ}5'$  to  $74^{\circ}75'E$  longitude) and evaporation data of Pimpalgaonjoga weather station for the year 2002 to 2009. After many trial and errors by manual calibration, the optimum parameters were obtained for Manikdoh catchment which are shown in Table 4.1. The graphs of simulated and observed runoff are shown in Figure 4.8. The coefficient of determination ( $R^2$ ) and water balance error were obtained 0.76 and -0.10%, respectively in graphical evaluation. While the numerical performance measure, Nash Sutcliff efficiency index and correlation coefficient were found to be 0.76 and 0.88, respectively for Manikdoh catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in the Table 4.2.

#### **4.1.2.4 Calibration of MIKE 11 NAM model for Pimpalgaonjoga catchment**

MIKE 11 NAM model was set for assessing water availability of Pimpalgaonjoga catchment using rainfall data of Pimpalgaonjoga, Savale rain gauge stations and Grid 9 data ( $18^{\circ}5'$  to  $18^{\circ}75' N$  latitude and  $74^{\circ}5'$  to  $74^{\circ}75'E$  longitude) and evaporation data of Pimpalgaonjoga weather station for the year 2002 to 2009. After many trial and errors by manual calibration the optimum parameters were obtained for Pimpalgaonjoga catchment which are shown in Table 4.1. The graphs of simulated and

observed runoff are shown in Figure 4.9. The coefficient of determination ( $R^2$ ) and water balance error were obtained 0.71 and 0.00%, respectively in graphical evaluation. While the numerical performance measures, Nash Sutcliff efficiency index and correlation coefficient were found to be 0.70 and 0.85 respectively for Pimpalgaonjoga catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in the Table 4.2.

#### **4.1.2.5 Calibration of MIKE 11 NAM model for Wadaj catchment**

MIKE 11 NAM model was set for assessing water availability of Wadaj catchment using rainfall data of Pimpalgaonjoga, Aundhe rain gauge stations and Grid 8 data ( $18^{\circ}75'$  to  $19^{\circ}$ N latitude and  $74^{\circ}5'$  to  $75^{\circ}0'E$  longitude) and evaporation data of Pimpalwandi weather station for the year 2002 to 2009. After many trial and errors by manual calibration the optimum parameters were obtained for Wadaj catchment which are shown in Table 4.1. The graphs of simulated and observed runoff are shown in Figure 4.10. The coefficient of determination ( $R^2$ ) and water balance error were obtained 0.68 and 0.10 %, respectively in graphical evaluation. While the numerical performance measure, Nash Sutcliff efficiency index and correlation coefficient were found to be 0.68 and 0.84, respectively for Wadaj catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in the Table 4.2.

#### **4.1.2.6 Calibration of MIKE 11 NAM model for Yedgaon catchment**

Yedgaon is intermediate catchment comprises spills from reservoirs in the upstream i.e. Chilewadi Pimpalgaonjoga and Manikdoh. The specific runoff for Yedgaon catchment was obtained using linear reservoir routing procedure as illustrated in section 3.3.4. The results obtained using routing procedure were given at section 4.1.1. The intermediate flow obtained after routing procedure was treated as observed runoff for calibration and validation of MIKE 11 NAM model. MIKE 11 NAM model was set for assessing water availability of Yedgaon catchment using rainfall data of Pimpalgaonjoga, Pimpalwandi rain gauge stations and Grid 9 data ( $18^{\circ}5'$  to  $18^{\circ}75'$  N latitude and  $74^{\circ}5'$  to  $74^{\circ}75'E$  longitude) and evaporation data of Pimpalwandi weather station for the year 2002 to 2009. After many trial and errors by manual calibration, the optimum parameters were obtained for Yedgaon catchment which are shown in Table 4.1. The graphs of simulated and observed runoff are shown in Figure 4.11. The coefficient of determination ( $R^2$ ) and water balance error were obtained 0.58 and -0.30%, respectively in graphical evaluation. While the numerical performance measure, Nash Sutcliff efficiency index and correlation coefficient were found to be 0.58 and 0.76, respectively for Yedgaon catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in the Table 4.2.

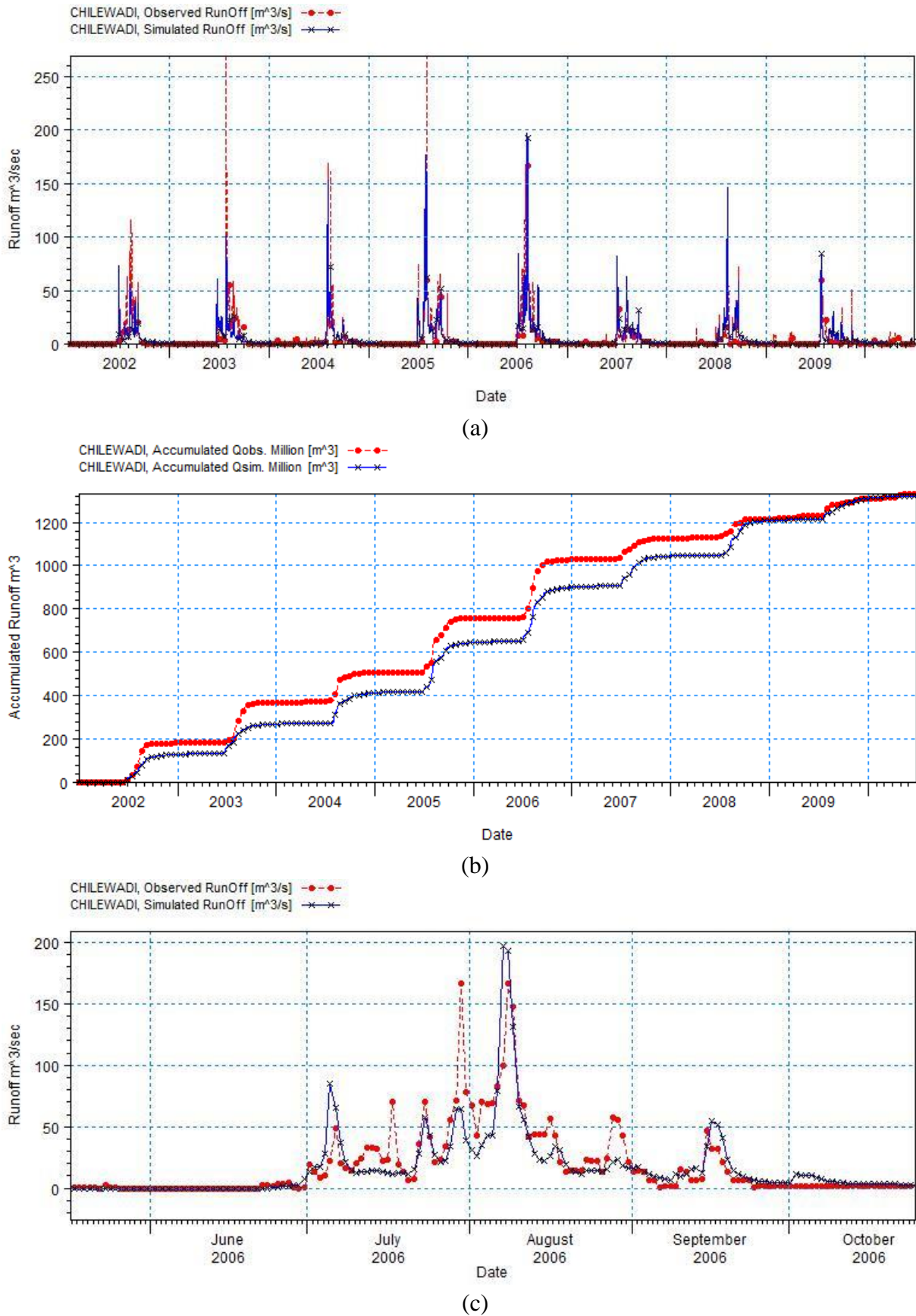
#### 4.1.2.7 Calibration of MIKE 11 NAM model for Ghod catchment

Ghod is intermediate catchment situated at downstream of the study area and comprises spills from three reservoirs in the upstream i.e. Dimbhe, Wadaj and Yedgaon. Therefore, the specific runoff for Ghod catchment was obtained using linear reservoir routing procedure as illustrated in section 3.3.4. The results obtained using routing procedure were given at section 4.1.1. The intermediate flow obtained after routing procedure was treated as observed discharge for calibration and validation of MIKE 11 NAM model. MIKE 11 NAM model was set for assessing water availability of Ghod catchment using rainfall data of Shirur, Pimpalwandi, Kurwandi rain gauge stations, Grid 5 (18°75' to 19° N latitude and 73°75' to 74°E longitude), Grid 6 (18°75' to 19° N latitude and 74° to 74°25' E longitude) and evaporation data of Shirur weather station for the year 2002 to 2009. After many trial and errors by manual calibration, the optimum parameters obtained for Ghod catchment are shown in Table 4.1. The graphs of simulated and observed runoff are shown in Figure 4.12. The coefficient of determination ( $R^2$ ) and water balance error were obtained 0.64 and -3.80 %, respectively in graphical evaluation. While the numerical performance measure, Nash Sutcliff efficiency index and correlation coefficient were found be 0.64 and 0.81, respectively for Ghod catchment. The summary of numerical performance measures for MIKE11 NAM model during calibration period is provided in the Table 4.2.

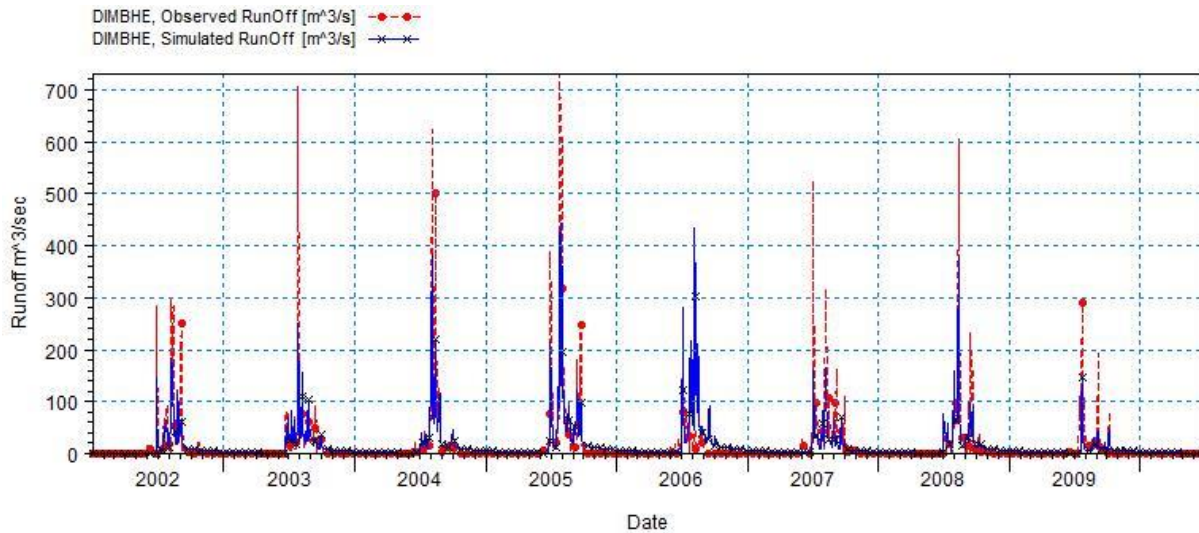
**Table 4.2 Statistical evaluation of MIKE 11 NAM model during calibration**

Catchments	EI	r	$R^2$	WBE (%)
Chilewadi	0.66	0.81	0.66	0.60
Dimbhe	0.60	0.79	0.61	0.00
Manikdoh	0.76	0.88	0.76	-0.10
Pimpalgaonjoga	0.70	0.85	0.71	0.00
Wadaj	0.68	0.84	0.68	0.10
Yedgaon	0.58	0.76	0.58	-0.30
Ghod	0.64	0.81	0.64	-3.80

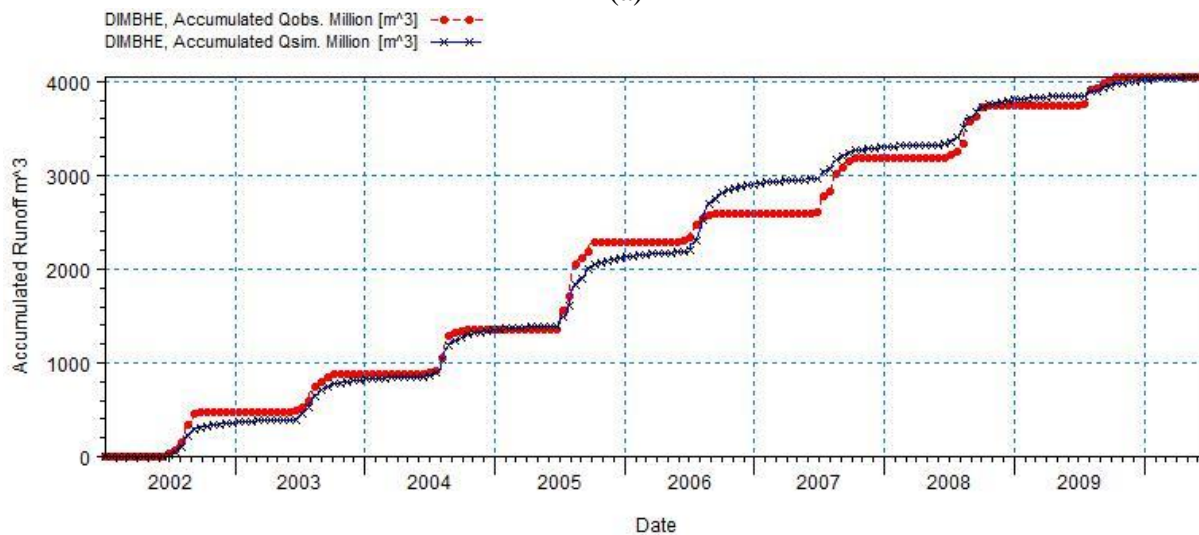
From the overall analysis, it was indicated that, the time of beginning and termination of observed and simulated runoff events were matching with good accuracy, whereas the amplification in peak values of runoff events were matching with moderate accuracy. The graphs of accumulated observed and accumulated simulated flows matched well with minimum water balance error. The numerical performance measures were found in permissible limits for all the sub catchments of Ghod complex study area during calibration period. The performance of MIKE 11 NAM model was found good for Manikdoh catchment followed by Pimpalgaonjoga, Wadaj, Chilewadi, Dimbhe, Ghod and Yedgaon during calibration of model.



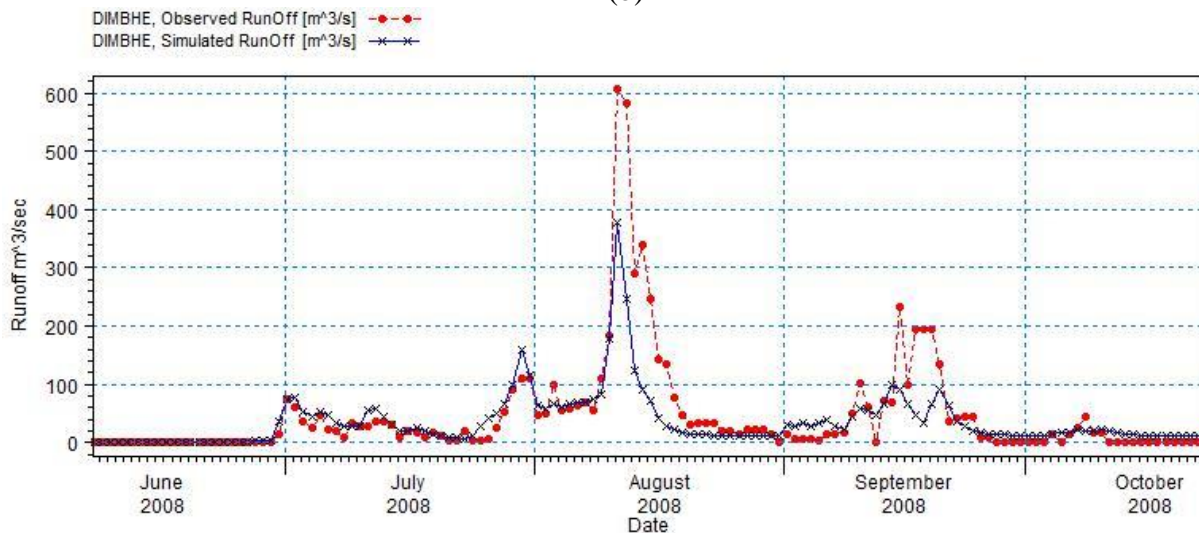
**Figure 4.6** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in the year 2006 (c) during calibration period of MIKE 11 NAM model for Chilewadi catchment



(a)

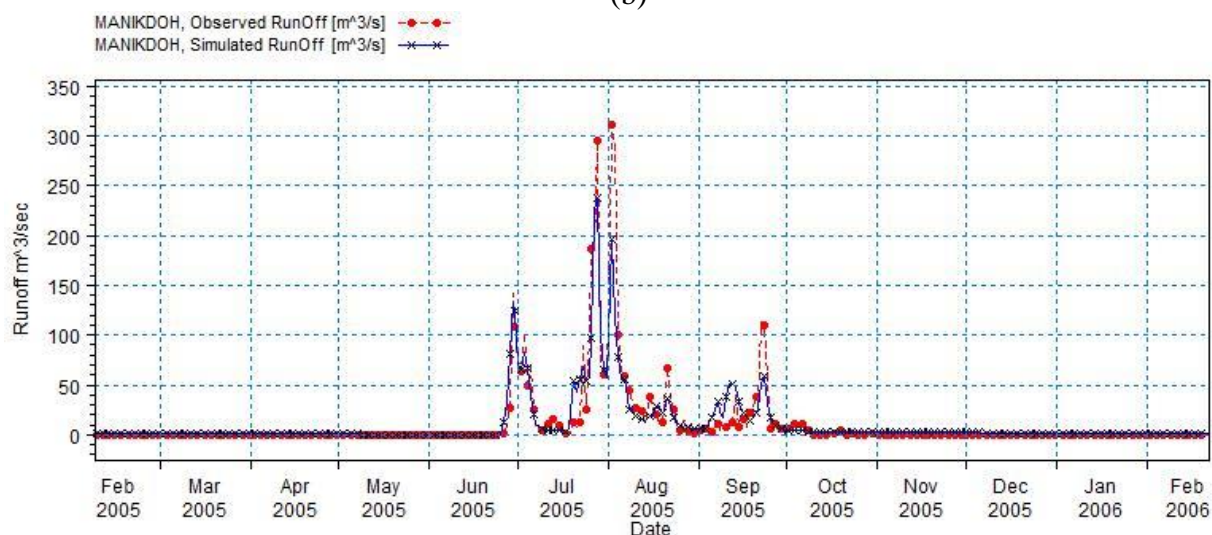
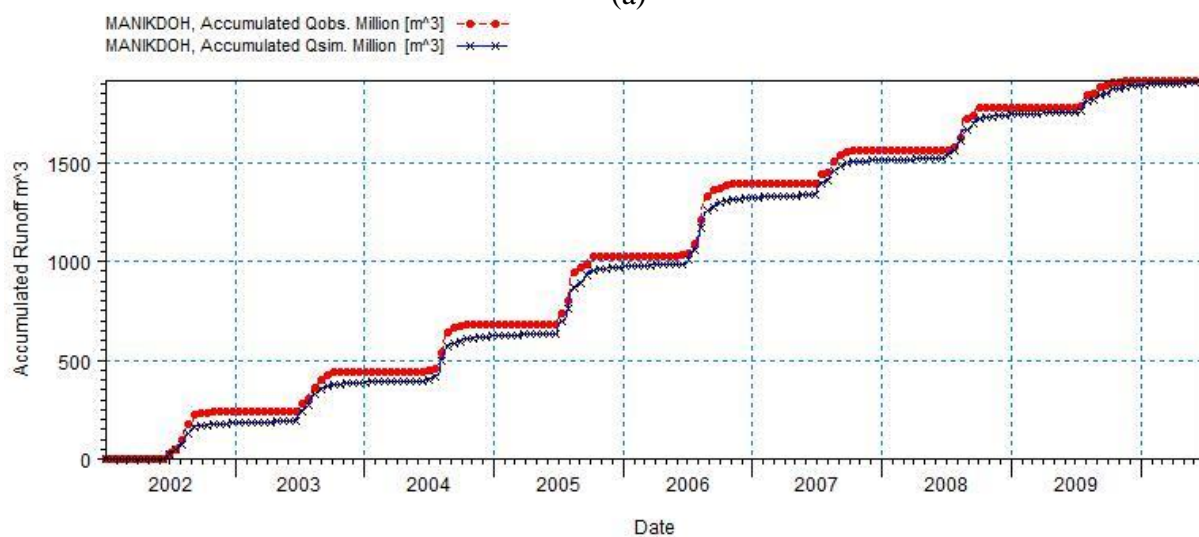
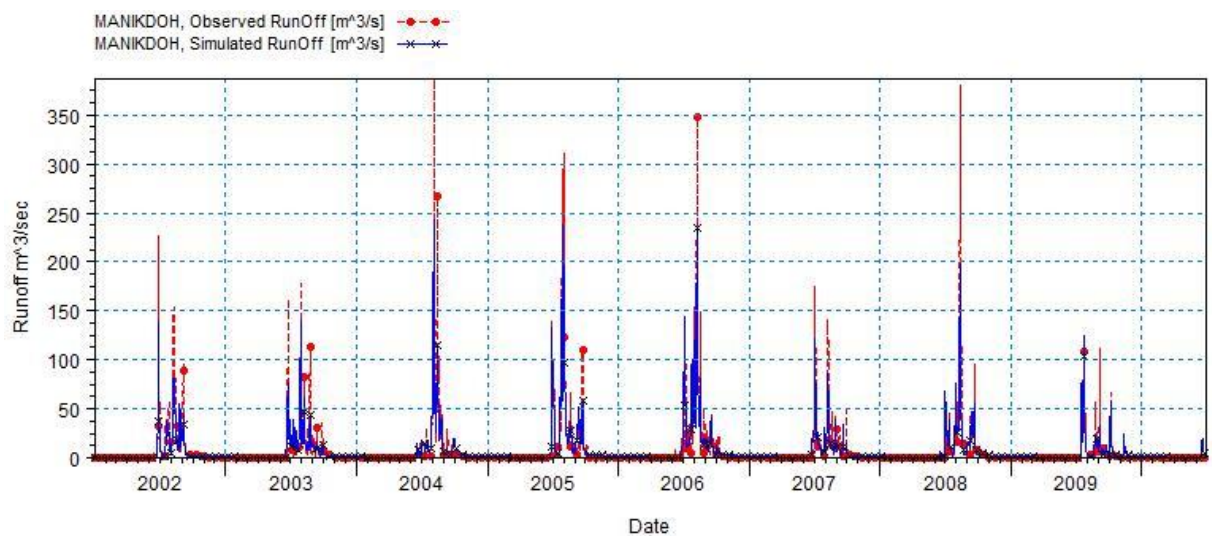


(b)

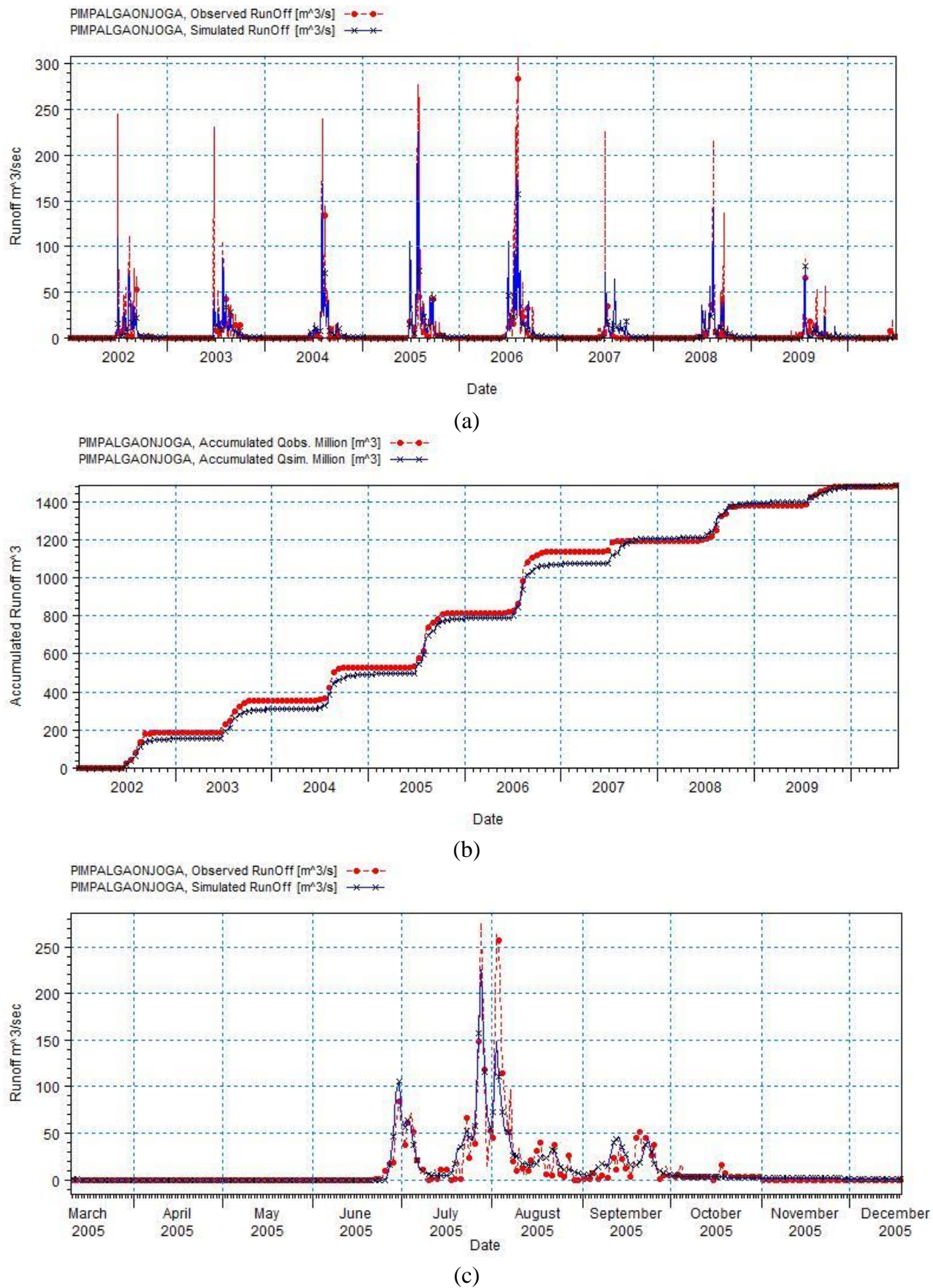


(c)

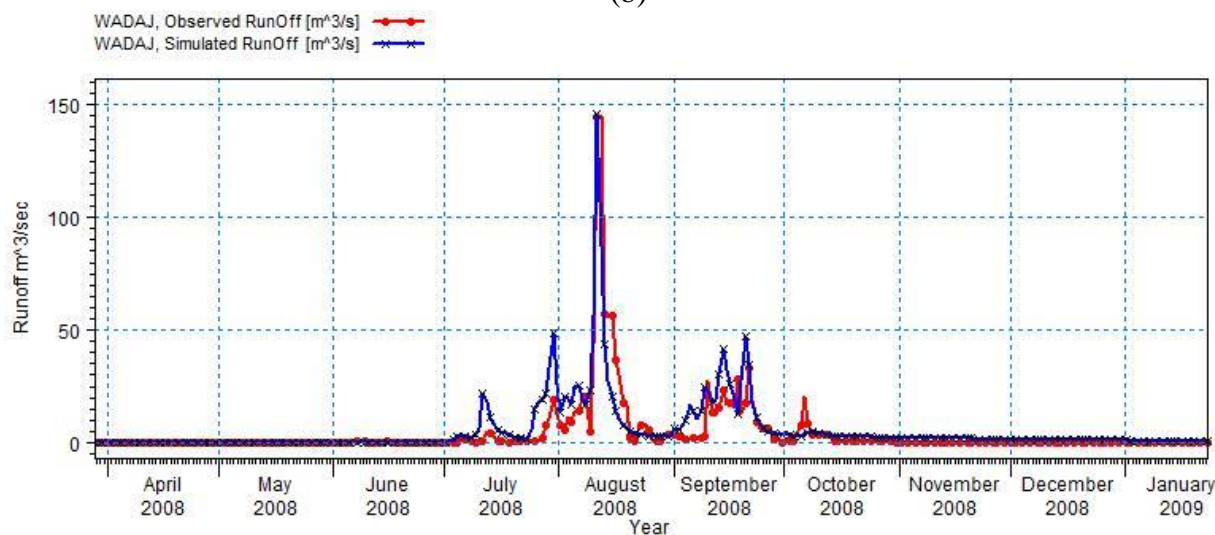
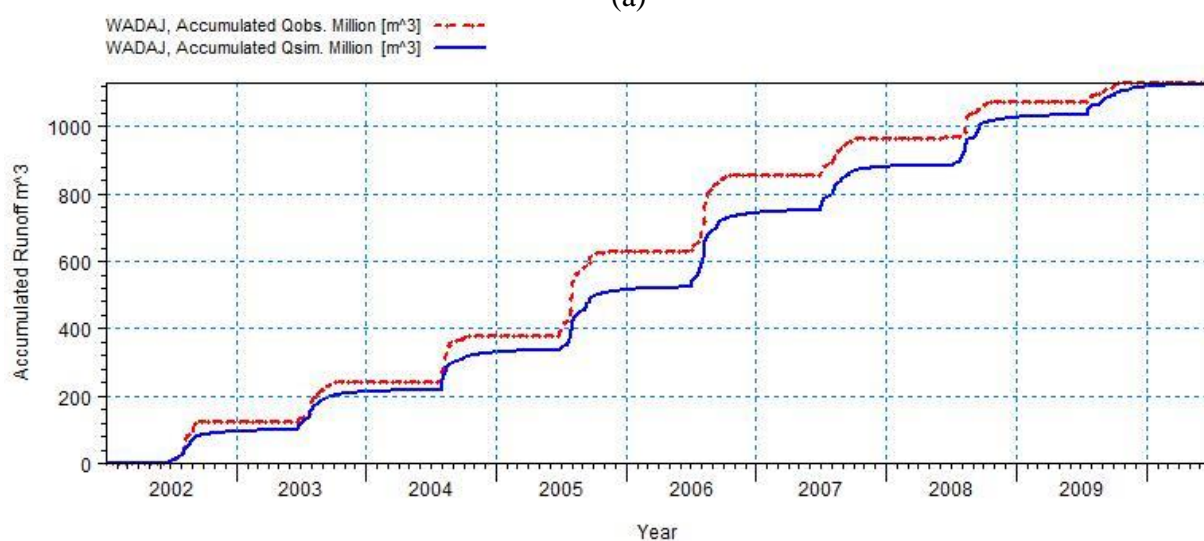
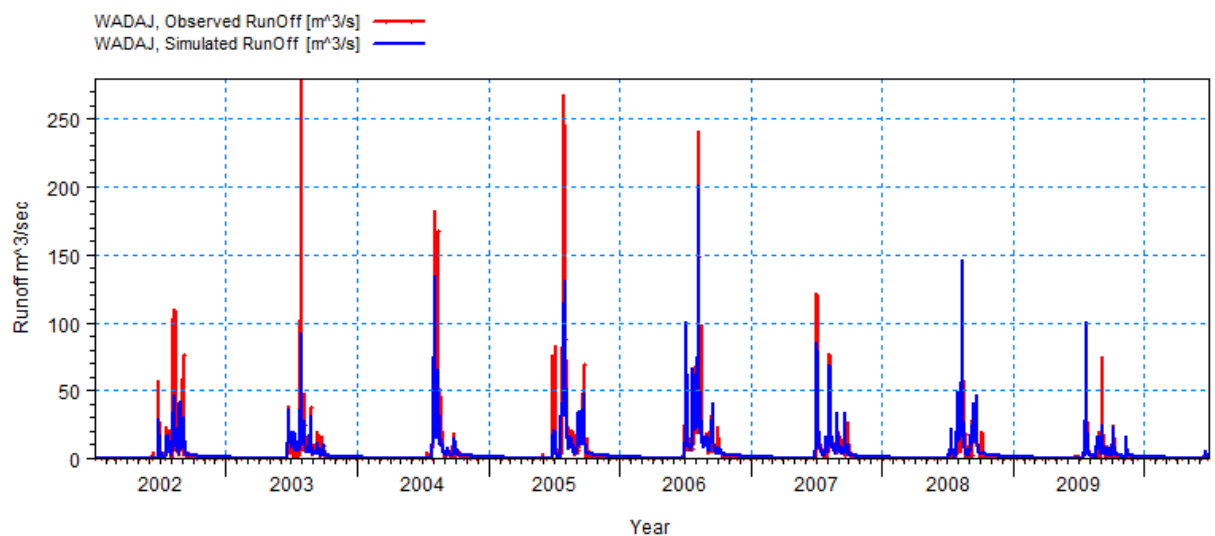
**Figure 4.7** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in the year 2008 (c) during calibration period of MIKE 11 NAM model for Dimbhe catchment



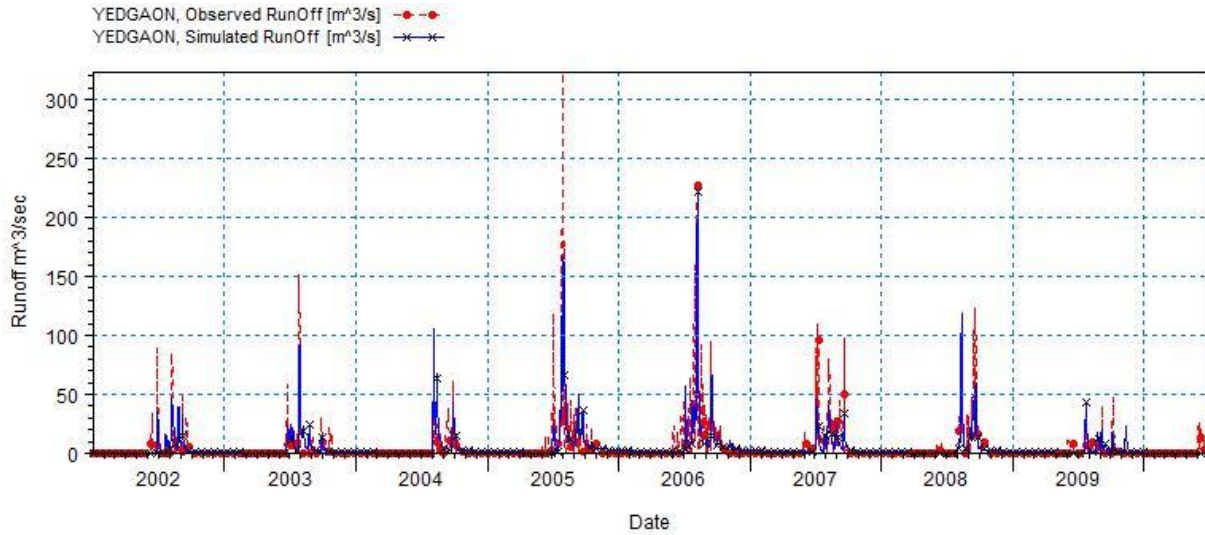
**Figure 4.8** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in year 2006 (c) during calibration period of MIKE 11 NAM model for Manikdoh catchment



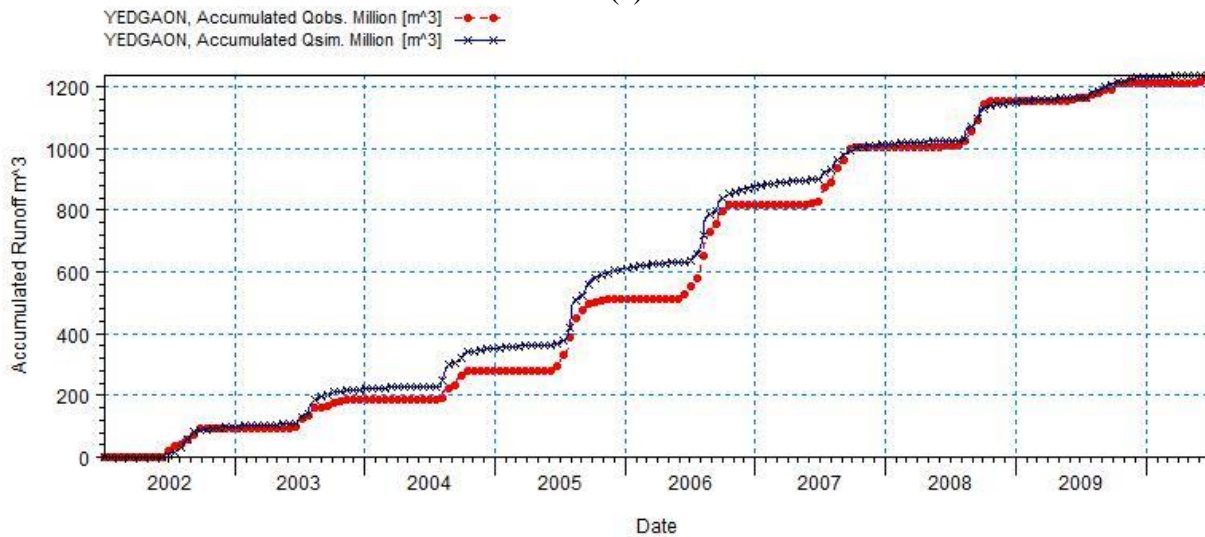
**Figure 4.9** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in year 2005 (c) during calibration period of MIKE 11 NAM model for Pimpalgaonjoga catchment



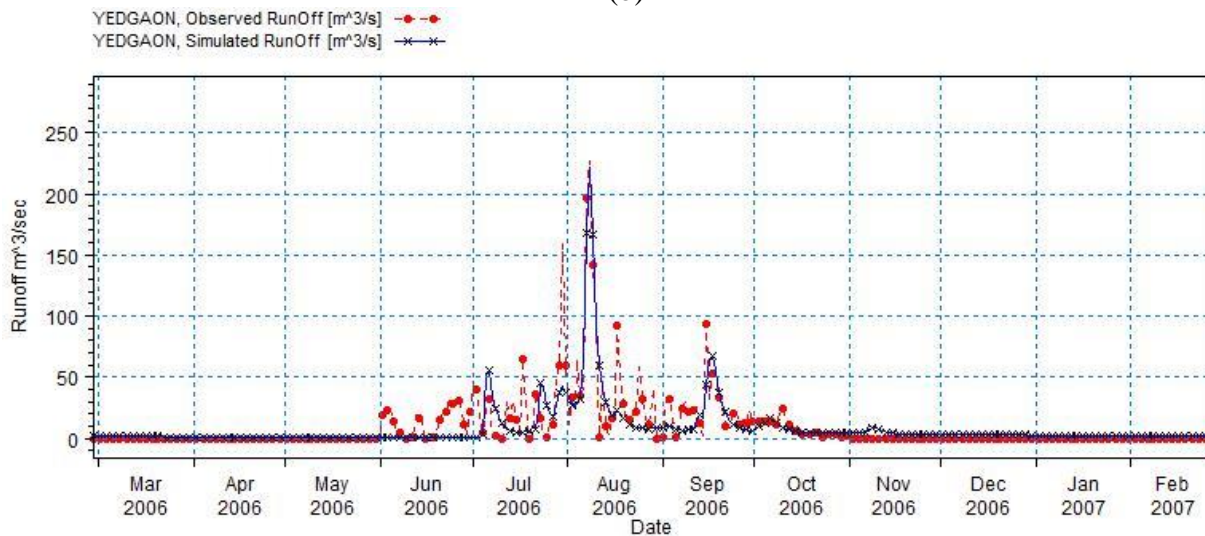
**Figure 4.10** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in year 2006 (c) during calibration period of MIKE 11 NAM model for Wadaj catchment



(a)

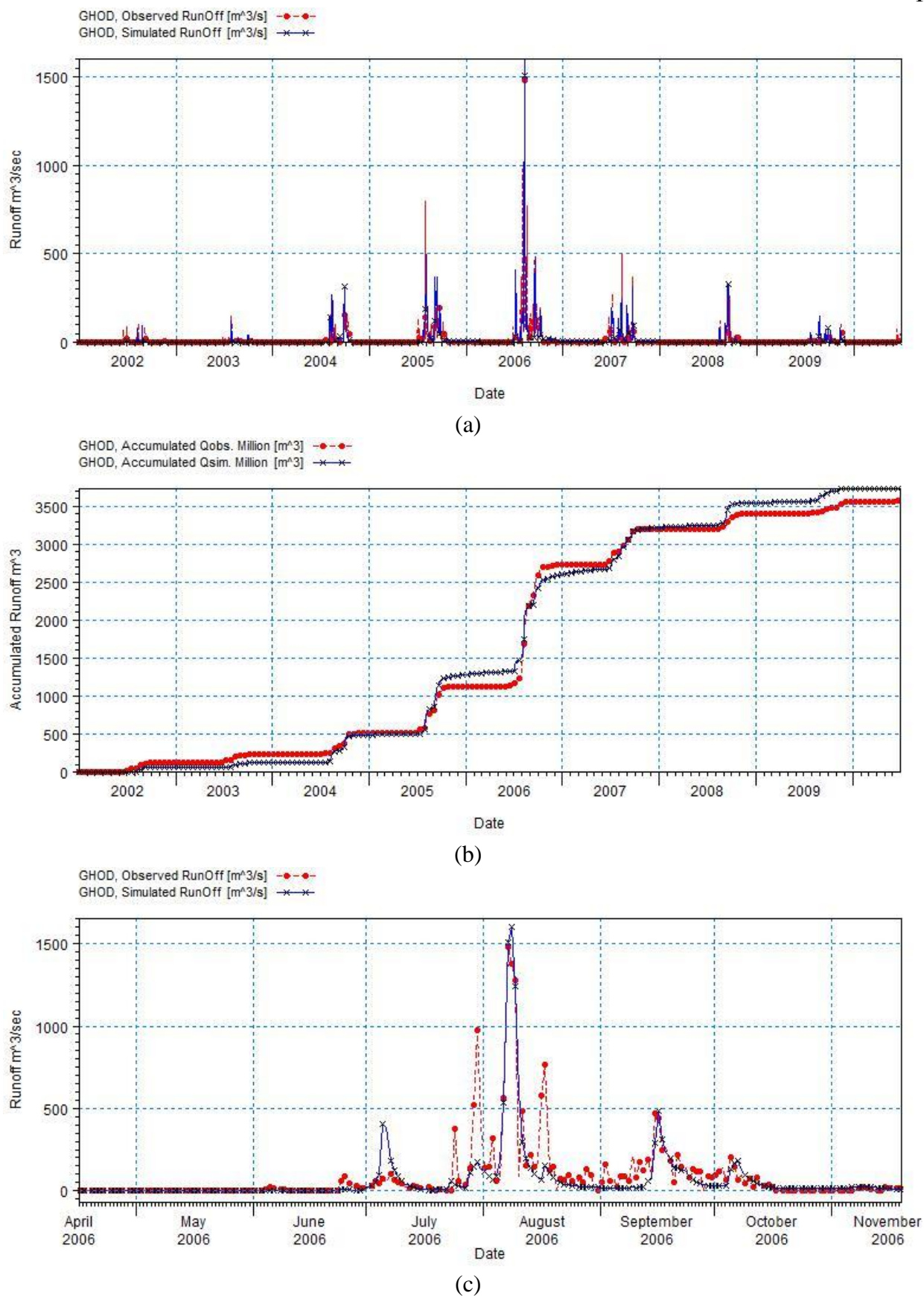


(b)



(c)

**Figure 4.11** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in year 2006 (c) during calibration period of MIKE 11 NAM model for Yedgaon catchment



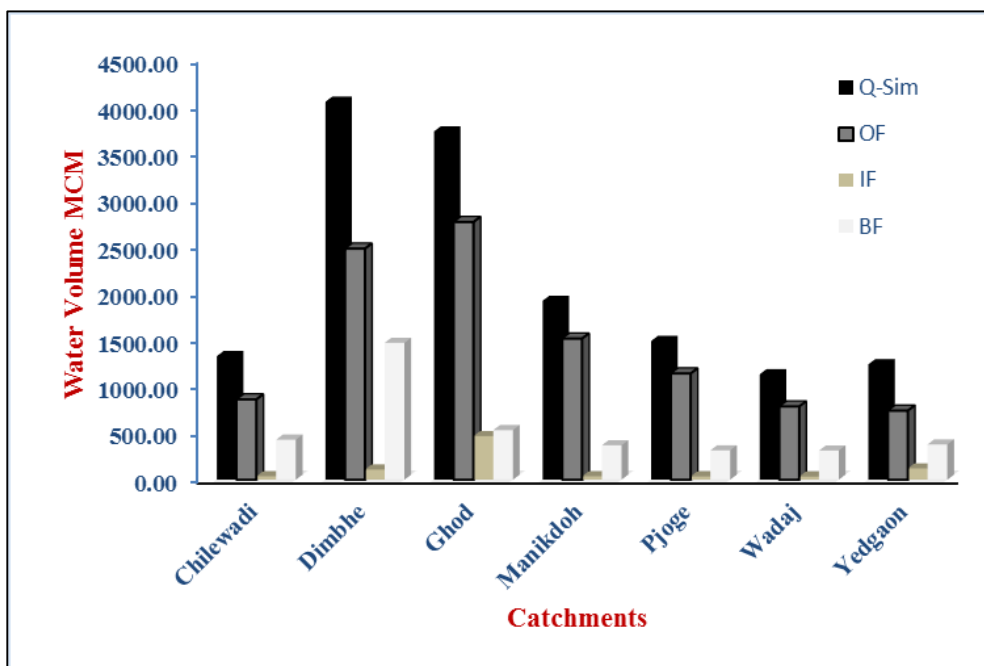
**Figure 4.12** Plot showing graph of observed and simulated runoff (a), accumulated observed and accumulated simulated runoff (b) and peaks of observed and simulated runoff in year 2006 (c) during calibration period of Ghod catchment

### 4.1.3 Water balance of MIKE 11 NAM model during calibration

The statistics of simulated runoff and other components of hydrologic cycle such as overland flow, inter flow and base flow for all sub catchments of Ghod complex are given in Table 4.3. From the analysis of simulation results, it was observed that, during the calibration of eight years (2002 to 2009), for Chilewadi catchment, out of total simulated flow of 1323.73 MCM, overland flow formed as 859.76 MCM, the water contributed as interflow and baseflow were 35.40 and 428.57 MCM, respectively. The ground water recharge water was accumulated of 4206.24 mm. Similarly, results were obtained for other catchments are presented in Table 4.3. The contribution of different hydrological components in total simulated flow is shown in Figure 4.13 for all sub catchments of Ghod complex.

**Table 4.3 Water balance of MIKE 11 NAM model during calibration**

Catchments	Q-Obs (MCM)	Q-Sim (MCM)	Diff. %	OF (MCM)	IF (MCM)	BF (MCM)	GWR (mm)
Chilewadi	1331.33	1323.73	0.60	859.76	35.40	428.57	4206.24
Dimbhe	4047.31	4047.16	0.00	2473.99	108.69	1464.47	5420.16
Ghod	3591.92	3729.23	-3.80	2759.62	465.90	530.48	208.32
Manikdoh	1913.72	1915.38	-0.10	1511.27	36.24	367.87	3557.28
Pimpalgaonjoga	1485.74	1485.54	0.00	1137.37	34.69	313.48	3230.88
Wadaj	1129.09	1128.29	0.10	783.76	32.87	311.66	2353.92
Yedgaon	1232.50	1236.26	-0.30	739.30	119.84	377.12	1035.12



**Figure 4.13 Water balance of MIKE 11 NAM model during calibration**

#### 4.1.4 Yearly water availability obtained during calibration process

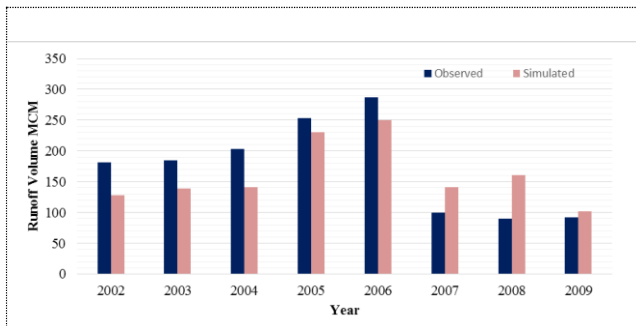
The total runoff in ( $\text{m}^3/\text{sec}$ ) obtained during calibration process was converted into Million Cubic Meter (MCM) for each year since 2002 to 2009 and the values of observed and simulated runoff in the form of water availability are given in Table 4.4. The comparison graphs of observed and simulated water availability in each year are shown in Figure 4.14, 4.15, 4.16, 4.17, 4.18, 4.19 and 4.20 for Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod, respectively. For Pimpalgaonjoga catchment, in the year 2006, Ghod catchment in the year 2008 and for Dimbhe catchment in the year 2006 and 2007 showed more difference in calibrated results because of data insufficiency. In Chilewadi catchment, average observed runoff and simulated runoff were obtained 173.8 MCM and 161.5 MCM with average difference of -3.2 %. For Dimbhe catchment, an average observed runoff and simulated runoff were obtained about 501.7 MCM and 558.1 MCM with an average difference of 5.2 %. In Manikdoh catchment, an average observed runoff and simulated runoff were obtained 254.7 MCM and 236.7 MCM with an average difference of 5.6 %. While, in the Pimpalgaonjoga catchment, an average observed runoff and simulated runoff were obtained 188.7 MCM and 184.7MCM with an average difference of -23.3%. The observed discharge data of Pimpalgaonjoga catchment, for the year 2006 was missing from the records and hence, in this year, the difference between observed and simulated runoff was found to be -281.9%. Therefore, average difference was found more for Pimpalgaonjoga catchment. For Wadaj catchment, average observed runoff and simulated runoff were obtained 146.5MCM and 139.8MCM with average difference of -1.1 %. Similarly, in the Yedgaon catchment, an average observed runoff and simulated runoff were obtained about 153.3 MCM and 151.6 MCM with an average difference of -12.9 %. However, for Ghod catchment, the average observed runoff and simulated runoff were obtained 490.9 MCM and 519.9 MCM with average difference of -15.0 %.

Overall, the MIKE 11 NAM model has underestimated the simulated runoff over the observed runoff with minimum average difference between them during calibration period of year 2002- 2009 for all sub catchments, except for Ghod catchment where it was observed to be overestimated. Also, the water availability during year 2005 and 2006 was more as there was good rainfall during these years.

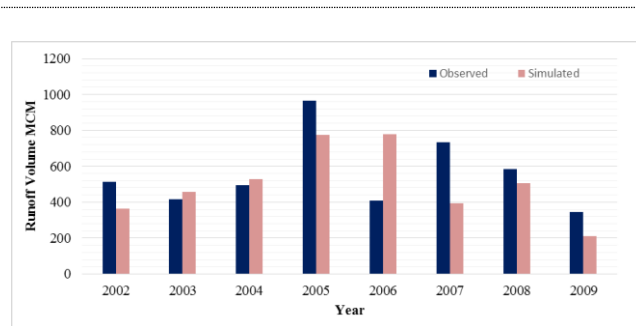
**Table 4.4 Yearly water availability obtained during calibration of MIKE 11 NAM model for Ghod complex sub catchments**

Year	Chilewadi			Dimbhe			Manikdoh			Pimpalgaonjoga		
	Observed Q MCM	Simulated Q MCM	% Difference	Observed Q MCM	Simulated Q MCM	% Difference	Observed Q MCM	Simulated Q MCM	% Difference	Observed Q MCM	Simulated Q MCM	% Difference
<b>2002</b>	181.6	127.8	29.6	514.4	365.2	29.0	264.0	182.2	31.0	187.2	153.9	17.8
<b>2003</b>	184.0	138.6	24.7	417.9	456.1	-9.1	225.3	206.0	8.5	184.1	154.9	15.8
<b>2004</b>	202.6	141.5	30.2	493.2	529.3	-7.3	251.0	234.0	6.8	290.3	183.7	36.7
<b>2005</b>	253.5	230.0	9.3	964.5	775.5	19.6	374.1	351.4	6.1	337.9	293.8	13.0
<b>2006</b>	287.3	250.0	13.0	409.3	778.0	-90.1	373.1	349.5	6.3	74.8	285.6	-281.9
<b>2007</b>	99.2	141.1	-42.2	734.9	395.1	46.2	182.6	190.4	-4.3	184.3	135.3	26.6
<b>2008</b>	89.7	161.1	-79.6	584.7	504.2	13.8	231.0	229.8	0.5	127.1	185.4	-45.9
<b>2009</b>	92.1	101.7	-10.4	345.8	210.5	39.1	136.5	150.4	-10.2	123.8	85.2	31.2
<b>Average</b>	<b>173.8</b>	<b>161.5</b>	<b>-3.2</b>	<b>558.1</b>	<b>501.7</b>	<b>5.2</b>	<b>254.7</b>	<b>236.7</b>	<b>5.6</b>	<b>188.7</b>	<b>184.7</b>	<b>-23.3</b>

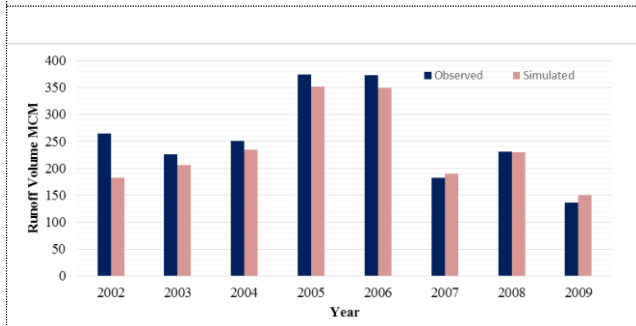
Year	Wadaj			Yedgaon			Ghod		
	Observed Q MCM	Simulated Q MCM	% Difference	Observed Q MCM	Simulated Q MCM	% Difference	Observed Q MCM	Simulated Q MCM	% Difference
<b>2002</b>	131.7	94.6	28.2	97.9	99.5	-1.6	164.4	131.4	20.1
<b>2003</b>	130.1	117.8	9.5	92.2	121.1	-31.3	121.7	107.9	11.3
<b>2004</b>	142.3	117.5	17.4	65.0	132.3	-103.5	291.2	356.2	-22.3
<b>2005</b>	249.8	185.5	25.8	231.9	258.2	-11.3	820.4	868.4	-5.8
<b>2006</b>	229.5	228.4	0.5	307.1	265.9	13.4	1608.2	1424.9	11.4
<b>2007</b>	112.7	137.3	-21.8	183.4	133.2	27.4	550.2	686.5	-24.8
<b>2008</b>	106.0	146.7	-38.4	188.3	123.8	34.2	202.0	365.9	-81.1
<b>2009</b>	69.9	91.0	-30.1	60.4	79.1	-30.8	168.8	217.7	-29.0
<b>Average</b>	<b>146.5</b>	<b>139.8</b>	<b>-1.1</b>	<b>153.3</b>	<b>151.6</b>	<b>-12.9</b>	<b>490.9</b>	<b>519.9</b>	<b>-15.0</b>



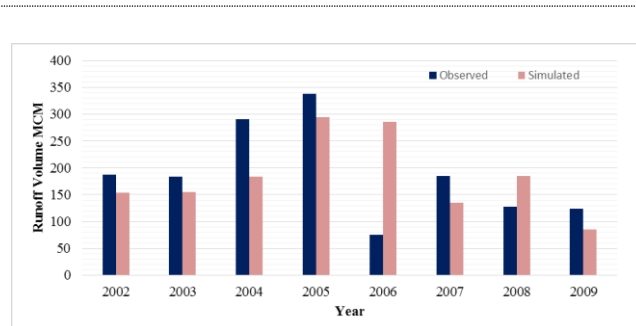
**Figure 4.14** Yearly water availability obtained during calibration of MIKE 11 NAM model for Chilewadi catchment



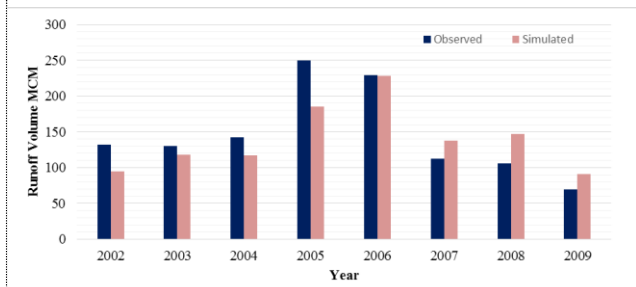
**Figure 4.15** Yearly water availability obtained during calibration of MIKE 11 NAM model for Dimbhe catchment



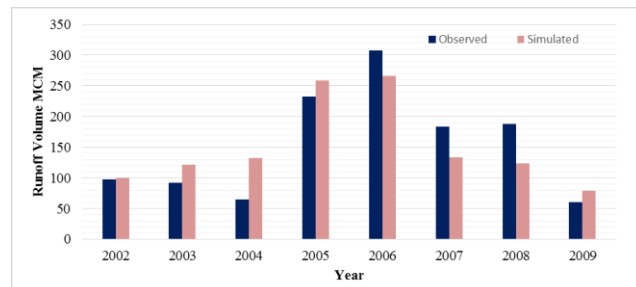
**Figure 4.16** Yearly water availability obtained during calibration of MIKE 11 NAM model for Manikdoh catchment



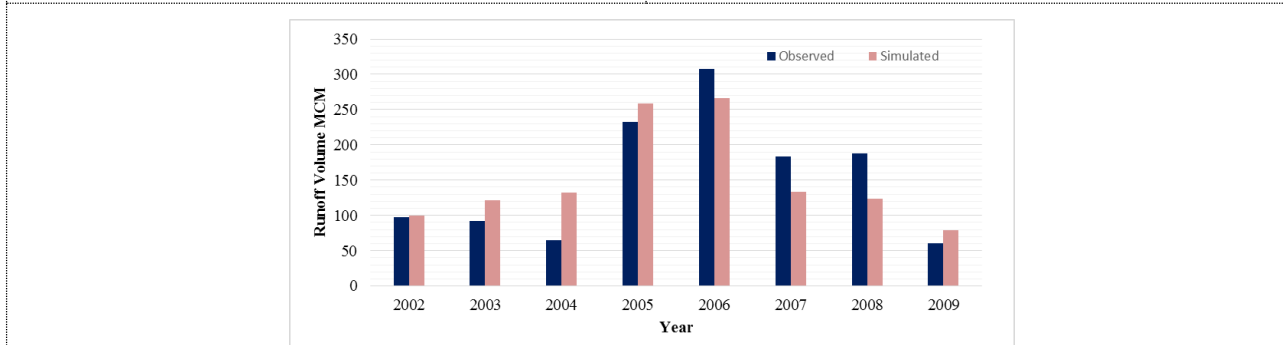
**Figure 4.17** Yearly water availability obtained during calibration of MIKE 11 NAM model for Pimpalgaonjoga catchment



**Figure 4.18** Yearly water availability obtained during calibration of MIKE 11 NAM model for Wadaj catchment



**Figure 4.19** Yearly water availability obtained during calibration of MIKE 11 NAM model for Yedgaon catchment



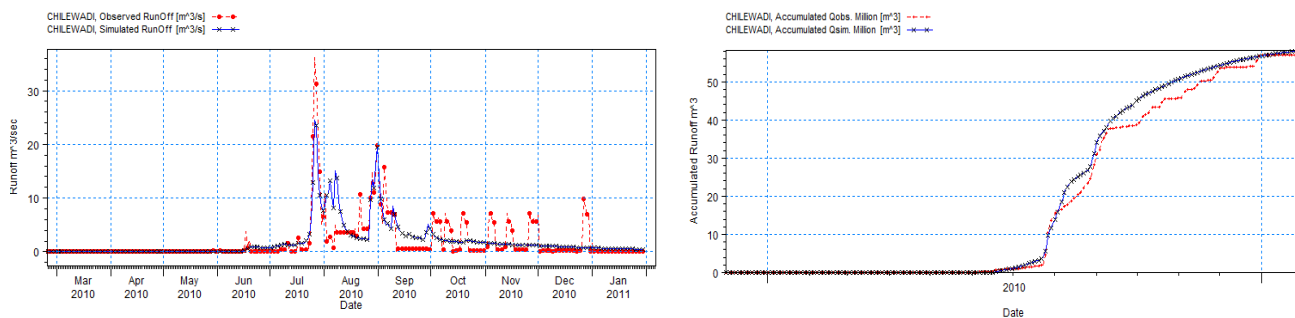
**Figure 4.20** Yearly water availability obtained during calibration of MIKE 11 NAM model for Ghod catchment

### 4.1.5 Validation of MIKE 11 NAM model

The MIKE 11 NAM model was validated for the period from 2010 to 2011 by using the optimum value of parameters obtained during the calibration process for all sub catchments of Ghod complex. For the model validation, model was run without auto-calibration mode using calibrated model parameters and statistics of the output were compared with the calibration results. The statistics of the simulated results were analyzed and output of the model were checked graphically to compare the observed and simulated runoff to verify the capability of calibrated model and to simulate the runoff for the extended period of time.

#### 4.1.5.1 Validation of MIKE 11 NAM model for Chilewadi catchment

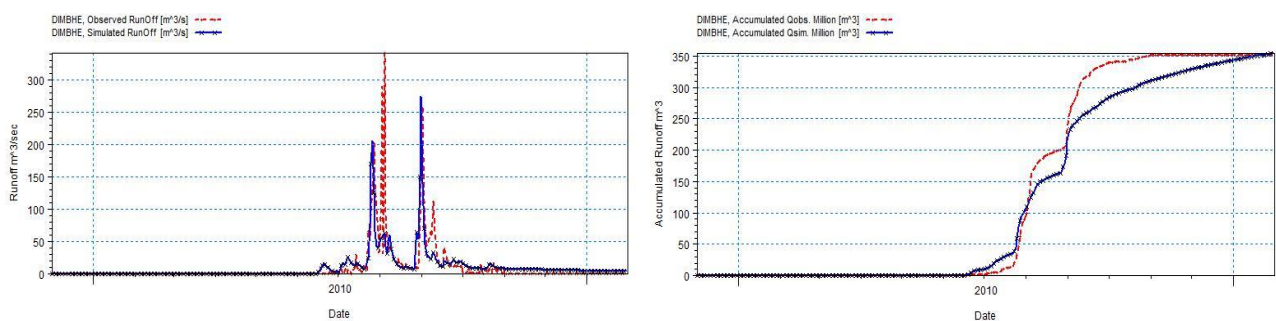
For the Chilewadi catchment, MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were given in Table 4.1 and the graphical results are shown in Figure 4.21. The values of  $R^2$ , WBE%, EI and r during validation of Chilewadi catchment were obtained to be 0.63, -2.29%, 0.63 and 0.80, respectively.



**Figure 4.21 Plot showing graph of observed and simulated runoff during validation of MIKE 11 NAM model for Chilewadi catchment**

#### 4.1.5.2 Validation of MIKE 11 NAM model for Dimbhe catchment

Similarly, for Dimbhe catchment MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were in Table 4.1.

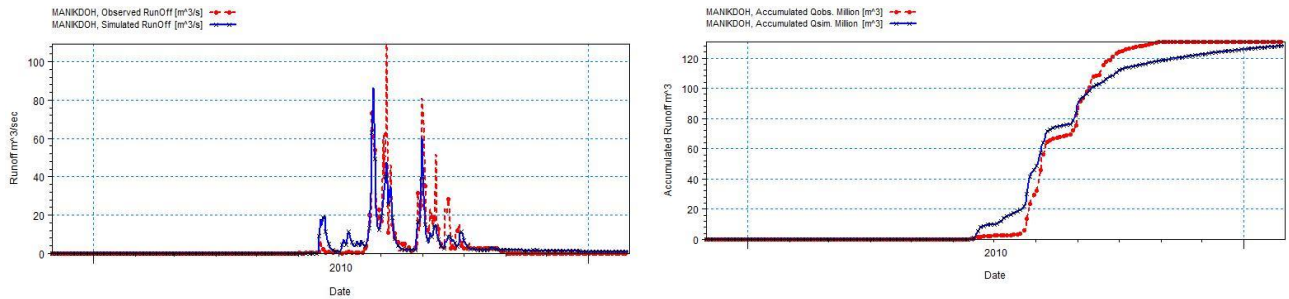


**Figure 4.22 Plot showing graph of observed and simulated flow during validation of MIKE 11 NAM model for Dimbhe catchment**

The graphical results are shown in Figure 4.22. The values of EI,  $r$ ,  $R^2$  and WBE% during validation of Dimbhe catchment were obtained to be 0.55, 0.76, 0.55 and -1.00%, respectively.

#### 4.1.5.3 Validation of MIKE 11 NAM model for Manikdoh catchment

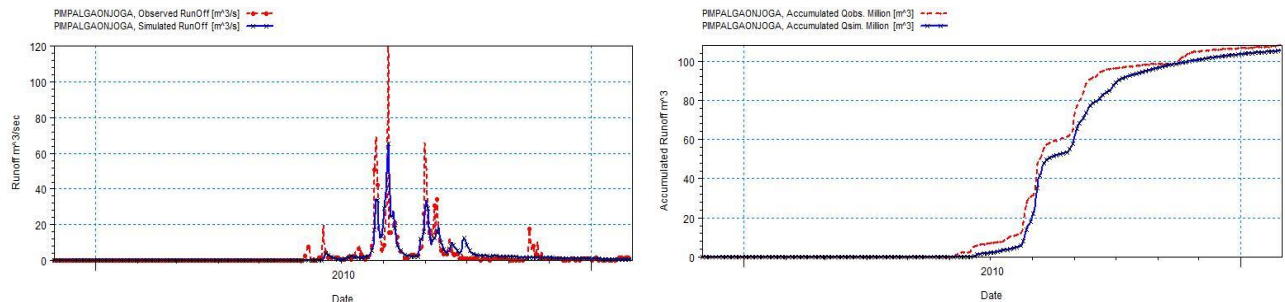
For the Manikdoh catchment, MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were given in Table 4.1 and the graphical results obtained are shown in Figure 4.23. The values of EI,  $r$ ,  $R^2$  and WBE% during validation of Manikdoh catchment were obtained to be 0.73, 0.86, 0.73 and 1.90%, respectively.



**Figure 4.23 Plot showing graph of observed and simulated flow during validation of MIKE 11 NAM model for Manikdoh catchment**

#### 4.1.5.4 Validation of MIKE 11 NAM model for Pimpalgaonjoga catchment

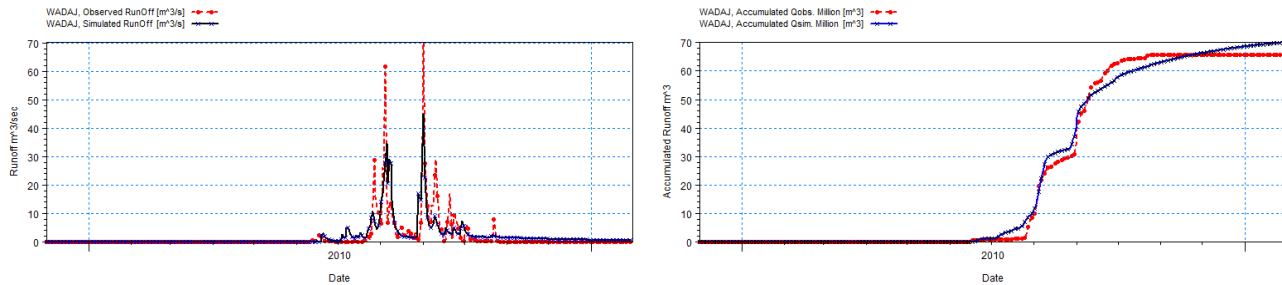
However, for the Pimpalgaonjoga catchment, MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were given in Table 4.1 and the graphical results are shown in Figure 4.24. The values of EI,  $r$ ,  $R^2$  and WBE% during validation of Pimpalgaonjoga catchment were obtained to be 0.66, 0.82, 0.67 and 2.60%, respectively.



**Figure 4.24 Plot showing graph of observed and simulated flow during validation of MIKE 11 NAM model for Pimpalgaonjoga catchment**

#### 4.1.5.5 Validation of MIKE 11 NAM model for Wadaj catchment

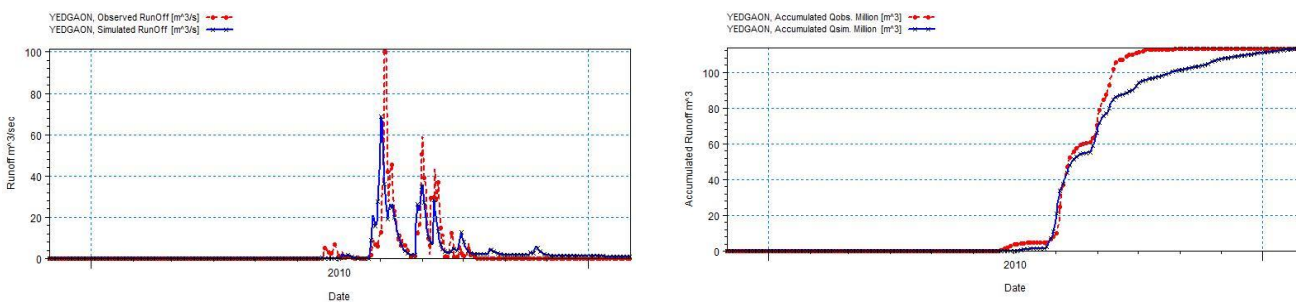
For the Wadaj catchment, MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were given in Table 4.1 and the graphical results are shown in Figure 4.25. The values of EI, r,  $R^2$ , and WBE% during validation of Wadaj catchment were obtained to be 0.65, 0.81, 0.65, and -6.60%, respectively.



**Figure 4.25** Plot showing graph of observed and simulated flow during validation of MIKE 11 NAM model for Wadaj catchment

#### 4.1.5.6 Validation of MIKE 11 NAM model for Yedgaon catchment

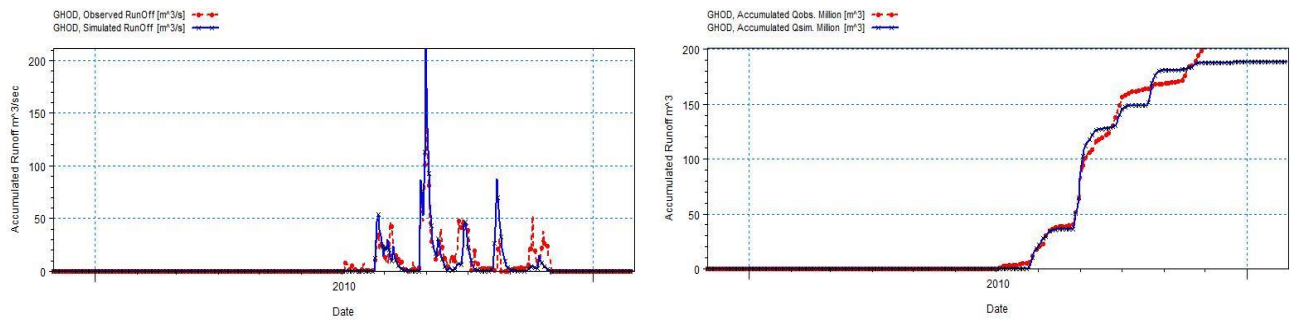
For the Yedgaon catchment, MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were given in Table 4.1 and the graphical results are shown in Figure 4.26. The values of EI, r, and  $R^2$ , WBE% during validation of Yedgaon catchment were obtained to be 0.52, 0.73, 0.52, and 0.60%, respectively.



**Figure 4.26** Plot showing graph of observed and simulated flow during validation of MIKE 11 NAM model for Yedgaon catchment

#### 4.1.5.7 Validation of MIKE 11 NAM model for Ghod catchment

For the Ghod catchment, MIKE 11 NAM model was validated for year 2010 to 2011 by using the optimum value of parameters obtained during the calibration process which were given in Table 4.1 and the graphical results are shown in Figure 4.27. The values of EI, r,  $R^2$ , and WBE% during validation of Ghod catchment were obtained to be 0.60, 0.85, 0.60 and 6.40%, respectively.



**Figure 4.27 Plot showing graph of observed and simulated flow during validation of MIKE 11 NAM model for Ghod catchment**

The validation graphs nearly matched with curves and peaks of the flows which shows that model parameter obtained during calibration were accurate. The analysis of model validation results indicated that, the MIKE 11 NAM model developed was performing well and seems to be capable of generating or predicting runoff time series for extended time period with accuracy in all catchments of Ghod complex. The summary of numerical performance measure obtained during validation of MIKE 11 NAM model for the period from year 2010 to 2011 are given in Table 4.5.

**Table 4.5 Statistical evaluation of MIKE 11 NAM model during validation**

Catchments	EI	r	R <sup>2</sup>	WBE (%)
Chilewadi	0.63	0.80	0.63	-2.20
Dimbhe	0.55	0.76	0.55	-1.00
Manikdoh	0.73	0.86	0.73	1.90
Pimpalgaonjoga	0.66	0.82	0.67	2.60
Wadaj	0.65	0.81	0.65	-6.60
Yedgaon	0.52	0.73	0.52	-0.60
Ghod	0.60	0.85	0.60	6.40

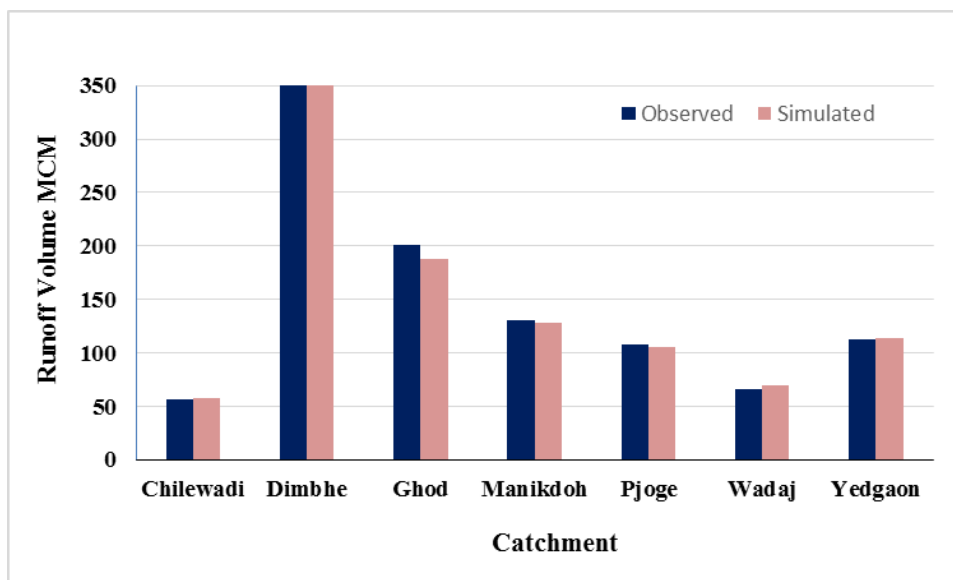
#### 4.1.6 Yearly water availability obtained during validation process

Observed runoff was obtained from water account data of each catchments which was converted into MCM and used as observed water availability. The observed water availability during calibration period of the year 2010 to 2011, for the catchments Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod was obtained to be 57MCM, 350.55MCM, 130.66MCM, 107.97MCM, 65.8 MCM, 112.96 MCM and 201.1 MCM, respectively. However, the simulated water availability estimated using optimum parameters obtained during calibration of MIKE 11 NAM model for Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod was 58.23MCM, 354.13MCM, 128.06MCM, 105.19MCM, 70.2 MCM, 113.55 MCM and 188.22 MCM, respectively.

The water availability estimated during model validation for all the catchments is given in Table 4.6 and shown graphically in Figure 4.28.

**Table 4.6 Water availability obtained during validation of MIKE 11 NAM model for Ghod complex sub catchments**

Catchments	Observed (MCM)	Simulated (MCM)	Difference (%)
Chilewadi	57.00	58.23	-2.17
Dimbhe	350.55	354.13	-1.02
Ghod	201.10	188.22	6.40
Manikdoh	130.66	128.16	1.92
Pimpalgaonjoga	107.97	105.19	2.58
Wadaj	65.80	70.12	-6.57
Yedgaon	112.96	113.55	-0.52



**Figure 4.28 Yearly water availability obtained during validation process of MIKE 11 NAM model**

#### 4.1.7 Water balance of MIKE 11 NAM model during validation

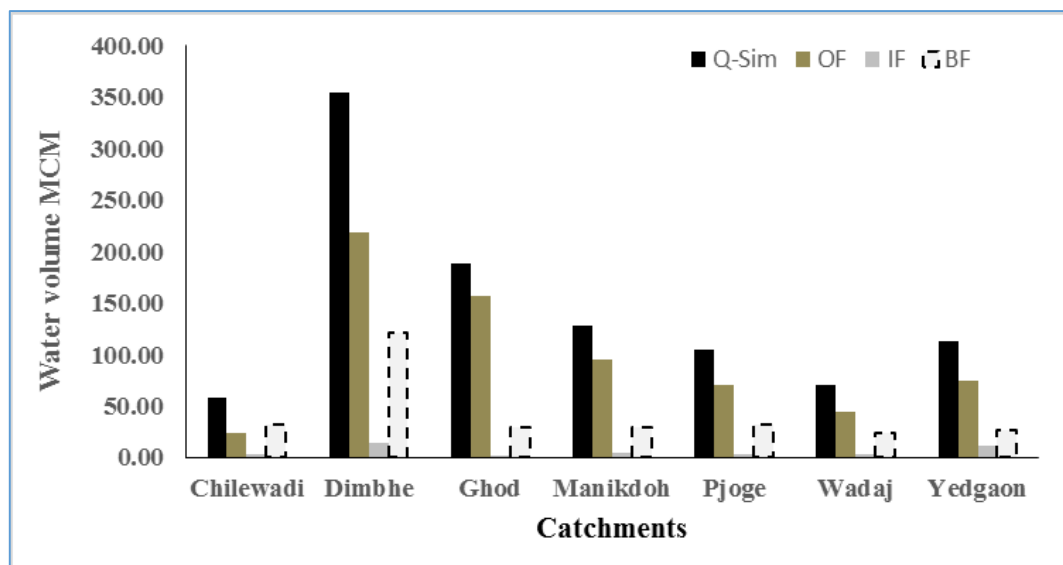
As like calibration period, the water balance for validation period was obtained from the output results files of MIKE 11 NAM model. The total simulated flow contributed into overland flow, interflow, baseflow and ground water recharge for all catchments are given in Table 4.7 and Figure 4.29.

During the validation period it was observed that, for Chilewadi catchment, out of total simulated flow of 58.23MCM, overland flow formed as 23.46MCM, interflow formed as 2.57 MCM and water contributed as baseflow 32.20 MCM. The ground water recharge water was accumulated of 332.40mm. Similarly, the results were obtained for all other catchments and presented in Table 4.7.

**Table 4.7 Water balance of MIKE 11 NAM model during validation**

Catchments	Q-Obs (MCM)	Q-Sim (MCM)	Diff. %	OF (MCM)	IF (MCM)	BF (MCM)	GWR (mm)
Chilewadi	57.00	58.23	-2.20	23.46	2.57	32.20	332.4
Dimbhe	350.55	354.13	-1.00	218.20	14.57	121.35	581.52
Ghod	201.10	188.22	6.40	157.35	1.75	29.12	256.00
Manikdoh	130.66	128.16	1.90	95.09	4.06	29.01	352.56
Pimpalgaonjoga	107.97	105.19	2.60	70.20	3.41	31.58	354.00
Wadaj	65.80	70.12	-6.60	43.80	2.86	23.47	201.60
Yedgaon	112.96	113.55	-0.60	74.79	11.92	26.84	102.00

Contribution different hydrological components in total simulated flow is shown in Figure 4.29 for all sub catchments of Ghod complex.

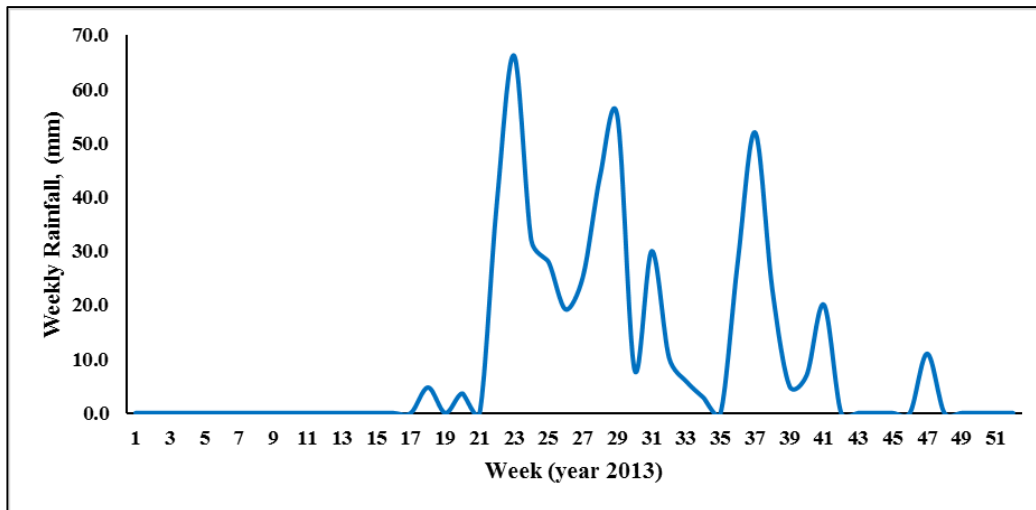
**Figure 4.29 Water balance of MIKE 11 NAM model obtained during validation**

It was observed from the Table 4.7 and Figure 4.29, the maximum part of simulated flow for all catchments was contributed to the overland flow followed by baseflow and then to interflow with minimum water balance error. Overall, the MIKE 11 NAM model has given good performance for the water balance during validation period of 2010 to 2011.

#### 4.1.8 Rainfall forecasting by using ANN model

The ANN model 4-10-1 developed by Popale (2016) for forecasting of weekly rainfall trained with resilient back propagation algorithm *trainrp* using cascade feed forward back propagation networks was used for the forecasting of rainfall timeseries. The details of the ANN model 4-10-1 were discussed in section 3.4. In the ANN model 4-10-1, weekly rainfall data of year 2011 and 2012 was

used to forecast rainfall of year 2013. Rainfall was forecasted for the year 2013 for weather stations Pimpalgaonjoga, Pimpalwandi, Shirur, Kurwandi, Aundhe and Savale.

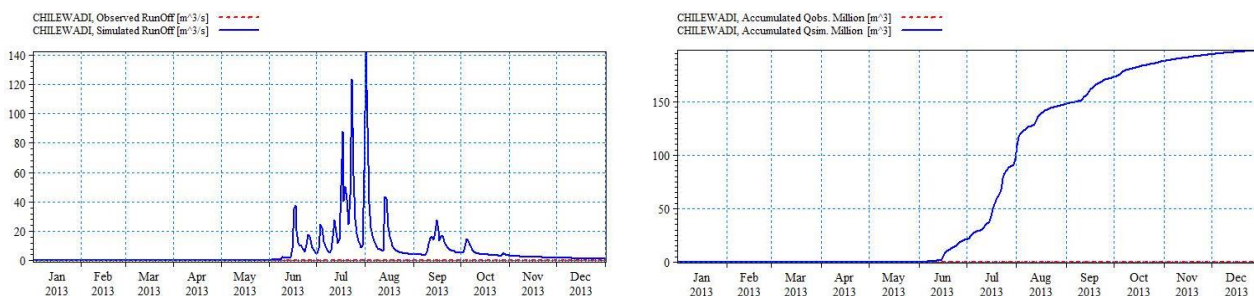


**Figure 4.30 Forecasted rainfall series for the Shirur station estimated using ANN model 4-10-1**

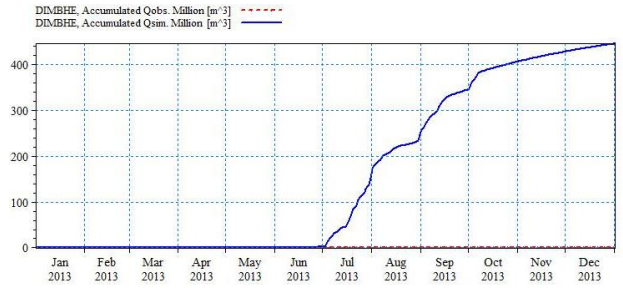
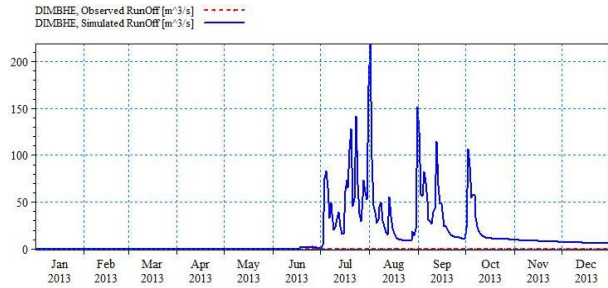
The rainfall of the same week of previous two years i.e. 2011 and 2012 and rainfall of two preceding weeks of same year was used as input to ANN model 4-10-1 to forecast the rainfall of same week of year 2013. The rainfall forecasted for the Shirur station using ANN model 4-10-1 is shown in Figure 4.30. The total rainfall presented in Figure 4.30 for Shirur station was obtained to be 520.2 mm for year 2013. Similarly, rainfall was forecasted for other stations viz. Pimpalgaonjoga, Pimpalwandi, Kurwandi, Aundhe and Savale etc. The results obtained are given at Appendix-K. The forecasted rainfall obtained using ANN 4-10-1 model was used for the estimation of water availability.

#### 4.1.9 Simulation of water availability by using forecasted rainfall data

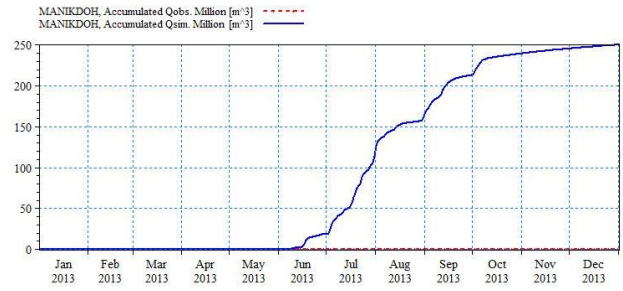
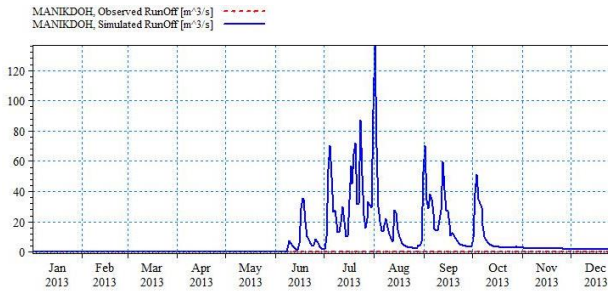
The calibration and validation of MIKE 11 NAM model was used to simulate the flow using forecasted rainfall series for all the catchments of Ghod complex for the year 2013. The results obtained by using forecasted data are presented in the form of graph in Figure 4.31 for the year 2013 for Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod catchments.



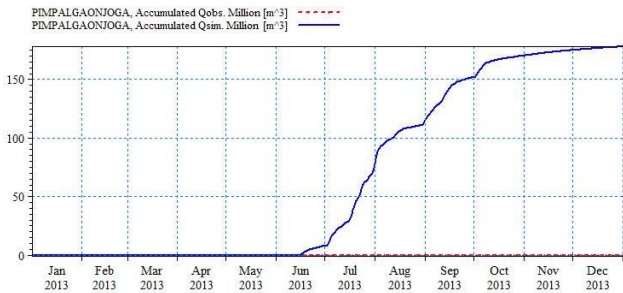
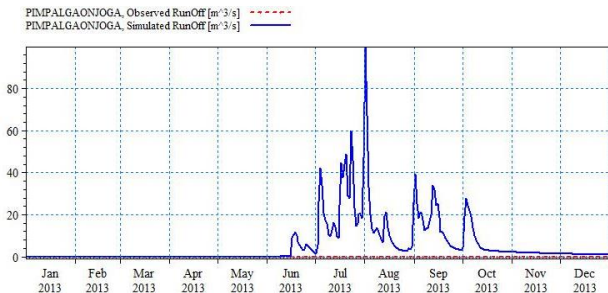
**Chilewadi catchment**



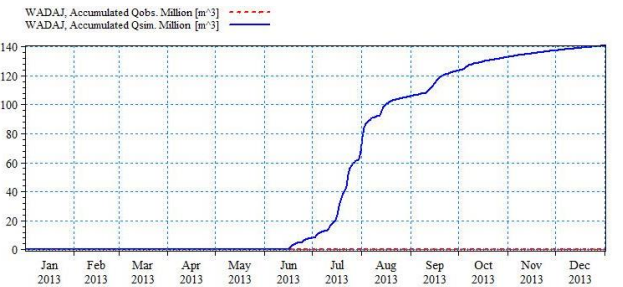
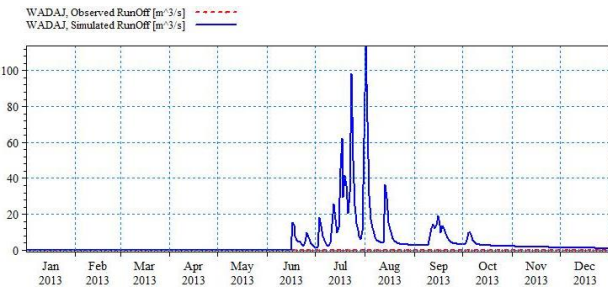
**Dimbhe catchment**



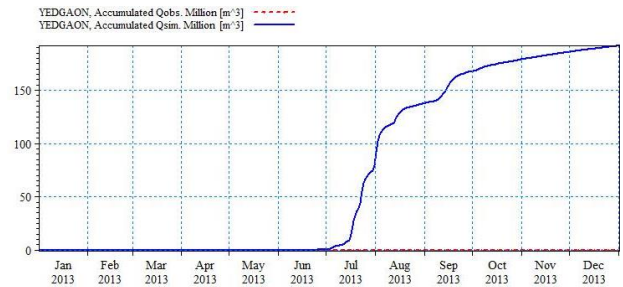
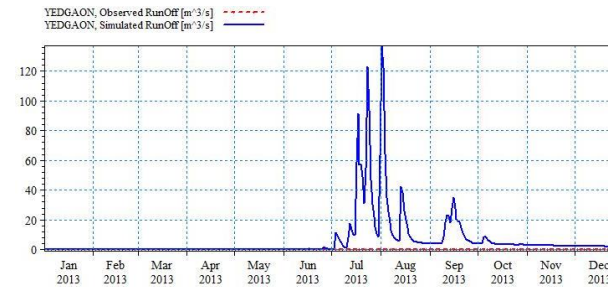
**Manikdoh catchment**



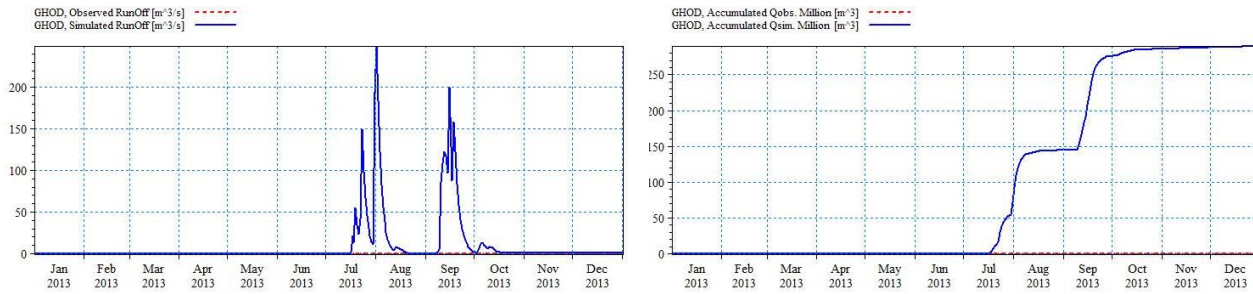
**Pimpalgaonjoga catchment**



**Wadaj catchment**



**Yedgaon catchment**



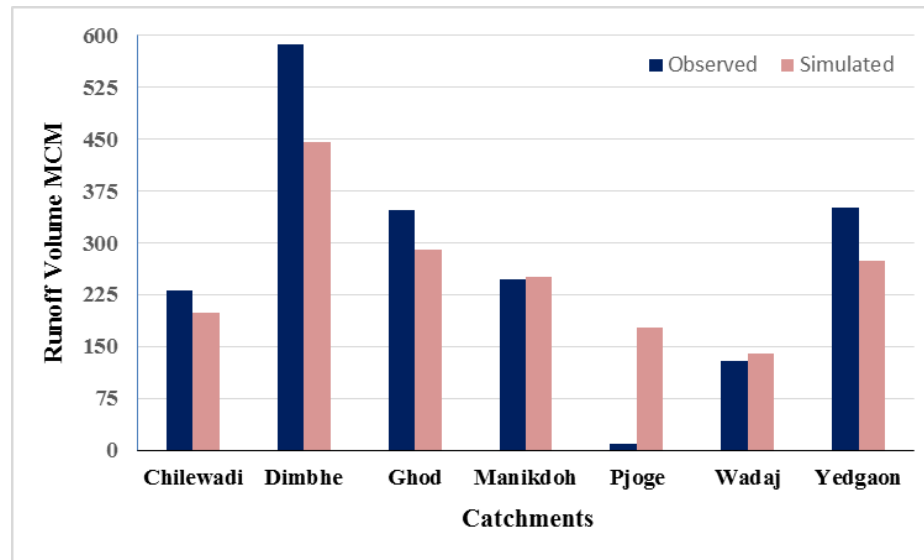
### Ghod catchment

**Figure 4.31 Simulation of runoff by using forecasted rainfall data in MIKE 11 NAM model**

For Chilewadi catchment, observed and simulated water availability was estimated as 230.7 MCM and 198.4 MCM respectively with difference of 14% and for Dimbhe catchment observed and simulated water availability was estimated as 586.8 MCM and 446.3 MCM respectively with difference of 23.9 %. Similarly, for Manikdoh catchment observed and simulated water availability was estimated as 246.96 MCM and 250.35 MCM respectively with minimum difference of -1.4 %. For Pimpalgaonjoga catchment observed and simulated water availability was estimated as 9.8 MCM and 178.0 MCM respectively. The observed inflow data of Pimpalgaonjoga reservoir was missing from the records for the period of 1<sup>st</sup> July 2013 to 31<sup>st</sup> December 2013. Hence, the observed water availability was obtained less around 9.8 MCM in the year 2013. In such case, forecasted water availability can take for gap filling of records. For Wadaj catchment, observed and simulated water availability was estimated as 128.4 MCM and 140.7 MCM respectively with minimum difference of -9.57 %, whereas for Yedgaon catchment, observed and simulated water availability were estimated as 350.8 MCM and 273.5 MCM respectively with minimum difference of 22.0 % and for Ghod catchment, observed and simulated water availability were estimated as 347.0 MCM and 289.6 MCM respectively with difference of 16.5 %. The water availability obtained using forecasted rainfall data during year 2013 is summarized in Table 4.8 and shown graphically in Figure 4.32.

**Table 4.8 Water availability obtained using forecasted rainfall data during year 2013**

Catchments	Observed (MCM)	Simulated (MCM)	Difference (%)
Chilewadi	230.7	198.4	14.0
Dimbhe	586.8	446.3	23.9
Ghod	347.0	289.6	16.5
Manikdoh	247.0	250.4	-1.4
Pimpalgaonjoga	9.8	178.0	-1711.1
Wadaj	128.4	140.7	-9.6
Yedgaon	350.8	273.5	22.0



**Figure 4.32 Water availability obtained using forecasted rainfall data during year 2013**

Maximum water availability of 446.3 MCM was obtained for the Dimbhe catchment and minimum water availability was found to be 140.7 MCM for Wadaj catchment. All the catchments indicated near matching between both observed and forecasted water availability except Pimpalgaonjoga catchment. Pimpalgaonjoga catchment showed least observed water availability of 9.83 MCM as the data was missing from the original records of water balance data sheets. In such case, calibrated and validated MIKE 11 NAM model can be used for the gap filling purpose.

#### **4.2 Simulation of irrigation water demand using MIKE HYDRO Basin model**

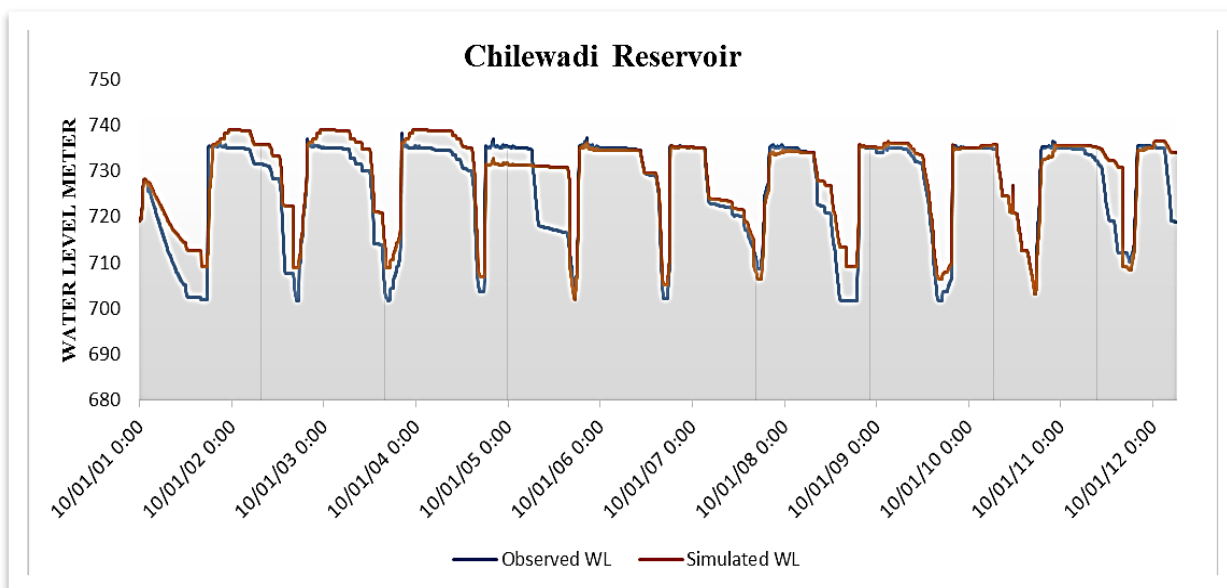
In Indian condition most of the reservoirs generally used for storage purpose, so that runoff generated in the monsoon can be stored in the reservoir and utilized to fulfill the water demand in optimal manner in dry season. MIKE HYDRO Basin model is used for a large variety of applications concerning allocation, management and planning aspects of water resources within a river basin. In present study, MIKE HYDRO Basin model was used to simulate the irrigation water demand for different cropping patterns under Ghod command area from 150 to 415 km<sup>2</sup> with increment of 50 km<sup>2</sup>. The study was done to estimate the irrigation water demand and deficit under variable Cultivable Command Area (CCA) and three different cropping patterns. Different cropping patterns used were discussed in section 3.5.4.3.

##### **4.2.1 Calibration of MIKE HYDRO Basin model**

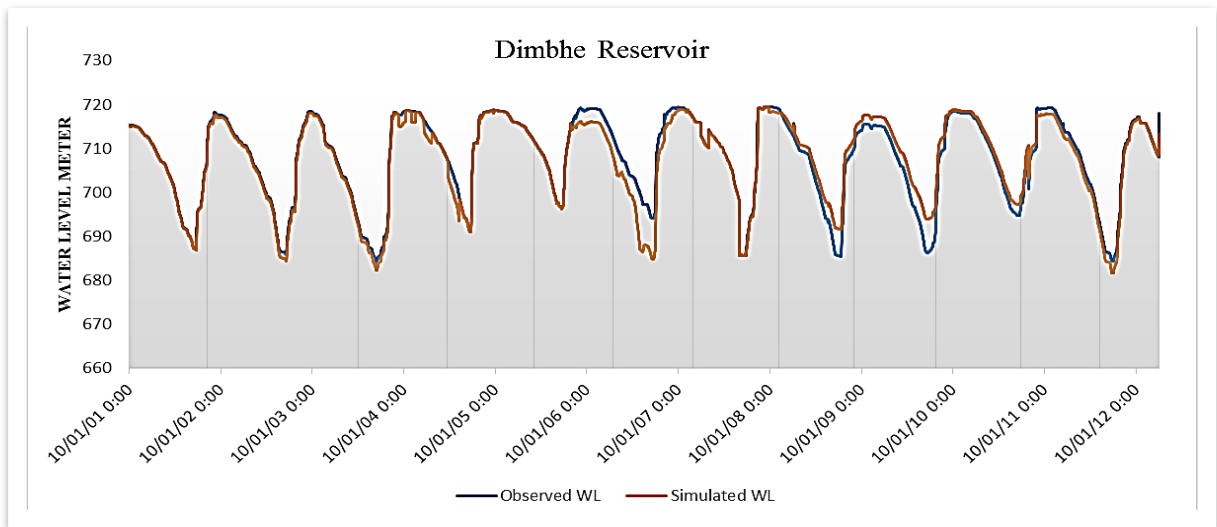
Prior to the calibration of MIKE HYDRO Basin model for Ghod reservoir, the model was set to calibrate and match the water levels with observed water levels for the six reservoirs viz., Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon situated at upstream of the Ghod reservoir. The long term (2001 to 2013) water release data of all reservoirs was obtained from Kukadi Irrigation

Division 1 and 2, Narayangaon, Pune. The initial water level was set to 1<sup>st</sup> October, 2001 for all upstream reservoirs, which was the actual water level in the model. The data of different releases such as spill over spillway, LBC, RBC, river, hydropower generation, irrigation industrial and domestic releases etc. were given as input to model in terms of time series. The calibration of MIKE HYDRO Basin model depends on the precise calibration of MIKE 11 NAM model. The runoff obtained from calibration of MIKE 11 NAM model was used as input for calibration of MIKE HYDRO Basin model. Then then model was run for longer duration from year 2001-2012. The results of observed and calibrated water level of all seven reservoirs were compared.

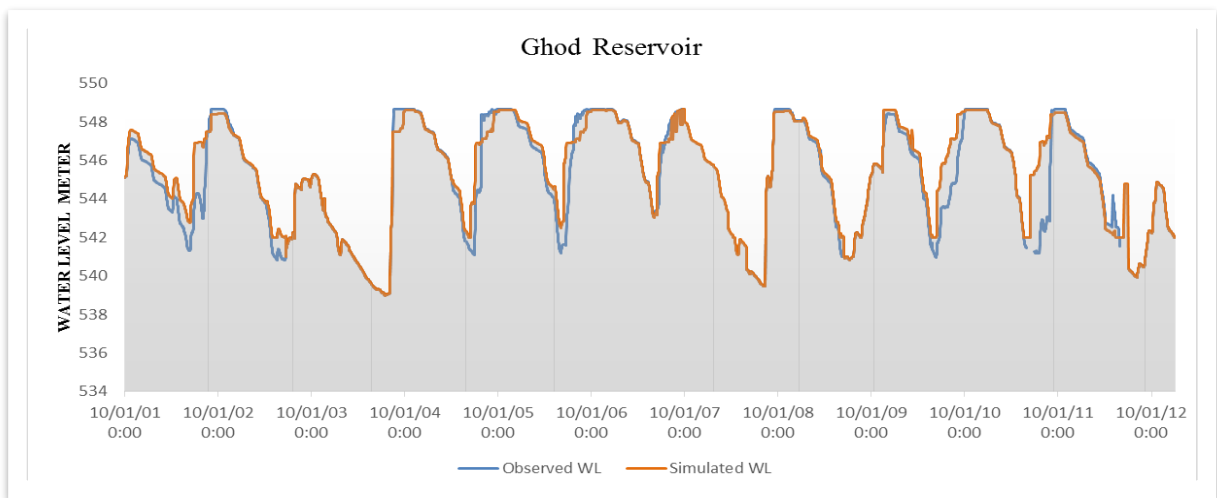
Figure 4.33 represented the graph of observed and calibrated water level of Chilewadi reservoir which was shown a good match between them with  $R^2$  of 0.78 and EI of 0.77. For Dimbhe reservoir, the graph of observed and calibrated water level is given in the Figure 4.34 and,  $R^2$  and EI values obtained to be 0.85 and 0.85, respectively. Also, Figure 4.35 represented the graph of observed and calibrated water level of Manikdoh reservoir having  $R^2$  and EI value of 0.92 and 0.91 respectively, with well matching between the two. Figure 4.36 shown the graph of observed and calibrated water level of Pimpalgaonjoga reservoir which with  $R^2$  and EI of 0.88 and 0.87. However, for Wadaj reservoir the graph of observed and calibrated water level is given at Figure 4.37 with  $R^2$  and EI value of 0.83 and 0.81, respectively. Similarly, for Ghod and Yedgaon reservoirs, the plots of observed and calibrated water level are given in Figure 4.38 and Figure 4.39 with  $R^2$  and EI value of 0.81 and 0.80, 0.72 and 0.72, respectively. All of these Figures 4.33. 4.34, 4.35. 4.36, 4.37, 4.38 and 4.39 represented the nearly perfect match between observed and calibrated water levels and hence, proved that, the calibration of MIKE HYDRO Basin model was appropriate.



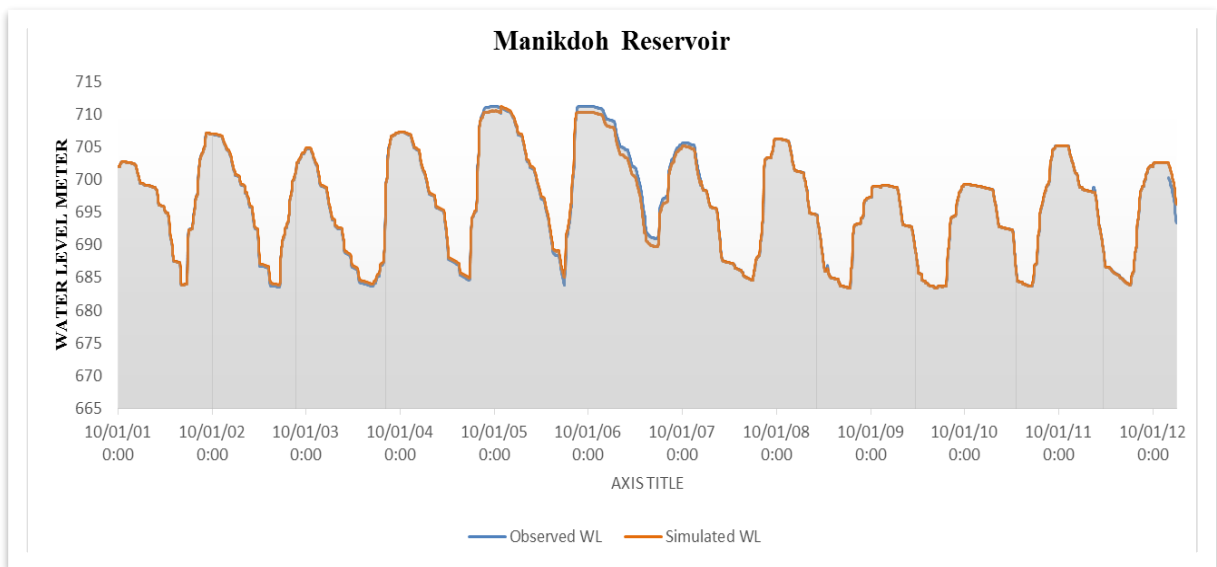
**Figure 4.33 Observed and calibrated water level of Chilewadi reservoir**



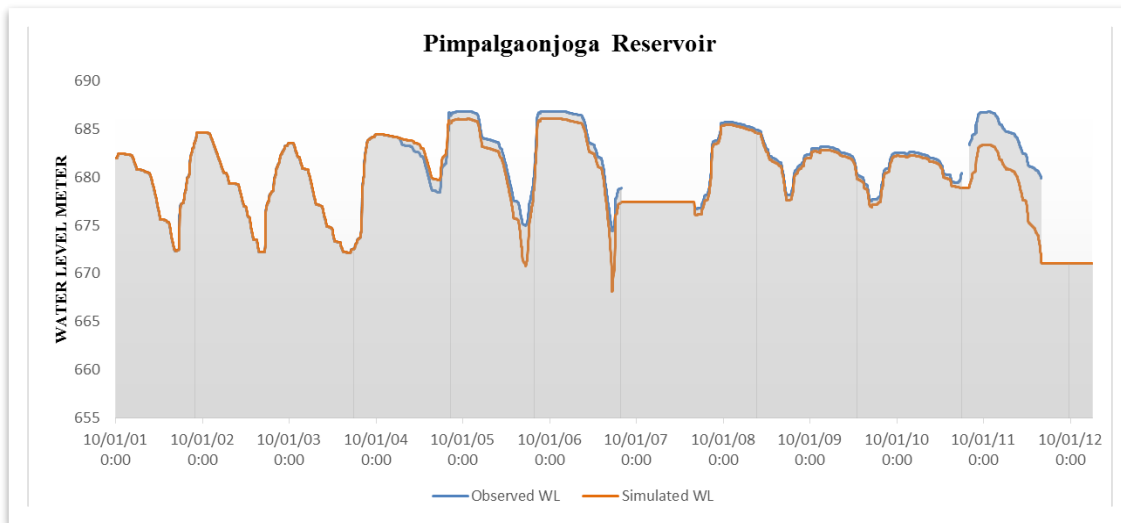
**Figure 4.34 Observed and calibrated water level of Dimbhe reservoir**



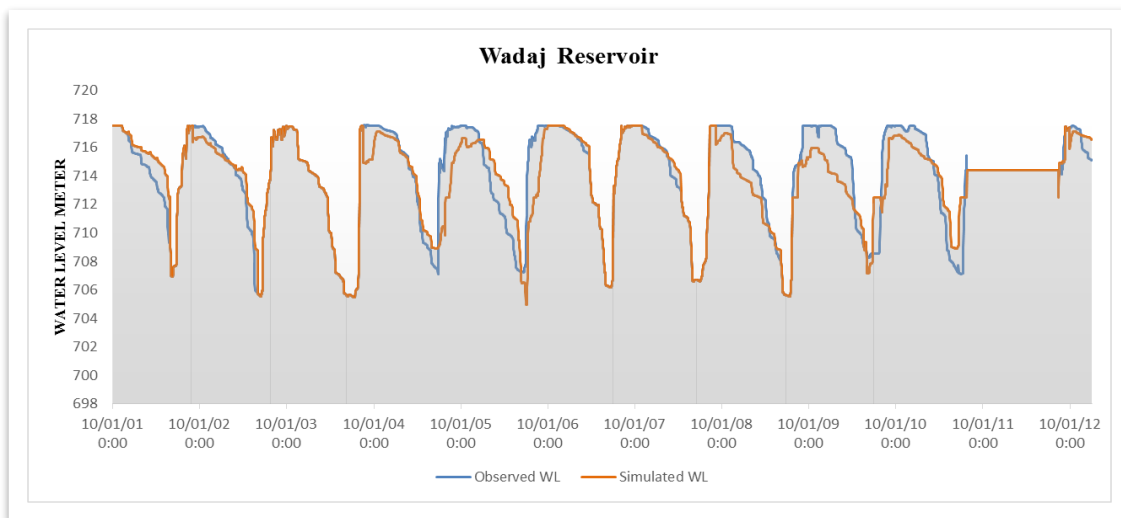
**Figure 4.35 Observed and calibrated water level of Ghod reservoir**



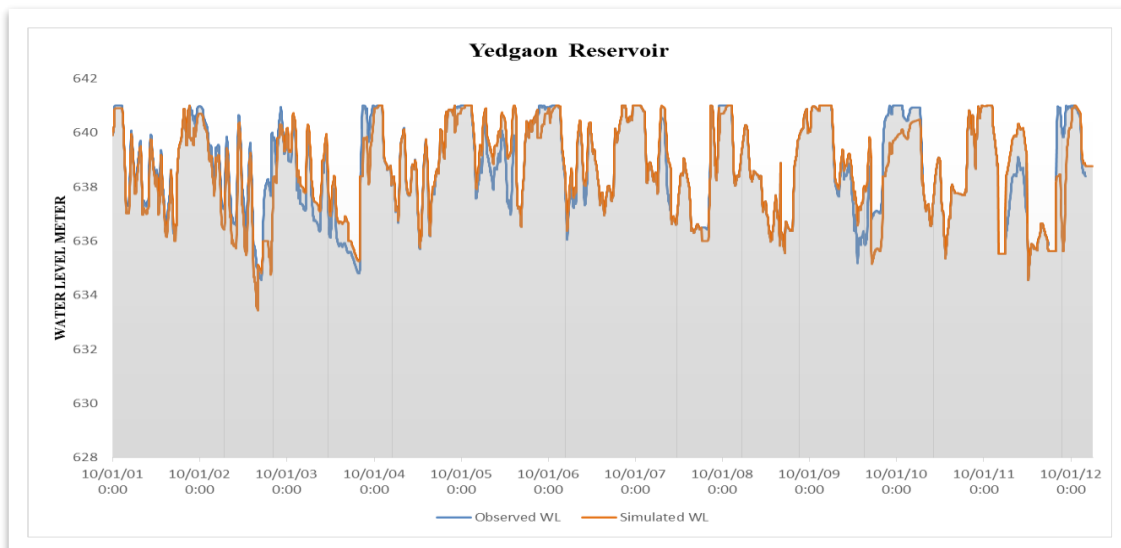
**Figure 4.36 Observed and calibrated water level of Manikdoh reservoir**



**Figure 4.37 Observed and calibrated water level of Pimpalgaonjoga reservoir**



**Figure 4.38 Observed and calibrated water level of Wadaj reservoir**



**Figure 4.39 Observed and calibrated water level of Yedgaon reservoir**

## 4.2.2 Historical irrigation water demand

MIKE HYDRO Basin model was set to determine irrigation water demand and deficit under Ghod command area. The historical irrigation water demand and deficits were estimated for the duration of year 2002 to 2012 against three different cropping patterns namely multi-crop, major crop and sugarcane only under variable cultivable command area *viz.* 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup>. The details of these cropping pattern were given at section 3.5.3.2. The results of irrigation water demand and deficit obtained for these three cropping pattern are discussed in this section.

### 4.2.2.1 Multi-crop cropping patterns

The multi-crop cropping pattern includes different commonly grown crops in the Ghod command area which covers all the three seasons of year. The model estimated irrigation water demand and deficits of multi-crop cropping pattern for variable area are presented in Table 4.9.

It was observed from the Table 4.9 that, the historical irrigation water demand obtained for 150 km<sup>2</sup> cultivable command area was less than other areas for multi-crop cropping pattern. The minimum irrigation water demand of 49.16 MCM was found for 150 km<sup>2</sup> CCA in the year 2010 and maximum irrigation water demand of 515.51 MCM was found for 415 km<sup>2</sup> CCA in the year 2012. The average irrigation water demand was found to be 58.19 MCM, 77.16 MCM, 100.60 MCM, 159.66 MCM, 224.23 MCM and 257.00 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

The Table 4.9 also showed, the yearly historical irrigation water demand-deficit for multi-crop cropping pattern for different CCA. In 150 km<sup>2</sup> of CCA, the irrigation water demand-deficit was found to be zero which reveals the irrigation water demand was fulfilled in all year. As the CCA increased the deficit was also increased. The average water demand-deficit was found to be 0.00 MCM, 1.41 MCM, 12.58 MCM, 51.99 MCM, 99.34 MCM and 128.42 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively. This represents, by using multi-crop cropping pattern in Ghod command area, 200 km<sup>2</sup> of CCA can be easily irrigated with sufficient supply of water to the users. Also, by optimum utilization of water, up to 250 km<sup>2</sup> of CCA can be irrigated with this multi-crop cropping pattern. However, total 415 km<sup>2</sup> of CCA showed maximum deficit, so there was no sufficient water to supply the users to irrigate all the CCA.

**Table 4.9 Historical irrigation water demand and deficit for multi-crop cropping pattern**

Year / CCA	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2002</b>	59.32	0.00	79.71	6.35	99.20	17.15	117.70	28.24	137.08	39.88	159.84	54.84
<b>2003</b>	74.13	0.00	95.67	2.91	120.76	22.72	189.29	82.69	259.13	147.50	303.15	183.08
<b>2004</b>	65.26	0.00	86.93	6.25	124.00	76.59	257.33	165.38	322.72	229.70	354.28	267.51
<b>2005</b>	55.91	0.00	73.54	0.00	86.41	5.76	106.01	20.84	164.90	56.17	209.82	96.62
<b>2006</b>	49.61	0.00	68.19	0.00	81.93	0.00	97.73	8.55	153.44	52.05	176.45	69.78
<b>2007</b>	57.71	0.00	72.96	0.00	92.45	0.00	112.48	7.30	131.47	20.88	149.54	35.78
<b>2008</b>	50.48	0.00	67.21	0.00	82.32	0.00	138.07	0.00	304.52	83.67	315.90	88.49
<b>2009</b>	51.87	0.00	67.46	0.00	84.94	6.51	125.42	33.94	214.78	115.69	244.53	144.56
<b>2010</b>	49.16	0.00	66.64	0.00	77.06	0.00	90.89	1.13	103.74	11.88	124.91	25.68
<b>2011</b>	62.33	0.00	84.24	0.00	101.35	0.00	121.28	9.57	180.78	37.63	273.08	118.78
<b>2012</b>	64.25	0.00	86.24	0.00	156.22	9.69	400.04	214.22	493.97	297.65	515.51	327.51
<b>Average</b>	<b>58.19</b>	<b>0.00</b>	<b>77.16</b>	<b>1.41</b>	<b>100.60</b>	<b>12.58</b>	<b>159.66</b>	<b>51.99</b>	<b>224.23</b>	<b>99.34</b>	<b>257.00</b>	<b>128.42</b>

(unit: Million Cubic Meter)

**Table 4.10 Historical irrigation water demand and deficit for major-crop cropping pattern**

<b>Year / CCA</b>	<b>150</b>		<b>200</b>		<b>250</b>		<b>300</b>		<b>350</b>		<b>415</b>	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2002</b>	129.99	33.92	167.08	59.69	230.34	100.96	267.42	130.08	268.50	139.47	309.23	151.44
<b>2003</b>	180.48	71.24	254.94	127.92	302.58	164.49	352.03	191.85	363.47	177.87	414.42	205.84
<b>2004</b>	221.13	120.54	288.50	185.86	322.44	216.99	354.94	253.79	348.59	253.43	368.04	275.83
<b>2005</b>	107.06	22.57	180.39	66.30	225.76	103.95	260.49	135.86	268.33	143.08	301.15	164.77
<b>2006</b>	84.96	2.63	149.36	46.59	174.64	76.80	207.36	106.47	216.79	105.15	238.10	136.39
<b>2007</b>	98.52	6.80	128.54	25.75	180.57	63.62	228.17	106.41	235.67	120.99	252.12	136.32
<b>2008</b>	104.63	0.00	236.05	23.85	287.52	66.30	329.16	90.14	333.54	100.67	352.82	117.14
<b>2009</b>	102.23	15.11	208.61	99.21	249.28	136.93	288.81	176.98	301.34	175.80	315.88	188.92
<b>2010</b>	94.82	1.14	121.92	20.32	160.46	53.60	204.27	93.91	224.56	112.51	242.87	127.71
<b>2011</b>	127.43	8.73	233.95	80.56	287.52	121.64	326.35	151.28	352.19	161.41	381.16	174.39
<b>2012</b>	254.31	63.23	362.17	168.11	395.83	209.53	432.83	247.00	439.11	261.91	459.25	284.31
<b>Average</b>	<b>136.87</b>	<b>31.45</b>	<b>211.95</b>	<b>82.20</b>	<b>256.09</b>	<b>119.53</b>	<b>295.62</b>	<b>153.07</b>	<b>304.73</b>	<b>159.30</b>	<b>330.46</b>	<b>178.46</b>

**(unit: Million Cubic Meter)**

#### 4.2.2.2 Major crops cropping pattern

Major-crops cropping pattern includes one major crop from each season namely, kharif, rabi, summer and annual season cultivated on 50% of Ghod command area. Table 4.10 represent the model estimated yearly historical irrigation water demand and deficit obtained for the major-crop cropping pattern under different CCA. The historical irrigation water demand for 150 km<sup>2</sup> cultivable command area was found less than other areas for major-crop cropping pattern. The minimum irrigation water demand of 84.96 MCM was found for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 459.25 MCM was found for 415 km<sup>2</sup> CCA in the year 2012. The average irrigation water demand was found to be 136.87 MCM, 211.95 MCM, 256.09 MCM, 295.62 MCM, 304.73 MCM and 330.46 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

For 150 km<sup>2</sup>, in the year 2006, 2007, 2008, 2010 and 2011 less deficit obtained as 2.63 MCM, 6.8 MCM, 0.00 MCM 1.14 MCM and 8.73 MCM respectively. As the CCA increased the deficit also increased. The average of water demand deficit was found to be 31.45 MCM, 82.20 MCM, 119.53 MCM, 153.07 MCM, 159.03 MCM and 178.46 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively. This represents that by using major-crop cropping pattern in Ghod command area, only 150 km<sup>2</sup> of CCA can be irrigated by minimizing losses and using measures for increasing irrigation efficiency.

#### 4.2.2.3 Sugarcane only cropping pattern

The historical irrigation water demand and deficit in 100 % of CCA for Sugarcane only cropping pattern is shown in Table 4.11. From the Table 4.11, it was observed, the minimum irrigation water demand of 99.43 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 328.86 MCM was obtained for 415 km<sup>2</sup> CCA in the year 2003. The average irrigation water demand was found to be 132.56 MCM, 181.92 MCM, 209.88 MCM, 227.25 MCM, 236.68 MCM and 245.29 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively. For 150 km<sup>2</sup>, in the year 2008, zero deficit was obtained. As the CCA increased the deficit also increased. The average of water demand deficit was found to be 30.64 MCM, 59.88 MCM, 75.90 MCM, 87.78 MCM, 94.53 MCM and 99.16 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively. This represents that by using Sugarcane as 100% cropping pattern in Ghod command area, only 150 km<sup>2</sup> of CCA can be irrigated by minimizing losses. Also, demand deficit obtained from this cropping pattern are comparatively less than the major crops cropping pattern.

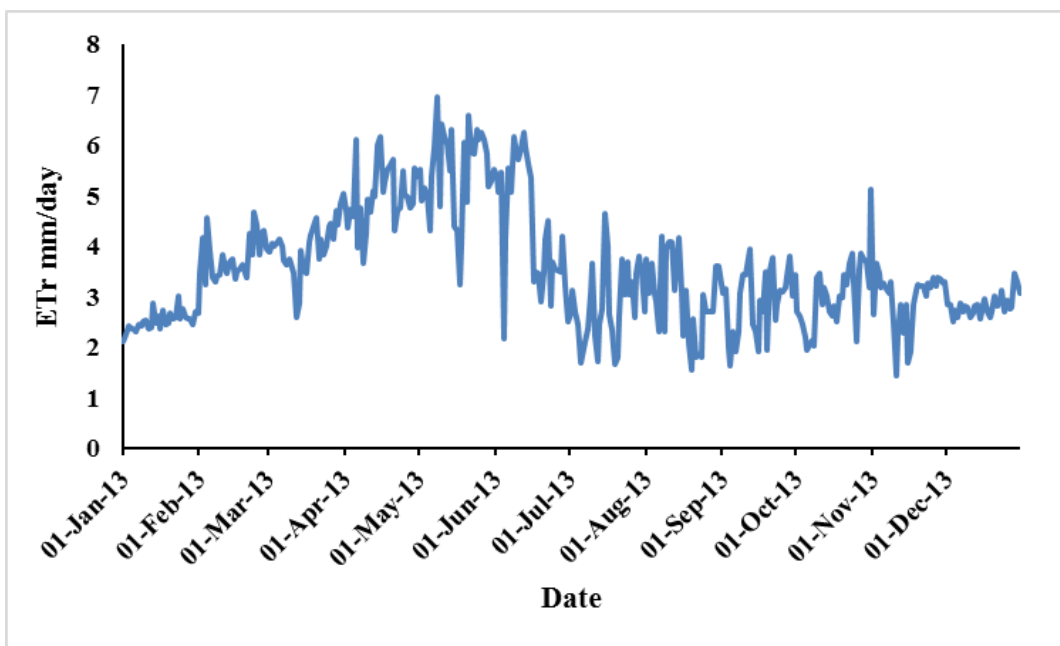
**Table 4.11 Historical irrigation water demand and deficit for Sugarcane only cropping pattern**

<b>Year / CCA</b>	<b>150</b>		<b>200</b>		<b>250</b>		<b>300</b>		<b>350</b>		<b>415</b>	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2002</b>	144.10	57.60	173.16	77.12	179.57	84.37	201.51	91.45	206.48	98.31	226.35	100.42
<b>2003</b>	160.46	50.15	238.49	82.92	271.72	90.55	285.17	114.47	298.13	117.38	328.86	127.13
<b>2004</b>	202.62	99.41	248.19	148.07	260.81	156.26	272.48	154.88	280.79	156.23	287.39	175.94
<b>2005</b>	113.38	33.73	162.40	57.64	190.68	69.78	205.90	73.72	206.57	79.86	203.08	81.09
<b>2006</b>	99.43	13.02	125.60	36.14	141.46	50.25	151.22	57.11	152.77	58.54	155.52	58.67
<b>2007</b>	100.13	12.42	121.77	34.90	138.27	42.61	154.49	51.98	163.79	58.34	167.19	62.63
<b>2008</b>	117.90	0.00	165.15	9.82	224.76	32.17	247.09	52.58	251.92	63.51	265.28	67.64
<b>2009</b>	113.33	21.33	155.61	44.72	200.64	72.61	223.95	95.58	242.38	113.83	241.12	112.45
<b>2010</b>	110.32	7.37	140.64	31.91	156.08	46.47	165.63	51.58	177.91	57.61	190.50	60.48
<b>2011</b>	140.55	12.26	202.89	50.70	242.11	73.55	274.88	94.00	298.59	101.29	307.98	107.43
<b>2012</b>	155.91	29.79	267.25	84.77	302.59	116.31	317.44	128.25	324.22	134.93	324.90	136.92
<b>Average</b>	<b>132.56</b>	<b>30.64</b>	<b>181.92</b>	<b>59.88</b>	<b>209.88</b>	<b>75.90</b>	<b>227.25</b>	<b>87.78</b>	<b>236.68</b>	<b>94.53</b>	<b>245.29</b>	<b>99.16</b>

**(unit: Million Cubic Meter)**

### 4.2.3 Forecasted irrigation water demand

The MIKE HYDRO Basin model was set to forecast the irrigation water demand and deficit using forecasted water availability as discussed in section 3.7. The model was set for three cropping patterns and demand- deficit were calculated for the year 2013. In the MIKE-HYDRO Basin model under the “Climate model” option, choice is there for selection of model between “Rainfall only” and “FAO 56” for the estimation of irrigation water demand. In present study, the “Rainfall only” model was used for estimation of irrigation water demand using rainfall time series and reference ET time series as input. Reference ET series was obtained by using already developed ANN ETo forecasting model of 6-11-1 network architecture trained with *trainlm* training function using Feed-Forward Back Propagation (FFB) network developed by Bhagat and Popale (2017). The forecasted rainfall of Shirur station for the year 2013 was used as input to the model. The forecasted series of reference evapotranspiration is presented in Figure 4.40 and data is given in Appendix-L.



**Figure. 4.40 Forecasted series of reference evapotranspiration obtained using ANN 6-11-1 model for Shirur station**

Forecasted irrigation water demand and deficit were estimated for the year 2013 for multi crop, major crop and sugarcane crop only cropping patterns under variable CCA condition viz. 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> and the results presented in Table 4.12.

Table 4.12 represents the forecasted irrigation water demand-deficit for the year 2013 for different cropping patterns in Ghod command area for different CCA. From the Table 4.12 it was observed

that, as CCA increases irrigation water demand also increases and thereby deficit also increases. For multi-crop cropping pattern, no deficit found for 150 km<sup>2</sup> and 200 km<sup>2</sup> of CCA.

**Table 4.12 Forecasted irrigation water demand-deficit for the year 2013 for different cropping patterns**

CCA km <sup>2</sup>	Multi-Crops		Major Crops		Sugarcane only	
	Demand (MCM)	Deficit (MCM)	Demand (MCM)	Deficit (MCM)	Demand (MCM)	Deficit (MCM)
<b>150</b>	65.22	0.00	160.86	22.22	185.57	25.87
<b>200</b>	84.52	0.00	236.11	54.93	230.51	49.34
<b>250</b>	105.64	4.51	276.43	76.70	243.15	61.26
<b>300</b>	123.75	12.34	318.45	94.10	255.47	64.88
<b>350</b>	215.68	44.98	334.89	104.28	264.87	72.82
<b>415</b>	244.69	62.31	370.58	114.94	288.94	79.01

The maximum irrigation water demand of 370.58 MCM was obtained in 415 km<sup>2</sup> of CCA for major-crops cropping pattern and the deficit found was 114.94 MCM. For multi-crop cropping pattern, the irrigation water demand-deficit obtained up to 250 km<sup>2</sup> was considerable. But for major-crops and sugarcane only cropping pattern, the irrigation water demand-deficit obtained up to 150 km<sup>2</sup> was considerable.

### **4.3 Comparison of SWAB-CRYB model with MIKE HYDRO Basin model for estimation of yield of different crops**

The yield of major crops is an important factor determining the agricultural development of a region. The actual yield of major crops that has been taken under Ghod command area was calculated by MIKE HYDRO Basin model and SWAB-CRYB model.

MIKE HYDRO Basin model and SWAB-CRYB model simulates actual crop yield. The comparison of crop yields estimated using MIKE HYDRO Basin model and SWAB-CRYB model were made for different crops. Crop yield is function of different climatic variables. Therefore, the input data was kept same for both of the model. The actual yield was simulated in MIKE HYDRO Basin model and SWAB-CRYB model for the period of 11 years from 2002 to 2012. The results obtained were discussed in the following section for Ghod command area.

#### **4.3.1 Estimation of crop yield using MIKE HYDRO Basin model**

MIKE HYDRO Basin model uses FAO-33 Yield model to calculate the crop yield. FAO-33 Yield model is based on a so-called potential yield ( $Y_p$ ), which is the crop yield under optimal conditions

(no soil moisture stress). The sensitivity of a crop to soil moisture stress depends on the growth stage. A crop will usually be more sensitive to soil moisture stress in early growth stages than in late stages. This is taken into account with a yield response factor ( $K_y$ ).  $K_y$  values for different crops were taken from the literature. The different climatic variables were used to calculate actual and potential evapotranspiration. The estimated yield obtained using MIKE HYDRO Basin model for different crops in Ghod command area for the period of 2002-2012 are given in Table 4.13.

#### **4.3.2 Estimation of crop yield using SWAB-CRYB model**

The actual crop yield of different crops grown in the Ghod command area is also estimated using SWAB-CRYB model developed by Gorantiwar (1995), using crop, soil, weather and irrigation data. The actual yield estimated using crop growth model (Stewart et. al., 1976). The purpose of crop growth model was to estimate the crop yield from the output such as actual evapotranspiration obtained from the soil water balance equation. The yield was estimated with the help of stress offered during individual crop growth period by stage wise crop growth models. The input parameters such as climatic variables, stage wise  $K_c$  and  $K_y$  values, soil parameters were used same as that used in MIKE HYDRO Basin model. The results obtained are presented in the Table 4.14.

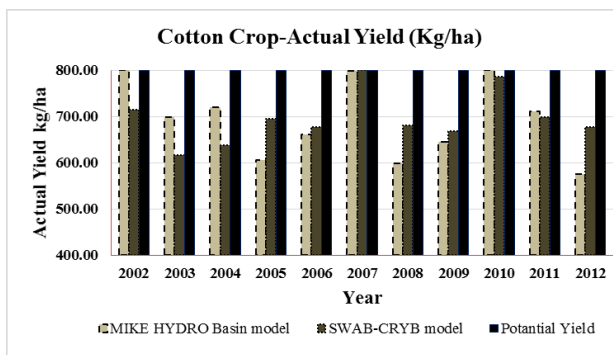
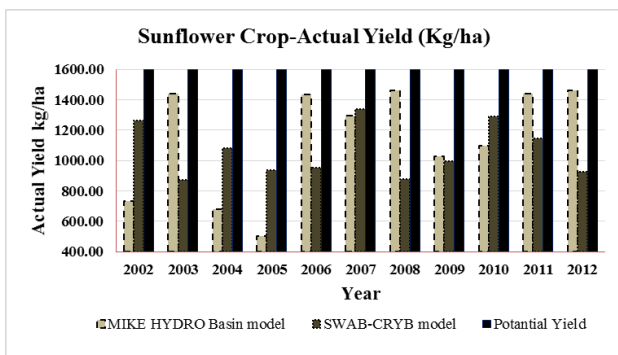
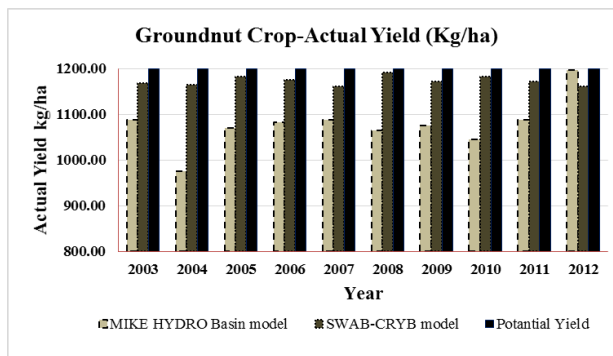
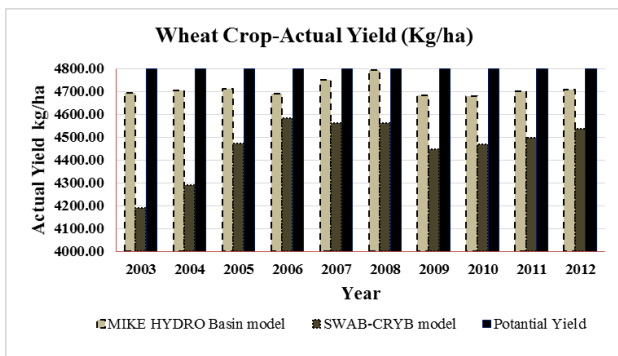
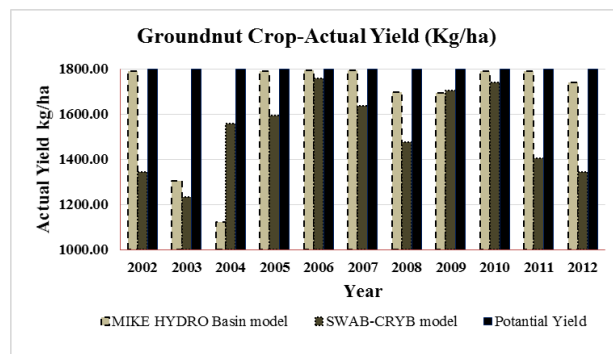
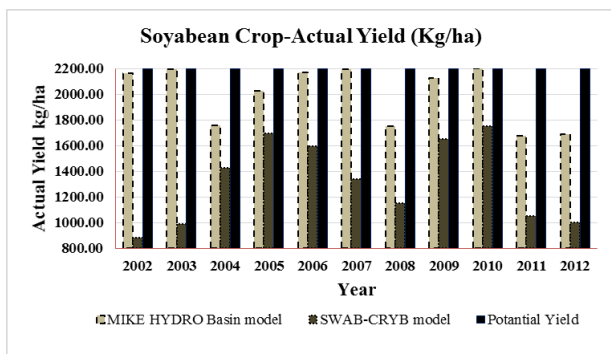
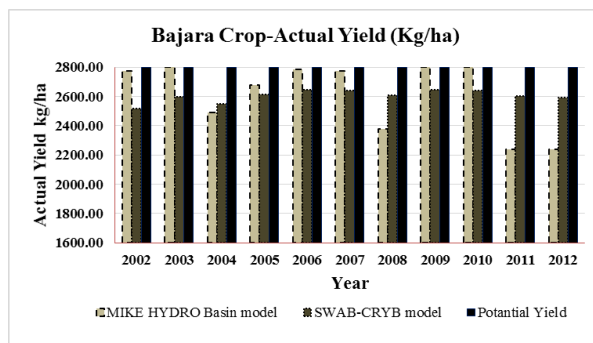
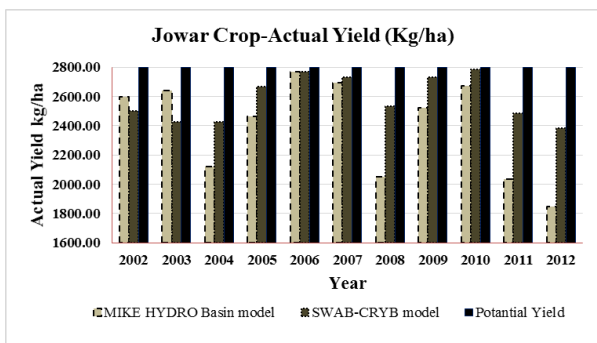
**Table 4.13. Crop yield of different crops estimated by using MIKE HYDRO Basin model**

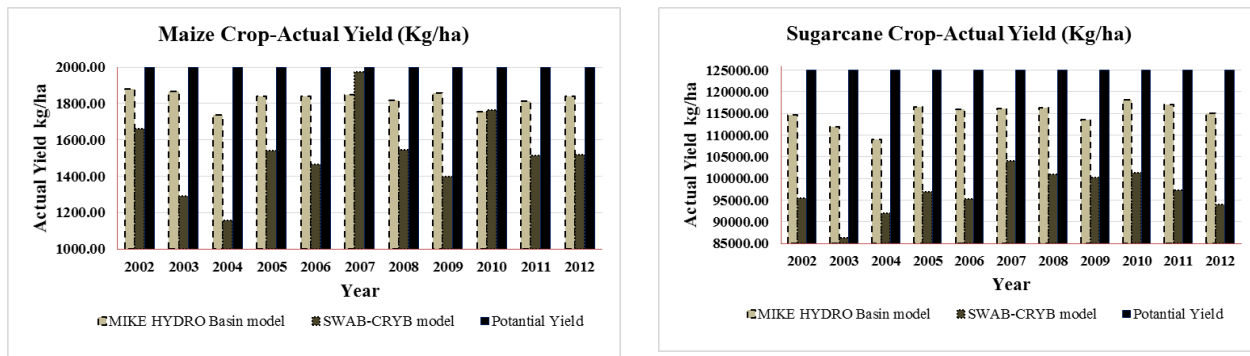
Year	Actual Yield (kg/ha)									
	Jowar	Bajara	Soybean	Groundnut	Wheat	Gram	Sunflower	Cotton	Maize	Sugarcane
<b>2002</b>	2597.97	2774.86	2160.00	1790.85	0.00	0.00	733.33	799.63	1880.63	114710.30
<b>2003</b>	2639.35	2799.52	2195.97	1304.63	4693.50	1087.69	1438.14	699.14	1865.00	111974.41
<b>2004</b>	2121.56	2491.15	1757.82	1121.36	4705.20	974.61	681.08	720.49	1735.69	108908.78
<b>2005</b>	2463.46	2674.64	2025.54	1790.08	4712.23	1069.37	501.93	604.95	1841.45	116416.16
<b>2006</b>	2767.09	2786.80	2170.41	1791.89	4690.23	1082.45	1433.69	661.35	1840.28	115960.34
<b>2007</b>	2695.85	2771.07	2194.94	1791.85	4749.55	1088.06	1293.36	798.92	1848.19	116096.13
<b>2008</b>	2050.20	2378.76	1750.68	1698.16	4793.06	1064.21	1462.87	598.71	1818.92	116360.44
<b>2009</b>	2521.36	2800.00	2124.42	1693.66	4680.64	1074.76	1025.42	644.34	1856.68	113595.88
<b>2010</b>	2673.70	2800.00	2200.00	1790.34	4678.46	1044.34	1098.17	799.69	1753.47	118122.81
<b>2011</b>	2034.76	2239.28	1674.08	1790.82	4701.30	1086.73	1440.52	710.33	1813.51	117079.00
<b>2012</b>	1847.93	2239.74	1690.35	1741.25	4707.61	1196.01	1461.84	574.87	1839.29	115038.50
<b>Average Yield(kg/ha)</b>	<b>2401.20</b>	<b>2614.17</b>	<b>1994.93</b>	<b>1664.08</b>	<b>4711.18</b>	<b>1076.82</b>	<b>1142.76</b>	<b>692.04</b>	<b>1826.65</b>	<b>114932.98</b>
<b>Reduction over Potential yield, %</b>	<b>14</b>	<b>7</b>	<b>9</b>	<b>8</b>	<b>2</b>	<b>10</b>	<b>29</b>	<b>13</b>	<b>9</b>	<b>8</b>

**Table 4.14. Crop yield of different crops estimated by using SWAB-CRYB model**

Year	Actual Yield (kg/ha)									
	Jowar	Bajara	Soybean	Groundnut	Wheat	Gram	Sunflower	Cotton	Maize	Sugarcane
<b>2002</b>	2500.40	2516.20	884.20	1342.80	0.00	0	1264.00	715.20	1660.00	95500
<b>2003</b>	2424.80	2594.60	985.40	1231.20	4190.00	1168	870.40	616.00	1290.00	86250
<b>2004</b>	2424.80	2549.80	1427.60	1557.00	4290.00	1165	1080.00	637.60	1154.17	91875
<b>2005</b>	2665.60	2611.40	1693.80	1594.80	4472.00	1182	937.60	694.40	1540.00	96875
<b>2006</b>	2769.20	2645.00	1594.80	1756.80	4584.00	1176	952.00	677.60	1464.17	95250
<b>2007</b>	2732.80	2639.40	1337.71	1634.40	4560.00	1160	1340.00	800.00	1971.67	104125
<b>2008</b>	2534.00	2605.80	1148.20	1476.00	4560.00	1192	876.00	680.80	1544.17	100875
<b>2009</b>	2730.00	2645.00	1650.43	1702.80	4448.00	1171	996.00	668.80	1395.83	100125
<b>2010</b>	2786.00	2642.20	1751.00	1740.60	4468.00	1182	1288.00	786.40	1765.83	101375
<b>2011</b>	2486.40	2603.00	1051.71	1404.00	4496.00	1171	1144.00	699.20	1512.50	97250
<b>2012</b>	2380.00	2589.00	1001.43	1344.60	4536.00	1160	924.00	676.00	1520.00	94000
<b>Average Yield (kg/ha)</b>	<b>2584.9</b>	<b>2603.8</b>	<b>1320.6</b>	<b>1525.9</b>	<b>4054.9</b>	<b>1066.1</b>	<b>1061.1</b>	<b>695.6</b>	<b>1528.9</b>	<b>96681.8</b>
<b>% Reduction over Potential yield</b>	<b>8</b>	<b>7</b>	<b>40</b>	<b>15</b>	<b>16</b>	<b>11</b>	<b>34</b>	<b>13</b>	<b>24</b>	<b>23</b>

The actual yield of different crops simulated by MIKE HYDRO Basin Model and SWAB-CRYB model is compared with potential yields for different crops viz. Jowar, Bajara, Soybean, Groundnut, Sunflower, Cotton, Maize and Sugarcane and represented in Figure 4.41.





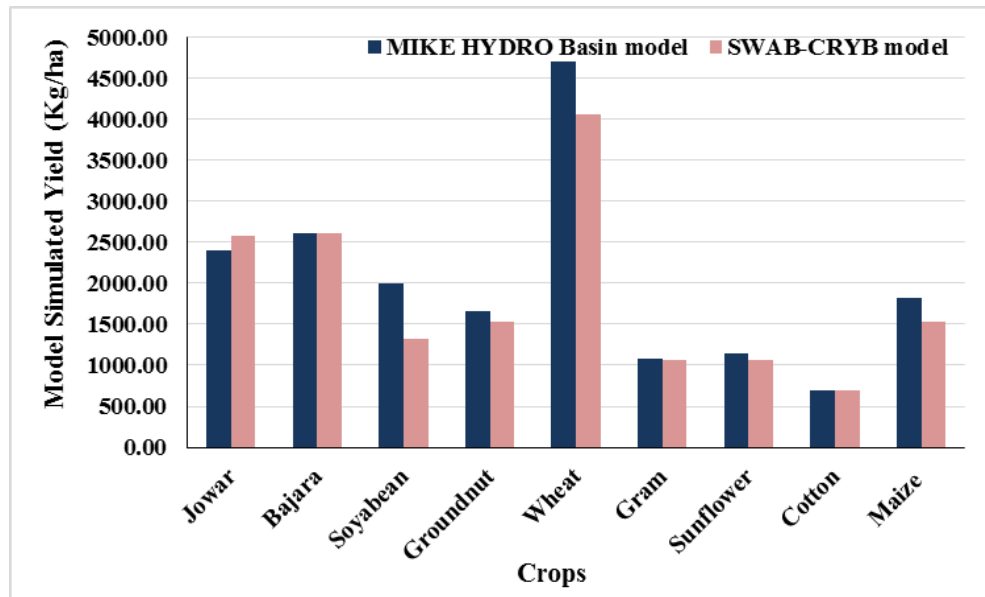
**Figure 4.41 Comparison of actual yield of different crops simulated by MIKE HYDRO Basin model and SWAB-CRYB model**

The actual crop yield of different crops estimated by using MIKE HYDRO Basin model is presented in Table 4.13. The average actual crop yield obtained was 2401.20 kg/ha for Jowar, 2614.17 kg/ha for Bajara, 1994.93 kg/ha for Soybean, 1664.08 kg/ha for Groundnut, 4711.18 kg/ha for Wheat, 1076.82 kg/ha for Gram, 1142.76 kg/ha for Sunflower, 692.04 kg/ha for Cotton, 1826.65 kg/ha for Maize and 114932.98 kg/ha for Sugarcane crop. The percentage reduction in yield was found to be 14%, 7%, 9%, 8%, 2%, 10%, 29%, 13%, 9% and 8% for Jowar, Bajara, Soybean, Groundnut, Wheat, Gram, Sunflower, Cotton, Maize and Sugarcane respectively, as compared to the potential yield.

The actual crop yield of different crops estimated by using SWAB-CRYB model is presented in Table 4.14. The average actual crop yield obtained was 2584.9 kg/ha for Jowar, 2603.8 kg/ha for Bajara, 1320.6 kg/ha for Soybean, 1525.9 kg/ha for Groundnut, 4054.9 kg/ha for Wheat, 1066.1 kg/ha for Gram, 1061.1 kg/ha for Sunflower, 695.6 kg/ha for Cotton, 1528.9 kg/ha for Maize and 96681.8kg/ha for Sugarcane crop. The percentage reduction in yield was found to be 8%, 7%, 40%, 15%, 16%, 11%, 34%, 13%, 24% and 23% for Jowar, Bajara, Soybean, Groundnut, Wheat, Gram, Sunflower, Cotton, Maize and Sugarcane respectively, as compared to the potential yield.

### **4.3.3 Comparison of crop yield obtained using MIKE HYDRO Basin model and SWAB-CRYB model**

The comparison of actual yield of different crops estimated by using MIKE HYDRO Basin model and SWAB-CRYB model is presented in Figure 4.42. MIKE HYDRO Basin model simulated actual crop yield was found to be comparatively more than SWAB-CRYB model for all crops grown in the Ghod command area.



**Figure 4.42 Average crop yield of different crops estimated by using MIKE HYDRO Basin model and SWAB-CRYB model**

#### **4.4 Water allocation scenarios**

Water allocation is one important aspect for managing the available water resources optimally. As the population is increasing day by day the demand for water is also increasing. Therefore, it is necessary to consider the increasing water demand for water allocation. In present study, two water allocation scenarios were studied using the historical and forecasted irrigation water demand in the Ghod command area catchment.

##### **4.4.1 Historical water allocation scenario**

The historical irrigation demand calculated by simulation was considered as baseline scenario as discussed in section 3.6. Two scenarios are considered for three cropping patterns *viz.* multi-crop, major-crop and sugarcane crop only. In first scenario the irrigation water demand of base scenario was increased by 25 %. In second scenario the irrigation water demand of base scenario was increased by 40 %.

The model setup for historical water allocation scenario was discussed in section 3.6. Two water allocation scenarios *viz.* 25% and 40% increase in irrigation water demand than historical irrigation water demand were studied using the historical water availability in the Ghod command area.

##### **4.4.1.1 Scenario 1: 25 % Increase in historical irrigation water demand**

The results of historical irrigation water demand for three different cropping pattern were discussed in section 4.2.2, which was considered as base scenario. In Scenario 1, the irrigation water demand of

base scenario was considered to be increased by 25 % and deficit calculated by running the model again for three different cropping pattern and results obtained are discussed in this section.

#### **4.4.1.1.1 Scenario 1 for Multi-crop cropping pattern**

The yearly historical irrigation water demand and deficit for multi-crop cropping pattern for Scenario 1 (25 % increase in historical irrigation water demand) is presented in Table 4.15. From the Table 4.15 it is observed that, irrigation water demand for 150 km<sup>2</sup> cultivable command area was found less than other areas for multi-crop cropping pattern. Minimum irrigation water demand of 61.45 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2010 and maximum irrigation water demand of 644.39 MCM was found for 415 km<sup>2</sup> CCA in the year 2012. The average irrigation water demand was found to be 72.73 MCM, 96.45 MCM, 130.33 MCM, 199.57 MCM, 280.29 MCM and 321.25 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

Also, the irrigation water demand- deficit for all years was found to be zero except 2002 and 2004 which means the irrigation water demand of all users was fulfilled for 150 km<sup>2</sup> CCA. As the CCA increased the deficit also increased. The average of water demand deficit was found to be 0.77 MCM, 7.68 MCM, 29.75 MCM, 83.40 MCM, 148.49 MCM and 185.20 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively. This represents, if the historical irrigation water demand is increased by 25 % by using multi-crop cropping pattern in Ghod command area, 150 km<sup>2</sup> of CCA can be easily irrigated with sufficient supply of water to users. Also, using combination of micro- irrigation systems and reducing different losses in system, up to 200 km<sup>2</sup> of CCA can be irrigated with this multi-crop cropping pattern.

#### **4.4.1.1.2 Scenario 1 for Major crops cropping pattern**

The yearly historical irrigation water demand- deficit for major-crops cropping pattern for Scenario 1-25 % increase in historical irrigation water demand is presented in Table 4.16. Similarly, as multi-crop cropping pattern, irrigation water demand for 150 km<sup>2</sup> cultivable command area was obtained less than other areas for this cropping pattern. Minimum irrigation water demand of 106.20 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 574.06 MCM was found for 415 km<sup>2</sup> CCA in the year 2012.

The average irrigation water demand was found to be 171.09 MCM, 264.94 MCM, 320.11 MCM, 369.53 MCM, 380.92 MCM and 413.07 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

For 150 km<sup>2</sup>, zero deficit was obtained in the year 2008. As the CCA increased the deficit also increased. The average of water demand deficit was found to be 57.14 MCM, 126.66 MCM, 174.18 MCM, 216.78 MCM, 225.08 MCM and 250.37 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively, which was very high. This represents, by using major-crops cropping pattern for Scenario 1 (25 % increase in historical irrigation water demand) in Ghod command area, only 150 km<sup>2</sup> of CCA can be irrigated by minimizing losses and using measures for increasing irrigation efficiency.

#### **4.4.1.1.3 Scenario 1 for Sugarcane only cropping pattern**

The yearly historical irrigation water demand and deficit obtained for Sugarcane only cropping pattern for 25 % increase in historical irrigation water demand (Scenario 1) are presented in Table 4.17. It was observed from Table 4.17 that, the minimum irrigation water demand of 124.28 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 411.08 MCM was obtained for 415 km<sup>2</sup> CCA in the year 2003. Irrigation water demand for 150 km<sup>2</sup> cultivable command area was obtained less than other areas for this cropping pattern. Also, this cropping pattern simulated irrigation water demand was less than that of major-crops cropping pattern. The average irrigation water demand was found to be 165.70 MCM, 227.40 MCM, 262.35 MCM, 284.06 MCM, 295.85 MCM and 306.61 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

In the year 2008, minimum deficit of 14.74 MCM was obtained for 150 km<sup>2</sup> of CCA. The average irrigation water demand-deficit was found to be 56.90 MCM, 95.90 MCM, 114.49 MCM, 133.21 MCM, 142.00 MCM and 148.82 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively, which was very high.

In the scenario 1 for all three selected cropping patterns it was observed that, the irrigation water demand simulated for multi-crop cropping pattern was less than major-crop and sugarcane only cropping patterns.

**Table 4.15 Scenario 1- 25 % increase in historical irrigation water demand-deficit for multi-crop cropping pattern**

<b>Year / CCA (km<sup>2</sup>)</b>	<b>150</b>		<b>200</b>		<b>250</b>		<b>300</b>		<b>350</b>		<b>415</b>	
	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>
<b>2002</b>	74.15	4.03	99.63	18.50	124.01	31.88	147.13	46.20	171.35	61.04	199.79	80.18
<b>2003</b>	92.66	0.00	119.59	20.38	150.95	45.78	236.62	121.79	323.91	204.30	378.94	249.94
<b>2004</b>	81.58	4.48	108.66	23.54	205.34	115.10	321.66	227.63	403.40	309.27	442.85	356.87
<b>2005</b>	69.88	0.00	91.92	7.26	108.01	23.91	132.51	43.34	206.13	93.45	262.27	144.22
<b>2006</b>	62.02	0.00	85.24	0.00	102.42	9.50	122.16	31.65	191.81	89.30	220.56	112.08
<b>2007</b>	72.14	0.00	91.20	0.00	115.56	9.98	140.60	26.54	164.34	44.46	186.92	63.38
<b>2008</b>	63.10	0.00	84.01	0.00	102.90	0.00	172.59	0.00	380.65	141.88	394.88	147.69
<b>2009</b>	64.84	0.00	84.32	5.64	106.18	25.03	156.77	62.52	268.47	165.82	305.67	201.83
<b>2010</b>	61.45	0.00	83.30	0.00	96.32	5.69	113.61	19.17	129.67	32.71	156.14	50.04
<b>2011</b>	77.91	0.00	105.30	0.00	126.69	13.04	151.60	28.93	225.98	72.15	341.35	174.79
<b>2012</b>	80.31	0.00	107.80	9.11	195.27	47.36	500.05	309.64	617.47	418.99	644.39	456.20
<b>Average</b>	<b>72.73</b>	<b>0.77</b>	<b>96.45</b>	<b>7.68</b>	<b>130.33</b>	<b>29.75</b>	<b>199.57</b>	<b>83.40</b>	<b>280.29</b>	<b>148.49</b>	<b>321.25</b>	<b>185.20</b>

**(unit: Million Cubic Meter)**

**Table 4.16 Scenario 1- 25 % increase in historical irrigation water demand-deficit for major-crop cropping pattern**

<b>Year / CCA (km<sup>2</sup>)</b>	<b>150</b>		<b>200</b>		<b>250</b>		<b>300</b>		<b>350</b>		<b>415</b>	
	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>
<b>2002</b>	162.49	53.51	208.85	85.73	287.92	138.05	334.28	174.71	335.63	186.44	386.54	201.43
<b>2003</b>	225.60	109.17	318.67	180.79	378.22	226.20	440.04	260.38	454.34	244.09	518.03	300.00
<b>2004</b>	276.42	170.63	360.63	254.98	403.04	294.81	443.67	339.66	435.74	337.43	460.05	356.72
<b>2005</b>	133.83	44.60	225.49	106.04	282.20	153.52	325.61	193.42	335.41	202.57	376.43	229.47
<b>2006</b>	106.20	21.01	186.70	83.02	218.31	121.15	259.20	158.93	270.99	157.65	297.62	196.44
<b>2007</b>	123.15	25.53	160.67	51.22	225.72	102.09	285.21	156.71	294.59	175.81	315.16	194.96
<b>2008</b>	130.78	0.00	295.06	61.03	359.40	114.34	411.45	145.91	416.92	158.17	441.03	179.47
<b>2009</b>	127.78	35.18	260.76	147.28	311.60	195.44	361.01	248.43	376.67	250.92	394.85	267.37
<b>2010</b>	118.52	17.82	152.40	45.26	200.58	88.52	255.34	139.31	280.69	162.71	303.59	181.64
<b>2011</b>	159.29	28.45	292.44	126.54	359.40	178.34	407.94	215.76	440.23	228.47	476.45	244.83
<b>2012</b>	317.89	122.61	452.71	251.35	494.79	303.51	541.04	351.32	548.88	371.58	574.06	401.68
<b>Average</b>	<b>171.09</b>	<b>57.14</b>	<b>264.94</b>	<b>126.66</b>	<b>320.11</b>	<b>174.18</b>	<b>369.53</b>	<b>216.78</b>	<b>380.92</b>	<b>225.08</b>	<b>413.07</b>	<b>250.37</b>

**(unit: Million Cubic Meter)**

**Table 4.17 Scenario 1- 25 % increase in historical irrigation water demand-deficit for Sugarcane only cropping pattern**

<b>Year / CCA (km<sup>2</sup>)</b>	<b>150</b>		<b>200</b>		<b>250</b>		<b>300</b>		<b>350</b>		<b>415</b>	
	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>
<b>2002</b>	180.13	82.79	216.45	107.44	224.46	116.45	251.89	125.50	258.10	134.13	282.93	136.81
<b>2003</b>	200.57	81.74	298.11	128.44	339.64	141.32	356.46	174.06	372.66	178.28	411.08	190.26
<b>2004</b>	253.28	146.59	310.24	207.84	326.01	218.20	340.60	216.55	350.99	218.25	359.24	248.26
<b>2005</b>	141.72	58.92	203.00	89.22	238.35	106.22	257.38	112.75	258.21	122.29	253.85	124.01
<b>2006</b>	124.28	34.17	157.00	66.47	176.82	84.41	189.02	93.40	190.96	95.40	194.39	95.65
<b>2007</b>	125.16	33.12	152.21	61.68	172.83	72.12	193.11	87.16	204.74	96.12	208.99	101.54
<b>2008</b>	147.38	14.74	206.43	38.79	280.96	65.07	308.86	91.09	314.90	104.45	331.61	113.49
<b>2009</b>	141.67	45.94	194.51	75.67	250.80	121.73	279.94	150.61	302.97	173.51	301.40	171.94
<b>2010</b>	137.90	28.74	175.80	59.81	195.10	78.81	207.03	85.34	222.38	93.19	238.13	96.80
<b>2011</b>	175.69	37.49	253.61	88.50	302.64	117.49	343.60	143.26	373.24	152.45	384.98	160.08
<b>2012</b>	194.89	61.70	334.06	131.05	378.24	170.52	396.80	185.53	405.27	193.94	406.12	198.17
<b>Average</b>	<b>165.70</b>	<b>56.90</b>	<b>227.40</b>	<b>95.90</b>	<b>262.35</b>	<b>117.49</b>	<b>284.06</b>	<b>133.21</b>	<b>295.86</b>	<b>142.00</b>	<b>306.61</b>	<b>148.82</b>

(unit: Million Cubic Meter)

#### **4.4.1.2 Scenario 2: 40 % Increase in irrigation water demand**

In Scenario 2, the irrigation water demand of base scenario was increased by 40 % and deficit calculated by running the model again for three different cropping pattern and results are discussed here in this section.

##### **4.4.1.2.1 Scenario 2 for Multi-crop cropping pattern**

The yearly historical irrigation water demand- deficit obtained for multi-crop cropping pattern for 40 % increase in historical irrigation water demand (Scenario 2) are presented in Table 4.18. From the Table 4.18, it was observed, irrigation water demand for 150 km<sup>2</sup> cultivable command area was found less than other areas for multi-crop cropping pattern. Minimum irrigation water demand of 72.16 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 721.72 MCM was found for 415 km<sup>2</sup> CCA in the year 2012. The average irrigation water demand was found to be 81.46 MCM, 108.03 MCM, 145.97 MCM, 223.52 MCM, 313.92 MCM and 359.80 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

Also, the irrigation water demand- deficit was obtained to be zero except in the year 2002, 2003 and 2004 which means the irrigation water demand of all users was fulfilled. As the CCA increased the deficit also increased. The average of water demand deficit was found to be 2.59 MCM, 13.92 MCM, 41.75 MCM, 102.64 MCM, 178.20 MCM and 219.32 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively. This represents, if the historical irrigation water demand is increased 40 % by using multi-crop cropping pattern in Ghod command area, 150 km<sup>2</sup> of CCA can be easily irrigated with sufficient supply of water to users. Also, using combination of micro- irrigation systems and reducing different losses in system, up to 200 km<sup>2</sup> of CCA can be irrigated with this multi-crop cropping pattern.

##### **4.4.1.2.2 Scenario 2 for Major crops cropping pattern**

The yearly historical irrigation water demand and deficit obtained for major-crop cropping pattern for 40 % increase in historical irrigation water demand (Scenario 2) are represented in Table 4.19. From the Table 4.19, it was observed, the minimum irrigation water demand of 118.95 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 642.95 MCM was found for 415 km<sup>2</sup> CCA in the year 2012. The average irrigation water demand was found to be 191.62 MCM, 296.74 MCM, 358.52 MCM, 413.87 MCM, 426.63 MCM and 462.64 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

Also, in the year 2008, the irrigation water demand- deficit was obtained to be zero. As the CCA increased the deficit also increased. The average of water demand deficit was found to be 73.06 MCM,

153.88 MCM, 207.64 MCM, 255.72 MCM, 265.33 MCM and 293.64 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup> respectively.

The irrigation water demand and deficit obtained for major-crop cropping pattern using Scenario-2 (40 % increase in historical irrigation water demand) was considerably higher.

#### **4.4.1.2.3 Scenario 2 for Sugarcane only cropping pattern**

The yearly historical irrigation water demand and deficit obtained for 100% Sugarcane only cropping pattern for 40 % increase in historical irrigation water demand (Scenario 2) are represented in Table 4.20. It is observed from Table 4.20 that, the minimum irrigation water demand of 139.20 MCM was obtained for 150 km<sup>2</sup> CCA in the year 2006 and maximum irrigation water demand of 460.41 MCM was found for 415 km<sup>2</sup> CCA in the year 2003. The average irrigation water demand was found to be 185.58 MCM, 254.59 MCM, 293.83 MCM, 318.15 MCM, 331.36 MCM and 343.40 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup>, respectively.

Also, the minimum irrigation water demand- deficit of 28.47 MCM was obtained in the year 2008 for 150 km<sup>2</sup> of CCA. The average of water demand deficit was found to be 73.31 MCM, 118.05 MCM, 143.51 MCM, 161.76 MCM, 171.79 MCM and 179.84 MCM for CCA of 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup> and 415 km<sup>2</sup>, respectively.

The irrigation water demand and deficit simulated in for major-crop cropping pattern in Scenario-2 (40 % Increase in historical irrigation water demand) was considerably higher than 100% 'Sugarcane only' cropping pattern. Also, in this scenario, it was observed, as the irrigation water demand was increased, the deficit was also increased for the three cropping patterns.

**Table 4.18 Scenario 2- 40 % increase in historical irrigation water demand-deficit for multi-crop cropping pattern**

Year / CCA (km <sup>2</sup> )	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2002</b>	83.05	8.97	111.59	25.24	138.89	40.90	164.79	57.15	191.91	74.11	223.77	95.17
<b>2003</b>	103.78	7.15	133.94	30.84	169.06	60.23	265.01	145.57	362.78	239.15	424.41	289.54
<b>2004</b>	91.37	12.35	121.70	34.37	229.98	138.80	360.26	265.72	451.81	357.28	495.99	409.92
<b>2005</b>	78.27	0.00	102.95	16.26	120.97	34.95	148.41	57.81	230.87	115.62	293.75	172.90
<b>2006</b>	69.46	0.00	95.47	4.70	114.71	20.36	136.82	45.09	214.82	112.17	247.03	137.81
<b>2007</b>	80.80	0.00	102.15	2.58	129.43	19.97	157.47	38.83	184.06	58.50	209.36	80.88
<b>2008</b>	70.67	0.00	94.10	0.00	115.24	0.00	193.30	0.00	426.33	176.80	442.26	183.31
<b>2009</b>	72.62	0.00	94.44	14.48	118.92	36.17	175.58	80.44	300.69	195.98	342.35	236.19
<b>2010</b>	68.83	0.00	93.30	0.00	107.88	14.77	127.24	29.91	145.23	45.31	174.87	65.20
<b>2011</b>	87.26	0.00	117.94	6.17	141.89	22.80	169.79	40.05	253.10	93.26	382.32	208.24
<b>2012</b>	89.94	0.00	120.74	18.46	218.71	70.25	560.06	368.51	691.56	491.98	721.72	533.33
<b>Average</b>	<b>81.46</b>	<b>2.59</b>	<b>108.03</b>	<b>13.92</b>	<b>145.97</b>	<b>41.75</b>	<b>223.52</b>	<b>102.64</b>	<b>313.92</b>	<b>178.20</b>	<b>359.80</b>	<b>219.32</b>

(unit: Million Cubic Meter)

**Table 4.19 Scenario 2- 40 % increase in historical irrigation water demand-deficit for major-crop cropping pattern**

<b>Year / CCA (km<sup>2</sup>)</b>	<b>150</b>		<b>200</b>		<b>250</b>		<b>300</b>		<b>350</b>		<b>415</b>	
	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>	<b>Demand</b>	<b>Deficit</b>
<b>2002</b>	181.99	65.36	233.92	101.61	322.47	160.30	374.39	201.53	375.90	214.67	432.93	231.48
<b>2003</b>	252.67	132.41	356.91	212.77	423.61	263.77	492.85	304.79	508.86	288.94	580.19	360.71
<b>2004</b>	309.59	202.29	403.90	296.97	451.41	341.48	496.92	390.47	488.03	388.10	515.26	401.09
<b>2005</b>	149.89	58.08	252.55	129.18	316.07	183.40	364.68	227.88	375.66	238.11	421.60	268.39
<b>2006</b>	118.95	31.39	209.10	104.73	244.50	148.46	290.30	190.54	303.51	189.46	333.34	232.82
<b>2007</b>	137.93	37.57	179.96	66.21	252.80	125.47	319.44	187.08	329.94	208.75	352.97	230.25
<b>2008</b>	146.48	0.00	330.47	85.95	402.52	145.66	460.83	181.02	466.95	194.76	493.95	218.61
<b>2009</b>	143.12	48.84	292.05	176.57	348.99	230.56	404.33	292.92	421.87	295.89	442.24	314.55
<b>2010</b>	132.75	28.73	170.68	60.72	224.65	109.59	285.98	166.67	314.38	192.89	340.02	214.02
<b>2011</b>	178.40	41.53	327.53	154.20	402.52	212.56	456.89	254.59	493.06	268.80	533.62	287.23
<b>2012</b>	356.04	157.49	507.03	303.73	554.17	362.78	605.96	415.43	614.75	438.30	642.95	470.85
<b>Average</b>	<b>191.62</b>	<b>73.06</b>	<b>296.74</b>	<b>153.88</b>	<b>358.52</b>	<b>207.64</b>	<b>413.87</b>	<b>255.72</b>	<b>426.63</b>	<b>265.33</b>	<b>462.64</b>	<b>293.64</b>

(unit: Million Cubic Meter)

**Table 4.20 Scenario 2- 40 % increase in historical irrigation water demand-deficit for Sugarcane only cropping pattern**

Year / CCA (km <sup>2</sup> )	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2002</b>	201.75	98.05	242.43	125.78	251.40	135.86	282.11	145.98	289.08	155.69	316.89	158.60
<b>2003</b>	224.64	100.62	333.89	159.17	380.40	172.81	399.23	210.43	417.38	215.64	460.41	228.61
<b>2004</b>	283.67	175.13	347.47	243.77	365.13	255.40	381.48	253.65	393.11	261.37	402.35	291.93
<b>2005</b>	158.73	74.19	227.37	108.28	266.95	129.81	288.27	137.24	289.19	148.12	284.32	149.90
<b>2006</b>	139.20	47.05	175.84	84.78	198.04	105.14	211.70	115.59	213.87	117.81	217.72	118.09
<b>2007</b>	140.18	45.78	170.47	77.98	193.57	91.27	216.28	108.43	229.31	118.97	234.07	125.14
<b>2008</b>	165.06	28.47	231.21	57.06	314.67	89.00	345.93	119.36	352.69	129.01	371.40	144.64
<b>2009</b>	158.66	60.97	217.85	94.47	280.89	151.36	313.53	183.80	339.33	209.60	337.57	207.70
<b>2010</b>	154.45	41.63	196.90	77.02	218.51	98.31	231.88	105.71	249.07	114.64	266.70	118.68
<b>2011</b>	196.77	53.55	284.04	111.34	338.96	144.05	384.83	172.91	418.03	183.19	431.17	191.78
<b>2012</b>	218.28	80.97	374.15	158.94	423.62	205.63	444.42	226.22	453.90	235.71	454.86	243.11
<b>Average</b>	<b>185.58</b>	<b>73.31</b>	<b>254.69</b>	<b>118.05</b>	<b>293.83</b>	<b>143.51</b>	<b>318.15</b>	<b>161.76</b>	<b>331.36</b>	<b>171.79</b>	<b>343.40</b>	<b>179.84</b>

(unit: Million Cubic Meter)

#### 4.4.2 Forecasted water allocation scenarios

Forecasted water allocation scenarios were generated using the data estimated for the year 2013 using forecasted rainfall and ETr data timeseries. The model setup for forecasted water allocation scenarios was discussed in Section 3.7. The forecasted irrigation demand estimated by simulation was considered as baseline scenario which was discussed in section 4.2.3. In first scenario, the irrigation water demand of base scenario was increased by 25%. In second scenario, the irrigation water demand of base scenario was increased by 40%.

##### 4.4.2.1 Forecasted irrigation water demand for scenario 1

The forecasted irrigation water demand and deficit obtained for 25 % increase in irrigation water demand (Scenario 1) in the year 2013 for the selected threes cropping patterns in Ghod command area under variable CCA condition are presented in Table 4.21. From Table 4.21, it was observed, as CCA increases irrigation water demand also increases and thereby deficit also increases. For multi-crop cropping pattern, minimum irrigation water demand was observed to be 81.53 MCM in 150 km<sup>2</sup> and deficit was found to be 3.45 MCM. Maximum irrigation water demand of 436.23 MCM was obtained in 415 km<sup>2</sup> of CCA for major-crops cropping pattern and deficit obtained was 154.85 MCM. For multi-crop cropping pattern, the irrigation water demand-deficit obtained up to 250 km<sup>2</sup> was considerable. But for major-crops and Sugarcane only cropping pattern, the irrigation water demand and deficit obtained were considerably higher.

**Table 4.21 Scenario 1: 25 % increase in forecasted irrigation water demand**

CCA (km <sup>2</sup> )	Multi-Crops		Major Crops		Sugarcane only	
	Demand (MCM)	Deficit (MCM)	Demand (MCM)	Deficit (MCM)	Demand (MCM)	Deficit (MCM)
150	81.53	3.45	201.08	34.68	231.96	44.13
200	105.65	13.15	295.14	81.84	288.14	78.97
250	132.05	24.28	345.54	106.12	303.94	82.84
300	154.69	38.57	398.06	128.31	319.34	94.25
350	269.60	74.88	418.61	141.43	331.09	95.71
415	305.86	94.62	463.23	154.85	361.18	99.27

##### 4.4.2.2 Forecasted irrigation water demand for scenario 2

The forecasted irrigation water demand and deficit obtained for Scenario 2: 40 % Increase in irrigation water demand in the year 2013 for different cropping patterns in Ghod command area for different

CCA are presented in Table 4.22. It was observed from Table 4.22, as the CCA increases irrigation water demand also increases and thereby deficit also increased. For multi-crop cropping pattern, minimum irrigation water demand was observed to be 91.31 MCM in 150 km<sup>2</sup> and deficit was found to be 8.51 MCM. Maximum irrigation water demand of 518.81 MCM was obtained in 415 km<sup>2</sup> of CCA for major-crops cropping pattern and deficit was 186.05 MCM. For multi-crop cropping pattern, the irrigation water demand-deficit obtained up to 250 km<sup>2</sup> was considerable. But for major-crops and sugarcane only cropping pattern, the irrigation water demand and deficit obtained were higher and hence, not suitable.

**Table 4.22 Scenario 2: 40 % increase in forecasted irrigation water demand**

CCA (km <sup>2</sup> )	Multi-Crops		Major Crops		Sugarcane only	
	Demand (MCM)	Deficit (MCM)	Demand (MCM)	Deficit (MCM)	Demand (MCM)	Deficit (MCM)
150	91.31	8.51	225.20	47.67	259.80	61.6
200	118.33	17.42	330.55	96.4	322.71	92.11
250	147.90	35.76	387.00	131.91	340.41	105.54
300	173.25	47.3	445.83	154.91	357.66	111.43
350	301.95	84.52	468.85	167.09	370.82	113.68
415	342.57	114.94	518.81	186.05	404.52	128.47

#### 4.5 Climate change study using MIKE ZERO

MIKE ZERO Climate Change Module was used to study the impact of climate change on water availability and water allocation estimated using MIKE 11 NAM and MIKE HYDRO Basin model respectively. The details of the climate change study were discussed in section 3.9.

##### 4.5.1 Effect of climate change on water availability of catchments

The MIKE 11 NAM model was calibrated for period of 2002 to 2009 and results of the water availability for all sub catchments of Ghod complex were given at section 4.1.6. This water availability considered as baseline for studying the climate change effect on water availability. For climate change study, MIKE Zero climate change functionality tool was used which uses the simulation file of MIKE 11 NAM as baseline input for the model. Input data also includes the location of study area, emission scenario, GCM model and scenario year. The fifty-five different combinations of GCM and CO<sub>2</sub> emission scenarios present under MIKE Zero climate change functionality tool were given in Table 3.4. To select suitable GCM and CO<sub>2</sub> emission scenario, the model was validated by taking initial scenario year of 2002, using all fifty-five combinations and compared with baseline scenario. From

the statistics of different 55 scenarios, following three best combinations were found best and used for further analysis.

1. Climate change scenario 1- CC1  
GCM model used- CNRM-CM3 (CNCM3)  
Emission Scenario- SRB1
2. Climate Change Scenario 2- CC2  
GCM model used- CNRM-CM3 (CNCM3)  
Emission Scenario- SRA1B
3. Climate Change Scenario 3- CC3  
GCM model used- CNRM-CM3 (CNCM3)  
Emission Scenario- SRA2

*CNRM-CM3 (CNCM3): Agency name: Centre National de Recherches Météorologiques, France.*

The statistical parameters of the CC1, CC2 and CC3 scenarios are given in Table 4.23

**Table 4.23 Statistical parameters of scenario CC1, CC2 and CC3 over baseline scenario**

Scenario	Root Mean Square Error (RMSE)	Correlation coefficient (r)	Nash Sutcliff efficiency index (EI)
CC1	0.00	1.00	1.00
CC2	0.01	1.00	0.99
CC3	0.16	0.99	0.98

The selected combinations were used to generate three climate change scenarios namely CC1, CC2 and CC3. The GCM model CNRM-CM3 (CNCM3) was used with combination of CO<sub>2</sub> emission scenarios SRB1, SRA1B and SRA2. The climate change scenarios were generated for year of 2020's, 2050's and 2080's and the water availability was accessed for these three scenario for 2020's, 2050's and 2080's for all the sub catchments of Ghod complex.

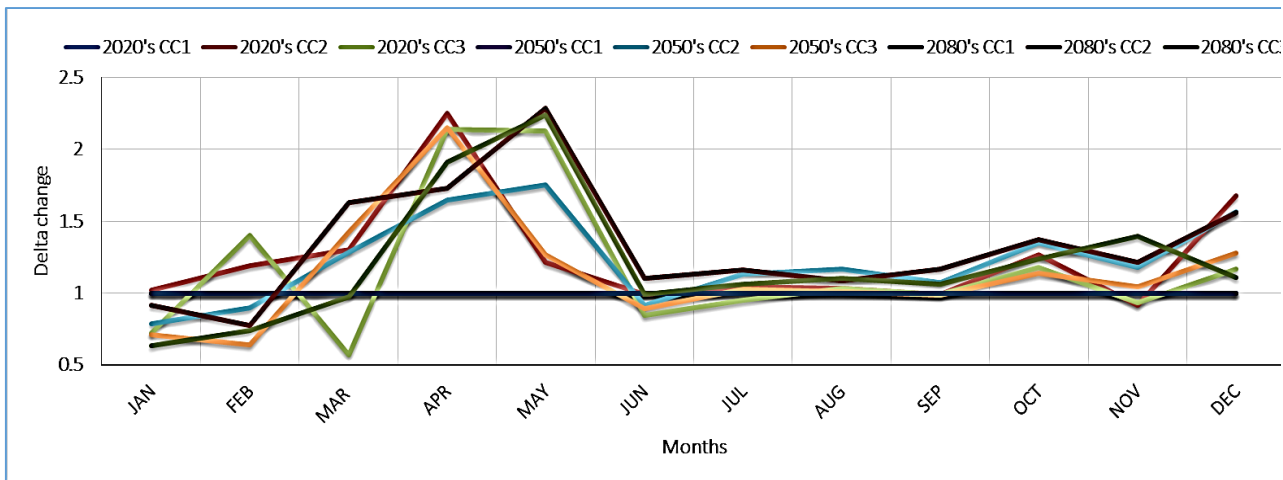
### **Delta change values**

Delta change values represent the absolute deviation from the reference values. In the present study, the delta change values were taken at any geo-referenced position represented by a latitude and longitude coordinate set for all seven catchments as defined in Table 4.1. The formulas for calculating delta change value for precipitation and evapotranspiration were given in section 3.9.4 and 3.9.5, respectively. The MIKE climate change tool make a copy of an existing setup and modifies the time series of climate data according to a given future year, selected GCMs and emission scenario. These time series were then used in the climate change scenario model setup instead of the original climate time series to assess the possible impact of climate change on water availability.

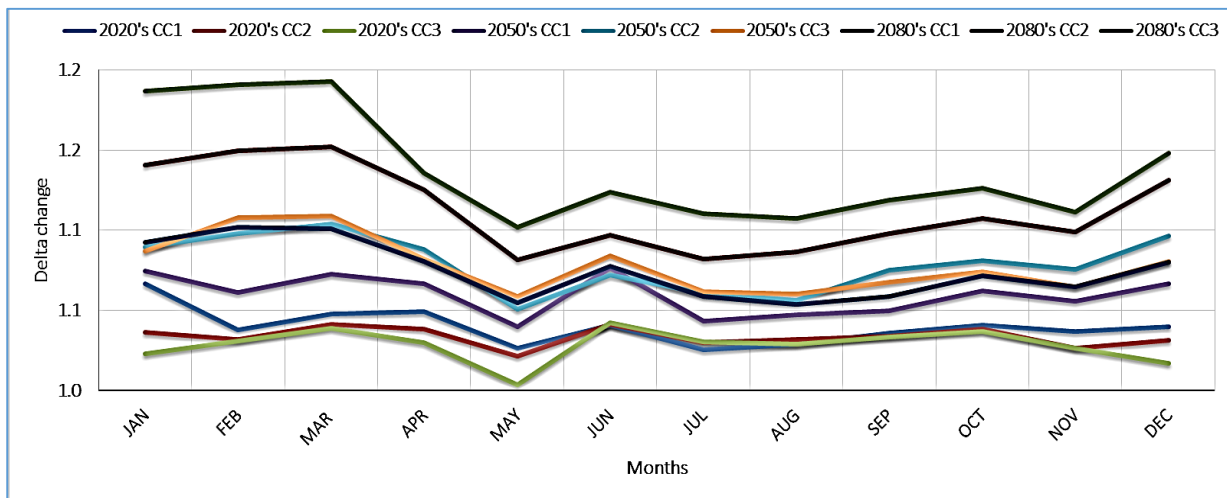


		<b>Evaporation</b>	1.09	1.10	1.10	1.08	1.05	1.08	1.06	1.05	1.06	1.07	1.06	1.08
		<b>Temperature</b>	2.13	2.59	2.99	2.67	1.93	2.50	1.70	1.54	1.71	2.02	1.70	1.89
		<b>Precipitation</b>	0.91	0.78	1.63	1.73	2.29	1.10	1.16	1.08	1.17	1.37	1.22	1.56
<b>CC2</b>		<b>Evaporation</b>	1.14	1.15	1.15	1.13	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13
		<b>Temperature</b>	3.23	3.80	4.49	4.16	2.86	3.15	2.37	2.48	2.84	3.02	2.59	3.10
		<b>Precipitation</b>	0.63	0.74	0.97	1.91	2.24	0.99	1.06	1.10	1.06	1.24	1.40	1.11
<b>CC3</b>		<b>Evaporation</b>	1.19	1.19	1.19	1.14	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15
		<b>Temperature</b>	4.30	4.84	5.70	4.50	3.58	4.02	3.19	3.07	3.45	3.55	2.92	3.51
		<b>Precipitation</b>	0.63	0.74	0.97	1.91	2.24	0.99	1.06	1.10	1.06	1.24	1.40	1.11

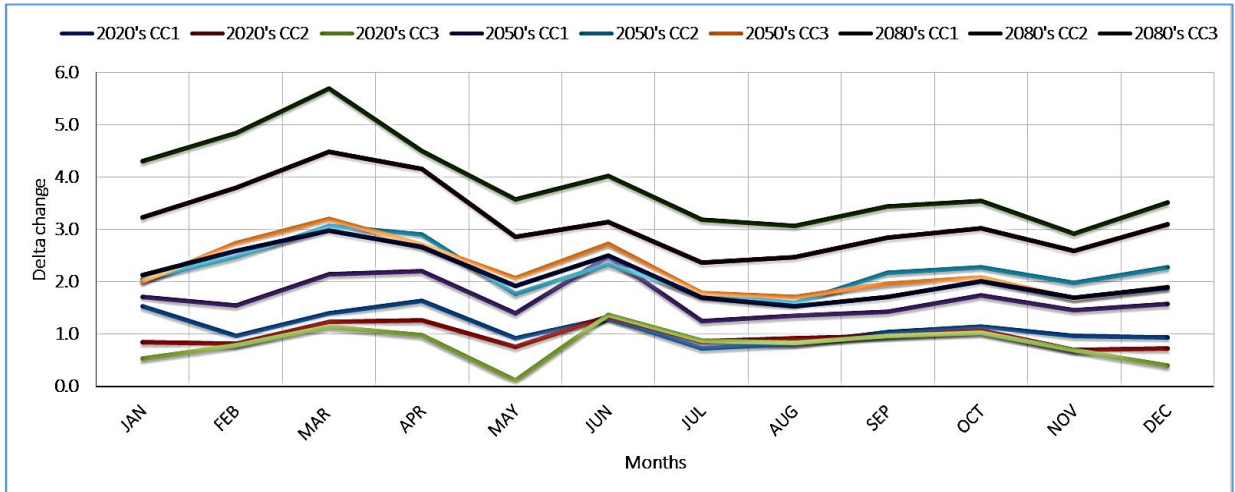
It was observed from Table 4.24 and Figure 4.43 that, the delta change values for Chilewadi catchment, except for scenario CC1, all other scenarios had shown variation in delta change value for precipitation from January to June. For evaporation and temperature, similar trend was seen in all months. Temperature delta change values were found to be higher than precipitation and evaporation. The comparison between estimated accumulated runoff for the year 2020's, 2050's and 2080's and baseline scenario was carried out. The results obtained are presented graphically in Figure 4.44.



(a)



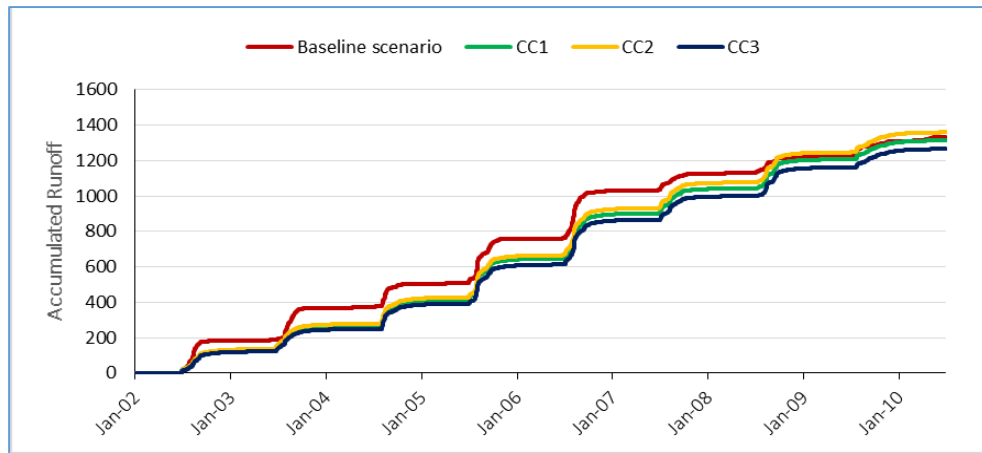
(b)



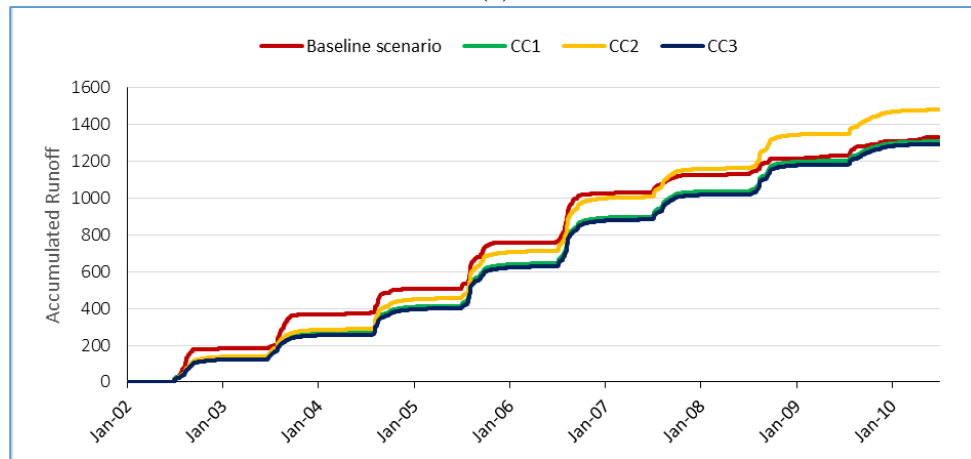
(c)

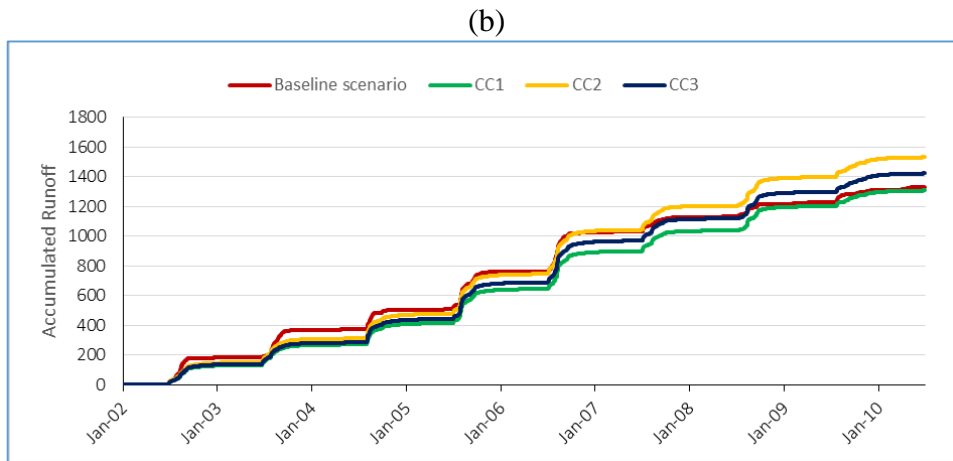
**Figure 4.43 Delta change values of precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Chilwadi catchment**

It was observed from Figure 4.44, that the accumulated runoff was increased by 3.5%, 11.3% and 15.3% in scenario CC2 for 2020's, 2050's and 2080's years, respectively.



(a)





(c)

**Figure 4.44 Comparison plot of accumulated runoff with baseline scenarios in 2020's (a), 2050's (b) and 2080's (c) for Chilewadi catchment**

For scenario CC1, the accumulated runoff was decreased by 1.17%, 1.55% and 1.70% in 2020's, 2050's and 2080's years, respectively. However, for scenario CC3, the accumulated runoff was decreased by 4.9% and 2.71% for 2020's and 2050's respectively. But the accumulated runoff was seen increased by 6.95% for 2080's.

#### 4.5.1.2 Effect of climate change on water availability of Dimbhe catchment

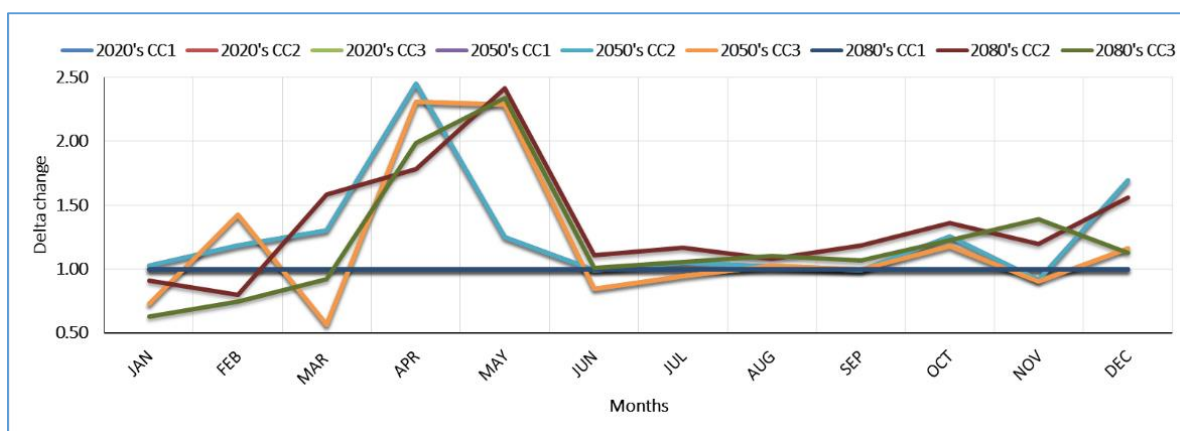
The results of effect of climate change on climate variables viz. precipitation, evaporation and temperature, accumulated runoff in the year 2020's, 2050's and 2080's for Dimbhe catchment are presented in Table 4.25 and Figure 4.45, and discussed in this section.

**Table 4.25 Delta change values of climate variables for Dimbhe catchment**

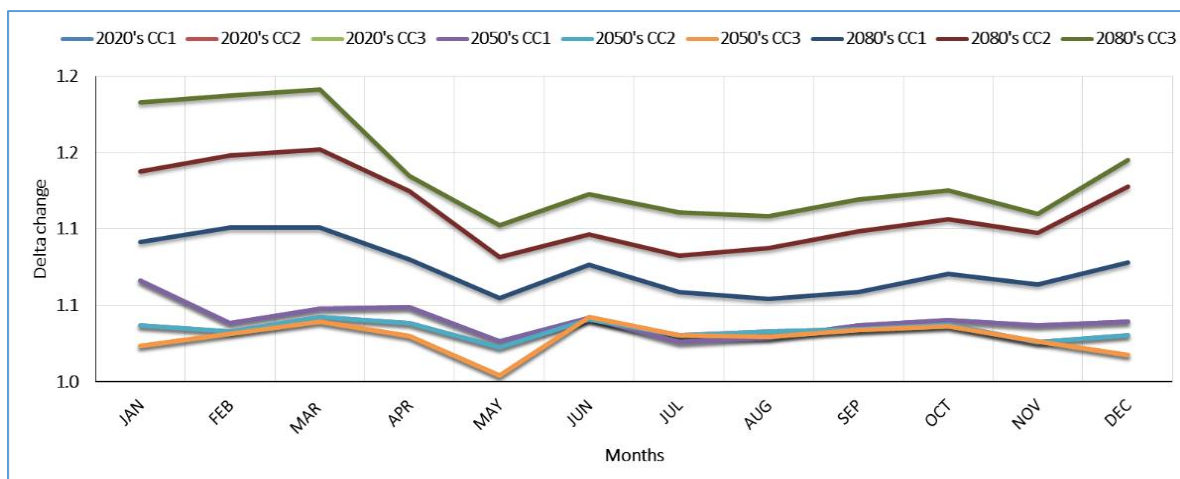
Year	Scenarios		Delta change values for different emission scenarios												
			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	
2020's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.04	1.05	1.05	1.03	1.04	1.03	1.03	1.04	1.04	1.04	1.04	1.04
		Temperature	1.55	1.00	1.42	1.62	0.93	1.35	0.74	0.83	1.06	1.14	0.98	0.95	0.95
	CC2	Precipitation	1.02	1.19	1.30	2.45	1.25	0.99	1.05	1.02	0.99	1.26	0.92	1.69	1.69
		Evaporation	1.04	1.03	1.04	1.04	1.02	1.04	1.03	1.03	1.03	1.04	1.03	1.03	1.03
		Temperature	0.88	0.85	1.26	1.27	0.78	1.32	0.88	0.94	0.99	1.05	0.69	0.73	0.73
	CC3	Precipitation	0.73	1.43	0.57	2.31	2.28	0.85	0.94	1.03	1.00	1.18	0.91	1.16	1.16
		Evaporation	1.02	1.03	1.04	1.03	1.00	1.04	1.03	1.03	1.03	1.04	1.03	1.02	1.02
		Temperature	0.56	0.81	1.18	0.98	0.14	1.36	0.88	0.84	0.98	1.03	0.71	0.43	0.43
2050's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		Evaporation	1.07	1.04	1.05	1.05	1.03	1.04	1.03	1.03	1.04	1.04	1.04	1.04	
		Temperature	1.55	1.00	1.42	1.62	0.93	1.35	0.74	0.83	1.06	1.14	0.98	0.95	
	CC2	Precipitation	1.02	1.19	1.30	2.45	1.25	0.99	1.05	1.02	0.99	1.26	0.92	1.69	

		Evaporation	1.04	1.03	1.04	1.04	1.02	1.04	1.03	1.03	1.03	1.04	1.03	1.03
		Temperature	0.88	0.85	1.26	1.27	0.78	1.32	0.88	0.94	0.99	1.05	0.69	0.73
	CC3	Precipitation	0.73	1.43	0.57	2.31	2.28	0.85	0.94	1.03	1.00	1.18	0.91	1.16
		Evaporation	1.02	1.03	1.04	1.03	1.00	1.04	1.03	1.03	1.03	1.04	1.03	1.02
		Temperature	0.56	0.81	1.18	0.98	0.14	1.36	0.88	0.84	0.98	1.03	0.71	0.43
	2080's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Evaporation			1.09	1.10	1.10	1.08	1.05	1.08	1.06	1.05	1.06	1.07	1.06	1.08
Temperature			2.15	2.59	2.99	2.65	1.91	2.48	1.69	1.55	1.71	2.00	1.69	1.88
CC2		Precipitation	0.91	0.80	1.58	1.78	2.41	1.11	1.17	1.08	1.18	1.36	1.20	1.56
		Evaporation	1.14	1.15	1.15	1.12	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13
		Temperature	3.22	3.81	4.52	4.13	2.85	3.11	2.39	2.51	2.85	3.00	2.58	3.08
CC3		Precipitation	0.63	0.74	0.92	1.99	2.34	1.01	1.06	1.10	1.07	1.23	1.39	1.13
		Evaporation	1.18	1.19	1.19	1.13	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15
		Temperature	4.28	4.82	5.68	4.47	3.58	3.96	3.20	3.10	3.46	3.55	2.91	3.50

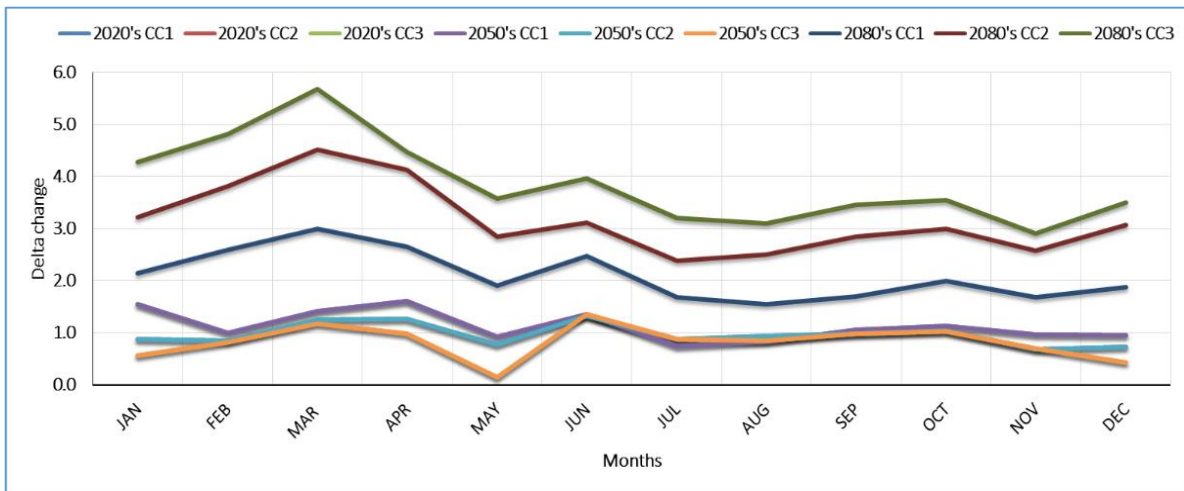
The delta change values for Dimbhe catchment are presented in Table 4.25 and Figure 4.45. It was observed from the Table 4.25 and Figure 4.45 that, in 2020's and 2050's, all the climatic variables gave similar trend for climate change scenario CC1, CC2 and CC3.



(a)



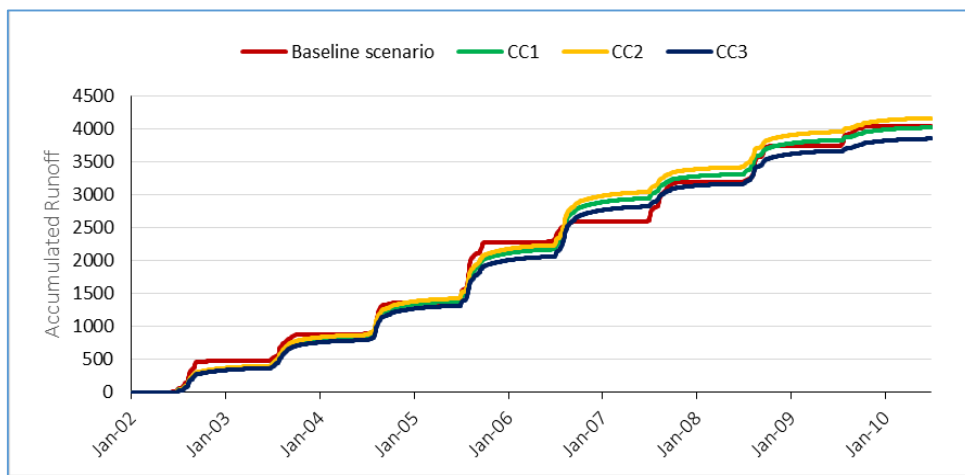
(b)



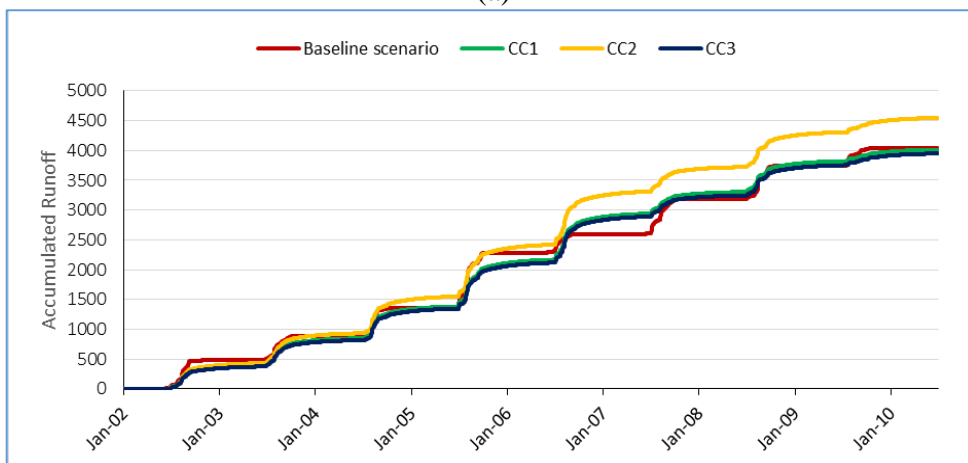
(c)

**Figure 4.45 Delta change values of precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Dimbhe catchment**

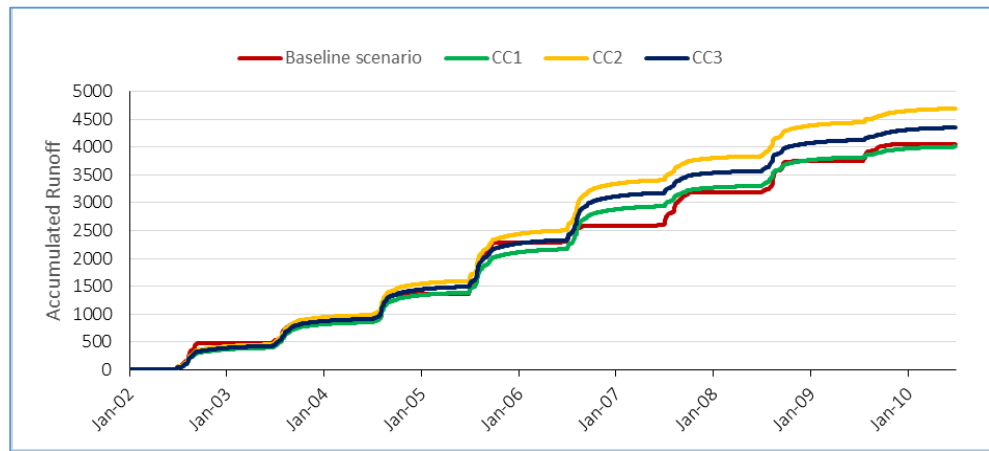
Precipitation delta change values were same in all climate change scenario for the year 2020's, 2050's and 2080's. Temperature delta change values were found to be higher than precipitation and evaporation.



(a)



(b)



(c)

**Figure 4.46 Comparison plot of accumulated runoff with baseline scenarios in 2020's (a), 2050's (b) and 2080's (c) for Dimbhe catchment**

The comparison between estimated accumulated runoff for the year 2020's, 2050's and 2080's and baseline scenario was carried out and the results obtained are presented graphically in Figure 4.46. It was observed from Figure 4.46, that the accumulated runoff was increased by 3.5%, 12.34% and 16% was in scenario CC2 for the year 2020's, 2050's and 2080's, respectively. For scenario CC1, the the accumulated runoff was decreased by 0.53%, 0.85% and 0.98% for 2020's, 2050's and 2080's, respectively. However, for scenario CC3, the accumulated runoff was decreased by 4.72% and 2.43% for 2020's and 2050's but it was increased by 7.52% for 2080's.

#### 4.5.1.3 Effect of climate change on water availability of Ghod catchment

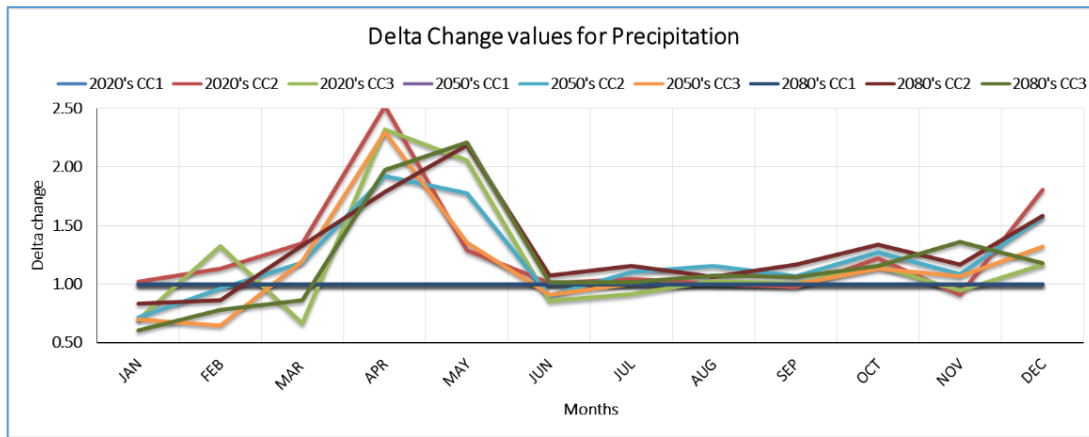
The results of effect of climate change on climate variables viz. precipitation, evaporation and temperature, accumulated runoff in the year 2020's, 2050's and 2080's for Ghod catchment are presented in Table 4.26 and Figure 4.47, and discussed in this section.

**Table 4.26 Delta change values of climate variables for Ghod catchment**

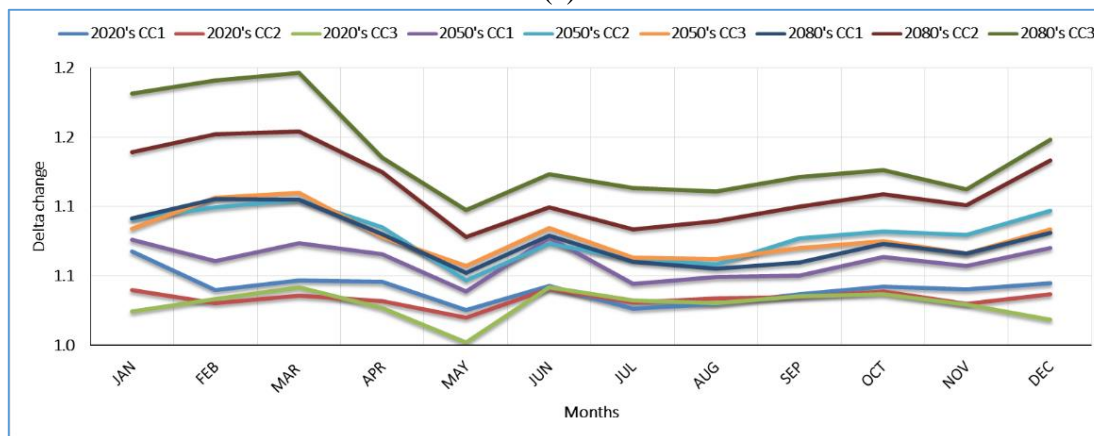
Year	Scenarios		Delta change values for different emission scenarios											
			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2020's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.04	1.05	1.05	1.03	1.04	1.03	1.03	1.04	1.04	1.04	1.04
		Temperature	1.56	1.02	1.38	1.52	0.89	1.36	0.75	0.84	1.07	1.18	1.05	1.05
	CC2	Precipitation	1.02	1.13	1.35	2.52	1.29	1.01	1.04	1.01	0.97	1.22	0.91	1.81
		Evaporation	1.04	1.03	1.04	1.03	1.02	1.04	1.03	1.03	1.03	1.04	1.03	1.04
		Temperature	0.92	0.78	1.07	1.06	0.70	1.30	0.89	0.96	1.01	1.08	0.77	0.86
	CC3	Precipitation	0.70	1.32	0.66	2.32	2.05	0.86	0.92	1.03	1.00	1.16	0.95	1.17
		Evaporation	1.02	1.03	1.04	1.03	1.00	1.04	1.03	1.03	1.04	1.04	1.03	1.02
		Temperature	0.57	0.84	1.23	0.89	0.08	1.34	0.93	0.86	1.02	1.03	0.77	0.44
2050's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.08	1.06	1.07	1.07	1.04	1.08	1.04	1.05	1.05	1.06	1.06	1.07

		<b>Temperature</b>	1.75	1.54	2.16	2.16	1.36	2.48	1.26	1.40	1.44	1.77	1.49	1.65
	<b>CC2</b>	<b>Precipitation</b>	0.72	0.96	1.19	1.92	1.78	0.90	1.10	1.16	1.07	1.27	1.08	1.57
		<b>Evaporation</b>	1.09	1.10	1.10	1.09	1.05	1.07	1.06	1.06	1.08	1.08	1.08	1.10
		<b>Temperature</b>	2.10	2.52	3.09	2.82	1.64	2.33	1.77	1.64	2.22	2.29	2.07	2.29
	<b>CC3</b>	<b>Precipitation</b>	0.70	0.65	1.20	2.30	1.36	0.91	1.01	1.00	1.00	1.14	1.07	1.32
		<b>Evaporation</b>	1.08	1.11	1.11	1.08	1.06	1.08	1.06	1.06	1.07	1.07	1.07	1.08
		<b>Temperature</b>	1.94	2.70	3.24	2.59	1.99	2.71	1.80	1.76	2.01	2.09	1.73	1.97
<b>2080's</b>	<b>CC1</b>	<b>Precipitation</b>	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		<b>Evaporation</b>	1.09	1.11	1.11	1.08	1.05	1.08	1.06	1.06	1.06	1.07	1.07	1.08
		<b>Temperature</b>	2.12	2.67	3.09	2.65	1.83	2.52	1.71	1.57	1.72	2.03	1.72	1.92
	<b>CC2</b>	<b>Precipitation</b>	0.83	0.86	1.33	1.79	2.19	1.08	1.16	1.06	1.17	1.34	1.17	1.58
		<b>Evaporation</b>	1.14	1.15	1.15	1.12	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13
		<b>Temperature</b>	3.20	3.85	4.53	4.13	2.73	3.18	2.39	2.53	2.88	3.04	2.63	3.14
	<b>CC3</b>	<b>Precipitation</b>	0.60	0.78	0.87	1.98	2.21	1.02	1.02	1.07	1.06	1.16	1.36	1.18
		<b>Evaporation</b>	1.18	1.19	1.20	1.14	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15
		<b>Temperature</b>	4.18	4.83	5.78	4.48	3.40	3.94	3.23	3.13	3.48	3.52	2.93	3.51

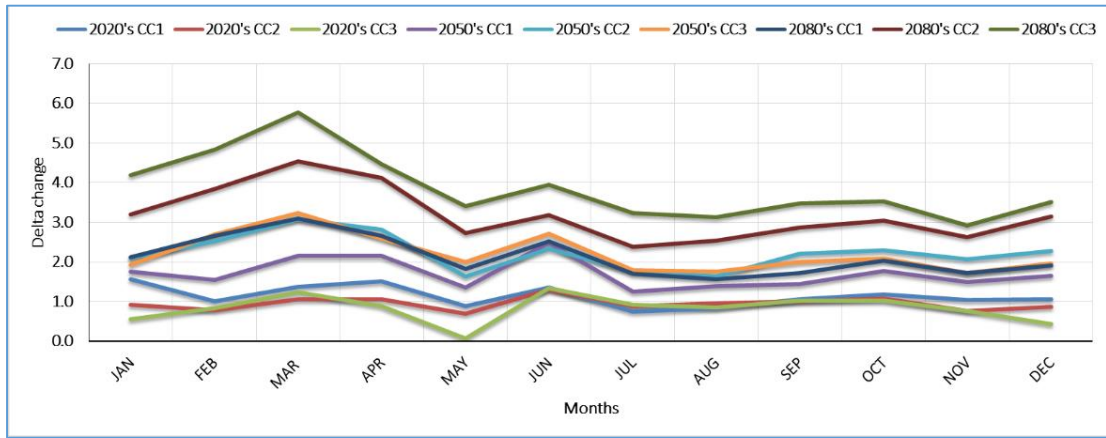
It was observed from Table 4.26 and Figure 4.47, that except for scenario CC1, the variation in delta change value for precipitation from January to June and November to December was observed for all other scenarios.



(a)



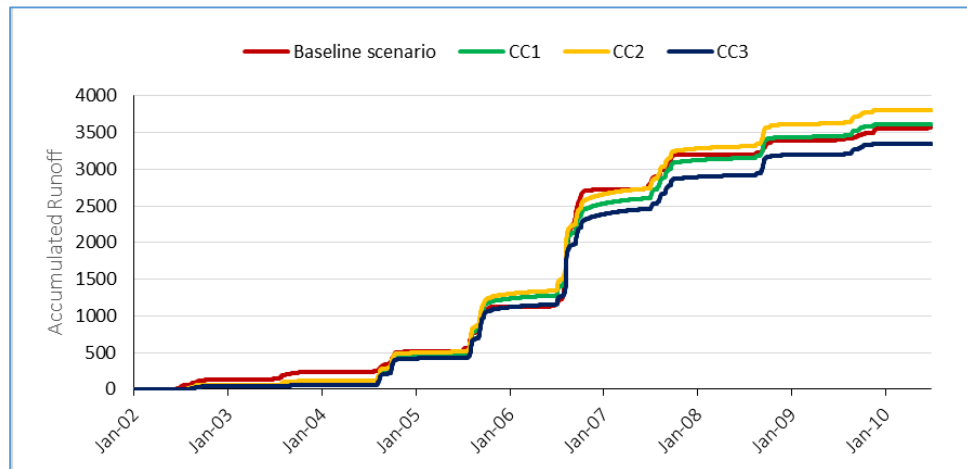
(b)



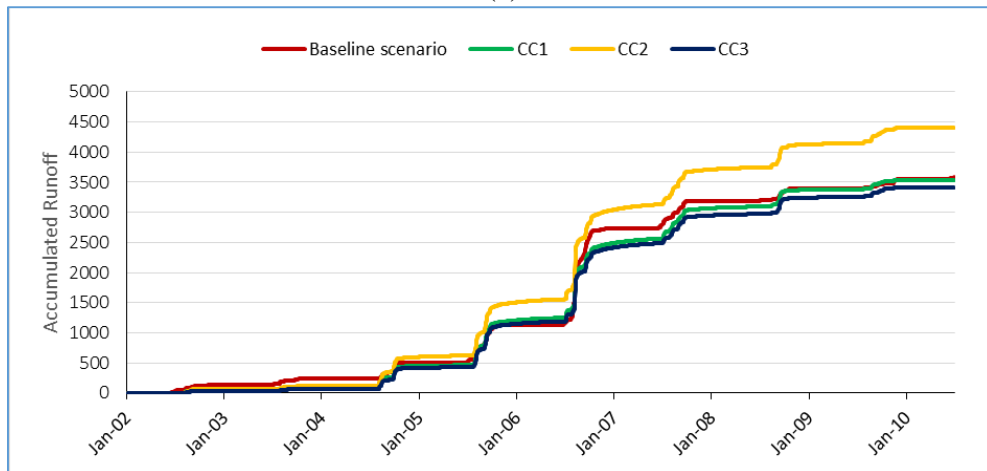
(c)

**Figure 4.47 Delta change values of precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Ghod catchment**

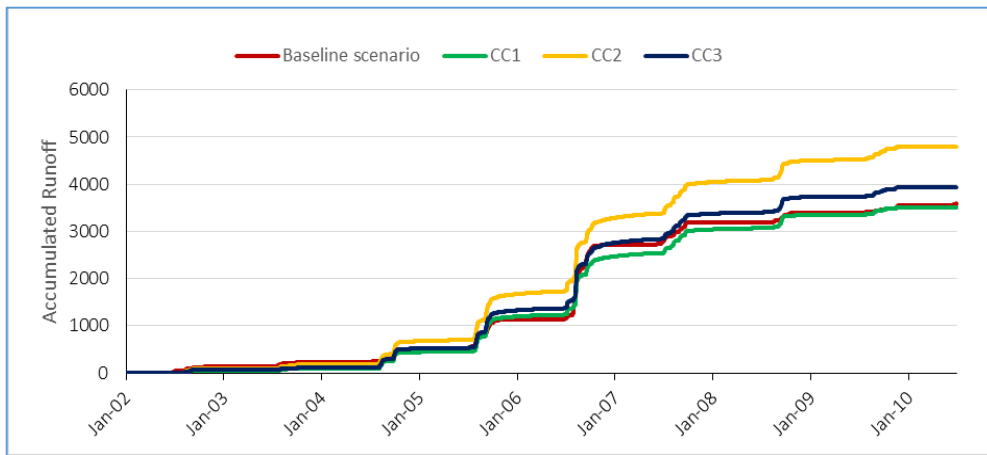
For evaporation and temperature, increasing trend was observed in January to March and then there was a fall up to May. Temperature delta change values were found to be higher than precipitation and evaporation.



(a)



(b)



(c)

**Figure 4.48 Comparison plot of accumulated runoff with baseline scenarios in 2020's (a), 2050's (b) and 2080's (c) for Ghod catchment**

The comparison between estimated accumulated runoff for the year 2020's, 2050's and 2080's and baseline scenario was carried out and the results obtained are presented graphically in Figure 4.48. It was observed from Figure 4.48, that the accumulated runoff was seen increased by 5.87%, 22.62% and 33.62% in scenario CC2 for the year 2020's, 2050's and 2080's, respectively. For scenario CC1, accumulated runoff was increased by 0.45% for the year 2020's and decreased by 1.46% and 2.34% for the year 2050's and 2080's, respectively. Also, for scenario CC3, there was decrease in accumulated runoff by 6.7% and 4.9% for 2020's and 2050's but for 2080's, it was increased by 9.64%.

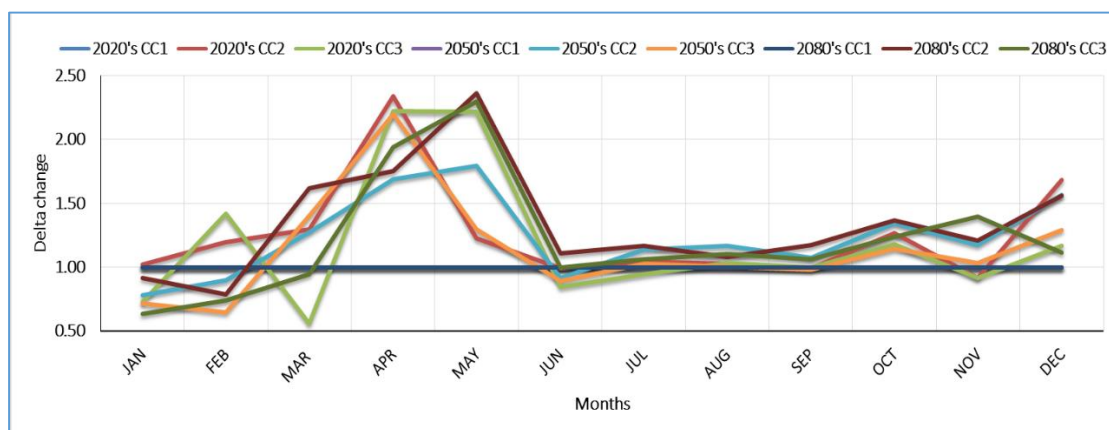
#### 4.5.1.4 Effect of climate change on water availability of Manikdoh catchment

The results of effect of climate change on climate variables viz. precipitation, evaporation and temperature, accumulated runoff in the year 2020's, 2050's and 2080's for Manikdoh catchment are presented in Table 4.27 and Figure 4.49, and discussed in this section.

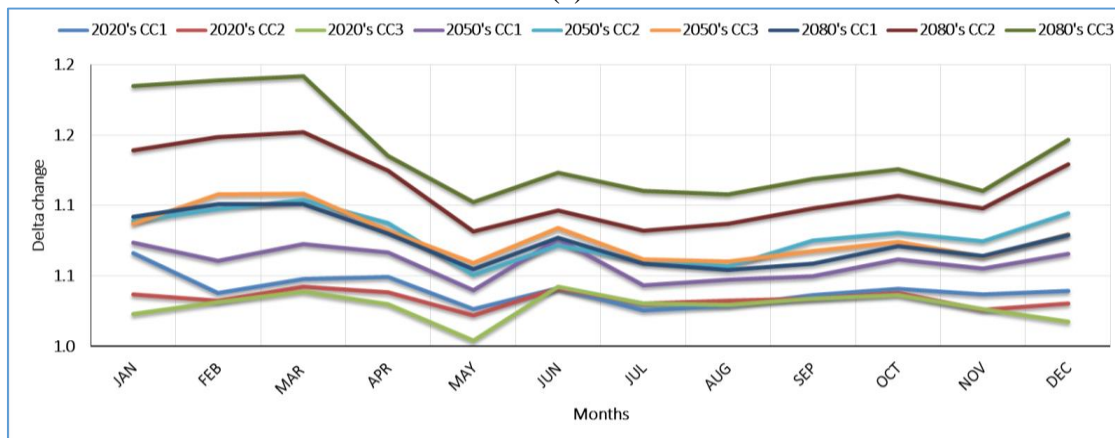
**Table 4.27 Delta change values of climate variables for Manikdoh catchment**

Year	Scenarios	Delta change values for different emission scenarios												
		JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	
2020's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.04	1.05	1.05	1.03	1.04	1.03	1.03	1.04	1.04	1.04	1.04
		Temperature	1.54	0.98	1.42	1.63	0.93	1.33	0.74	0.82	1.06	1.14	0.97	0.94
	CC2	Precipitation	1.02	1.19	1.30	2.34	1.23	0.99	1.05	1.03	0.99	1.26	0.92	1.68
		Evaporation	1.04	1.03	1.04	1.04	1.02	1.04	1.03	1.03	1.03	1.04	1.03	1.03
		Temperature	0.86	0.84	1.25	1.28	0.77	1.33	0.87	0.93	0.98	1.06	0.69	0.73
	CC3	Precipitation	0.73	1.42	0.56	2.22	2.21	0.85	0.95	1.03	1.00	1.18	0.92	1.17
		Evaporation	1.02	1.03	1.04	1.03	1.00	1.04	1.03	1.03	1.03	1.04	1.03	1.02

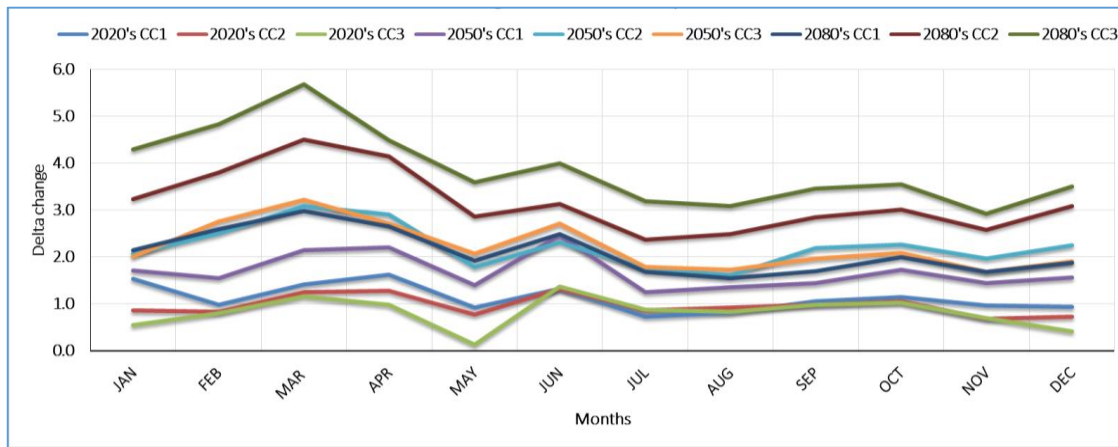
2050's	CC1	Temperature	0.55	0.80	1.16	0.99	0.13	1.37	0.87	0.84	0.98	1.03	0.70	0.42	
		Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.06	1.07	1.07	1.04	1.08	1.04	1.05	1.05	1.05	1.06	1.06	1.07
	CC2	Precipitation	0.78	0.90	1.27	1.69	1.80	0.92	1.14	1.17	1.07	1.35	1.17	1.56	
		Evaporation	1.09	1.10	1.10	1.09	1.05	1.07	1.06	1.06	1.08	1.08	1.07	1.09	
		Temperature	2.07	2.50	3.08	2.90	1.79	2.31	1.76	1.62	2.19	2.27	1.97	2.26	
	CC3	Precipitation	0.72	0.65	1.40	2.20	1.30	0.89	1.03	1.01	0.98	1.15	1.03	1.29	
		Evaporation	1.09	1.11	1.11	1.08	1.06	1.08	1.06	1.06	1.07	1.07	1.06	1.08	
		Temperature	2.02	2.76	3.21	2.72	2.08	2.72	1.79	1.73	1.97	2.09	1.68	1.91	
2080's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		Evaporation	1.09	1.10	1.10	1.08	1.05	1.08	1.06	1.05	1.06	1.07	1.06	1.08	
		Temperature	2.14	2.59	2.99	2.66	1.92	2.49	1.69	1.55	1.71	2.01	1.69	1.89	
	CC2	Precipitation	0.92	0.79	1.62	1.75	2.36	1.11	1.17	1.08	1.18	1.37	1.21	1.56	
		Evaporation	1.14	1.15	1.15	1.12	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13	
		Temperature	3.23	3.80	4.50	4.14	2.86	3.12	2.38	2.49	2.85	3.01	2.59	3.09	
	CC3	Precipitation	0.63	0.74	0.95	1.94	2.29	1.00	1.06	1.10	1.07	1.24	1.40	1.12	
		Evaporation	1.19	1.19	1.19	1.14	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15	
		Temperature	4.30	4.83	5.69	4.49	3.59	3.99	3.19	3.08	3.46	3.55	2.92	3.51	



(a)



(b)

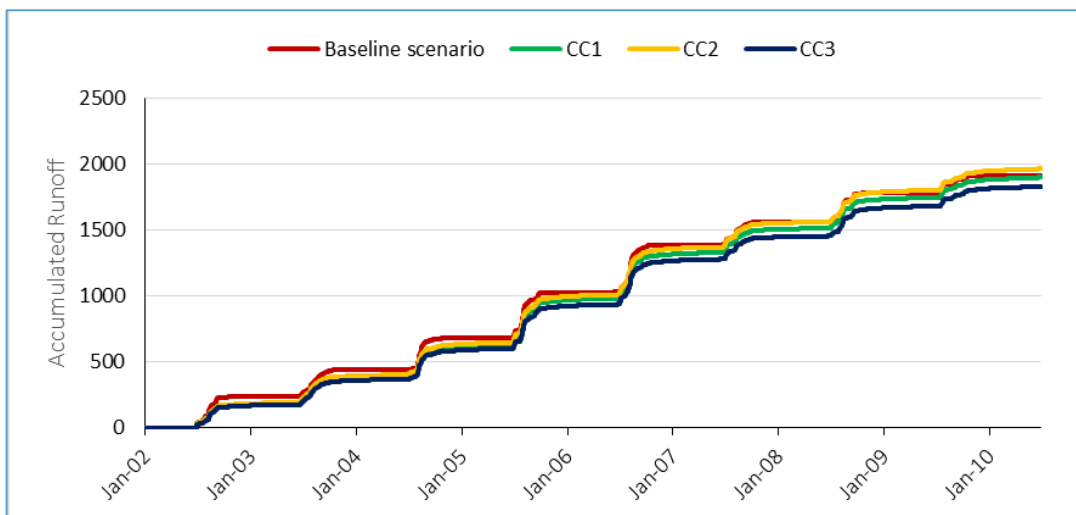


(c)

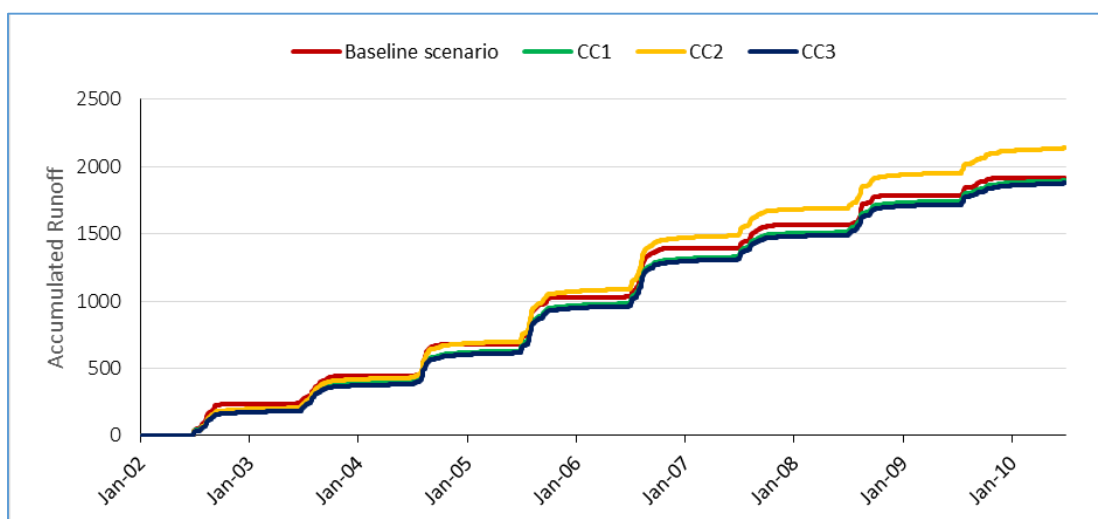
**Figure 4.49 Delta change values of precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Manikdoh catchment**

The delta change values of precipitation, evaporation and temperature for Manikdoh catchment are presented in Table 4.27 and shown graphically in Figure 4.49. It was observed from Table 4.27 and Figure 4.49, that except scenario CC1 all the other scenarios had shown variation in delta change values for precipitation from January to June and November to December. For evaporation, a very small variation in delta change values for all the scenarios in all years was observed. But the temperature delta change values were found to be higher than precipitation and evaporation. For evaporation and temperature, increasing trend was seen in January to March and then there was a fall up to May. Also for a particular scenario, the variation in the delta value for different variables was random.

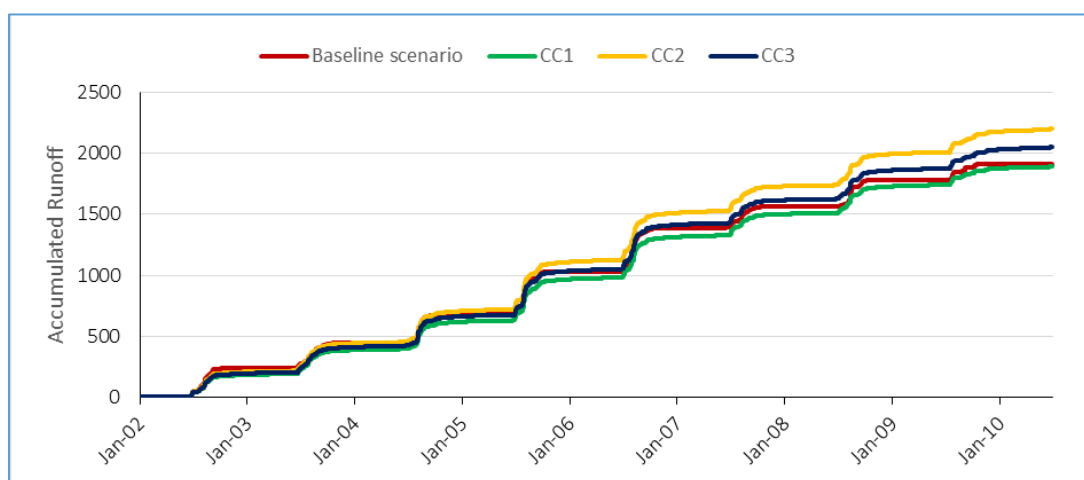
The comparison between estimated accumulated runoff for the years, 2020's, 2050's and 2080's and baseline scenario for Manikdoh catchment was carried out and results are presented graphically in Figure 4.50.



(a)



(b)



(c)

**Figure 4.50 Comparison plot of accumulated runoff with baseline scenarios in 2020's (a), 2050's (b) and 2080's (c) for Manikdoh catchment**

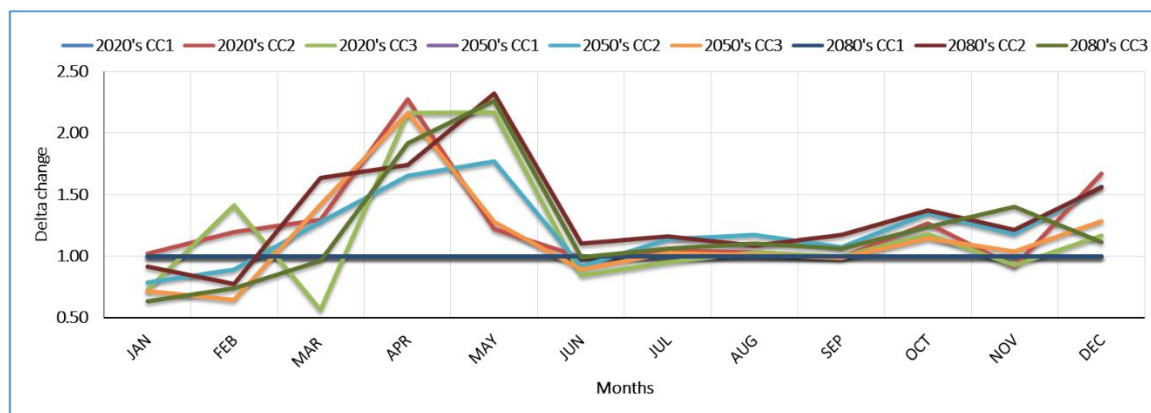
It was observed from the Figure 4.50, that the accumulated runoff was found increased by 3.45%, 11.83% and 15.33% for scenario CC2 in the year 2020's, 2050's and 2080's, respectively. For scenario CC1, the accumulated runoff was decreased by 0.37%, 0.65% and 0.76% for the year 2020's, 2050's and 2080's, respectively. However, for scenario CC3, the decrease in accumulated runoff by 4.1% and 1.81% for 2020's and 2050's was observed but for 2080's, accumulated runoff was increased by 7.46%.

#### **4.5.1.5 Effect of climate change on water availability of Pimpalgaonjoga catchment**

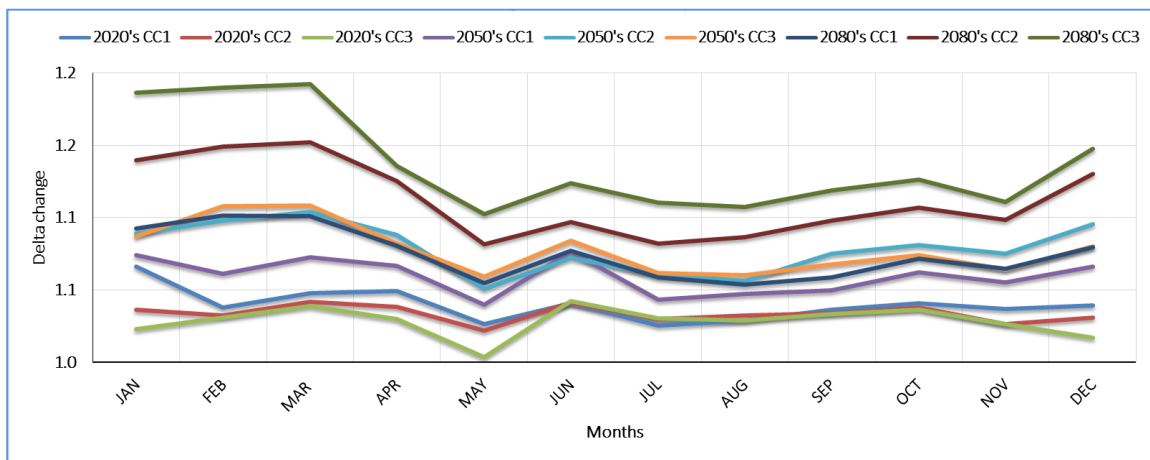
The results of effect of climate change on climate variables viz. precipitation, evaporation and temperature, accumulated runoff in the year 2020's, 2050's and 2080's for Pimpalgaonjoga catchment are presented in Table 4.28 and Figure 4.51, and discussed in this section.

**Table 4.28 Delta change values of climate variables for Pimpalgaonjoga catchment**

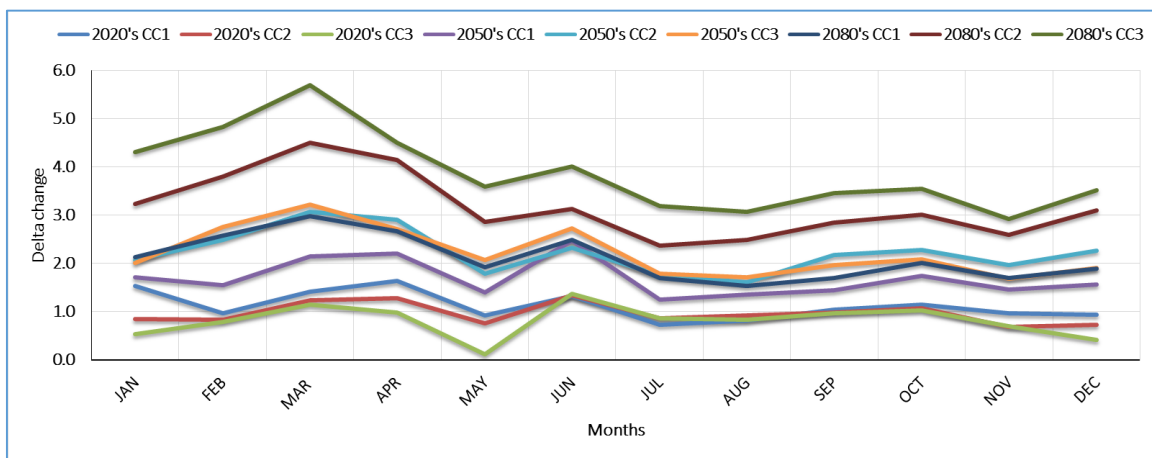
Year	Scenarios		Delta change values for different emission scenarios											
			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2020's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.04	1.05	1.05	1.03	1.04	1.03	1.03	1.04	1.04	1.04	1.04
		Temperature	1.54	0.97	1.41	1.64	0.93	1.32	0.73	0.82	1.05	1.15	0.97	0.94
	CC2	Precipitation	1.02	1.20	1.30	2.28	1.22	0.99	1.05	1.03	0.99	1.27	0.92	1.67
		Evaporation	1.04	1.03	1.04	1.04	1.02	1.04	1.03	1.03	1.03	1.04	1.03	1.03
		Temperature	0.85	0.83	1.25	1.28	0.76	1.34	0.87	0.92	0.98	1.07	0.69	0.73
	CC3	Precipitation	0.73	1.41	0.56	2.16	2.17	0.85	0.95	1.03	1.00	1.18	0.93	1.17
		Evaporation	1.02	1.03	1.04	1.03	1.00	1.04	1.03	1.03	1.03	1.04	1.03	1.02
		Temperature	0.54	0.80	1.15	0.99	0.13	1.37	0.87	0.83	0.97	1.03	0.70	0.41
2050's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		Evaporation	1.07	1.06	1.07	1.07	1.04	1.08	1.04	1.05	1.05	1.06	1.06	1.07
		Temperature	1.72	1.55	2.15	2.21	1.40	2.48	1.25	1.35	1.44	1.74	1.46	1.57
	CC2	Precipitation	0.79	0.90	1.28	1.65	1.77	0.92	1.14	1.17	1.07	1.35	1.18	1.57
		Evaporation	1.09	1.10	1.10	1.09	1.05	1.07	1.06	1.06	1.08	1.08	1.08	1.10
		Temperature	2.07	2.49	3.07	2.91	1.78	2.33	1.76	1.61	2.18	2.28	1.97	2.27
	CC3	Precipitation	0.72	0.65	1.42	2.16	1.28	0.89	1.03	1.01	0.98	1.14	1.04	1.28
		Evaporation	1.09	1.11	1.11	1.08	1.06	1.08	1.06	1.06	1.07	1.07	1.06	1.08
		Temperature	2.02	2.75	3.21	2.72	2.07	2.72	1.79	1.72	1.97	2.09	1.69	1.91
2080's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
		Evaporation	1.09	1.10	1.10	1.08	1.05	1.08	1.06	1.05	1.06	1.07	1.06	1.08
		Temperature	2.14	2.59	2.98	2.66	1.93	2.50	1.69	1.54	1.71	2.01	1.70	1.89
	CC2	Precipitation	0.92	0.78	1.64	1.74	2.32	1.11	1.16	1.08	1.17	1.37	1.21	1.56
		Evaporation	1.14	1.15	1.15	1.13	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13
		Temperature	3.23	3.80	4.50	4.15	2.86	3.13	2.37	2.48	2.84	3.02	2.59	3.10
	CC3	Precipitation	0.64	0.74	0.96	1.92	2.26	0.99	1.06	1.10	1.06	1.24	1.40	1.11
		Evaporation	1.19	1.19	1.19	1.14	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15
		Temperature	4.30	4.83	5.69	4.50	3.59	4.01	3.19	3.08	3.45	3.55	2.92	3.51



(a)



(b)

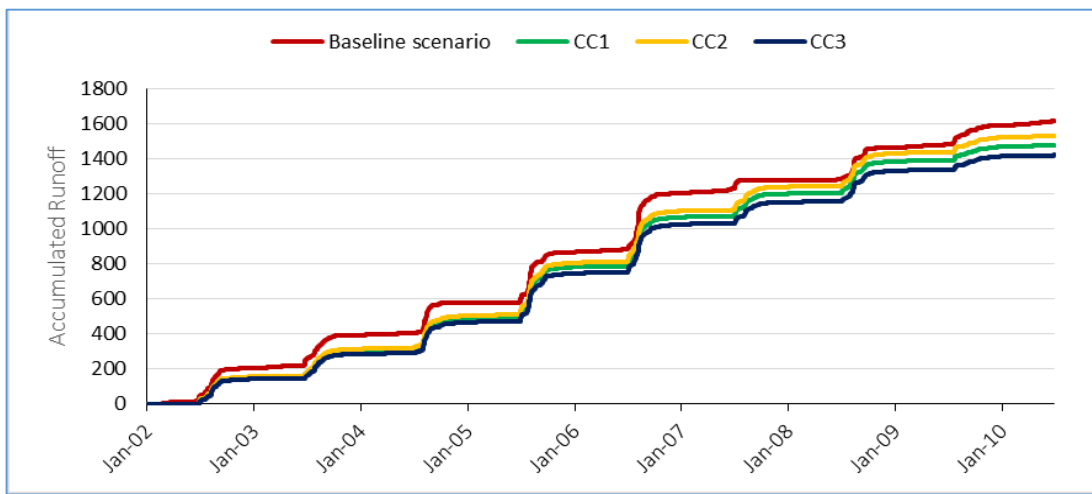


(c)

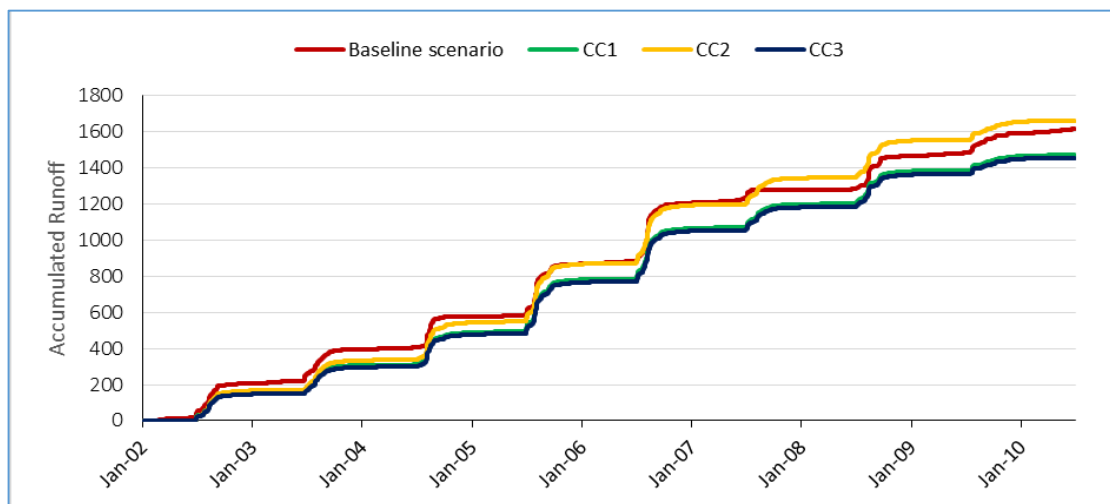
**Figure 4.51 Delta change values of precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Pimpalgaonjoga catchment**

The delta change values of precipitation, evaporation and temperature for Pimpalgaonjoga catchment are presented in Table 4.28 and shown graphically in the Figure 4.51. No common trend for seasonal variation was observed from Table 4.28 and Figure 4.51. Precipitation delta change values were observed same in all climate change scenario for 2020's, 2050's and 2080's, respectively. For evaporation and temperature, increasing trend was seen in January to March, fall up to May and constant from July to November. Temperature delta change values were found higher than precipitation and evaporation.

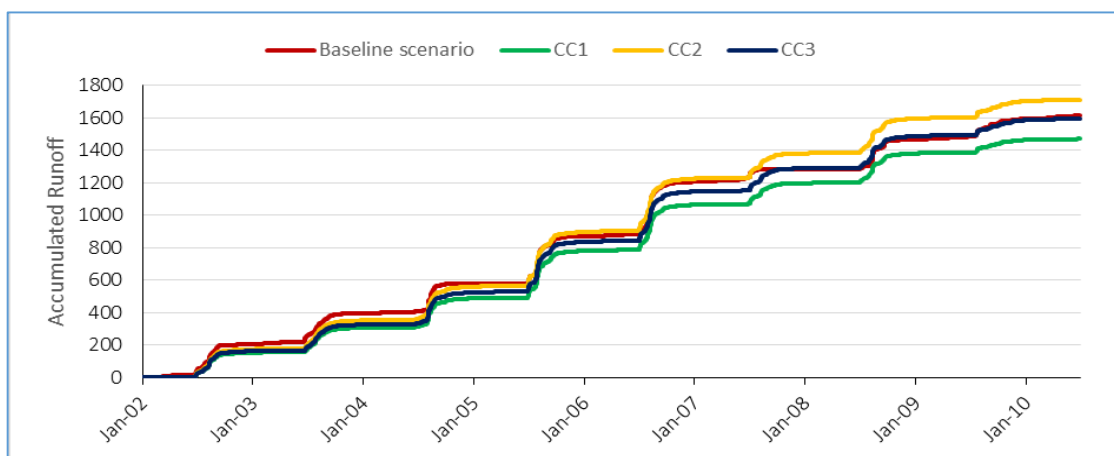
The comparison between estimated accumulated runoff for the years, 2020's, 2050's and 2080's and baseline scenario for Pimpalgaonjoga catchment was carried out and results are presented graphically in Figure 4.52.



(a)



(b)



(c)

**Figure 4.52 Comparison plot of accumulated runoff with baseline scenarios in 2020's (a), 2050's (b) and 2080's (c) for Pimpalgaonjoga catchment**

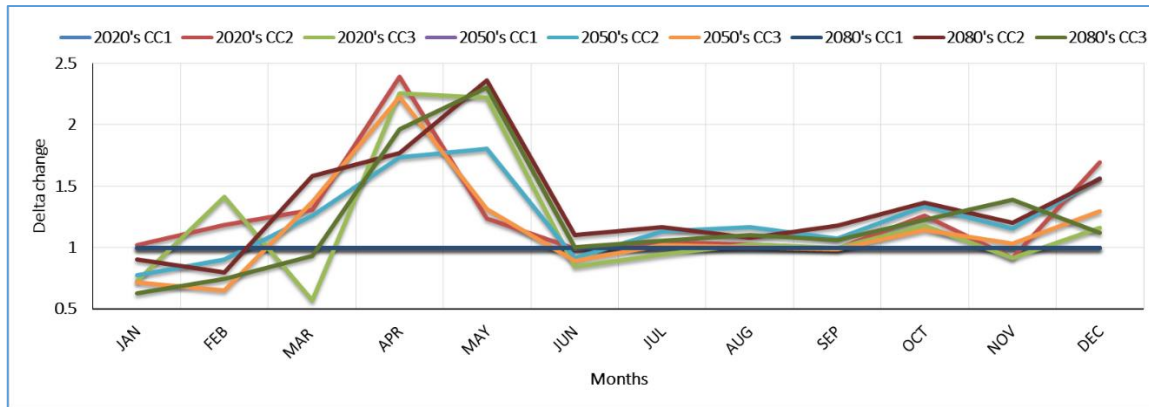
It was observed from the Figure 4.52, that for scenario CC1, there was a decrease in accumulated runoff by 8.58%, 8.88% and 8.99% in the year 2020's, 2050's and 2080's respectively. Similarly, for scenario CC3, the decrease in accumulated runoff by 12.04%, 8.87% and 1.37% for the year 2020's, 2050's and 2080's respectively, was observed. However, for scenario CC2, accumulated runoff was increased by, 3.61%, 2.92% and 5.94% in the year 2020's, 2050's and 2080's, respectively.

#### 4.5.1.6 Effect of climate change on water availability of Wadaj catchment

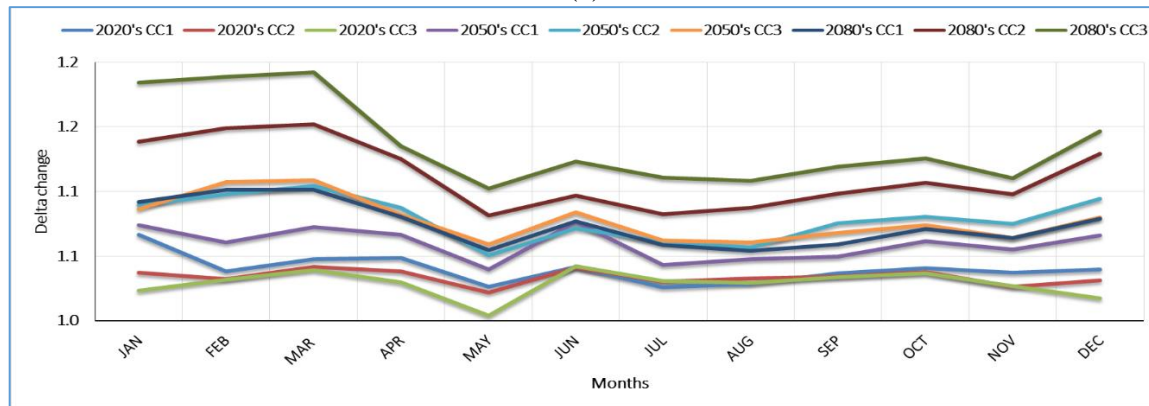
The results of effect of climate change on climate variables viz. precipitation, evaporation and temperature, accumulated runoff in the year 2020's, 2050's and 2080's for Wadaj catchment are presented in Table 4.29 and Figure 4.53, and discussed in this section.

**Table 4.29 Delta change values of climate variables for Wadaj catchment**

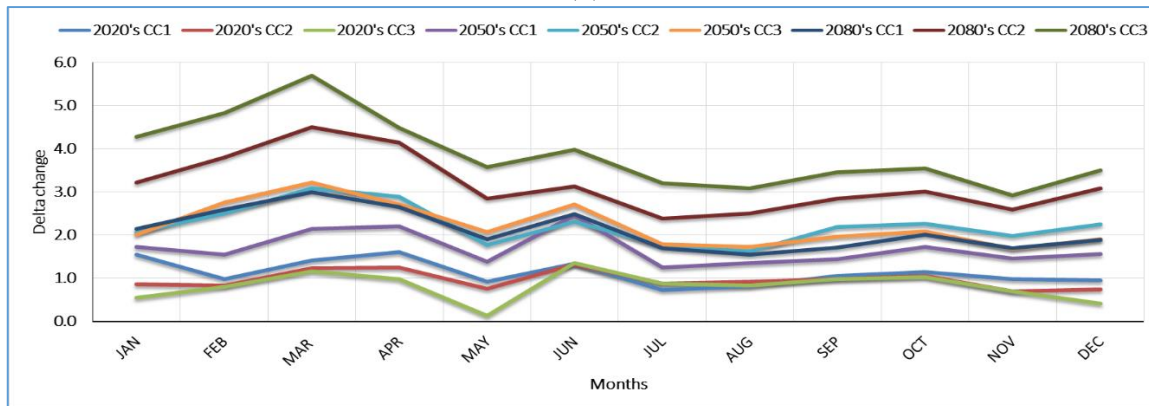
Year	Scenarios		Delta change values for different emission scenarios											
			JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2020's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.04	1.05	1.05	1.03	1.04	1.03	1.03	1.04	1.04	1.04	1.04
		Temperature	1.55	0.99	1.42	1.62	0.93	1.34	0.74	0.83	1.06	1.15	0.98	0.95
	CC2	Precipitation	1.02	1.19	1.31	2.39	1.24	0.99	1.05	1.03	0.99	1.26	0.92	1.69
		Evaporation	1.04	1.03	1.04	1.04	1.02	1.04	1.03	1.03	1.03	1.04	1.03	1.03
		Temperature	0.87	0.83	1.24	1.26	0.77	1.33	0.88	0.93	0.99	1.06	0.70	0.74
	CC3	Precipitation	0.73	1.41	0.57	2.26	2.22	0.85	0.94	1.03	1.00	1.18	0.92	1.16
		Evaporation	1.02	1.03	1.04	1.03	1.00	1.04	1.03	1.03	1.03	1.04	1.03	1.02
		Temperature	0.55	0.81	1.17	0.98	0.13	1.36	0.88	0.84	0.98	1.03	0.71	0.42
2050's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.07	1.06	1.07	1.07	1.04	1.08	1.04	1.05	1.05	1.06	1.06	1.07
		Temperature	1.72	1.55	2.15	2.21	1.39	2.47	1.25	1.36	1.44	1.74	1.45	1.57
	CC2	Precipitation	0.77	0.91	1.26	1.73	1.81	0.91	1.13	1.17	1.07	1.34	1.16	1.56
		Evaporation	1.09	1.10	1.10	1.09	1.05	1.07	1.06	1.06	1.08	1.08	1.07	1.09
		Temperature	2.08	2.50	3.09	2.89	1.77	2.31	1.76	1.62	2.19	2.27	1.98	2.25
	CC3	Precipitation	0.72	0.65	1.37	2.23	1.31	0.89	1.02	1.00	0.98	1.15	1.03	1.29
		Evaporation	1.09	1.11	1.11	1.08	1.06	1.08	1.06	1.06	1.07	1.07	1.06	1.08
		Temperature	2.01	2.75	3.22	2.71	2.07	2.71	1.79	1.73	1.97	2.09	1.68	1.92
2080's	CC1	Precipitation	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		Evaporation	1.09	1.10	1.10	1.08	1.05	1.08	1.06	1.05	1.06	1.07	1.06	1.08
		Temperature	2.14	2.59	3.00	2.66	1.91	2.49	1.69	1.55	1.71	2.01	1.69	1.89
	CC2	Precipitation	0.91	0.80	1.58	1.77	2.36	1.11	1.17	1.08	1.18	1.37	1.20	1.56
		Evaporation	1.14	1.15	1.15	1.12	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13
		Temperature	3.23	3.81	4.51	4.14	2.85	3.13	2.38	2.50	2.85	3.01	2.59	3.09
	CC3	Precipitation	0.63	0.74	0.93	1.96	2.30	1.00	1.06	1.10	1.07	1.23	1.39	1.12
		Evaporation	1.18	1.19	1.19	1.14	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15
		Temperature	4.28	4.82	5.69	4.48	3.57	3.98	3.20	3.09	3.46	3.55	2.92	3.50



(a)



(b)



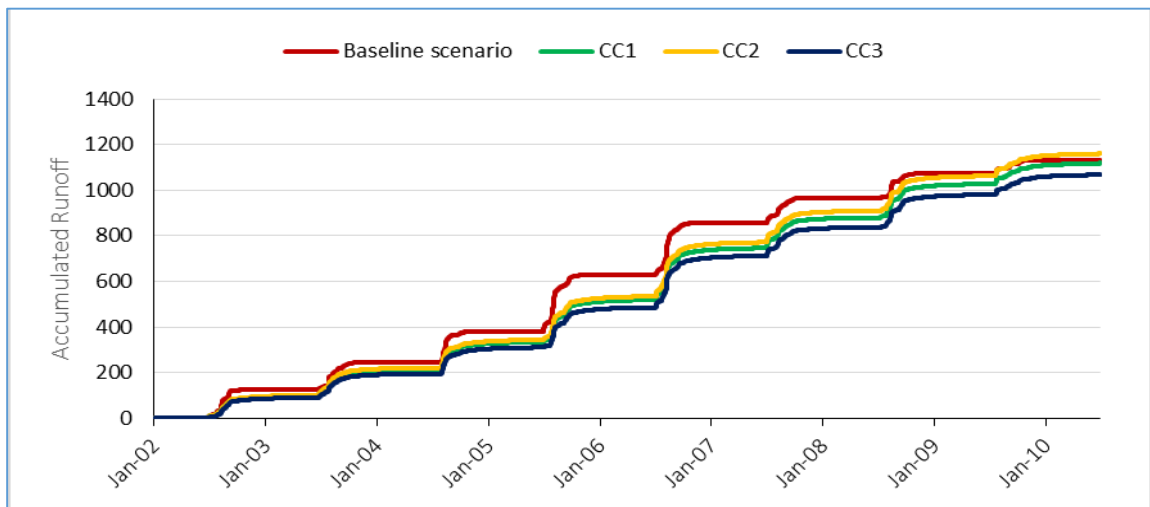
(c)

**Figure 4.53 Delta change values of precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Wadaj catchment**

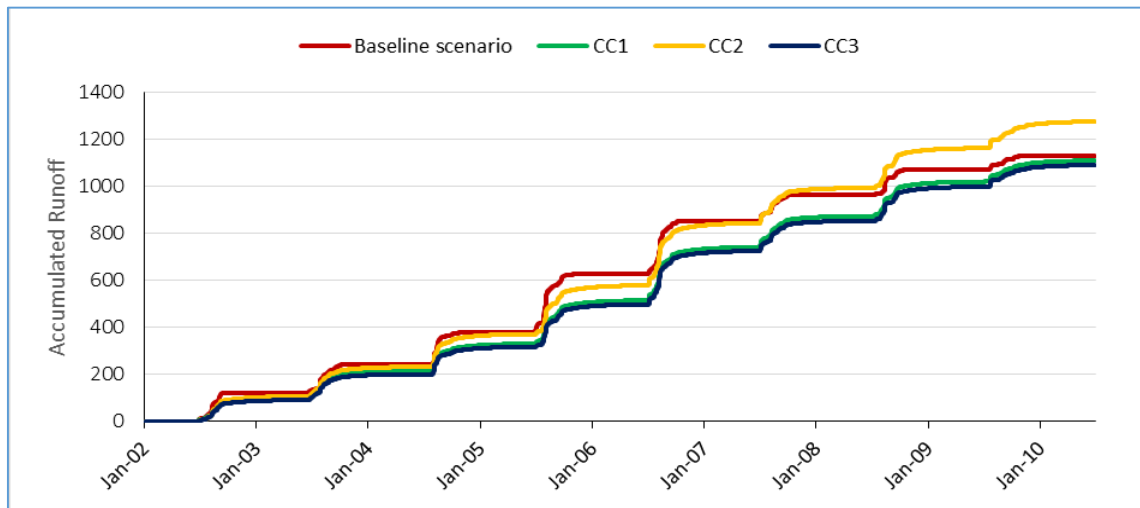
Referring the Table 4.29 and Figures 4.53, it was observed, the delta values of precipitation CC1 have no change in all years. Also for evaporation there it was seen very small variation for all the scenarios in all years. But for temperature no common trend found in their seasonal variation. Also for a

particular scenario, the variation in the delta values for different variables was random. Evaporation and temperature delta change values had shown similar trend for all months of year.

The comparison between estimated accumulated runoff for the years, 2020's, 2050's and 2080's and baseline scenario for Wadaj catchment was carried out and results are presented graphically in Figure 4.53. It was observed from the Figure 4.54, that the scenario CC2 had given higher runoff values among all the scenarios. The scenario CC2 had shown an increase in accumulated runoff by 3.77%, 13.08% and 17.74% in the year 2020's, 2050's and 2080's respectively. While scenario CC1 showed decrease in runoff by 1.00%, 1.54% and 1.76% in 2020's, 2050's and 2080's respectively. However, for scenario CC3 there was decrease in accumulated runoff by 5.54% and 3.33% in 2020's and 2050's respectively and increase in accumulated runoff by 7.53% in 2080's.



(a)

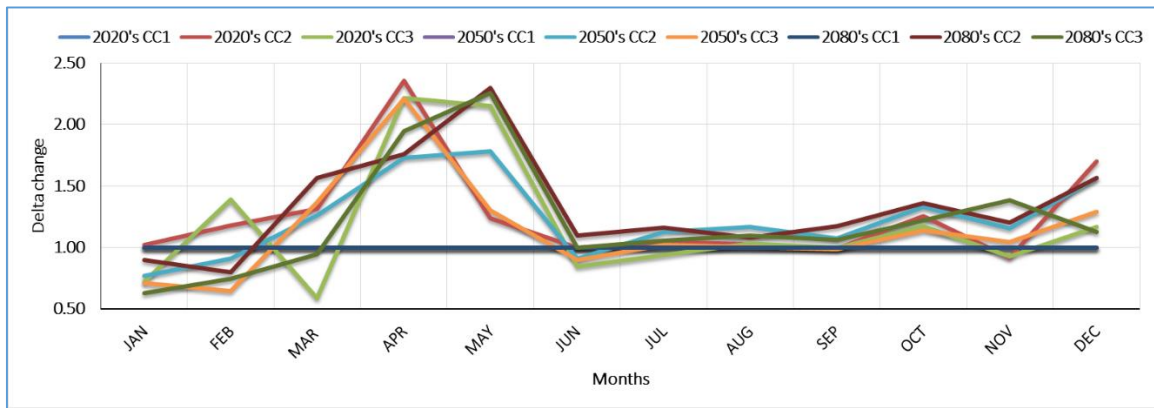


(b)

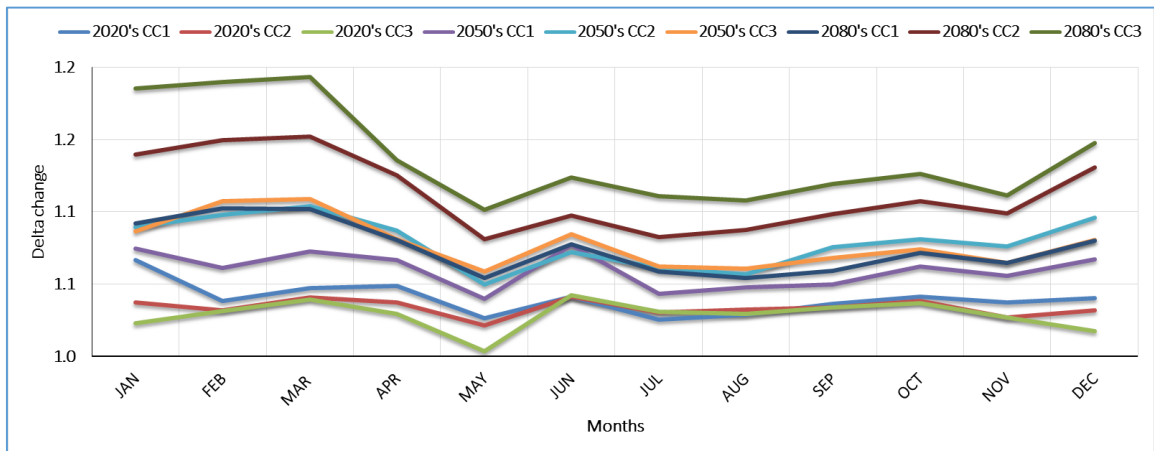


		<b>Evaporation</b>	1.09	1.10	1.10	1.08	1.05	1.08	1.06	1.05	1.06	1.07	1.06	1.08
		<b>Temperature</b>	2.13	2.60	3.01	2.66	1.91	2.50	1.70	1.55	1.71	2.02	1.70	1.90
		<b>Precipitation</b>	0.90	0.80	1.56	1.76	2.30	1.10	1.16	1.08	1.17	1.36	1.20	1.56
	<b>CC2</b>	<b>Evaporation</b>	1.14	1.15	1.15	1.13	1.08	1.10	1.08	1.09	1.10	1.11	1.10	1.13
		<b>Temperature</b>	3.22	3.81	4.50	4.15	2.84	3.15	2.38	2.49	2.85	3.02	2.60	3.11
		<b>Precipitation</b>	0.63	0.75	0.94	1.95	2.26	1.00	1.05	1.10	1.06	1.22	1.39	1.12
	<b>CC3</b>	<b>Evaporation</b>	1.19	1.19	1.19	1.14	1.10	1.12	1.11	1.11	1.12	1.13	1.11	1.15
		<b>Temperature</b>	4.27	4.83	5.71	4.49	3.55	4.00	3.20	3.09	3.46	3.55	2.92	3.51

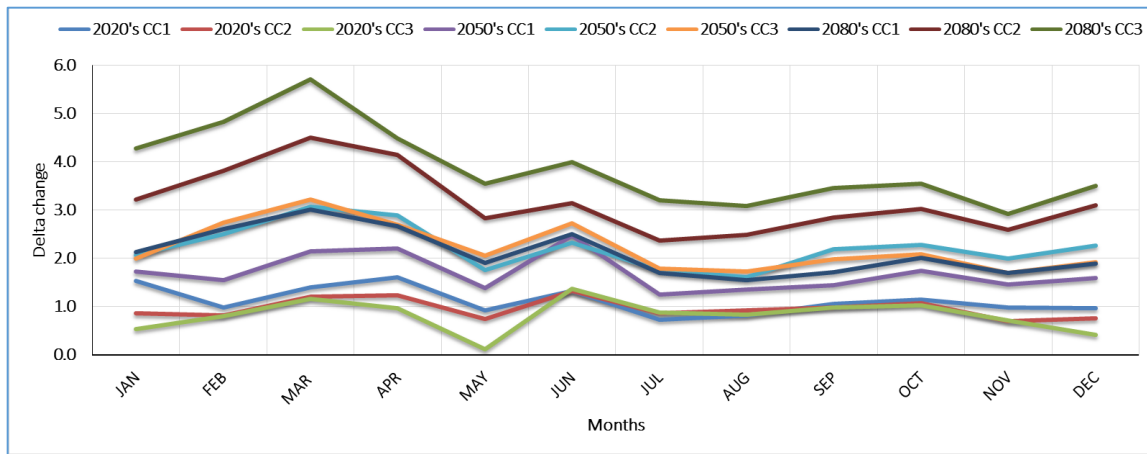
The delta change values of precipitation, evaporation and temperature for Yedgaon catchment are presented in Table 4.30 and shown graphically in Figure 4.55. It was observed from Table 4.30 and Figure 4.55, that except scenario CC1, all other scenarios had shown variation in delta change value for precipitation from January to June and November to December. For evaporation, a very small variation for all the scenarios in all years was observed. But for temperature, the delta change values were found to be higher than precipitation and evaporation. For both, evaporation and temperature, increasing trend in January to March, fall up to May and constant from June to November was observed. Also for a particular scenario, the variation in the delta values for different variables was random.



(a)

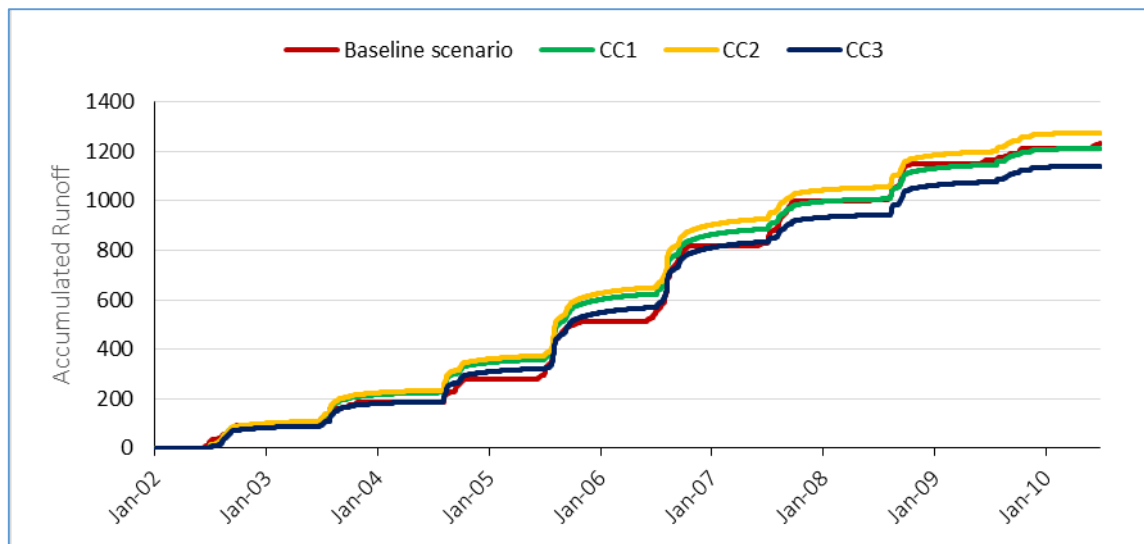


(b)

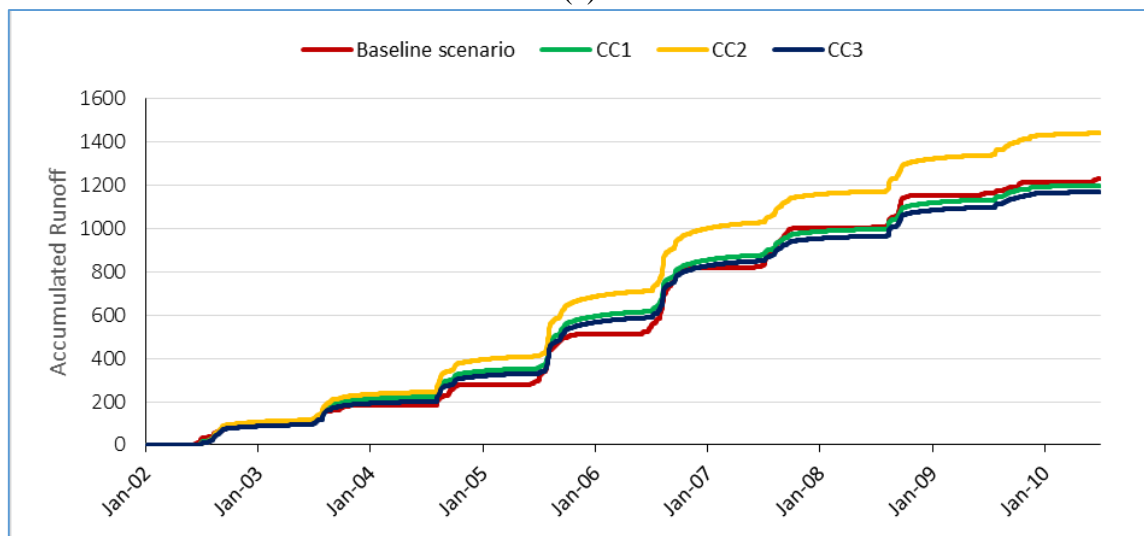


(c)

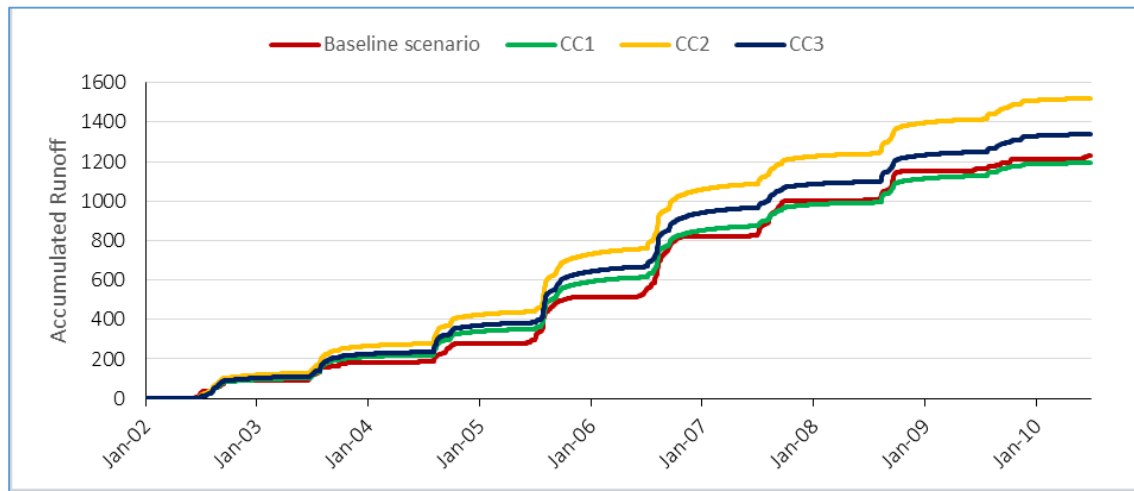
**Figure 4.55 Delta change values precipitation (a), evaporation (b) and temperature (c) in 2020's, 2050's and 2080's for Yedgaon catchment**



(a)



(b)



(c)

**Figure 4.56 Comparison plot of accumulated runoff with baseline scenarios in 2020's (a), 2050's (b) and 2080's (c) for Yedgaon catchment**

The comparison between estimated accumulated runoff for the years, 2020's, 2050's and 2080's and baseline scenario for Yedgaon catchment was carried out and results are presented graphically in Figure 4.56. It was observed from the Figure 4.56, that higher runoff among all the scenarios was observed for the scenario CC2. For the scenario CC2, an increase in accumulated runoff by 5.23%, 17% and 23.37% in 2020's, 2050's and 2080's respectively, was observed. But for scenario CC1, runoff was decreased by 1.54%, 2.66% and 3.18% in 2020's, 2050's and 2080's, respectively. However, for scenario CC3, the decrease in accumulated runoff by 7.36% and 5.08% in 2020's and 2050's, respectively was observed and in 2080's in accumulated runoff was increased by 8.62%.

#### 4.6 Effect of climate change on water allocation

The future water availability and series of different climatological variables obtained using MIKE Zero model as discussed under section 4.5.1.3 for Ghod catchment were used for studying the effect of climate change on water allocation pattern. The procedure for estimating futuristic irrigation water demand-deficit for multi-crop, major crops and sugarcane only cropping pattern for the year of 2020's, 2050's and 2080's for Ghod command area under variable area condition was discussed in section 3.11. The "Rainfall only" Climate model of MIKE-HYDRO Basin model was used to estimate futuristic irrigation water demand. Future climate series of rainfall and evaporation of Shirur station obtained using CC2 scenario were used as input to the model. Reference crop evapotranspiration was calculated using evaporation obtained in CC2 scenarios for 2020's, 2050's and 2080's as per the equation 3.27. Obtained series of reference crop evapotranspiration and rainfall for Shirur station were used as input to "Rainfall only" Climate model of MIKE-HYDRO Basin model to estimate irrigation water demand for 2020s, 2050's and 2080s. The futuristic irrigation water demand-deficit was

simulated for the different cropping patterns *viz.* multi-crop, major- crop and Sugarcane only cropping pattern, under Ghod command area from 150 to 415 km<sup>2</sup> with increment of 50 km<sup>2</sup>.

#### **4.6.1 Effect of climate change on water allocation using multi-crop cropping pattern**

The multi-crop cropping pattern used to estimate irrigation water demand was given in section 3.5.3.2. The procedure adopted for studying effect of climate change on water allocation was discussed in section 3.10. Accordingly, water availability obtained in scenario CC2 for 2020's for Ghod reservoir was used as input to MIKE-HYDRO Basin model. The irrigation water demand and deficit obtained for multi-crop cropping pattern during 2020's for variable area condition is given in Table 4.31. From the Table 4.31 it was observed that, minimum and maximum average irrigation water demand was found to be, 60.36 MCM for 150 km<sup>2</sup> CCA and 248.84 MCM for 450 km<sup>2</sup> CCA respectively. The average minimum irrigation water demand in 2020's was observed to be increased by 3.28 % than historical irrigation water demand. However, average maximum irrigation water demand in 2020's was observed to be decreased by 3.18 % than historical irrigation water demand. Zero demand-deficit was obtained for 150 km<sup>2</sup> of CCA and average maximum deficit of 115.64 MCM was found for 415 km<sup>2</sup> CCA. Deficit obtained for 200 km<sup>2</sup> CCA was also found to be considerably less than the other areas.

Similarly, water availability was obtained in scenario CC2 for 2050's and corresponding series of rainfall and reference crop evapotranspiration were used as input to the model. Table 4.32 represents the irrigation water demand and deficit obtained for multi-crop cropping pattern during 2050's for variable area condition. From the Table 4.32 it was found that, minimum and maximum average irrigation water demand was 66.51 MCM for 150 km<sup>2</sup> CCA and 274.20 MCM for 450 km<sup>2</sup> CCA, respectively. The minimum and maximum average irrigation water demand in 2050's was observed to be increased by 14.30 % and 6.69 % respectively than historical irrigation water demand. Also, minimum deficit was found to be for 150 km<sup>2</sup> CCA and 200 km<sup>2</sup> CCA.

Also, for estimating irrigation water demand deficit in 2080's, water availability obtained in scenario CC2 for 2080's and corresponding series of rainfall and reference crop evapotranspiration were used as input to the model. The irrigation water demand deficit for multi-crop cropping pattern during 2080's is shown in Table 4.33. In 2080's overall irrigation water demand and deficit were found to be increased than 2020's and 2050's. The minimum and maximum average irrigation water demand was found to be, 72.31 MCM for 150 km<sup>2</sup> CCA and 298.13 MCM for 450 km<sup>2</sup> CCA respectively. Also, minimum and maximum average irrigation water demand in 2080's was found to be increased by 24.27 % and 16 % respectively than historical irrigation water demand.

**Table 4.31 Irrigation water demand and deficit for multi- crop cropping pattern in 2020's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2020</b>	61.70	0.00	83.03	8.28	103.34	19.42	122.52	31.15	143.27	43.13	166.89	58.86
<b>2021</b>	77.09	0.00	99.50	13.80	125.59	36.91	196.87	102.32	269.49	171.76	315.28	209.26
<b>2022</b>	67.87	0.00	90.40	11.05	170.84	88.11	267.62	183.13	335.63	251.00	368.45	290.75
<b>2023</b>	58.14	0.00	76.48	0.00	89.86	0.00	110.25	11.99	171.50	49.38	218.21	91.32
<b>2024</b>	51.60	0.00	70.92	0.00	85.21	0.00	101.64	0.00	159.58	28.41	183.51	46.40
<b>2025</b>	60.02	0.00	75.88	0.00	96.15	0.00	116.98	0.00	136.73	0.00	155.52	0.00
<b>2026</b>	52.50	0.00	69.90	0.00	85.61	0.00	143.59	0.00	316.70	79.32	328.54	84.60
<b>2027</b>	53.94	0.00	70.15	0.00	88.34	0.00	130.43	29.10	223.37	114.27	254.31	143.95
<b>Average</b>	<b>60.36</b>	<b>0.00</b>	<b>79.53</b>	<b>4.14</b>	<b>105.62</b>	<b>18.06</b>	<b>148.74</b>	<b>44.71</b>	<b>219.53</b>	<b>92.16</b>	<b>248.84</b>	<b>115.64</b>

(Unit: Million Cubic Meter)

**Table 4.32 Irrigation water demand and deficit for multi- crop cropping pattern in 2050's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2050</b>	67.98	0.27	91.49	13.51	113.88	25.44	135.00	38.76	157.87	52.19	183.90	69.57
<b>2051</b>	84.95	0.86	109.64	20.67	138.39	47.24	216.93	118.90	296.96	195.85	347.41	236.56
<b>2052</b>	74.79	0.29	99.62	17.69	188.25	102.81	294.90	207.84	369.84	282.71	406.00	326.19
<b>2053</b>	64.07	0.00	84.27	0.00	99.02	0.00	121.49	11.64	188.98	54.78	240.45	101.02
<b>2054</b>	56.86	0.00	78.15	0.00	93.90	0.00	112.00	0.00	175.85	37.50	202.21	57.38
<b>2055</b>	66.14	0.00	83.62	0.00	105.94	0.00	128.90	0.00	150.66	0.00	171.37	0.00
<b>2056</b>	57.85	0.00	77.02	0.00	94.34	0.00	158.23	0.00	348.98	101.88	362.02	107.53
<b>2057</b>	59.44	0.00	77.30	0.00	97.34	0.00	143.73	33.50	246.14	127.50	280.23	160.18
<b>Average</b>	<b>66.51</b>	<b>0.18</b>	<b>87.64</b>	<b>6.48</b>	<b>116.38</b>	<b>21.94</b>	<b>163.90</b>	<b>51.33</b>	<b>241.91</b>	<b>106.55</b>	<b>274.20</b>	<b>132.30</b>

(Unit: Million Cubic Meter)

**Table 4.33 Irrigation water demand and deficit for multi- crop cropping pattern in 2080's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2080</b>	73.92	3.87	99.48	18.41	123.81	31.68	146.78	45.92	171.65	60.71	199.95	79.79
<b>2081</b>	92.36	5.97	119.20	27.92	150.46	56.83	235.86	134.78	322.87	218.55	377.73	262.69
<b>2082</b>	81.32	5.39	108.31	24.56	204.68	118.23	320.63	229.99	402.11	310.05	441.43	356.51
<b>2083</b>	69.66	0.00	91.62	0.00	107.66	0.00	132.09	18.28	205.47	67.15	261.43	117.29
<b>2084</b>	61.82	0.00	84.96	0.00	102.09	0.00	121.77	0.00	191.19	46.84	219.86	68.07
<b>2085</b>	71.91	0.00	90.91	0.00	115.19	0.00	140.15	0.00	163.81	0.00	186.33	2.75
<b>2086</b>	62.90	0.00	83.75	0.00	102.57	0.00	172.04	0.00	379.43	122.23	393.61	128.46
<b>2087</b>	64.63	0.00	84.05	0.00	105.84	3.76	156.27	41.49	267.61	143.83	304.69	179.76
<b>Average</b>	<b>72.31</b>	<b>1.90</b>	<b>95.29</b>	<b>8.86</b>	<b>126.54</b>	<b>26.31</b>	<b>178.20</b>	<b>58.81</b>	<b>263.02</b>	<b>121.17</b>	<b>298.13</b>	<b>149.41</b>

(Unit: Million Cubic Meter)

**Table 4.34 Irrigation water demand and deficit for major- crop cropping pattern in 2020's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2020</b>	135.19	37.04	173.90	63.83	239.68	106.97	278.26	137.39	279.38	147.15	321.74	159.47
<b>2021</b>	187.70	92.54	265.13	152.12	314.68	190.68	366.12	226.97	378.01	213.23	431.00	252.31
<b>2022</b>	229.98	136.11	300.04	205.68	335.33	238.86	369.14	276.59	362.54	274.78	382.76	297.30
<b>2023</b>	111.34	15.48	187.61	61.14	234.79	102.84	270.90	136.58	279.06	143.71	313.19	168.17
<b>2024</b>	88.36	0.00	155.33	30.87	181.63	55.15	215.65	82.13	225.46	82.90	247.62	108.44
<b>2025</b>	102.46	0.00	133.68	0.00	187.80	26.22	237.30	68.76	245.10	80.65	262.21	93.12
<b>2026</b>	108.81	0.00	245.49	19.23	299.02	62.39	342.33	87.66	346.88	98.15	366.94	114.40
<b>2027</b>	106.32	7.54	216.95	99.31	259.25	138.36	300.36	179.92	313.39	177.64	328.52	191.34
<b>Average</b>	<b>133.77</b>	<b>36.09</b>	<b>209.77</b>	<b>79.02</b>	<b>256.52</b>	<b>115.18</b>	<b>297.51</b>	<b>149.50</b>	<b>303.73</b>	<b>152.28</b>	<b>331.75</b>	<b>173.07</b>

(Unit: Million Cubic Meter)

#### **4.6.2 Effect of climate change on water allocation using major-crop cropping pattern**

The major-crop cropping pattern used to estimate irrigation water demand was given in section 3.5.3.2. The procedure adopted for studying effect of climate change on water allocation was discussed in section 3.11. Accordingly, water availability obtained in scenario CC2 for 2020's for Ghod reservoir was used as input to MIKE-HYDRO Basin model. The irrigation water demand and deficit obtained for major-crop cropping pattern during 2020's for variable area condition is presented in Table 4.34. It was seen that, minimum and maximum average irrigation water demand were found to be, 133.77 MCM for 150 km<sup>2</sup> CCA and 331.75 MCM for 450 km<sup>2</sup> CCA respectively. The average minimum irrigation water demand in 2020's was observed to be decreased by 2.27 % than historical irrigation water demand. However, average maximum irrigation water demand in 2020's was observed to be decreased by 1.29 % than historical irrigation water demand. Also, minimum deficit was found to be for 150 km<sup>2</sup> CCA.

Irrigation water demand and deficit for major-crop cropping pattern in 2050's is presented in Table 4.35. Minimum irrigation water demand and deficit was observed for 150 km<sup>2</sup> CCA. Minimum and maximum average irrigation water demand were found to be, 147.40 MCM for 150 km<sup>2</sup> CCA and 365.56 MCM for 450 km<sup>2</sup> CCA respectively. The average minimum and maximum irrigation water demand in 2050's were observed to be increased by 7.7 % and 10.62% than historical irrigation water demand.

Also, in 2080's, irrigation water demand and deficit obtained for major-crop cropping pattern is given in Table 4.36. From the table, it was observed, that the irrigation water demand and deficit for major-crop cropping in 2080's were found to be increased more than the multi-crop cropping pattern. Minimum and maximum average irrigation water demand were found to be, 160.27 MCM for 150 km<sup>2</sup> CCA and 397.46 MCM for 450 km<sup>2</sup> CCA respectively. The average minimum and maximum irrigation water demand in 2050's were observed to be increased by 17.1 % and 20.27% than historical irrigation water demand.

Table 4.35 Irrigation water demand and deficit for major-crop cropping pattern in 2050's

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2050</b>	148.97	45.29	191.63	74.84	264.11	122.71	306.62	156.27	307.85	166.90	354.53	180.63
<b>2051</b>	206.83	108.81	292.16	174.37	346.75	219.54	403.43	258.00	416.54	244.76	474.93	291.88
<b>2052</b>	253.42	155.87	330.62	232.91	369.51	269.50	406.76	311.01	399.49	308.72	421.78	328.66
<b>2053</b>	122.69	17.68	206.73	73.10	258.72	119.26	298.52	156.69	307.50	164.99	345.11	191.89
<b>2054</b>	97.37	0.00	171.16	41.01	200.14	66.21	237.63	96.21	248.44	98.84	272.86	126.22
<b>2055</b>	112.90	0.00	147.31	0.00	206.94	35.59	261.48	82.79	270.08	96.12	288.94	109.96
<b>2056</b>	119.90	0.00	270.51	31.56	329.49	79.69	377.22	108.46	382.24	119.20	404.34	137.73
<b>2057</b>	117.15	10.50	239.07	112.76	285.67	155.87	330.97	201.35	345.33	197.51	362.00	212.40
<b>Average</b>	<b>147.40</b>	<b>42.27</b>	<b>231.15</b>	<b>92.57</b>	<b>282.67</b>	<b>133.55</b>	<b>327.83</b>	<b>171.35</b>	<b>334.68</b>	<b>174.63</b>	<b>365.56</b>	<b>197.42</b>

(Unit: Million Cubic Meter)

Table 4.36 Irrigation water demand and deficit for major-crop cropping pattern in 2080's

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2080</b>	161.97	53.18	208.35	85.29	287.16	137.53	333.37	174.07	334.71	185.76	385.47	200.71
<b>2081</b>	224.88	123.93	317.65	195.20	377.01	244.81	438.63	287.58	452.89	274.32	516.37	327.55
<b>2082</b>	275.53	173.44	359.47	255.56	401.75	294.72	442.25	340.05	434.35	337.73	458.58	358.24
<b>2083</b>	133.40	23.94	224.77	84.57	281.30	134.22	324.56	174.30	334.34	183.37	375.23	212.83
<b>2084</b>	105.86	0.00	186.10	51.05	217.61	77.59	258.37	110.21	270.12	114.30	296.67	144.01
<b>2085</b>	122.76	0.00	160.16	0.00	224.99	46.74	284.30	98.73	293.64	113.19	314.15	128.34
<b>2086</b>	130.36	0.00	294.12	45.43	358.25	97.27	410.14	129.44	415.59	141.09	439.62	161.22
<b>2087</b>	127.37	16.80	259.93	128.89	310.60	176.04	359.85	225.39	375.46	221.17	393.59	235.42
<b>Average</b>	<b>160.27</b>	<b>48.91</b>	<b>251.32</b>	<b>105.75</b>	<b>307.33</b>	<b>151.12</b>	<b>356.44</b>	<b>192.47</b>	<b>363.89</b>	<b>196.37</b>	<b>397.46</b>	<b>221.04</b>

(Unit: Million Cubic Meter)

#### 4.6.3 Effect of climate change on water allocation using sugarcane only cropping pattern

In “sugarcane only” cropping pattern, sugarcane crop was considered to be sown on whole command area. The futuristic irrigation water demand and deficit for 2020’s, 2050’s and 2080’s was estimated using increasing command area condition. Water availability obtained in scenario CC2 for 2020’s, 2050’s and 2080’s and corresponding futuristic series of rainfall and reference crop evapotranspiration for Ghod reservoir were used as input to MIKE-HYDRO Basin model.

Irrigation water demand and deficit for sugarcane only cropping pattern obtained in 2020’s is presented in Table 4.37. From the Table 4.37 it was observed that, minimum and maximum average irrigation water demand was found to be, 136.68 MCM for 150 km<sup>2</sup> CCA and 243.72 MCM for 450 km<sup>2</sup> CCA respectively. The average minimum irrigation water demand in 2020’s was observed to be increased by 3.11 % than historical irrigation water demand. However, average maximum irrigation water demand in 2020’s was observed to be decreased by 0.64 % than historical irrigation water demand. The average deficit obtained for variable area was considerably higher than historical irrigation demand deficit.

The irrigation water demand and deficit obtained for sugarcane only cropping pattern during 2050’s for variable area condition is given in Table 4.38. From the table it was found that, minimum and maximum average irrigation water demand were 150.61 MCM for 150 km<sup>2</sup> CCA and 268.56 MCM for 450 km<sup>2</sup> CCA, respectively. The average minimum and maximum irrigation water demand in 2050’s were observed to be increased by 13.61 % and 9.49 % than historical irrigation water demand. The deficit obtained was also found to be increased as the CCA increased.

Also, in 2080’s, irrigation water demand and deficit obtained for sugarcane only cropping pattern is given in Table 4.39. From the table it was observed that the irrigation water demand and deficit for major-crop cropping in 2080’s were found to be increased more than major-crop cropping pattern. Minimum and maximum average irrigation water demand were found to be, 163.75 MCM for 150 km<sup>2</sup> CCA and 292 MCM for 450 km<sup>2</sup> CCA respectively. The average minimum and maximum irrigation water demand in 2080’s were observed to be increased by 23.53 % and 19.04 % than historical irrigation water demand. The irrigation water demand and deficit obtained for sugarcane only cropping pattern in 2080’s was considerably higher than other cropping patterns.

The findings of this study on the assessment of historical and futuristic water availability, water allocation, comparison of crop yield and scenarios on climate change effect on water availability and water allocation were presented and discussed in this chapter. The summery of the findings and conclusions drawn are presented in the next chapter.

**Table 4.37 Irrigation water demand and deficit for sugarcane only cropping pattern in 2020's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2020</b>	149.87	61.62	180.09	81.96	186.75	89.49	209.57	96.91	214.74	104.19	235.40	106.28
<b>2021</b>	166.88	68.41	248.03	118.71	282.59	128.32	296.58	156.77	310.05	160.86	342.02	169.92
<b>2022</b>	210.73	116.20	258.12	166.93	271.24	175.51	283.38	174.18	292.03	175.59	298.89	198.80
<b>2023</b>	117.91	26.67	168.90	51.35	198.31	64.63	214.14	70.56	214.83	77.07	211.21	78.71
<b>2024</b>	103.41	0.00	130.63	26.21	147.12	39.01	157.27	46.02	158.88	47.52	161.74	47.66
<b>2025</b>	104.14	0.00	126.64	9.25	143.80	20.62	160.67	34.70	170.34	43.68	173.88	47.00
<b>2026</b>	122.62	0.00	171.75	6.18	233.76	28.03	256.98	48.86	262.00	60.34	275.90	63.92
<b>2027</b>	117.87	16.49	161.83	40.89	208.66	70.89	232.91	94.89	252.07	113.72	250.77	112.21
<b>Average</b>	<b>136.68</b>	<b>36.17</b>	<b>180.75</b>	<b>62.68</b>	<b>209.03</b>	<b>77.06</b>	<b>226.44</b>	<b>90.36</b>	<b>234.37</b>	<b>97.87</b>	<b>243.72</b>	<b>103.06</b>

(Unit: Million Cubic Meter)

**Table 4.38 Irrigation water demand and deficit for sugarcane only cropping pattern in 2050's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2050</b>	165.14	72.17	198.44	94.83	205.79	103.11	230.93	111.30	236.63	119.33	259.39	121.68
<b>2051</b>	183.88	81.37	273.31	140.21	311.39	150.83	326.80	182.01	341.66	186.83	376.88	196.73
<b>2052</b>	232.21	133.93	284.43	189.97	298.89	199.46	312.27	197.96	321.79	199.40	329.35	226.37
<b>2053</b>	129.93	33.06	186.12	60.40	218.52	80.34	235.97	87.03	236.73	94.25	232.73	96.11
<b>2054</b>	113.94	5.90	143.94	36.70	162.11	50.77	173.30	58.78	175.07	60.32	178.22	60.46
<b>2055</b>	114.75	0.00	139.54	16.96	158.45	30.33	177.04	45.78	187.70	55.65	191.60	59.04
<b>2056</b>	135.12	0.00	189.26	16.62	257.58	40.63	283.17	63.59	288.70	76.29	304.02	80.87
<b>2057</b>	129.88	23.18	178.33	50.07	229.93	82.33	256.65	108.64	277.77	129.38	276.33	127.83
<b>Average</b>	<b>150.61</b>	<b>43.70</b>	<b>199.17</b>	<b>75.72</b>	<b>230.33</b>	<b>92.23</b>	<b>249.52</b>	<b>106.89</b>	<b>258.26</b>	<b>115.18</b>	<b>268.56</b>	<b>121.14</b>

(Unit: Million Cubic Meter)

**Table 4.39 Irrigation water demand and deficit for sugarcane only cropping pattern in 2080's**

Year\ CCA km <sup>2</sup>	150		200		250		300		350		415	
	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit	Demand	Deficit
<b>2080</b>	179.56	82.39	215.76	106.96	223.74	116.05	251.08	125.01	257.28	133.63	282.03	136.33
<b>2081</b>	199.93	93.75	297.16	160.28	338.56	171.70	355.32	205.65	371.47	210.96	409.76	221.81
<b>2082</b>	252.47	146.90	309.25	207.94	324.97	218.28	339.51	216.63	349.87	219.58	358.09	250.03
<b>2083</b>	141.27	41.98	202.36	71.97	237.59	91.55	256.56	98.77	257.38	106.71	253.04	108.64
<b>2084</b>	123.89	12.75	156.50	46.80	176.26	62.33	188.42	71.03	190.35	72.90	193.77	73.12
<b>2085</b>	124.76	0.00	151.72	25.75	172.28	40.90	192.49	57.75	204.08	68.51	208.32	72.37
<b>2086</b>	146.91	5.95	205.78	27.04	280.06	52.08	307.88	77.03	313.89	90.89	330.54	97.67
<b>2087</b>	141.21	31.46	193.89	60.89	249.99	96.84	279.04	123.33	302.00	146.02	300.44	144.32
<b>Average</b>	<b>163.75</b>	<b>51.90</b>	<b>216.55</b>	<b>88.45</b>	<b>250.43</b>	<b>106.22</b>	<b>271.29</b>	<b>121.90</b>	<b>280.79</b>	<b>131.15</b>	<b>292.00</b>	<b>138.04</b>

(Unit: Million Cubic Meter)

## 5. SUMMARY AND CONCLUSIONS

Ghod complex sub catchments include Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga and Wadaj as separate individual catchments, situated at upstream of the study area and Yedgaon and Ghod as intermediate catchments. These catchments are located at Junnar Tehsil of Pune district. The water availability study was conducted for all these catchments and water allocation study was under taken for Ghod command area. The summary of this investigation and conclusions drawn from this research work are presented in this chapter.

### 5.1 Summary

This section presents the importance of the study and summary of the results obtained by the application of the procedures and methodologies described in previous chapters.

#### 5.1.1 Importance

Water is a basic necessity for sustaining life and developing society. The increasing demand of water due to population growth and industrialization has created pressure on the available water resources. This problem can be solved by optimum utilization of the available resources in the existing reservoir system. Assessment of seasonal and long-term water availability is not only important for sustaining human life, biodiversity and the environment, but also helpful for water authorities and farmers to determine agricultural water management and water allocation. The allocation of water resources in the river basin is one of the critical issues now a day. For definite estimates of water allocation policies, and hence for the potential of improving system performance, an integrated analysis at basin-scale is important, where individual water related sectors, such as agriculture, municipal, and industrial water supply are brought together in a framework for an integrated analysis.

Also, climate change is one of the greatest pressures on the hydrological cycle which affects water availability and water allocation patterns. In this regard, mathematical models provide the opportunity for the well-structured basin-wide analyses of water availability and water demands and offer a framework for a coordinated planning and management.

MIKE models provide a platform for studying all the issues related to the water sector. Therefore, the present study was undertaken to investigate the applicability of MIKE models for water availability and water allocation scenarios in context of climate change with following specific objectives:

1. To simulate water availability in Ghod complex sub catchment of Upper-Bhima basin using MIKE 11 RR model for historical and synthetically generated series of rainfall

2. To simulate water demand in Ghod complex sub catchment for different cropping patterns using MIKE HYDRO BASIN model for historical and synthetically generated series of climatological variables influencing evapotranspiration
3. To compare the SWAB-CRYB model with MIKE HYDRO BASIN model for estimation of yield of different crops
4. To evaluate the effect of different water allocation scenarios for different water availability and demand
5. To study the influence of climate variability and climate change on water allocation pattern in Ghod complex sub catchment

### **5.1.2 Input data required for models**

The Ghod complex sub catchment which includes seven reservoirs as Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon was selected for assessment of water availability, water demand, water allocation scenarios, crop yield and climate change impact on water availability using different models such as MIKE 11 NAM model, MIKE HYDRO Basin model, MIKE Zero climate change functionality tool and SWAB-CRYB model. Ghod and Kukadi rivers are the main tributaries of Bhima river and located in the Upper Bhima catchment. The study area lies on these two rivers and fall under Pune and Ahmednagar districts of Maharashtra.

Climatological data such as rainfall, evaporation, maximum and minimum temperature, wind speed, relative humidity and bright sunshine hours were collected from State Data Storage Center, Hydrology Project (Surface Water), Jal Vidnyan Bhavan, Nasik for the period of 1982 to 2012. Daily water account data was collected for all seven catchments from Kukadi Irrigation Division I and II, Narayangaon, Pune. Daily water account data includes daily water levels, lake content, spill over spillways, different releases from dam such as irrigation use, domestic use etc. The data was collected for the period of 1997 to 2014.

In GIS data, SRTM Digital Elevation Model (cell size 90 m x 90 m), shape files of raingauge stations, reservoirs and catchments were used. Crop data of crop coefficient values, crop length according to crop growth stages, root depth, maximum height of crop and depletion fraction were collected from FAO 56 manual and other literature. Common crops grown in the catchment are Soybean, Jowar, Groundnut, Tur, Bajara, Maize, Sugarcane, Wheat, Gram, Cotton and Sunflower. Soil properties such porosity, field capacity and permanent wilting point for the Ghod command area were obtained from literature. Pre-processing of input data was performed for setting up the MIKE 11 NAM model and MIKE HYDRO Basin model, which includes preparation of time series data. The time series data files of rainfall, potential evaporation, specific runoff, climate data, irrigation and non-irrigation demand, water supply fraction, Level-Area-Volume (LAV), flow control level, characteristic levels of

reservoirs were prepared for running the simulation. This information was stored as 'dfs0' (time series) data files.

### **5.1.3 Estimation of intermediate flow of Yedgaon and Ghod catchment**

Specific runoff of intermediate catchments Yedgaon and Ghod was required in MIKE 11 NAM model. The Yedgaon catchment comprises three reservoirs in the upstream i.e. Chilewadi, Pimpalgaonjoga and Manikdoh. Also Ghod catchment comprises three reservoirs in the upstream i.e. Dimbhe, Wadaj and Yedgaon. The routing model for Yedgaon and Ghod was set separately in MIKE HYDRO Basin model. Linear reservoir routing method was used for routing inflow in Yedgaon and Ghod reservoir. The delay parameters/ travel time of 48 hr, 25 hr and 35 hr were fixed for Chilewadi, Pimpalgaonjoga and Manikdoh reservoir respectively, in Yedgaon reservoir routing. The delay parameters/ travel time of 50 hr, 70 hr and 25 hr were fixed for Dimbhe, Wadaj and Yedgaon reservoir respectively, in Ghod reservoir routing. The difference obtained between observed inflow and routed flow was then considered as intermediate flow of the respective catchments. This intermediate flow was then used as observed inflow and compared with simulated flow for the calibration and validation of MIKE 11 NAM model

### **5.1.4 Calibration and Validation of MIKE 11 NAM model**

The MIKE 11 NAM model was setup by using the data of daily rainfall time series, evaporation time series, and observed runoff time series for the period of year 2002 to 2009 for calibration in the seven catchments of Ghod complex. The model was refined to obtain the best match between observed and simulated runoff. The model parameters were adjusted until a satisfactory fit between simulated flow contributions (overland flow, inter flow, and base flow) and observed stream flow was attained. The values of all the nine model parameters obtained during the model calibration for all catchments were found within the permissible range.

The graphical evaluation during calibration period represented the graphs of accumulated observed and accumulated simulated flow were matched well with minimum water balance error of 0.6%, 0.0%, -0.1%, 0.0%, -0.1%, 0.3% and -3.8% for Chilewadi, Dimbhe, Manikdoh, Pimpalgaonjoga, Wadaj, Yedgaon and Ghod catchments respectively. Also, coefficient of determination ( $R^2$ ) was obtained in the range of 0.58 to 0.76 during calibration which indicated the good agreement between the observed and simulated runoff catchment. From the statistical evaluation, EI was obtained in the range of 0.58 to 0.76 and correlation coefficient was obtained in the range of 0.76 to 0.88.

The optimum values of model parameters obtained during calibration were then used for validation of model for judging the performance of the calibrated model. The MIKE 11 NAM model was validated for the period of two years from 2010 to 2011. The water balance error varied from -0.6 to

6.4 which was within acceptable limit. The value of correlation coefficient was 0.73 to 0.86 and EI was obtained in the range of 0.52 to 0.73.

The water balance of MIKE 11 NAM model in terms of overland flow, inter flow and base flow for all sub catchments of Ghod complex was studied for both calibration and validation period. The observed and simulated water availability were also studied by converting the yearly runoff rate into MCM for calibration and validation periods.

#### **5.1.5 Rainfall forecasting by using ANN model and Simulation of water availability by using forecasted data**

The ANN model 4-10-1 network architecture with ten hidden nodes and CFB network trained with resilient back propagation algorithm (*trainrp*) training function was used for forecasting of rainfall. The number of input includes input weekly rainfall of same week of previous two years (two inputs) and rainfall of two preceding weeks of same year (two input). The ANN model of 4-10-1 network architecture was developed by Popale (2016). Rainfall was forecasted for the year 2013 for the stations Pimpalgaonjoga, Pimpalwandi, Shirur, Kurwandi, Aundhe and Savale. This forecasted rainfall was then used in MIKE 11 NAM model for simulating runoff for all the catchments of Ghod complex. The water availability of 198.37MCM, 446.3MCM, 289.60MCM, 250.35MCM, 178.03MCM, 140.69MCM, 191.78MCM was simulated for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon catchments respectively. The forecasted water availability was then compared with observed water availability.

#### **5.1.6 Calibration of MIKE HYDRO Basin model**

MIKE HYDRO Basin model was calibrated from the year 2002 to 2012. For model calibration, the “initial water level” was set to same as actual water level at the start of simulation i.e. 1<sup>st</sup> October, 2001 (i.e. 548.48 m). The calibration of model was done by comparing calibrated and actual water levels of all seven reservoirs. The  $R^2$  values between calibrated and actual water levels of 0.78, 0.85, 0.81, 0.92, 0.88, 0.83 and 0.72 were found to be in permissible limits for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaonjoga, Wadaj and Yedgaon catchments respectively. This calibrated MIKE HYDRO Basin model was then used for simulation of irrigation water demand in Ghod command area.

#### **5.1.7 Historical water allocation scenarios**

Simulation of irrigation water demand for Ghod command area was performed by MIKE HYDRO Basin model from the year 2002-2012. Irrigation and non-irrigation water user properties were specified in the model. The non-irrigation water user includes domestic and industrial water demands, spill over spillways and water diverted for the hydro-power generation. The simulations were

performed by giving first priority to non-irrigation water user and second priority to irrigation water user. The simulation was performed using historical and forecasted water availability which was calculated by calibrated MIKE 11 NAM model.

The three different cropping patterns namely multi-crop, major-crop and sugarcane only were considered for water allocation study under Ghod command area for varying area condition. Cultivable command area was considered as 150 km<sup>2</sup>, 200 km<sup>2</sup>, 250 km<sup>2</sup>, 300 km<sup>2</sup>, 350 km<sup>2</sup>, and 415 km<sup>2</sup> to estimate irrigation water demand and deficit. Multi-crop cropping patterns include different crops commonly sown under the Ghod command area which covers all the three seasons of year. Major crops cropping pattern includes three main crops (Bajara, Jowar and Maize) each from the three season on 50% of command area and sugarcane on remaining 50% of area. Sugarcane only cropping pattern represented 100% of only single crop of sugarcane sown on all command area. The irrigation water demand and deficit were studied for these three cropping patterns under varying area condition.

Three water allocation scenarios were studied using the historical and forecasted water availability and irrigation water demand in Ghod command area. The irrigation water demand calculated by simulation for historical period was considered as base scenario. In first scenario the irrigation water demands of base scenario was increased by 25 %. In second scenario the irrigation water demand of base scenario was increased by 40 %. Average irrigation water demand and deficit obtained for all the three water allocation scenarios for three different cropping patterns under varying command area condition are summarized below.

Baseline multi-crop scenario: Average irrigation water demand was found in range of 58.2 MCM to 257.0 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 12.6 MCM was obtained for CCA of 250 km<sup>2</sup>.

Baseline major crop scenario: Average irrigation water demand was found in range of 136.9 MCM to 330.5 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 31.6 MCM was obtained for CCA of 150 km<sup>2</sup> which was minimum than other considered areas.

Baseline Sugarcane crop scenario: Average irrigation water demand was found in range of 132.6 MCM to 245.3 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 30.7 MCM was obtained for CCA of 150 km<sup>2</sup> which was minimum than other considered areas.

25% multi-crop scenario: Average irrigation water demand was found in range of 72.7 MCM to 321.6 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The minimum deficit of 7.7 MCM was obtained for CCA of 200 km<sup>2</sup>.

25% major crop scenario: Average irrigation water demand was found in range of 171.1 MCM to 413.1 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 57.2 MCM obtained for CCA of 150 km<sup>2</sup> was minimum compared to other considered areas.

25% Sugarcane crop scenario: Average irrigation water demand was found in range of 165.7 MCM to 306.6 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 57.0 MCM obtained for CCA of 150 km<sup>2</sup> was minimum compared to other considered areas

40% multi-crop scenario: Average irrigation water demand was found in range of 81.5 MCM to 359.8 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 13.90 MCM obtained for CCA of 200 km<sup>2</sup> was minimum compared to other considered areas

40% major crop scenario: Average irrigation water demand was found in range of 191.6 MCM to 462.6 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 73.1 MCM obtained for CCA of 200 km<sup>2</sup> was minimum compared to other considered areas

40% Sugarcane crop scenario: Average irrigation water demand was found in range of 185.6 MCM to 343.4 MCM for incremental CCA from 150 km<sup>2</sup> to 415 km<sup>2</sup>. The deficit of 73.3 MCM obtained for CCA of 200 km<sup>2</sup> was minimum compared to other considered areas

In all these scenarios, multi crop cropping pattern showed minimum irrigation water demand and deficit as compared to major crop and sugarcane only cropping pattern.

### **5.1.8 Forecasted water allocation scenarios**

The forecasted water availability for the year 2013 for Ghod catchment, obtained by using forecasted series of rainfall by ANN was used as input to the MIKE HYDRO Basin model. "Rainfall only" climate model was used to estimate irrigation water demand using only reference crop evapotranspiration and rainfall data. Reference crop evapotranspiration for the year 2013 was forecasted using ANN forecasting model of 6-13-1 network architecture trained with *trainlm* training function using FFB (Feed-Forward Back Propagation) network developed by Bhagat and Popale (2017). The forecasted irrigation water demand was then estimated for year 2013 using rainfall only-climate model under MIKE HYDRO Basin model. Then, similarly as historical scenarios, three water allocation scenarios were considered in forecasted water allocation scenarios. In first scenario, the total irrigation water demand estimated for the year 2013 was considered as the base scenario. In first and second forecasted water allocation scenarios irrigation water demand was increased by 25% and 40%.

In base scenario, for multi-crop cropping pattern, no deficit was found for 150 km<sup>2</sup> and 200 km<sup>2</sup> CCA. Maximum irrigation water demand of 370.58 MCM was obtained in 415 km<sup>2</sup> of CCA for major-crops

cropping pattern and deficit was 114.94 MCM. In water allocation scenario-1 with 25 % increase in forecasted irrigation water demand for multi-crop cropping pattern, minimum irrigation water demand was observed to be 81.53 MCM in 150 km<sup>2</sup> and deficit was found to be 3.45 MCM. Maximum irrigation water demand of 436.23 MCM was obtained in 415 km<sup>2</sup> of CCA for major-crops cropping pattern and deficit was 154.85 MCM. For multi-crop cropping pattern, the irrigation water demand-deficit obtained up to 250 km<sup>2</sup> was considerable. However, in water allocation scenario-2 with 40 % increase in forecasted irrigation water demand for multi-crop cropping pattern, minimum irrigation water demand was observed to be 91.31 MCM in 150 km<sup>2</sup> and deficit was found to be 8.51 MCM. Maximum irrigation water demand of 518.81 MCM was obtained in 415 km<sup>2</sup> of CCA for major-crops cropping pattern and deficit was 186.05 MCM. For multi-crop cropping pattern, the irrigation water demand-deficit obtained up to 250 km<sup>2</sup> was considerable.

#### **5.1.9 Crop yield estimation using MIKE HYDRO Basin model and SWAB-CRYB model**

Comparison of two models, MIKE HYDRO Basin and SWAB-CRYB was made on the basis of crop yield simulated from both the models. Crop yields for Jowar, Bajara, Wheat, Sorghum, Maize, Soybean, Gram, Sunflower, Sugarcane, Cotton crops were estimated yearly from the year 2002 to 2012. Input data for crops was kept same for both the models. MIKE HYDRO Basin estimates crop yield on basis of FAO 33 crop yield model (Doorenbos and Kassam, 1979), while SWAB-CRYB model estimates on basis of crop yield model of Stewart *et al.*, (1976). Average yield obtained from estimated yield of the year 2002 to 2012 for each crop was then compared for both the models. Overall the average crop yield simulated by MIKE HYDRO Basin model was found to be more compared to those estimated by SWAB-CRYB model for all crops.

#### **5.1.10 Climate change effect on water availability**

According to IPCC, water resources are vulnerable to be impacted by climate change. Therefore, impact of climate change on water availability and water allocation scenarios was under-taken in this study. MIKE Zero climate change functionality module is based on IPCC AR4 report, which takes projection of climate variables based on IPCC scenarios. Projection of climate variables were taken from the delta change factors. Delta change factors predicts how certain variable changes over period of time. Delta change factors for precipitation, evaporation and temperature were estimated for the selected GCM and CO<sub>2</sub> emission scenarios. There were 55 combinations of GCM and CO<sub>2</sub> emission scenarios. To select the proper combination of GCM model and CO<sub>2</sub> emission scenarios, all 55 climate change scenarios were validated over base period (2002-2009) which was calibration period of MIKE 11 NAM model for all the seven sub catchment of Ghod complex. After statistical evaluation, three best scenarios including CNRM: CM3- SRB1, CNRM: CM3- SRA1B, and CNRM: CM3- SRA2 were selected for the climate change study and named as CC1, CC2 and CC3 respectively. Water

availability was estimated for the three scenario for 2020's, 2050's and 2080's for all the sub catchments of Ghod complex and the percentage increase or decrease with base period are summarized below.

Considering the scenario CC1, during 2020's, the water availability was found decreased by 1.17%, 0.53%, 0.37%, 8.59%, 1.00% and 1.54% for Chilewadi, Dimbhe, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively, whereas, found increased by 0.42% for Ghod catchment. For scenario CC2, during 2020's, the water availability was found increased by 3.51%, 3.52%, 5.87%, 3.45%, 3.60%, 3.78% and 5.23%, for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively, whereas, for scenario CC3, during 2020's, the water availability was found decreased by 4.88%, 4.72%, 6.70%, 4.10%, 12.04%, 5.53% and 7.76%, for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively.

During 2050's, in scenario CC1, the water availability was found decreased by 1.55%, 0.85%, 1.46%, 0.65%, 8.88%, 1.54% and 2.67% for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively. However, for scenario CC2, during 2050's, the water availability was found increased by 11.34%, 12.37%, 22.62%, 11.83%, 2.92%, 13.08% and 17%, for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively. For the scenario CC3, during 2050's, the water availability was found decreased by 2.71%, 2.43%, 4.86%, 1.81%, 9.87%, 3.33% and 5.08% for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively.

Furthermore, during 2080's, for the scenario CC1, the water availability was found decreased by 1.7%, 0.98%, 2.33%, 0.76%, 9%, 1.76%, and 3.18% for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively. But for scenario CC2, during 2080's, the water availability was found increased by 15.27%, 16%, 33.62%, 15.33%, 5.94%, 17.74% and 23.36% for Chilewadi, Dimbhe, Ghod, Manikdoh, Pimpalgaon Joga, Wadaj and Yedgaon catchments, respectively. However, for scenario CC3, during 2080's, the water availability was found increased by 6.95%, 7.5%, 9.64%, 7.46%, 7.53% and 8.62% for Chilewadi, Dimbhe, Ghod, Manikdoh, Wadaj and Yedgaon catchments, respectively whereas found decreased by 1.37% for Pimpalgaon Joga catchment.

Overall, in the year 2020's, 2050's and 2080's, for scenario CC2, the water availability was found to be increased than the scenario CC1 and CC3. Also, scenario CC1 showed decreased water availability in all these years.

### 5.1.11 Climate change effect on water allocation pattern

Futuristic irrigation water demand-deficit for multi-crop, major crops and sugarcane only cropping pattern for the year of 2020's, 2050's and 2080's for Ghod command area under variable area condition was estimated to study the effect of climate change on water allocation pattern. The water availability obtained by using CC2 scenario (CNRM: CM3- SRA1B) for the year of 2020's, 2050's and 2080's was used as input to MIKE HYDRO Basin model. Modified timeseries of rainfall and evaporation of Shirur station obtained using CC2 scenario were used as input to the model. The evaporation data was obtained for 2020s, 2050's and 2080s in CC2 scenarios and reference crop evapotranspiration was calculated using pan coefficient.

For multi-crop cropping pattern during 2020's, minimum and maximum average irrigation water demand was found to be, 60.36 MCM for 150 km<sup>2</sup> CCA and 248.84 MCM for 450 km<sup>2</sup> CCA which was increased by 3.28 % and 3.18 % than historical irrigation water demand respectively. In 2050's minimum and maximum average irrigation water demand was found to be, 66.51 MCM for 150 km<sup>2</sup> CCA and 274.20 MCM for 450 km<sup>2</sup> CCA respectively. The minimum and maximum average irrigation water demand in 2050's was observed to be increased by 14.30 % and 6.69 % respectively than historical irrigation water demand. In 2080's overall irrigation water demand and deficit were found to be increased than 2020's and 2050's. The minimum and maximum average irrigation water demand was found to be, 72.31 MCM for 150 km<sup>2</sup> CCA and 298.13 MCM for 450 km<sup>2</sup> CCA respectively. Also, minimum and maximum average irrigation water demand in 2080's was found to be increased by 24.27 % and 16 % respectively than historical irrigation water demand.

For major-crop cropping pattern in 2020's, the minimum and maximum average irrigation water demands were found to be, 133.77 MCM for 150 km<sup>2</sup> CCA and 331.75 MCM for 450 km<sup>2</sup> CCA. The average minimum and maximum irrigation water demand in 2020's was observed to be decreased by 2.27 % and 1.29 % than historical irrigation water demand. The average minimum and maximum irrigation water demand in 2050's were observed to be increased by 7.7 % and 10.62% than historical irrigation water demand. Minimum and maximum average irrigation water demand were found to be, 147.40 MCM for 150 km<sup>2</sup> CCA and 365.56 MCM for 450 km<sup>2</sup> CCA. In 2080's minimum and maximum average irrigation water demand were found to be, 160.27 MCM for 150 km<sup>2</sup> CCA and 397.46 MCM for 450 km<sup>2</sup> CCA. The average minimum and maximum irrigation water demand in 2050's were observed to be increased by 17.1 % and 20.27% than historical irrigation water demand.

For 'sugarcane only' cropping pattern, in 2020's, minimum and maximum average irrigation water demand was found to be, 136.68 MCM for 150 km<sup>2</sup> CCA and 243.72 MCM for 450 km<sup>2</sup> CCA. The average minimum irrigation water demand in 2020's was observed to be increased by 3.11 % than historical irrigation water demand. However, average maximum irrigation water demand in 2020's

was observed to be decreased by 0.64 % than historical irrigation water demand. In 2050's, minimum and maximum average irrigation water demand were found to be, 150.61 MCM for 150 km<sup>2</sup> CCA and 268.56 MCM for 450 km<sup>2</sup> CCA. The average minimum and maximum irrigation water demand in 2050's were observed to be increased by 13.61 % and 9.49 % than historical irrigation water demand. Also, in 2080's, minimum and maximum average irrigation water demand were found to be, 163.75 MCM for 150 km<sup>2</sup> CCA and 292 MCM for 450 km<sup>2</sup> CCA. The average minimum and maximum irrigation water demand in 2080's were observed to be increased by 23.53 % and 19.04 % than historical irrigation water demand.

## 5.2 Conclusions

This research was mainly focused on water availability and water allocation scenario study for Ghod complex sub catchments and Ghod command area using MIKE models. The study was also conducted to know the effect of climate change on water availability and water allocation scenarios. The following specific conclusions were derived from the observations, analysis and comparison of results in this study:

1. A satisfactory and reliable results were obtained during calibration and validation of MIKE 11 NAM rainfall runoff model in terms of statistical and graphical measures. 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. MIKE 11 NAM rainfall runoff model was found suitable to forecast water availability using forecasted series of runoff.
2. The multi-crop cropping pattern provided better results for given water availability with minimum deficit for irrigating up to 250 km<sup>2</sup> of Ghod CCA. As the total sown area (CCA) increased, the irrigation water demand was found to be increased and thereby deficit also increased. Major crop cropping pattern resulted into maximum irrigation water demand and deficit than multi crop and sugarcane only cropping pattern.
3. Crop yield simulated by MIKE HYDRO Basin model was found to be considerably more than SWAB-CRYB model.
4. The delta change values of precipitation and evaporation for different scenarios have no considerable change in their seasonal variation. However, it is increasing for temperature and have no common trend in their seasonal variation.
5. The GCM model CNRM-CM3 (CNM3) provided proximity values for three emission scenarios. Thus the results obtained from CC2 (CNRM-CM3 with SRA1B) can used for future climate change scenario to take appropriate decisions.

6. Water availability was found to be increased by 3.6 to 33.62% in 2020 to 2080 by climate change scenario CC2. Water availability found to be decreased using climate change scenario CC1 and CC3 in 2020, 2050 and 2080.
7. Irrigation water demand and deficit obtained by using water availability in the scenario CC2 were observed to be increased approximately by 3%, 10-15% and 20-25% than baseline scenario in the year 2020, 2050 and 2080 respectively, for all three cropping pattern.
8. Overall, the different MIKE models (MIKE 11 NAM, MIKE HYDRO Basin and MIKE Zero Climate Change functionality) were found to be efficient in terms of assessing water availability, water allocation scenarios, crop yield, climate change and climate variability effect on water availability and water allocation. Hence, MIKE models provide a platform for studying the issues related to water sector.

## 6. LITERATURE CITED

- Abdul kadir, T. S., A. W. Salami and A. G. Kareem. 2012. Artificial neural network modeling of rainfall in Ilorin, Kwara state, Nigeria. *Journal of Research Information in Civil Engineering*, 9(1): 108-120.
- Abdullahi, J. and G. Elkiran. 2017. Prediction of the future impact of climate change on reference evapotranspiration in Cyprus using artificial neural network. *Procedia Computer Science*, 120(2017): 276–283.
- Abudu, S., C. Cui, J. P. King, J. Moreno and A. S. Bawazir. 2011. Modeling of daily pan evaporation using partial least squares regression, *Science China Technological Sciences*, 54(1): 163-174.
- ADB (Asian Development Bank) 2010. Climate Change Adaptation in Himachal Pradesh: Sustainable Strategies for Water Resources. Chapter 3- Climate Change Risks.
- Aitken, A.P. 1973. Assessing systematic errors in rainfall-runoff models. *Journal of Hydrology*. 20: 121-136.
- Alam, M. S. and P. Willems. 2012. Assessing impacts of urbanization and climate change on urban flood risks: A case study on Turnhout in Belgium. *Journal of Civil Engineering (IEB)*, 40(1): 79-93.
- Allen, R. C., L. S. Smith, D. R. Pereira and M. Smith. 1998. Crop Evapotranspiration: Guideline for computing crop water requirements. *FAO Irrigation and Drainage Paper 56*. FAO Rome. Italy.
- AL-Suhaili, R. H. and R. A. Karim. 2014. Spatial prediction of monthly precipitation in Sulaimani Governorate using artificial neural network models. *Journal of Engineering*. 20(3): 15-27.
- Amir, I. and F.M. Fisher. 1999. Analyzing agricultural demand for water with an optimizing model. *Agricultural Systems*, 61: 45-56.
- Amir, Md. S.I.I., Md. M.K. Khan, Md. G. Rasul, R. H. Sharma and F. Akram. 2013. Automatic multi-objective calibration of a rainfall runoff model for the Fitzroy Basin, Queensland, Australia. *International Journal of Environmental Science and Development*, 4(3): 311-315.
- Amrit, K., S. Singh, and R.M. Singh. 2016. Estimation of natural groundwater recharge using MIKE 11 NAM model. *Indian Journal of Soil Conservation*, 44(2): 216-220.

- Anandhi, A., V. V. Srinivas, R. S. Nanjundiah and D. N. Kumar. 2008. Downscaling precipitation to river basin in India for IPCC SRES scenarios using support vector machine. *International Journal of Climatology*, 28: 401-420.
- Andersen, H. E., B. Kronvang, S. E. Larsen, C. C. Hoffmann, T. S. Jensen and E. K. Rasmussen. 2006. Climate-change impacts on hydrology and nutrients in a Danish lowland river basin. *Science of the Total Environment*, 365: 223–237.
- Anonymous. 2003. Irrigation development in India, [www.agricola.com](http://www.agricola.com).
- Ariapour A. and M. N. Zavareh. 2010. Estimation of daily evaporation using of Artificial Neural Networks (Case study; Borujerd Meteorological Station), Islamic Azad University, Borujerd Branch, Borujerd, Lorestan, Iran. 125-132.
- ASCE, Task committee on application of Artificial Neural Networks in hydrology. 2000. Artificial neural networks in hydrology-II: Hydrologic applications. *Journal of Hydrologic Engineering*, 5(2): 124-137.
- ASCE. 1993. Criteria for evaluation of watershed models. *Journal of Irrigation and Drainage Engineering* 119(3): 429-442.
- Babel, M.S., A.D. Gupta and D.K. Nayak. 2005. A model for optimal allocation of water to competing demands. *Water Resources Management*, 19: 693-712.
- Bakker, M., J.H.G. Vreeburg, K.M. van Schagen and L.C. Rietveld. 2013. A fully adaptive forecasting model for short-term drinking water demand. *Environmental Modelling and Software*, 48: 141-151.
- Balan, I., L. Crenganis and F. Corduneanu. 2016. Flood analysis using Mike 11 by Dhi and ArcGIS. Case study – The flood in the upper catchment of river Geru, Galați County, Romania. *Conference Paper*, 27-38.
- Bangash, R.F., A. Passuello, M. Hammond and M. Schumacher. 2012. Water allocation assessment in low flow river under data scarce conditions: A study of hydrological simulation in Mediterranean basin. *Science of the Total Environment*, 440: 60-71.
- Berhe, F.T., A.M. Melesse, D. Hailu and Y. Sileshi. 2013. MODSIM-based water allocation modeling of Awash river basin, Ethiopia. *Catena*, 109: 118-128.
- Bhagat, A. D. and P. G. Popale 2017. Estimation of Pomegranate Evapotranspiration for Orchard Management using Artificial Neural Network. *International Journal of Current Research*, 9(10): 59205-59209.

- Bhagat, A. D. and P. G. Popale. 2017. Estimation of reference evapotranspiration by Artificial Neural Network. *International Journal of Innovative Research in Science, Engineering and Technology*, 6(10): 20141-20148.
- Birsan, M.V. 2013. Application of a distributed physically-based hydrological model on the upper river basin of *Somesul Mare* (Northern Romania). *Romanian Reports in Physics*, 65(4): 1469-1478.
- Boughton, W. C. 2004. The Australian water balance model. *Environmental Modelling and Software*. 19: 943-956.
- Buontempo, C., J. K. Lorup, M. Sanderson, M. Butts, E. Palin, R. McCarthy, R. Jones, R. Betts and M. Antar. 2011. The impact of uncertainties in climate impacts assessments: the case of the Nile basin, *In: Coping with Global Environmental Change: Climate Change, Soil and Desertification, Water Management, Food and Health, Hexagon Series on Human, Environmental Security and Peace* (HESP). Berlin – Heidelberg – New York: 5: 765-772.
- Burnash, R., J. C. Ferral, R. L. and R. A. McGuire. 1973. A generalized streamflow simulation system – conceptual modelling for digital computers. *Joint Federal and State River Forecast Center, Sacramento, Technical Report: 204*.
- Butler, S., T. Webster, A. Redden, J. Rand, N. Crowell and W. Livingstone. 2014. Using remote sensing to identify changes in land use and sources of *fecal* bacteria to support a watershed transport model. *Water*, 6:1925-1944.
- Butts, M. B., C. Buontempo, J. K. Lorup, K. Williams, C. Mathison, N. D. Riegels, O. Z. Jessen, P. Glennie, C. Mcsweeney, M. Wilson, R. Jones and A.H. Seid. 2013. Developing a regional methodology for climate adaptation in the Nile Basin. Proceedings of the 13<sup>th</sup> International Conference on Environmental Science and Technology Athens, Greece, 5-7 September. 488.
- Campling, P., A. Gobin, K. Beven and J. Feyen. 2002. Rainfall-runoff modelling of a humid tropical catchment: the TOPMODEL approach. *Hydrological Processes*. 16: 231–253.
- Chauhan, Seema and R. K. Shrivastava. 2012. Estimating reference evapotranspiration using neural computing technique, *Journal of Indian Water Resources Society*, 32:1-2
- Chiew, F. and T. McMahon. 1994. Application of the daily rainfall-runoff model MODHYDROLOG to 28 Australian catchments. *Journal of Hydrology*. 153: 383 416

- Chiew, F. H. S., M. C. Peel and A. W. Western. 2002. Application and testing of the simple rainfall-runoff model SIMHYD, *Mathematical Models of Small Watershed Hydrology and Applications*, Singh, V. P. & Frevert, D. K. (editors), Water Resources Publications, Littleton, USA :335-367.
- Chowdhary, A. and R. K. Shrivastava. 2010. Reference crop evapotranspiration estimation using Artificial Neural Networks. *International Journal of Engineering Science and Technology*, 2(9): 4205-4212.
- Christensen, J. H., T. R. Carter, M. Rummukainen and G. Amanatidis. 2007. Evaluating the performance and utility of regional climate models: the PRUDENCE Project. *Climatic Change*, 81:1-6.
- Collins, M. and S. K. Knight. 2007. Ensembles and probabilities: A new era in the prediction of climate change. *Phil. Trans. Roy. Soc. A 365, Number 1857 / August 15, 2007*.
- Croke, B. F., W. Andrews, F. Jakeman, A.J. Cuddy, S.M. and A. Luddy. 2006. IHACRES Classic Plus: A redesign of the IHACRES rainfall-runoff model. *Environmental Modelling and Software*. 21: 426-427.
- Dagade, S. J. 2003. Optimum utilization of land and water resources in canal command area of Nazare medium irrigation project using RS and GIS techniques. An unpublished M. Tech. thesis submitted to MPKV, Rahuri.
- Dai, Z. Y. and Y. P. Li. 2013. A multistage irrigation water allocation model for agricultural land-use planning under uncertainty. *Agricultural Water Management*. 129: 69-79.
- Deshpande, R. R. 2012. On the rainfall time series prediction using multilayer perceptron artificial neural network. *International Journal of Emerging Technology and Advanced Engineering*, 2(1): 148-153.
- DHI, 2008. McKenzie River MIKE BASIN Model. DHI Water and Environment, Inc. 2008.
- DHI, 2013. MIKE 11: A Modeling System for Rivers and Channels. Reference Manual, Danish Hydraulic Institute, Denmark.
- DHI, 2013. MIKE HYDRO user guide. 2013.
- Diamantopoulou, M.J., P. E. Georgiou and D. M. Papamichail. 2011. Performance evaluation of artificial neural networks in estimating reference evapotranspiration with minimal meteorological data. *Global NEST Journal*, 13(1): 18-27.

- Diaz, G.E., T.C. Brown and O. Sveinsson. 1997. Aquarius: A modeling system for river basin water allocation. General Technical Report RM-GTR-299. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station: 172.
- Dlamini, Md R. K., Md A. B. Mohd Soom, Mohd S. F. Mohd, Ahmad Fikri Bin Abdullah and L. S. Hin. 2017. Modeling potential impacts of climate change on streamflow using projections of the 5th assessment report for the *Bernam* river Basin, Malaysia. *Water* 9: 226.
- Dogra, P., V.N. Sharda., P.R. Ojasvi., S.O. Prasher and R.M. Patel. 2011. Optimal allocation of water for enhanced food production in a mid-Himalayan watershed. *Indian Journal of Soil Conservation*, 39(3): 251-262.
- Doorenbos, J., and A.H. Kassam, 1979. Yield response to water. FAO Irrigation and Drainage Paper No. 33. Rome, FAO.
- Elsaesser, B., A. K. Bell and G. Glasgow. 2006. Climate change scenarios and impact on catchment and rainfall runoff response. *National Hydrology Seminar*: 50-58.
- EnviStats-India 2018: Environmental Accounts. Chapter 3 Water-The Nectar of Life. :4.
- Fleming, G. 1975. Computer simulation techniques in hydrology. Elsevier Environmental Science Series, American Elsevier, New York. 18-53.
- Gad, M. A. 2013. A useful automated rainfall-runoff model for engineering applications in semi-arid regions. *Computer and Geosciences*, 52: 443-452.
- Galkate, R. V., R. K. Jaiswal, T. Thomas, and T. R. Nayak, 2014. Rainfall runoff modeling using conceptual NAM Model. International Conference on Sustainability and management strategy, *Institute of Management and Technology*, Nagpur.
- Geeta, G. and R. S. Selvaraj. 2011. Prediction of monthly rainfall in Chennai using back propagation neural network model. *International Journal of Engineering Science and Technology*, 3(1): 211-213.
- George, B., H. Malanoa, B. Davidsonb, P. Hellegersc, L. Bharatid and S. Massuel. 2011. An integrated hydro-economic modelling framework to evaluate water allocation strategies I: Model Development. *Agricultural Water Management*, 98: 733-746.
- Ghule, P. S., 2014. Water Allocation for a Sub Catchment in Bhima River Basin Using MIKE BASIN Model. An unpublished M-Tech thesis submitted to MPKV, Rahuri, MS, India.

- Giang, N. T. and T. A. Phuong. 2010. Calibration and verification of a hydrological model using event data. *VNU Journal of Science, Earth Sciences*, 26: 64-74.
- Giorgi, F. and R. Francisco. 2000. Evaluating uncertainties in the prediction of regional climate change. *Geophys. Res. Lett.* 27: 1295–1298.
- Gleick, P.H., 1993. World fresh water resources. *Water in Crisis: A Guide to the World's Fresh Water Resources*, Oxford University Press, New York.
- Godase, Y. R. 2001. Alternative crop plans for *Mula* command area using remote sensing and GIS techniques. An Unpublished M. Tech. thesis submitted to MPKV, Rahuri. pp. 209.
- Gorantiwar, S.D. 1995. Model for planning and operation of heterogeneous irrigation scheme in semi-arid regions under rotational water supply. An unpublished Ph.D. thesis submitted to Loughborough University of Technology, Loughborough, UK. pp. 483.
- Gorantiwar, S.D. and I. K. Smout. 1995. Optimizing the use of water in multi crop soil irrigation scheme. *Proceeding of the Congress-International Association for Hydraulic Research*, 4: 386-391.
- Gorantiwar, S.D. and I. K. Smout. 2003. Allocation of scarce water resources using deficit irrigation in rotational systems. *Journal of Irrigation and Drainage Engineering*, 129(3):155-163.
- Gorkalanderas, M. D., A.O. Barredo and J. J. Lopez. 2009. Forecasting weekly evapotranspiration with ARIAM and artificial neural network models. *Journal of Irrigation and Drainage Engineering*, 223-234
- Goswami, M., K. M. O'Connor, and A. Y. Shamseldin. 2002. Structures & performances of five rainfallrunoff models for continuous river-flow simulation. *Proc. 1st Biennial Meeting of Int. Env. Modeling and Software Soc., Lugano, Switzerland*. 1: 476-481.
- Gulati, H.S. and V.V.N. Murty. 1979. A Model for optimal allocation of canal water based on crop production functions. *Agricultural Water Management*, 2: 79-91.
- Hafezparast, M., S. Araghinejad, S. E. Fatemi and H. Bressers. 2013. A conceptual rainfall-runoff model using the auto calibrated NAM models in the *Sarisoo* River. *Hydrology Current Research*, 4(1):1000148: 1-6.
- Hamer, W., D. Love, M.J. Booija and A.Y. Hoekstra. 2007. A rainfall-runoff model for two small ungauged catchment using the water balance of a reservoir for calibration. Paper

presented at the 8th WaterNet/WARFSA/GWP-SA Annual Symposium, Lusaka, Zambia, and Amsterdam, Netherlands.

- Hayat, A. 2007. Flash flood forecasting system for Lai Nullah basin (A case study of March 19, 2007 rainfall event). *Pakistan Journal of Meteorology*, 4(7): 75-84.
- Herron, N. and B. Croke. 2009. Including the influence of groundwater exchanges in a lumped rainfall-runoff model. *Mathematics and Computers in Simulation*, 79: 2689-2700.
- Hewitt, C. D. 2005. The ENSEMBLES Project: Providing ensemble-based predictions of climate changes and their impacts. Published article appears in the *EGGS newsletter*, 13: 22-25. URL: <http://www.the-eggs.org/?issueSel=24>
- Hossain, S., M. M. Hoque and S. M. U. Ahmed. 1994. Application of rainfall-runoff model NAM in the North-West region of Bangladesh. *Irrigation Engineering and Rural Planning No. 27*: 31-38.
- [http://gdata1.sci.gsfc.nasa.gov/daacbin/G3/gui.cgi?instance\\_id=TRMM\\_3-Hourly](http://gdata1.sci.gsfc.nasa.gov/daacbin/G3/gui.cgi?instance_id=TRMM_3-Hourly) June, 2015.
- <http://srtm.csi.cgiar.org/> March, 2016.
- Hung, N. Q., M. S. Babel, S. Weesakul and N. K. Tripathi. 2009. An artificial neural network model for rainfall forecasting in Bangkok, Thailand. *Journal of Hydrology Earth System Science Discuss*, 5: 183–218. *Journal of Hydrology Science*, 41(3): 399-417.
- Hussein, I. and R. Al–Weshah. 2009. Optimizing the water allocation system at Jordan Valley through adopting water evaluation and planning system model (WEAP). *13<sup>th</sup> International Water Technology Conference, IWTC 13, Hurghada, Egypt*. 753-777.
- Ireson, A., C. Makropoulos and C. Maksimovic. 2006. Water resources modelling under data scarcity: coupling MIKE BASIN and ASM groundwater model. *Water Resources Management*, 20: 567-590.
- Jain, S. K., P. C. Nayak and K. P. Sudheer. 2008. Models for estimating evapotranspiration using Artificial Neural Networks and their physical interpretation. *Hydrological Processes*, 22: 2225-2234
- Jaiswal, S.K., M. K. Verma and M. Gupta. 2013. Planning for optimum use of water resources of MRP complex using MIKE Basin. *Journal of Water Resource Society*, 33(1): 15-22.
- Jensen, R.A., A. Lasarte and M.B. Butts. 2009. Integrating short-term and long-term forecasting with reservoir optimization in Mantaro Basin, Peru. *Geophysical Research Abstracts*, 11

- Jeppesen, E., and B. Kronvang. 2009. Climate change effects on runoff, catchment phosphorus loading and lake ecological state and potential adaptations. *Journal of Environmental Quality*, 38: 1930–1941.
- Jha, M.K. and A.D. Gupta. 2003. Application of MIKE basin for water management strategies in a watershed. *Water International*, 28(1): 27-35.
- Jin, W. and C. Webb. 2003. Experience of creek and lagoon restoration feasibility study. *International Conference on Estuaries and Coasts*, November 9-11, 2003, Hangzhou, China: 708-715.
- Joshi, M.B., J.S.R. Murthy and M.M. Shah. 1995. CROSOWAT: A decision tool for irrigation schedule. *Agricultural Water Management*, 27: 203-223.
- Juiping, X. and T. Zhimiao. 2012. Rough Multiple Objective Decision Making. *CRC Press, Taylor and Francis Group*. 125.
- Jukic, D. and V.D. Jukic. 2009. Groundwater balance estimation in karst by using a conceptual rainfall–runoff Model. *Journal of Hydrology*, 373: 302-315.
- Kadam, S.A. 2014. Spatial Decision Support System based on Remote Sensing Approach for Irrigation Water Management. Ph.D. Thesis submitted to Mahatma Phule Krishi Vidyapeeth, Rahuri, Dist. Ahmednagar, Maharashtra (India).
- Kaiglova, J. and J. Langhammer. 2014. Analysis of efficiency of pollution reduction measures in rural basin using MIKE basin model. Case study: Olsava River Basin. *Journal of Hydrology Hydromechanics*, 62(1): 43-54.
- Kamel, A. H. 2008. Application of a hydrodynamic MIKE11 model for the Euphrates River in Iraq. *Slovak Journal of Civil Engineering*, 2: 1-7.
- Keskin, F., A.A. Sensoy and A.U. Sorman. 2007. Application of MIKE11 model for the simulation of snowmelt runoff in Yuvacik Dam basin, Turkey. *International Congress on River Basin Management. The Role of General Directorate of State Hydraulic Works (DSI) in Development of Water Resources of Turkey*. 472-484.
- Khan, M. A., B. Mujtaba, R. Masood and T. Ali. 2014. Rainfall-runoff modeling of a part-catchment area of River Dhunn based on physiographic and land use characteristics using MIKE basin. *Science International*, 26(5): 2379-2384.
- Khoshhal, J. and M. Mokarram. 2012. Model for prediction of evapotranspiration using MLP neural network. *International Journal of Environmental Sciences*, 3(3): 1000-1009.

- Khu, S. T., D. Savik, Y. Liu and H. Madsen. 2004. A fast evolutionary based meta-modelling approach for the calibration of a rainfall-runoff model. *International Congress on Environmental Modeling and Software-Osnabruck, Germany*, 1:7.
- Kishore, V. and M. Pushpalatha. 2017. Forecasting evapotranspiration for irrigation scheduling using neural networks and ARIMA. *International Journal of Applied Engineering Research*, 12(21): 10841-10847.
- Kumar, J. and A. K. Tiwari. 2012. Evaporation estimation using artificial neural networks and adaptive Neuro-Fuzzy inference system techniques. *Pakistan Journal of Meteorology*, 8(16): 81-88.
- Kumar, R. and G.S. Yadav. 2013. Forecasting of rainfall in Varanasi District, Uttar Pradesh using artificial neural network. *Journal of Environmental Science, Computer Science and Engineering & Technology*. 2 (3): 721-729.
- Kumarsiri, A. D. and D. U. J. Sonnadara. 2006. Rainfall forecasting: an artificial neural network approach. *Proceedings of the technical sessions*, 22: 1-13.
- Lafdani, A. K., A. M. Nia and A. Pahlavanravi. 2013. Comparison of rainfall-runoff simulation by intelligent techniques and a conceptual hydrological model (a case study). *Technical Journal of Engineering and Applied Sciences*, 3(15): 1685-1691.
- Lan Anh, N. T., P. Willems, J.B. Boxall and A.J. Saul. 2008. An evaluation of three lumped conceptual rainfall-runoff models at catchment scale. *The 13<sup>th</sup> World Water Congress 2008*, 1:12
- Leemhuis, C., G. Jung., R. Kasei and J. Liebe. 2009. The Volta basin water allocation system: assessing the impact of small-scale reservoir development on the water resources of the Volta basin, West Africa. *Advances in Geosciences*, 21: 57-62.
- Liden, R. and J. Harlin. 2000. Analysis of conceptual rainfall-runoff modelling performance in different climates. *Journal of Hydrology*, 238: 231-243.
- Liebe, J., N.van de Giesen, W. Andah, M. Andreini, T. Walter, and T. Steenhuis. 2008. Calibrating runoff models in ungauged basins using small reservoirs as satellite observed runoff gauges. *Proceedings of the CGIAR Challenge Program on Water and Food 2nd International Forum on Water and Food. Addis Ababa, Ethiopia* :135–142.
- Linsley, R.L. 1982. Rainfall-runoff models - an overview in rainfall-runoff relationship. *Proceedings of the International Symposium on Rainfall-Runoff Modelling*, May 18-21: 3-22.

- Loliyana, V. D. and P. L. Patel. 2015. Lumped conceptual hydrological model for *Purna* river basin, India. *Indian Academy of Sciences, Sadhana*, 40(8): 2411–2428.
- Luk, C K., J.E. Ball and A. Sharma. 2001. An application of artificial neural networks for rainfall forecasting. *Journal of Mathematical and Computer Modelling*, 33: 683-693.
- Makungo, R., J.O. Odiyo, J.G. Ndiritu and B. Mwaka. 2010. Rainfall runoff modelling approach for ungauged catchments- a case study of *Nzhelele* river sub-quaternary catchment. *Physics and Chemistry of Earth Parts A/B/C*, 35(13-14): 596-607.
- Meehl, G.A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, I.G. Watterson, A.J. Weaver and Z. C. Zhao, 2007. Global Climate Projections. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Meshram, R.V., M.M. Deshmukh, S.B. Wadatkar, M.U. Kale and A.N. Mankar. 2015. Prediction of reference evapotranspiration using artificial neural network. *International Journal of Agricultural Engineering*, 8(1):1-8.
- Moore, R. J. 2007. The PDM rainfall-runoff model. *Hydrology and Earth System Sciences Discussions, European Geosciences Union*, 11 (1): 483-499.
- Moretti, G. and A. Montanari. 2007. AFFDEF: A spatially distributed grid based rainfall-runoff model for continuous time simulations of river discharge. *Environmental Modelling and Software*, 22: 823-836.
- Moriasi ,D. N., J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel and T. L. Veith. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the American Society of Agricultural and Biological Engineers*. 50(3): 885–900.
- Murphy, J. M., D. M. H. Sexton, D. N. Barnett, G. S. Jones, M. J. Webb, M. Collins and D. A. Stainforth. 2004. Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, 430: 768–772.
- MWRRRA, 2018. Maharashtra Water Resources Regulatory Authority. Overview of the state water resources. <https://mwrra.org/overview-of-the-state/>

- Narasayya, K., U. C. Roman, B. L. Meena, S. Sreekanth and S. N. Ali. 2013. Prediction of storm-runoff using physically based hydrological model for burhanpur watershed, India. *International Journal of Remote Sensing and Geoscience*, 2(3): 76-85.
- Nash, J. E. and J. V. Sutcliffe, (1970). River flow forecasting through conceptual models part I - A discussion of principles. *Journal of Hydrology*. 10 (3): 282–290.
- Ngoc, T. A., K. Hiramatsu and M. Harada. 2013. Optimizing parameters for two conceptual hydrological models using a genetic algorithm: a case study in the *Dau Tieng* river watershed, Vietnam. *Japan Agricultural Research Quarterly*, 47(1): 85-96.
- Odiyo, J. O., J.I. Phangisa and R. Makungo. 2012. Rainfall–runoff modelling for estimating *Latonyanda* river flow contributions to *Luvuvhu* river downstream of *Albasini* dam. *Physics and Chemistry of the Earth*, 52: 5-13.
- Ojha, S. and S. R. Bhakar. 2012. Estimation of evapotranspiration for wheat crop using artificial neural network. *Journal of Indian Water Resources Society*, 32: 1-2.
- Ojha, S., and S. R. Bhakar. 2012. Estimation of evapotranspiration for wheat crop using artificial neural network. *Journal of Indian Water Resources Society*. 32: 1-2.
- Palkar, H. M. 2011. Development of NDVI based decision support system for irrigation water management. M. Tech. thesis submitted to Mahatma Phule Krishi Vidyapeeth, Rahuri.
- Pathak, P., S.A. Swaify, V.V.N. Murty and R. Sudi. 1989. Runoff model for small Semi-arid watersheds. Paper presented at 21<sup>st</sup> Annual Convocation of ISAE, held at IARI, New Delhi.
- Perrin, C., C. Michel, and V. Andreassian. 2003. Improvement of a parsimonious model for streamflow simulations. *Journal of Hydrology*. 279: 275-289.
- Pieri, L., M. Bittelli, J.Q. Wu, S. Dun, D.C. Flanagan, P.R. Pisa, F. Ventura, and F. Salvatorelli. 2007. Using the Water Erosion Prediction Project (WEPP) model to simulate field observed runoff and erosion in the Apennines mountain range. *Italy Journal of Hydrology*. 336: 84-97
- Popale, P. G. 2016. Forecasting and generation of rainfall using stochastic models and ANN techniques. Ph.D. thesis submitted to Mahatma Phule Krishi Vidyapeeth, Rahuri.

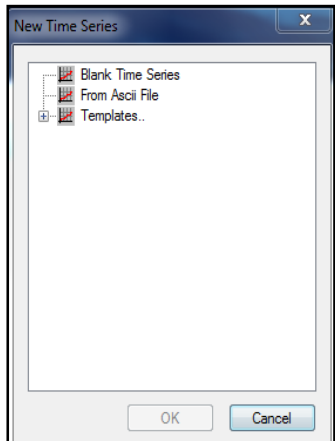
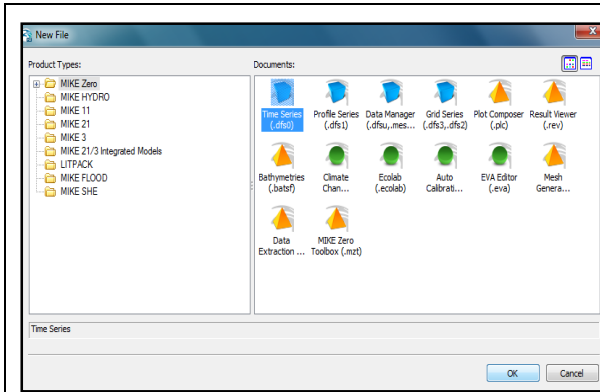
- Roelevink, A., J. Udo, G. Koshinchanov and S. Balabanova, 2010. Flood forecasting system for the *Maritsa and Tundzha* rivers. *Scientific Journal of the Technical University of Civil Engineering - Mathematical Modelling in Civil Engineering*, 4: 1-14.
- Rusli, S.R., D. Yudianto and J. Liu. 2015. Effects of temporal variability on HBV model calibration. *Water Science and Engineering*, 8(4): 291-300.
- Sahai, A. K., M. K. Soman and V. Satyan. 2000. All India summer monsoon rainfall prediction using an artificial neural network, *Climate Dynamics*, 16: 291-302.
- Santhi, C., J. G. Arnold, J. R. Williams, W. A. Dugas, R. Srinivasan and L. M. Hauck. 2001. Validation of the swat model on a large river basin with point and nonpoint sources. *Journal of the American Water Resources Association*. 37(5):1169 – 1188.
- Sawant, S.A. and S.D. Patil. 2008. Evaluation of operating policies of Sina medium irrigation project by using SWAB-CRYB simulation model. An unpublished B. Tech. thesis submitted to MPKV, Rahuri. pp.104.
- Shamsudin, S. and N. Hashim. 2002. Rainfall runoff simulation using MIKE11 NAM. *Journal of Civil Engineering*, 15(2): 1-13.
- Sharma, M. 2012. Rainfall-Runoff Modelling Using MIKE 11 NAM Model. M.Tech. Thesis submitted to the Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur.
- Sharma, S. and D.G. Regulwar. 2016. Prediction of evapotranspiration by artificial neural network and conventional methods. *International Journal of Engineering Research*, 5(1): 184-187.
- Shoemaker, L., M. Lahlou, M. Bryer, D. Kumar, and K. Kratt. 1997. *Compendium of tools for watershed assessment and TMDL development*. U.S. Environmental Protection Agency, EPA 841-B-97-006.
- Singh, A., S. Singh, A. K. Nema, G. Singh and A. Gangwar. 2014. Rainfall-runoff modeling using MIKE 11 NAM model for Vinayakpur intercepted catchment, Chhattisgarh. *Indian Journal of Dryland Agriculture Research*, 29(2): 1-4.
- Srivastava, S. and K. C. Tripathi. 2012. Artificial neural network and non-linear regression: a comparative study. *International Journal of Scientific and Research Publications*. 2(12): 1-5.

- Stainforth, D.A., T. Aina, C. Christensen, M. Collins, N. Faull, D. J. Frame, J. A. Kettleborough, S. Knight, A. Martin, J. M. Murphy, C. Piani, D. Sexton, L. A. Smith, R. A. Spicer, A. J. Thorpe and M. R. Allen. 2005. Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature*, 433: 403–406.
- Stewart, J.I., R.M. Hagan and W.O. Pruitt. 1976. Production functions and predicted irrigation program for principle crops required for water resources planning and increased water use efficiency. U. S. Dept. of Interior, Bureau of Reclamation, Washington, D. C., USA.
- Surajit C. and C. Manojit. 2007. A soft computing technique in rainfall forecasting. *Proceeding of International Conference on IT*, Haldia Institute of Technology, March-19-21, 2007, 523-526.
- Tiwari, H.L., A. Balvanshi and D. Chouhan. 2016. Simulation of rainfall runoff of *Shipra* river basin. *International Journal of Civil Engineering and Technology*, 7(6): 364–370.
- Todini, E. 1996. The ARNO rainfall-runoff model. *Journal of Hydrology*, 175: 339-382.
- Toth, E., A. Brath and A. Montanari. 2000. Comparison of short-term rainfall prediction models for real time flood forecasting. *Journal of Hydrology*, 239(1-4): 132–147.
- UNESCAP (United Nations, Economic and Social Commission for Asia and the Pacific), 2000. Principles and Practices of Water Allocation among Water-Use Sectors. ESCAP Water Resources Series No. 80, Bangkok, Thailand.
- UNESCO. 2003. The United Nations World Water Development Report (WWDR1): Water for people, water for life. UNESCO publishing 2003.
- Vamsidhar E., K.V.S.R.P. Varma, P.S. Rao and R. Satapati. 2010. Prediction of rainfall using backpropagation neural network model. *International Journal on Computer Science and Engineering*, 2(4): 1119-1121.
- Vansteenkiste T., M. Tavakoli, N. V. Steenbergen, F. D. Smedt, O. Batelaan, F. Pereira and P. Willems. 2014. Intercomparison of five lumped and distributed models for catchment runoff and extreme flow simulation. *Journal of Hydrology*. 511: 335-349.
- Vaze, J., F. H. S. Chiew, J. M. Perraud, N. Viney, D. Post, J. Teng, B. Wang, J. Lerat and M. Goswami. 2015. Rainfall-Runoff Modelling Across Southeast Australia: Datasets, Models and Results. *Australian Journal of Water Resources*. 14:2, 101-116.

- Xu, Z. X., K. Takeuchi and H. Ishidaira. 2002. A conceptually-based distributed rainfall-runoff model applied in arid regions. *International Conference on Urban Hydrology for the 21<sup>st</sup> Century*, 14-16 October 2002, Kuala Lumpur.
- Yawatkar, A. P. 2008. Development of irrigation water management model based on NDVI. M. Tech. Thesis submitted to Mahatma Phule Krishi Vidyapeeth, Rahuri.
- Zhang, Y. 1995. Calibration of a physically-based distributed rainfall-runoff model with radar data. A published M.Sc. thesis submitted to the Department of Civil and Environmental Engineering, Massachusetts Institute of Technology. 17-113.

## APPENDIX - A

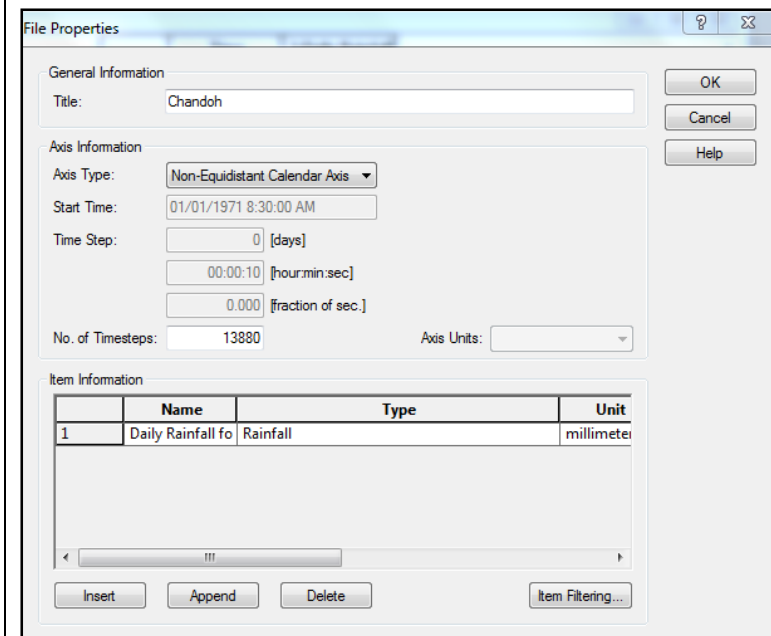
This appendix presents the snap shots and step by step procedure for preparation timeseries (.dfs0) required for input data handling and pre-processing in MIKE models.



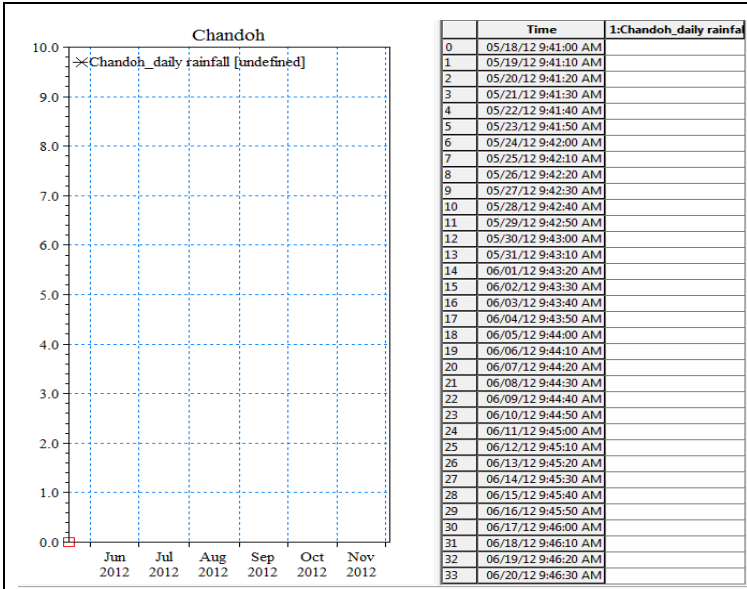
**Start MIKE ZERO from the windows program manager.**

- MIKE Zero > File > New > File > MIKE Zero

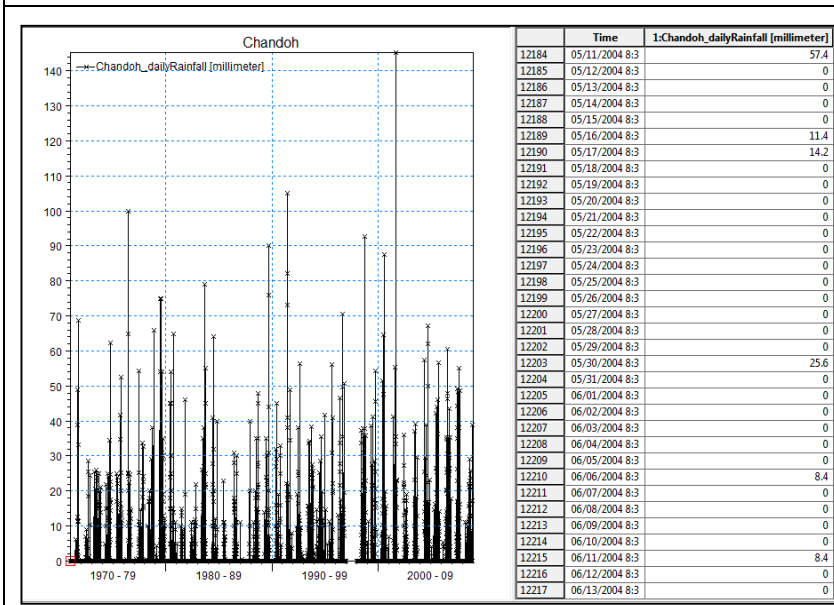
Select 'Time Series (.dfs0)' from the documents. Then new time series window will open, select 'Blank Time Series' icon



Specify the file properties like title of the time series, information about axis of the time series, number of time steps, type and unit of time series



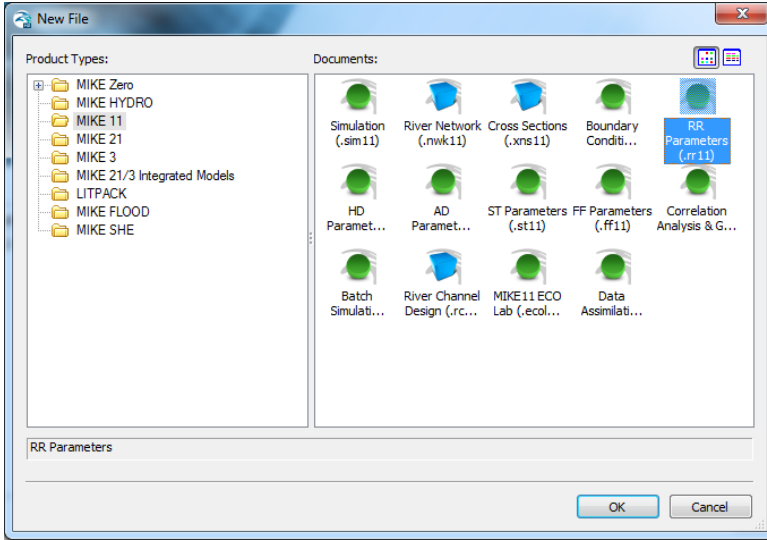
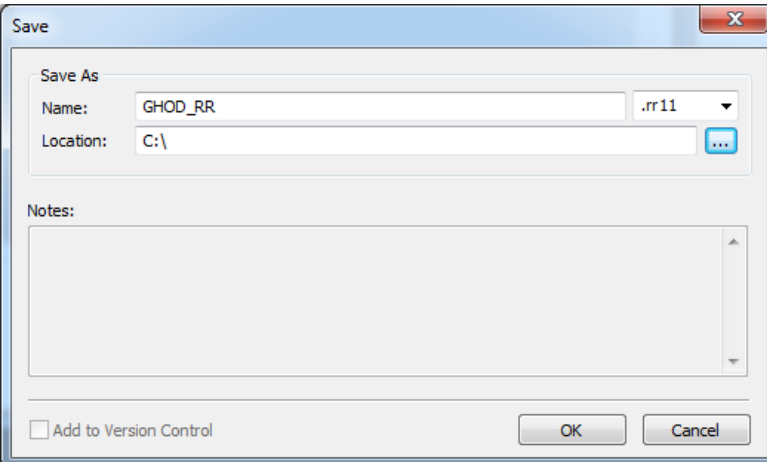
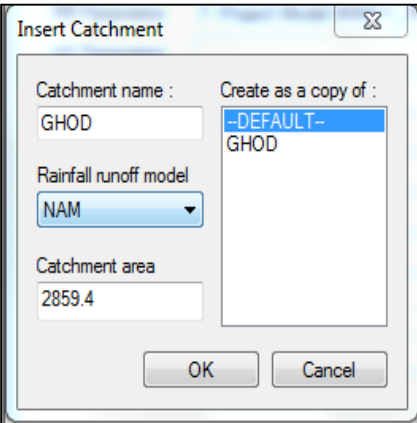
Blank timeseries will be generated

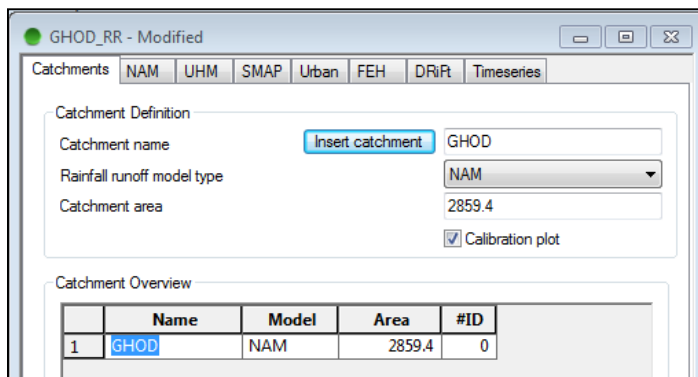


Copy and paste the data from excel file or type the data in blank timeseries

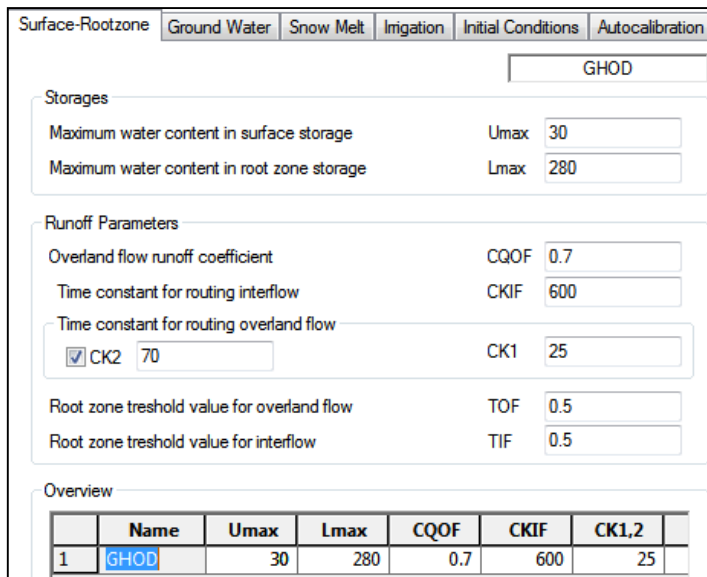
## APPENDIX - B

This appendix presents the snap shots and step by step procedure of MIKE 11 NAM Rainfall –Runoff model setup

	<p><b>Step 1: Open RR parameter (.rr11) document</b></p> <p>MIKE Zero &gt; File &gt; New &gt; File&gt;MIKE 11&gt;RR Parameters (.rr11)&gt;OK</p>
	<p><b>Step 2: Create a MIKE 11 NAM model file</b></p> <p>Open the MIKE 11 RR model and save the .rr11 document. Specify the name to the model (GHOD_RR.rr11)</p>
	<p><b>Step 3: Specify catchment properties</b></p> <ul style="list-style-type: none"> <li>▪ Click on the “Catchments” tab.</li> <li>▪ Click “Insert catchment”.</li> <li>▪ Give “Catchment name” as ‘GHOD’.</li> <li>▪ Specify “Rainfall runoff model” as ‘NAM’.</li> <li>▪ Give “Catchment area” ‘2859.4 km<sup>2</sup>’.</li> </ul> <p style="text-align: center;">Click ‘OK’</p>

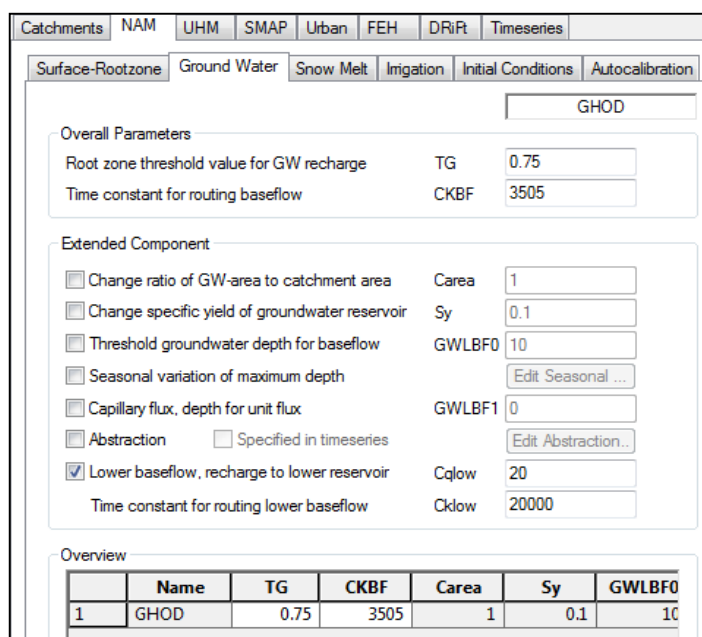


- Under catchment tab checked on the 'Calibration plot' so that after calibration of model it gives the calibration plot of output.



**Step 4: Specify Surface - Root zone MIKE 11 NAM model parameters.**

The parameters should be within the specified range.



**Step 5: Specify Ground Water parameters**

Catchments NAM UHM SMAP Urban FEH DRIR Timeseries

Surface-Rootzone Ground Water Snow Melt Irrigation Initial Conditions Autocalibration

GHOD

Surface and Rootzone

Relative water content in surface storage [0-1] U/Umax 0.4

Relative water content in root zone storage [0-1] L/Lmax 0.3

Overland flow QOF 0

Interflow QIF 0

Ground Water

Baseflow BF 0

Lower baseflow (if included on GW-page) BF-Low 0

Snow Melt

Snow storage Global value 0

Overview

	Name	U	L	QOF	QIF	BF	I
1	GHOD	0.4	0.3	0	0	0	

Specify the Initial Conditions of Surface Root zone and Groundwater

Catchments NAM UHM SMAP Urban FEH DRIR Timeseries

Hydrological Timeseries for Selected Catchment

Data type	Weighted timeseries	File name	Item	Browse
Rainfall	<input checked="" type="checkbox"/>	GHOD_RAINFALL	WEIGHTED	...
Evaporation	<input type="checkbox"/>	F:\PROJECT\MO	EVAPORATIO	...
(Observed discharge)	<input type="checkbox"/>	F:\PROJECT\MO	GHOD_RUNO	...

Mean Area Weighting

Weighted average Distribution in time

Browse	Station No.	1	2	3	4	5	6	7	8
Total		0.16	0.13	0.14	0.09	0.13	0.16	0.08	0.12
1. Combination	1.01	0	0	0	0	0	0	0	0
2. Combination	0	0	0	0	0	0	0	0	0
3. Combination	0	0	0	0	0	0	0	0	0
4. Combination	0	0	0	0	0	0	0	0	0
5. Combination	0	0	0	0	0	0	0	0	0
6. Combination	0	0	0	0	0	0	0	0	0
7. Combination	0	0	0	0	0	0	0	0	0

Catchment - MAW Overview

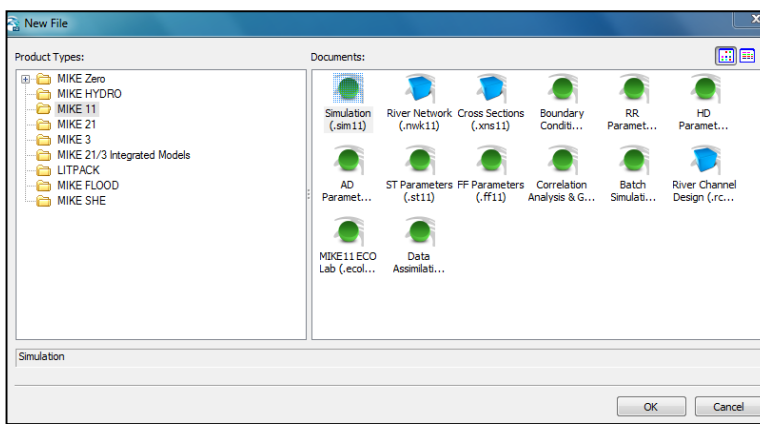
Data type Rainfall Type Weighted average Combination 1

Station No.	1	2	3	4	5	6	7	8
Catchm. Item	Belwandi_wee	Belwandi_wee	Kurwandi_wee	Pabal_weekly	Pimpalwandi	RanjangaonG	Supa_weekly	Shirur_weekly
1 GHOD	0.16	0.13	0.14	0.09	0.13	0.16	0.08	0.12

- After selection of time series station number 1 will appear. Likewise select other corresponding rainfall time series. Add the weightages of respected rainfall series in front of “1. Combination” option. The weightages of each raingauge station was calculated by Thissen polygon method.
- Click on “Browse” button to add evaporation time series and select respective time series. Also browse observed discharge time series for comparison with simulated discharge series.
- Save the .rr11 document.

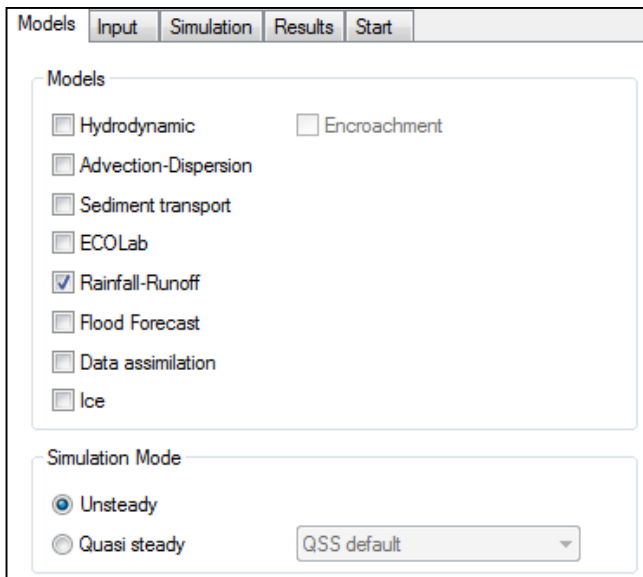
**Step 6: Selection of time series.**

- Select the time series tab in the parameter file.
- For weighted rainfall time series option check on ‘Blank Square’ below weighted time series option in front of “Rainfall”. Then the “Mean Area Weighting” box gets highlighted.
- Click on  tab and select corresponding rainfall time series.



### Step 6: Open simulation file

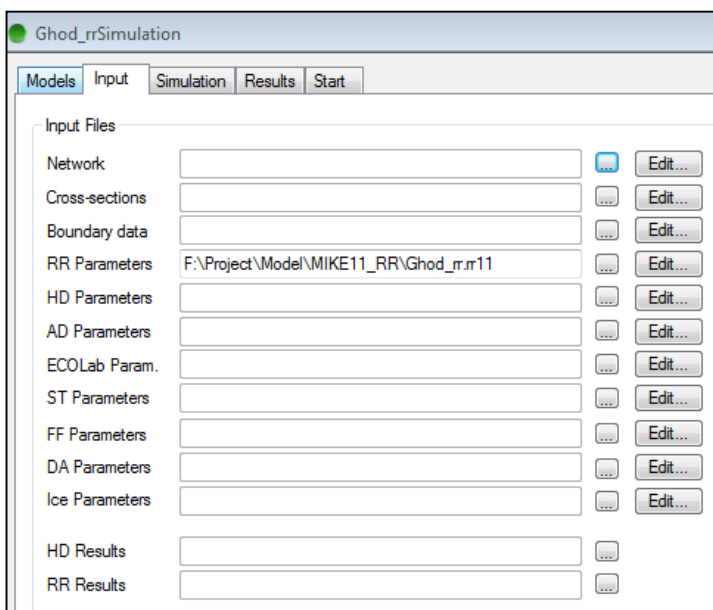
MIKE Zero > File > New > File  
> MIKE 11>Simulation  
(.sim11)>OK




### Step 7: Save a simulation model file

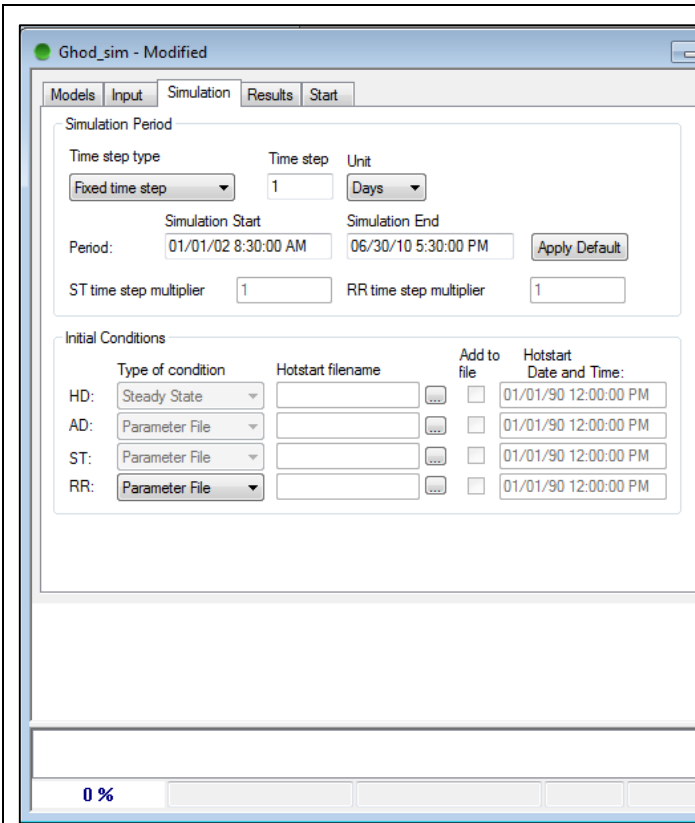
Open the MIKE 11 simulation model and save the .sim11 document. Specify the name to the model (GHOD\_rr simulation.sim11).

The simulation file has multiple tabs such as “Models”, “Input”, “Simulation”, “Results” and “Start”.



### Step 8: Selection of input file

Select the “Input” tab. Browse the Ghod\_rr .rr11 file by clicking on browse button  of the “RR Parameter” option.



### Step 9: Specify the simulation period

- Select “Simulation” tab.
- In “Simulation period” dialog select time step type as ‘**Fixed time step**’.

- Select “time step” as ‘**1days**’.

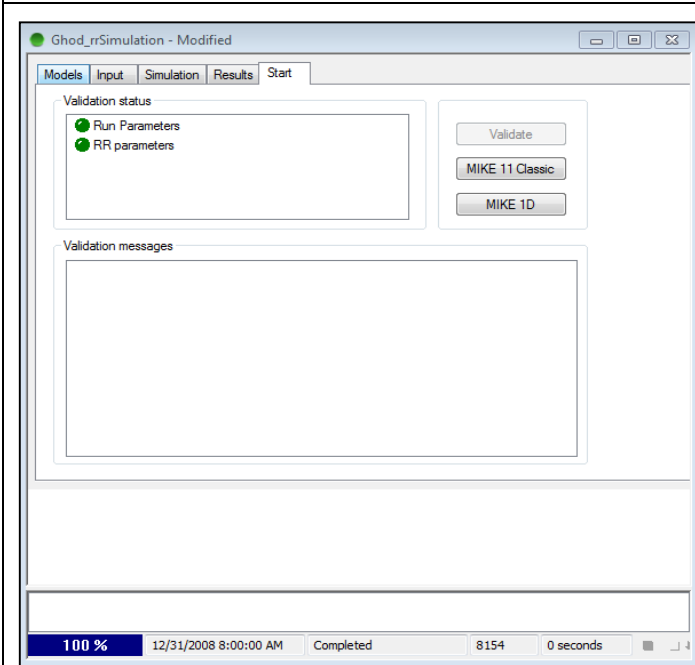
- Specify the simulation period

Simulation Start: 1<sup>st</sup> January 2002

Simulation End: 30<sup>st</sup> June 2009

The simulation start date for running simulation was chosen according to the availability of data. We can also apply the default simulation period by selecting ‘Apply Default’ button.

- In the “Initial Conditions” dialog select “parameter file” option in the “Type of conditions” of RR.



### Step 10: Run the simulation

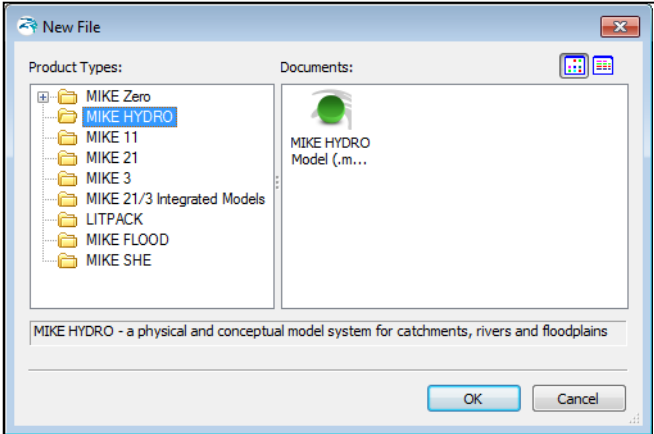
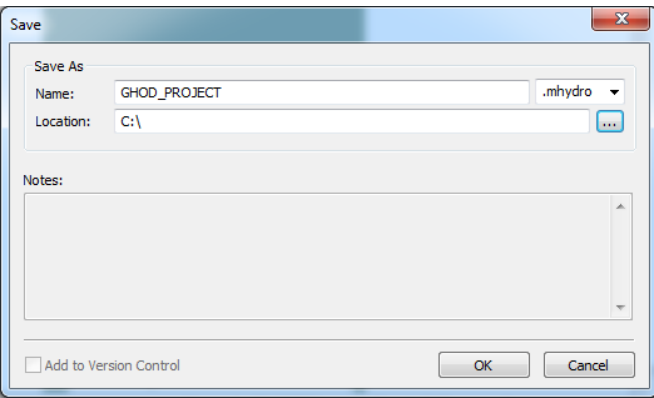
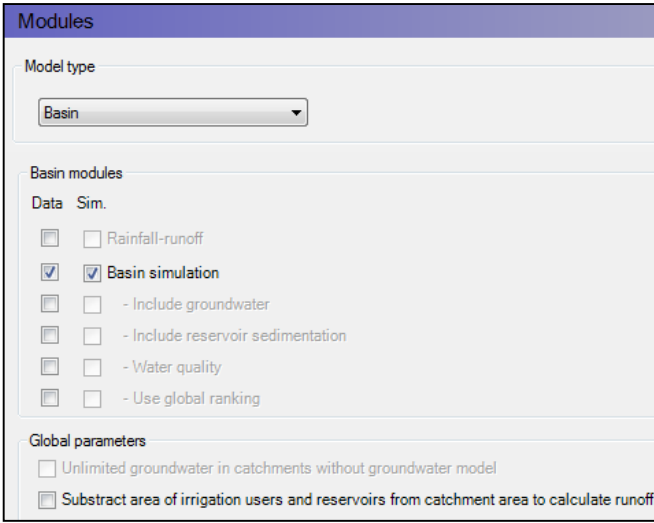
- Select “Start” tab of the simulation model.


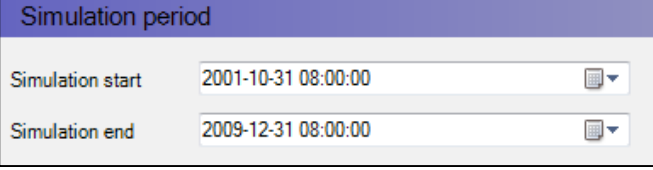
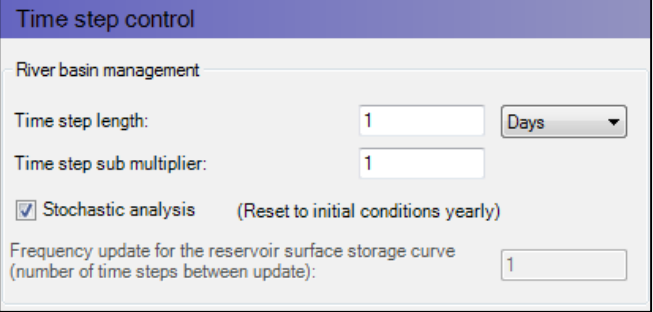
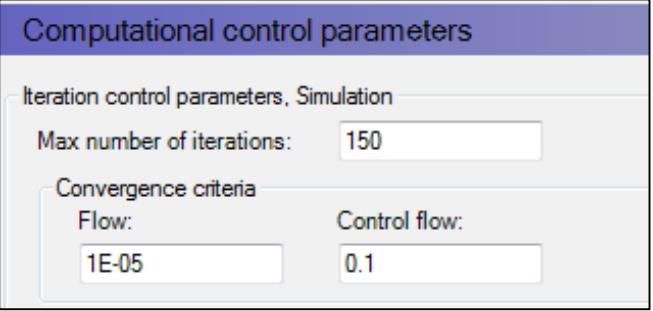
- Check the validation status before “Run Parameters” and “RR parameters” when the dot appears green then click “MIKE 11 classic” tab to run the simulation.

- Simulation status can be seen at the bottom of window.

## APPENDIX - C

This appendix presents the snap shots and step by step procedure of MIKE HYDRO Basin model.

	<p><b>Step 1: Start MIKE HYDRO Basin model</b></p> <p>Start &gt;Programs &gt;Mike by DHI 2016 &gt;MIKE Zero &gt; File &gt; New &gt;File &gt; MIKE HYDRO</p> <p>Then, in the dialog, select <i>MIKE HYDRO</i> &gt; <i>MIKE HYDRO model (.mhydro)</i>&gt; Click ‘OK’.</p>
	<p><b>Name and save the .mhydro document</b></p> <ul style="list-style-type: none"> <li>▪ Click on the “Save” icon in the top menu bar.</li> <li>▪ Specify a file name (e.g. <b>GHOD_PROJECT.mhydro</b>)</li> <li>▪ Give the specific location to save the model by name “<b>Ghod_Project</b>”. Click ‘OK’.</li> </ul>
<p><b>Step 2: Specify the simulation specifications</b></p>	
	<p>Define whether the project is a basin model or a river model. This selection is made in the upper drop down selection box. From this box, choose “Basin” option to activate the basin model types.</p>

	<p><b>Description:</b></p> <p>Specify the title for the simulation as ‘Irrigation Demand_Multicrop’</p>
	<p><b>Simulation period</b></p> <p>Specify the start and end time of the simulation</p>
	<p><b>Time step control</b></p> <ul style="list-style-type: none"> <li>▪ Select the time step length as ‘1 days’.</li> <li>▪ Give time step sub multiplier as ‘1’</li> </ul> <p>Tick on “Stochastic analysis”.</p>
	<p><b>Computational control parameters</b></p> <ul style="list-style-type: none"> <li>▪ A “maximum number of iterations” is defined to ensure that each time step will be completed within an acceptable amount of time. The default value is ‘<b>150</b>’ iterations.</li> <li>▪ Define “flow convergence criteria” as ‘<b>1E-05</b>’</li> <li>▪ Define “control flow convergence criteria” as ‘<b>0.1</b>’.</li> </ul>
<p><b>Step 3: Map configurations</b> The “Map configurations” option enables a user-defined customization of the “Map view” appearance to best suit the user’s preferences and requirements.</p>	

**Coordinate system**

Map view coordinate system

No projection

Map projection: Sphere Mercator (Radius = 6378137) ...

Sphere Mercator (Radius = 6378137) required for Google Map

Coordinate system for features stored in setup file

No projection

Feature projection: Sphere Mercator (Radius = 6378137) ...

Datum shift

None

dx: 0.00 [m] Rx: 0.00 [arcsec]

dy: 0.00 [m] Ry: 0.00 [arcsec] Scale: 0.00 [ppm]

dz: 0.00 [m] Rz: 0.00 [arcsec]

Apply datum shift parameters

### Coordinate system

Select map view coordinate system as “Sphere Mercator”

Browse “Sphere Mercator coordinate system” for features stored in setup file

**Background map**

Visible

Background map overlay

None

Google map

Google map type: Satellite Image

Countries/Coastline shape file (Network connection not required)

Color ramp

Map properties

Map legend

### Background map

Enable “visible” option in the background map.

Select background map overlay as “countries /coastline shape file”

**Shape file overlay (1)**

Title: Overlay 1

File name: F:\Project\Model Input\GIS\Shap File\Reservoir\_ghod\ ...

Read projection from PRJ - file: WGS\_1984\_UTM\_Zone\_43N

User specified: Sphere Mercator (Radius = 6378137) ...

Overlay visible

Symbology

Fill color: 0, 255, 255 Outline color: 0, 255, 255

Point size: 13 Outline thickness: 4

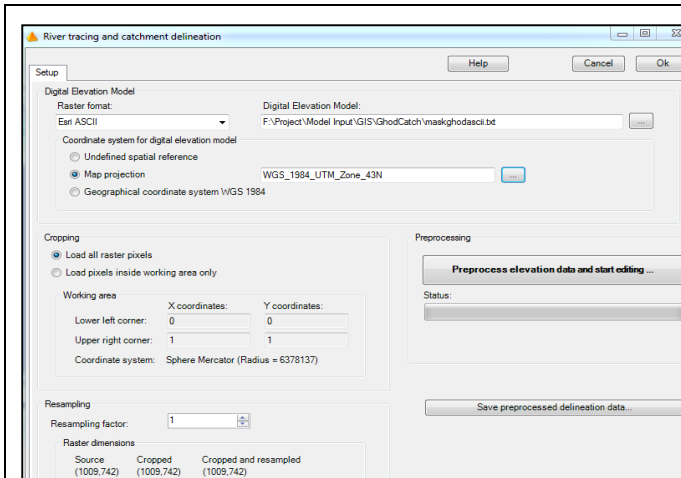
Point style: Triangle

+ - ↑ ↓

Title	Shape file name	Projection from file	File projection	Use
Overlay 1	F:\Project\Model Input\...	<input type="checkbox"/>	WGS_1984_UTM_Zone_...	Sph

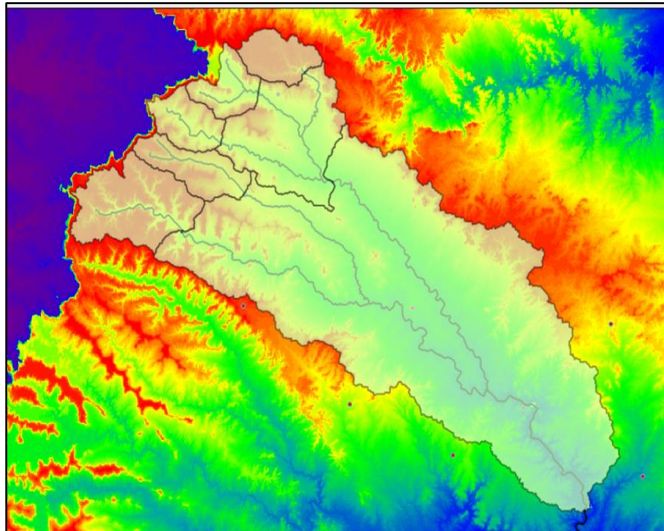
### Shape file overlay

Click **+** to add shape file overlay and browse to select the shape file.



## River network and catchment delineation

- Select “River tracing and catchment delineation” from the top tool menu. Then “River tracing and catchment delineation” window appears.
- Browse “Digital elevation model” in ASCII format i.e. maskghodascii.ascii. Specify coordinate system for digital elevation model.
- Select “Map projection” option and browse ‘WGS\_1984\_UTM\_Zone\_43N’ projections. Select “Preprocess elevation data and start editing” in preprocessing dialogue.
- Select “Start branch tracing” from the top of the document. Start branch tracing from the point just above the reservoir.
- After branch tracing select “Stop branch tracing”. Now select “Start catchment delineation” to delineate the catchment.
- After catchment delineation select “Stop catchment delineation”. Click ‘OK’.



## Step 5: Define catchment properties

Name	Area	Branch name	Chainage
Chilewadi	103.96	Branch 2	15281.67
Pimpalgao...	97.723	Branch 1	10601.21
Manikdoh	105.99	Branch 3	20273.57
Wadaj	134	Branch 4	24616.13
Dimbhe	273.1	Branch 5	23762.46
Yedgaon	366.22	Branch 1	37022.11
Ghod	2551	Branch 1	143326.89

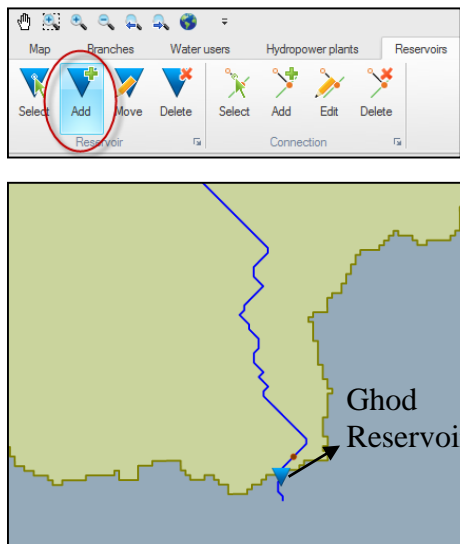
- Specify catchment name ‘Ghod’.

- Give the area of Ghod catchment ‘2551 km<sup>2</sup>’.

Browse runoff time series by clicking on button.

Similarly add all catchments properties and browse runoff timeseries of all catchments.

## Step 6: Reservoir properties



### Inserting reservoir

- Select “Add” button under the “Reservoirs” ribbon in “Map view” and click on the desired location of the reservoir.

- The reservoir must be located on a river Branch.

- Add reservoirs for all catchments.

Name	Branch name	Chainage	Reservoir Type
Dimbhe	Branch 5	23940.16	Rule curve reservoir
Wadaj	Branch 4	24781.61	Rule curve reservoir
Manikdoh	Branch 3	20332.83	Rule curve reservoir
Pimpalgaojga	Branch 1	10649.13	Rule curve reservoir
Chilewadi	Branch 2	15359.29	Rule curve reservoir
Yedgaon	Branch 1	37185.4	Rule curve reservoir
<input checked="" type="checkbox"/> Ghod	Branch 1	143412.53	Rule curve reservoir

### Specify the reservoir properties: General

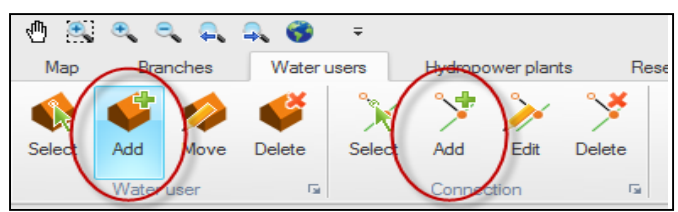
- Give reservoir name ‘Ghod’
- Specify reservoir type ‘Rule curve reservoir’.

Browse “Level area volume table” and “Characteristic levels time series”. Specify the ‘Initial water level’ for each reservoir according to the starting of simulation date.

	<p><b>Operations</b></p> <p>Under operations tab browse the “Flood control level time series”</p>
--	---------------------------------------------------------------------------------------------------

**Step 7: Irrigation water user**

Water users represent water consuming activities withdrawing water from the river or a reservoir.



**Inserting a water user**

- Select the “Add” button under the “Water user” ribbon in “Map view” and click on the desired location of the water user in the map.
- Select “Add” button in connection tab and connect water user to reservoir. The digitization of a connection must always be done in the direction of the flow
- Give name to the water user ‘**Irrigation Water User**’.
- Specify the water user type ‘**Irrigation user**’

Name	Type	Water use time series
▶ Ghod_irrigation	Irrigation user	

**Specify Irrigation scheme:**

Name	Type	Water use time series	Groundwater options	Supply catchment
▶ Ghod_irrigation	Irrigation user		Not using groundwater	

- Specify “climate model” as **FAO56**.

- Give “Rainfall and Climate time series”.
- Give “Altitude” value ‘550 MSL’.
- Select deficit distribution method ‘**Equal shortage**’

## Crops

	Initial	Development	Mid season	Late season
Length	15	25	90	30
Kcb	0.15		1.1	0.3
Root depth	100		900	
Max height			1	
Length (Yield)	15	25	90	30
Ky	0.2	0.6	0.5	0.2

- Specify the crop name. Select model type ‘**FAO 56 Dual Crop Coefficient**’.
- Specify the growing day/month and last irrigation day in the growing period ribbon.
- Specify the length and Kcb values of different crops according to their growth stages.
- Specify the “root depth of crop” and “maximum height of crop”.
- Enter the depletion factor value in the yield ribbon. Also specify the Ky vales for each soil stage of crop. Apply same procedure to add the other crops.

## Soil and Runoff properties

Soil name	Soil type	Soil moisture initial	Soil moisture field	Soil moisture wilting	Porosity	Depth evaporable layer
Clay Runoff Mod	FAO 56	0.25	0.35	0.2	0.45	0.05

- Specify the model name. Select the soil model type ‘**FAO 56**’ (Described on Section 3.1.7.3.1).
- Select runoff model type ‘**Modified SCS**’. The initial soil moisture content of 0.25, field capacity 0.35 and wilting point 0.2 are selected.
- Porosity of 0.45 and depth of evaporable layer is 0.05 selected.

## Specify Irrigation Method

**Irrigation method (11)**

Name:

Type:

Spray loss time series:  ...

Wetting fraction time series:  ...

Trigger option

Option:

Time series:  ...

Application option

Option:

Time series:  ...

+ - X


	Irrigation name	Irrigation Method	Spray loss time series	Wetting fraction time series
▶	Sugarcane	FAO 56	F:\Project\Model\Model Input\Timese...	F:\Project\Model\Model Input\Timese...
	K_Jowar	FAO 56	F:\Project\Model\Model Input\Timese...	F:\Project\Model\Model Input\Timese...
	Wheat	FAO 56	F:\Project\Model\Model Input\Timese...	F:\Project\Model\Model Input\Timese...
	HW-Veg(Cucumb...	FAO 56	F:\Project\Model\Model Input\Timese...	F:\Project\Model\Model Input\Timese...

- Give name to “Irrigation method” like Sugarcane, *kharif jowar*, wheat, *kharif bajara* etc.
- Give “Irrigation method type” FAO56.
- Browse “Spray loss time series” and “Wetting fraction time series”.
- In “Trigger option” ribbon select option ‘Fraction of TAW’ and browse the trigger time series. Total available water (TAW) is the total water available in the reservoir.
- In “Application option” ribbon select option ‘Fraction of TAW’ and browse the application time series.

## Specify Irrigation Field

General		Supply connections		Return flow connections		Irrigation scheme		Irrigated field	
ID	Name	Priority	Area	Min. cycle time	Recycle crop sequence	Soil and Runoff model			
▶ F12	Kharif Jowar		1	30	3	<input checked="" type="checkbox"/>	Clay Loam soil		
	Crop model	Sowing year	Irrigation method model	First sowing date	First harvest date				
	▶ Karif Jowar	2002	Karif Jowar	06/16/02	10/19/02				
▶ F13	Karif Bajara		2	15	2	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F14	Soybean		3	9	1	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F15	Groundnut		4	15	2	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F16	Rabi Jowar		5	75	8	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F17	Wheat		6	24	2	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F18	Gram		7	15	1	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F19	Sunflower		8	60	6	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F20	Cotton		9	6	1	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F21	Maize		10	15	2	<input checked="" type="checkbox"/>	Clay Loam soil		
▶ F22	Sugarcane		11	36	4	<input checked="" type="checkbox"/>	Clay Loam soil		

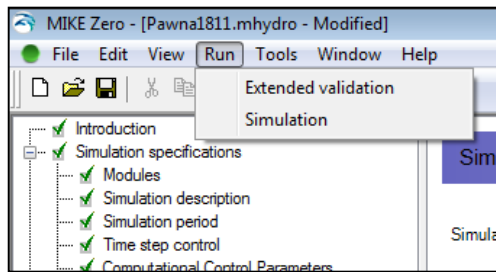
The total irrigated field is divided into seven sub-irrigated fields.

- A field is added to the Irrigated field node by clicking the “Append” button, designated with the symbol , which results in a line being added to the “Irrigated fields” table.
- When a new field is added to the model, field ID is automatically given every time.

- Give the field name to each irrigated fields. Give priority to each field.
- Specify “field area” of each crop. Specify “Minimum cycle time” to each field.
- Tick the “Recycle crop sequence” box for all fields so that same sequence of crops is cultivated in the field.
- Select “Soil and Runoff model” for the crop of interest ‘Clay Runoff Model’ by clicking on the box. The model is entered in the section ‘Irrigation data → Soil and runoff’.
- Click on the arrow next to the field’s ID, the tab expands and more attributes of the field appears.
- Chose the “Crop model” from those entered in the section ‘Irrigation data → Crops’.
- Specify the first sowing year for the crop.
- Select the ‘Irrigation method model’ from those entered in the section ‘Irrigation data → Irrigation method’.

First sowing and first harvest dates are automatically specified by model.

### Step 8: Run simulation



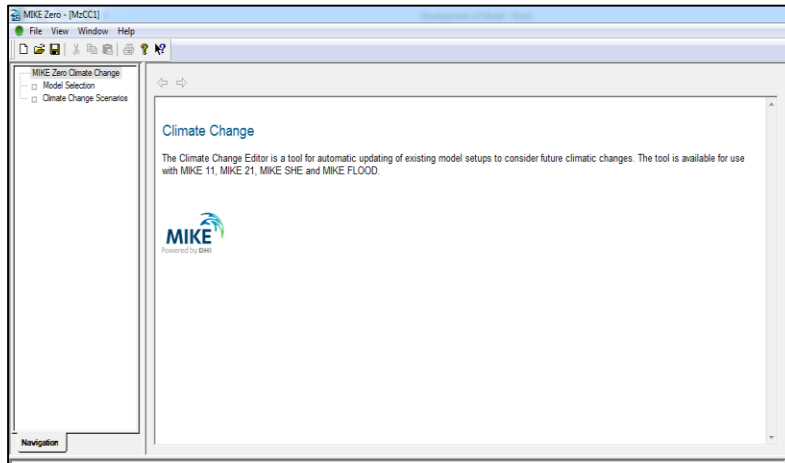
Select ‘**Run> simulation**’ from the top menu bar and “run the simulation”.

After successfully running of simulation, ‘End of basin calculation’ text will appear in the validation window.

## APPENDIX - D

This appendix presents the snap shots and step by step procedure of MIKE ZERO Climate Change Functionality Tool.

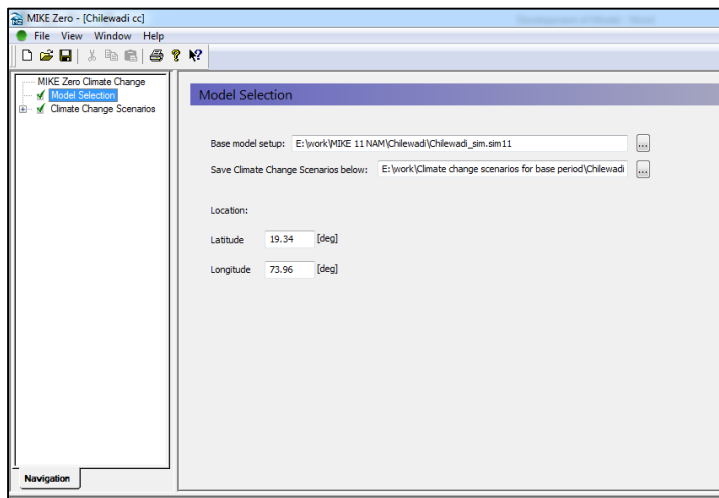
### Step 1: Start MIKE ZERO climate change module



**Start MIKE ZERO climate change module from MIKE ZERO platform.**

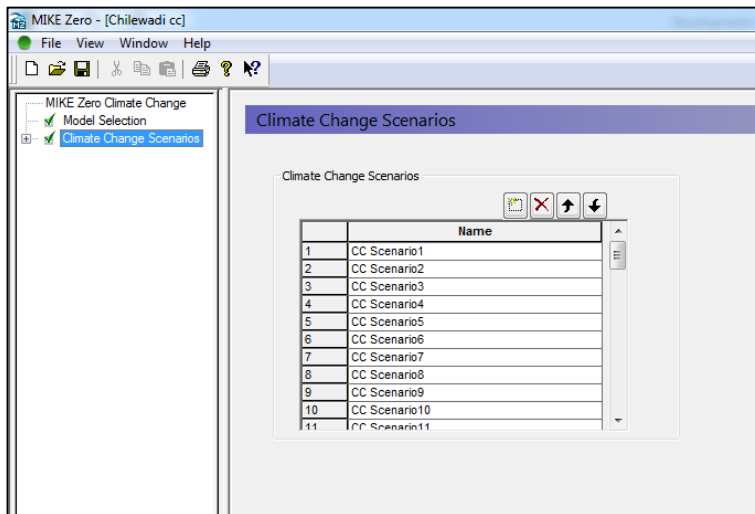
MIKE Zero > File > New  
> File > MIKE ZERO >  
Climate change (.mzcc) >



### Step 2: Model Selection



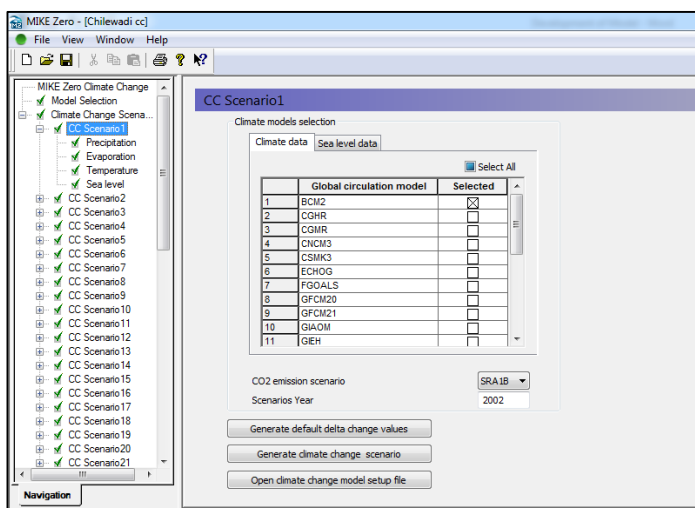
- Select base model setup and specify the simulation file of MIKE 11 NAM (.sim11)
- Specify the output location for saving the modified files of climate change in ‘Save climate change scenario below’ option.
- Give latitude and longitude of specified catchment
- Save the model.

### Step 3: Creating climate change scenario



- Create climate change scenario by clicking on . By default CC Scenario 1 is created.
- Then click on “Climate Change Scenarios ” to specify GCM model and Carbon Emission scenario for each CC Scenario.

### Step 4: Selection of climate data



- Select GCM model from available GCM models.
- Then select CO2 emission scenario.
- Specify the scenario year.

### Step 5: Generating delta change values and climate change scenarios

Generate the default delta change values and climate change scenario and open the modified climate change setup file. The data set of 12 monthly values per grid point per emission scenario. It generate modified timeseries of given setup file using delta change values.

### Step 6: Run simulation

The icon of “Open climate change model setup file” is directly locate to the modified simulation file of “.sim11” of given catchment. Here, specify the simulation properties and run the simulation. The result gives the climate change scenario impact on runoff of given catchment.

## APPENDIX - E

This appendix presents grid coordinates formed in Ghod complex catchments for downloading TRMM data from website and gridded rainfall data

Website: data [http://gdata1.sci.gsfc.nasa.gov/daac-bin/G3/gui.cgi?instance\\_id=TRMM\\_3-Hourly](http://gdata1.sci.gsfc.nasa.gov/daac-bin/G3/gui.cgi?instance_id=TRMM_3-Hourly)

Table E.1 Grid co-ordinates of study area.

Grid No	W	N	E	S
1	73.75	19.5	74	19.25
2	73.5	19.25	73.75	19
3	73.75	19.25	74	19
4	74	19.25	74.25	19
5	73.75	19	74	18.75
6	74	19	74.25	18.75
7	74.25	19	74.5	18.75
8	74.5	19	74.75	18.75
9	74.5	18.75	74.75	18.5
10	74.25	18.75	74.5	18.5
11	74.25	19.25	74.5	19
12	73.5	19.5	73.75	19.25
13	74.5	19.25	74.75	19

# W = West, N = North, E = East, S = South

**Table E.2 Sample of 3 hourly rainfall data for grid 2 for the year 2006**

Date and Time	Rainfall	Date and Time	Rainfall	Date and Time	Rainfall	Date and Time	Rainfall
01/01/06 1:30	0.0	04/02/06 7:30	0.0	07/02/06 13:30	0.0	10/01/06 19:30	0.0
01/01/06 4:30	0.0	04/02/06 10:30	0.0	07/02/06 16:30	0.0	10/01/06 22:30	0.0
01/01/06 7:30	0.0	04/02/06 13:30	0.0	07/02/06 19:30	0.0	10/02/06 1:30	0.0
01/01/06 10:30	0.0	04/02/06 16:30	0.0	07/02/06 22:30	1.8	10/02/06 4:30	0.0
01/01/06 13:30	0.0	04/02/06 19:30	0.0	07/03/06 1:30	0.0	10/02/06 7:30	0.0
01/01/06 16:30	0.0	04/02/06 22:30	0.0	07/03/06 4:30	4.0	10/02/06 10:30	0.0
01/01/06 19:30	0.0	04/03/06 1:30	0.0	07/03/06 7:30	4.1	10/02/06 13:30	0.0
01/01/06 22:30	0.0	04/03/06 4:30	0.0	07/03/06 10:30	1.7	10/02/06 16:30	0.0
01/02/06 1:30	0.0	04/03/06 7:30	0.0	07/03/06 13:30	1.2	10/02/06 19:30	0.0
01/02/06 4:30	0.0	04/03/06 10:30	0.0	07/03/06 16:30	0.0	10/02/06 22:30	0.0
01/02/06 7:30	0.0	04/03/06 13:30	0.0	07/03/06 19:30	0.0	10/03/06 1:30	0.0
01/02/06 10:30	0.0	04/03/06 16:30	0.0	07/03/06 22:30	0.0	10/03/06 4:30	0.0
01/02/06 13:30	0.0	04/03/06 19:30	0.0	07/04/06 1:30	0.0	10/03/06 7:30	0.0
01/02/06 16:30	0.0	04/03/06 22:30	0.0	07/04/06 4:30	0.0	10/03/06 10:30	0.0
01/02/06 19:30	0.0	04/04/06 1:30	0.0	07/04/06 7:30	4.0	10/03/06 13:30	0.0
01/02/06 22:30	0.0	04/04/06 4:30	0.0	07/04/06 10:30	3.0	10/03/06 16:30	0.0

01/03/06 1:30	0.0	04/04/06 7:30	0.0	07/04/06 13:30	2.1	10/03/06 19:30	0.0
01/03/06 4:30	0.0	04/04/06 10:30	0.0	07/04/06 16:30	6.3	10/03/06 22:30	0.0
01/03/06 7:30	0.0	04/04/06 13:30	0.0	07/04/06 19:30	6.2	10/04/06 1:30	0.0
01/03/06 10:30	0.0	04/04/06 16:30	0.0	07/04/06 22:30	14.5	10/04/06 4:30	0.0
01/03/06 13:30	0.0	04/04/06 19:30	0.0	07/05/06 1:30	6.6	10/04/06 7:30	0.0
01/03/06 16:30	0.0	04/04/06 22:30	0.0	07/05/06 4:30	2.0	10/04/06 10:30	6.0
01/03/06 19:30	0.0	04/05/06 1:30	0.0	07/05/06 7:30	2.3	10/04/06 13:30	0.0
01/03/06 22:30	0.0	04/05/06 4:30	0.0	07/05/06 10:30	0.0	10/04/06 16:30	0.0
01/04/06 1:30	0.0	04/05/06 7:30	0.0	07/05/06 13:30	0.0	10/04/06 19:30	0.0
01/04/06 4:30	0.0	04/05/06 10:30	0.0	07/05/06 16:30	0.0	10/04/06 22:30	0.0
01/04/06 7:30	0.0	04/05/06 13:30	0.0	07/05/06 19:30	0.0	10/05/06 1:30	0.0
01/04/06 10:30	0.0	04/05/06 16:30	0.0	07/05/06 22:30	0.0	10/05/06 4:30	0.0
01/04/06 13:30	0.0	04/05/06 19:30	0.0	07/06/06 1:30	0.0	10/05/06 7:30	8.8
01/04/06 16:30	0.0	04/05/06 22:30	0.0	07/06/06 4:30	0.0	10/05/06 10:30	3.4
01/04/06 19:30	0.0	04/06/06 1:30	0.0	07/06/06 7:30	0.0	10/05/06 13:30	0.0
01/04/06 22:30	0.0	04/06/06 4:30	0.0	07/06/06 10:30	0.0	10/05/06 16:30	0.0
01/05/06 1:30	0.0	04/06/06 7:30	0.0	07/06/06 13:30	0.0	10/05/06 19:30	0.0
01/05/06 4:30	0.0	04/06/06 10:30	0.0	07/06/06 16:30	0.0	10/05/06 22:30	0.0
01/05/06 7:30	0.0	04/06/06 13:30	0.0	07/06/06 19:30	0.0	10/06/06 1:30	0.0
01/05/06 10:30	0.0	04/06/06 16:30	0.0	07/06/06 22:30	0.0	10/06/06 4:30	0.0
01/05/06 13:30	0.0	04/06/06 19:30	0.0	07/07/06 1:30	0.0	10/06/06 7:30	0.0
01/05/06 16:30	0.0	04/06/06 22:30	0.0	07/07/06 4:30	0.0	10/06/06 10:30	3.5
01/05/06 19:30	0.0	04/07/06 1:30	0.0	07/07/06 7:30	0.0	10/06/06 13:30	0.0
01/05/06 22:30	0.0	04/07/06 4:30	0.0	07/07/06 10:30	0.0	10/06/06 16:30	0.0
01/06/06 1:30	0.0	04/07/06 7:30	0.0	07/07/06 13:30	0.0	10/06/06 19:30	0.0
01/06/06 4:30	0.0	04/07/06 10:30	0.0	07/07/06 16:30	0.0	10/06/06 22:30	0.0
01/06/06 7:30	0.0	04/07/06 13:30	0.0	07/07/06 19:30	0.0	10/07/06 1:30	0.0
01/06/06 10:30	0.0	04/07/06 16:30	0.0	07/07/06 22:30	0.0	10/07/06 4:30	0.0
01/06/06 13:30	0.0	04/07/06 19:30	0.0	07/08/06 1:30	0.0	10/07/06 7:30	0.0
01/06/06 16:30	0.0	04/07/06 22:30	0.0	07/08/06 4:30	0.0	10/07/06 10:30	0.0
01/06/06 19:30	0.0	04/08/06 1:30	0.0	07/08/06 7:30	0.0	10/07/06 13:30	0.0
01/06/06 22:30	0.0	04/08/06 4:30	0.0	07/08/06 10:30	0.0	10/07/06 16:30	0.0
01/07/06 1:30	0.0	04/08/06 7:30	0.0	07/08/06 13:30	0.0	10/07/06 19:30	0.0
01/07/06 4:30	0.0	04/08/06 10:30	0.0	07/08/06 16:30	0.0	10/07/06 22:30	0.0
01/07/06 7:30	0.0	04/08/06 13:30	0.0	07/08/06 19:30	0.0	10/08/06 1:30	0.0
01/07/06 10:30	0.0	04/08/06 16:30	0.0	07/08/06 22:30	0.0	10/08/06 4:30	0.0
01/07/06 13:30	0.0	04/08/06 19:30	0.0	07/09/06 1:30	0.0	10/08/06 7:30	0.0
01/07/06 16:30	0.0	04/08/06 22:30	0.0	07/09/06 4:30	0.0	10/08/06 10:30	0.6
01/07/06 19:30	0.0	04/09/06 1:30	0.0	07/09/06 7:30	0.0	10/08/06 13:30	0.0
01/07/06 22:30	0.0	04/09/06 4:30	0.0	07/09/06 10:30	0.0	10/08/06 16:30	0.0
01/08/06 1:30	0.0	04/09/06 7:30	0.0	07/09/06 13:30	0.0	10/08/06 19:30	0.0
01/08/06 4:30	0.0	04/09/06 10:30	0.0	07/09/06 16:30	0.0	10/08/06 22:30	0.0
01/08/06 7:30	0.0	04/09/06 13:30	0.0	07/09/06 19:30	0.0	10/09/06 1:30	0.0
01/08/06 10:30	0.0	04/09/06 16:30	0.0	07/09/06 22:30	0.0	10/09/06 4:30	0.0
01/08/06 13:30	0.0	04/09/06 19:30	0.0	07/10/06 1:30	0.0	10/09/06 7:30	0.0
01/08/06 16:30	0.0	04/09/06 22:30	0.0	07/10/06 4:30	0.0	10/09/06 10:30	0.0

01/08/06 19:30	0.0	04/10/06 1:30	0.0	07/10/06 7:30	0.0	10/09/06 13:30	0.0
01/08/06 22:30	0.0	04/10/06 4:30	0.0	07/10/06 10:30	0.0	10/09/06 16:30	0.0
01/09/06 1:30	0.0	04/10/06 7:30	0.0	07/10/06 13:30	0.0	10/09/06 19:30	0.0
01/09/06 4:30	0.0	04/10/06 10:30	0.0	07/10/06 16:30	0.0	10/09/06 22:30	0.0
01/09/06 7:30	0.0	04/10/06 13:30	0.0	07/10/06 19:30	0.0	10/10/06 1:30	0.0
01/09/06 10:30	0.0	04/10/06 16:30	0.0	07/10/06 22:30	0.0	10/10/06 4:30	0.0
01/09/06 13:30	0.0	04/10/06 19:30	0.0	07/11/06 1:30	0.0	10/10/06 7:30	0.0
01/09/06 16:30	0.0	04/10/06 22:30	0.0	07/11/06 4:30	0.0	10/10/06 10:30	0.0
01/09/06 19:30	0.0	04/11/06 1:30	0.0	07/11/06 7:30	0.0	10/10/06 13:30	0.0
01/09/06 22:30	0.0	04/11/06 4:30	0.0	07/11/06 10:30	0.0	10/10/06 16:30	0.0
01/10/06 1:30	0.0	04/11/06 7:30	0.0	07/11/06 13:30	0.0	10/10/06 19:30	0.0
01/10/06 4:30	0.0	04/11/06 10:30	0.0	07/11/06 16:30	0.0	10/10/06 22:30	0.0
01/10/06 7:30	0.0	04/11/06 13:30	0.0	07/11/06 19:30	0.0	10/11/06 1:30	0.0
01/10/06 10:30	0.0	04/11/06 16:30	0.0	07/11/06 22:30	0.0	10/11/06 4:30	0.0
01/10/06 13:30	0.0	04/11/06 19:30	0.0	07/12/06 1:30	0.0	10/11/06 7:30	0.0
01/10/06 16:30	0.0	04/11/06 22:30	0.0	07/12/06 4:30	0.0	10/11/06 10:30	0.0
01/10/06 19:30	0.0	04/12/06 1:30	0.0	07/12/06 7:30	0.0	10/11/06 13:30	0.0
01/10/06 22:30	0.0	04/12/06 4:30	0.0	07/12/06 10:30	0.0	10/11/06 16:30	0.0
01/11/06 1:30	0.0	04/12/06 7:30	0.0	07/12/06 13:30	0.0	10/11/06 19:30	0.0
01/11/06 4:30	0.0	04/12/06 10:30	0.0	07/12/06 16:30	0.0	10/11/06 22:30	0.0
01/11/06 7:30	0.0	04/12/06 13:30	0.0	07/12/06 19:30	0.0	10/12/06 1:30	0.0
01/11/06 10:30	0.0	04/12/06 16:30	0.0	07/12/06 22:30	0.0	10/12/06 4:30	0.0
01/11/06 13:30	0.0	04/12/06 19:30	0.0	07/13/06 1:30	0.0	10/12/06 7:30	0.0
01/11/06 16:30	0.0	04/12/06 22:30	0.0	07/13/06 4:30	0.0	10/12/06 10:30	0.0
01/11/06 19:30	0.0	04/13/06 1:30	0.0	07/13/06 7:30	0.0	10/12/06 13:30	0.0
01/11/06 22:30	0.0	04/13/06 4:30	0.0	07/13/06 10:30	0.0	10/12/06 16:30	0.0
01/12/06 1:30	0.0	04/13/06 7:30	0.0	07/13/06 13:30	0.0	10/12/06 19:30	0.0
01/12/06 4:30	0.0	04/13/06 10:30	0.0	07/13/06 16:30	0.0	10/12/06 22:30	0.0
01/12/06 7:30	0.0	04/13/06 13:30	0.0	07/13/06 19:30	0.0	10/13/06 1:30	0.0
01/12/06 10:30	0.0	04/13/06 16:30	0.0	07/13/06 22:30	0.0	10/13/06 4:30	0.0
01/12/06 13:30	0.0	04/13/06 19:30	0.0	07/14/06 1:30	0.0	10/13/06 7:30	0.0
01/12/06 16:30	0.0	04/13/06 22:30	0.0	07/14/06 4:30	0.0	10/13/06 10:30	0.0
01/12/06 19:30	0.0	04/14/06 1:30	0.0	07/14/06 7:30	0.0	10/13/06 13:30	0.0
01/12/06 22:30	0.0	04/14/06 4:30	0.0	07/14/06 10:30	0.0	10/13/06 16:30	0.0
01/13/06 1:30	0.0	04/14/06 7:30	0.0	07/14/06 13:30	0.0	10/13/06 19:30	0.0
01/13/06 4:30	0.0	04/14/06 10:30	0.0	07/14/06 16:30	0.0	10/13/06 22:30	0.0
01/13/06 7:30	0.0	04/14/06 13:30	0.0	07/14/06 19:30	0.0	10/14/06 1:30	0.0
01/13/06 10:30	0.0	04/14/06 16:30	0.0	07/14/06 22:30	0.0	10/14/06 4:30	0.0
01/13/06 13:30	0.0	04/14/06 19:30	0.0	07/15/06 1:30	0.0	10/14/06 7:30	0.0
01/13/06 16:30	0.0	04/14/06 22:30	0.0	07/15/06 4:30	0.0	10/14/06 10:30	0.0
01/13/06 19:30	0.0	04/15/06 1:30	0.0	07/15/06 7:30	0.0	10/14/06 13:30	0.0
01/13/06 22:30	0.0	04/15/06 4:30	0.0	07/15/06 10:30	0.0	10/14/06 16:30	0.0
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01/14/06 7:30	0.0	04/15/06 13:30	0.0	07/15/06 19:30	0.0	10/15/06 1:30	0.0
01/14/06 10:30	0.0	04/15/06 16:30	0.0	07/15/06 22:30	0.0	10/15/06 4:30	0.0

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01/14/06 16:30	0.0	04/15/06 22:30	0.0	07/16/06 4:30	0.0	10/15/06 10:30	0.0
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01/14/06 22:30	0.0	04/16/06 4:30	0.0	07/16/06 10:30	0.0	10/15/06 16:30	0.0
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01/15/06 7:30	0.0	04/16/06 13:30	0.0	07/16/06 19:30	0.0	10/16/06 1:30	0.0
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01/15/06 22:30	0.0	04/17/06 4:30	0.0	07/17/06 10:30	0.0	10/16/06 16:30	0.0
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01/16/06 4:30	0.0	04/17/06 10:30	0.0	07/17/06 16:30	0.0	10/16/06 22:30	0.0
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01/17/06 4:30	0.0	04/18/06 10:30	0.0	07/18/06 16:30	0.0	10/17/06 22:30	0.0
01/17/06 7:30	0.0	04/18/06 13:30	0.0	07/18/06 19:30	0.0	10/18/06 1:30	0.0
01/17/06 10:30	0.0	04/18/06 16:30	0.0	07/18/06 22:30	0.0	10/18/06 4:30	0.0
01/17/06 13:30	0.0	04/18/06 19:30	0.0	07/19/06 1:30	0.0	10/18/06 7:30	0.0
01/17/06 16:30	0.0	04/18/06 22:30	0.0	07/19/06 4:30	0.0	10/18/06 10:30	0.0
01/17/06 19:30	0.0	04/19/06 1:30	0.0	07/19/06 7:30	0.0	10/18/06 13:30	0.0
01/17/06 22:30	0.0	04/19/06 4:30	0.0	07/19/06 10:30	0.0	10/18/06 16:30	0.0
01/18/06 1:30	0.0	04/19/06 7:30	0.0	07/19/06 13:30	0.0	10/18/06 19:30	0.0
01/18/06 4:30	0.0	04/19/06 10:30	0.0	07/19/06 16:30	0.0	10/18/06 22:30	0.0
01/18/06 7:30	0.0	04/19/06 13:30	0.0	07/19/06 19:30	0.0	10/19/06 1:30	0.0
01/18/06 10:30	0.0	04/19/06 16:30	0.0	07/19/06 22:30	0.0	10/19/06 4:30	0.0
01/18/06 13:30	0.0	04/19/06 19:30	0.0	07/20/06 1:30	0.0	10/19/06 7:30	0.0
01/18/06 16:30	0.0	04/19/06 22:30	0.0	07/20/06 4:30	0.0	10/19/06 10:30	0.0
01/18/06 19:30	0.0	04/20/06 1:30	0.0	07/20/06 7:30	0.0	10/19/06 13:30	0.0
01/18/06 22:30	0.0	04/20/06 4:30	0.0	07/20/06 10:30	0.0	10/19/06 16:30	0.0
01/19/06 1:30	0.0	04/20/06 7:30	0.0	07/20/06 13:30	0.0	10/19/06 19:30	0.0
01/19/06 4:30	0.0	04/20/06 10:30	0.0	07/20/06 16:30	0.0	10/19/06 22:30	0.0
01/19/06 7:30	0.0	04/20/06 13:30	0.0	07/20/06 19:30	0.0	10/20/06 1:30	0.0
01/19/06 10:30	0.0	04/20/06 16:30	0.0	07/20/06 22:30	0.0	10/20/06 4:30	0.0
01/19/06 13:30	0.0	04/20/06 19:30	0.0	07/21/06 1:30	0.0	10/20/06 7:30	0.0
01/19/06 16:30	0.0	04/20/06 22:30	0.0	07/21/06 4:30	0.0	10/20/06 10:30	0.0
01/19/06 19:30	0.0	04/21/06 1:30	0.0	07/21/06 7:30	0.0	10/20/06 13:30	0.0
01/19/06 22:30	0.0	04/21/06 4:30	0.0	07/21/06 10:30	2.4	10/20/06 16:30	0.0
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01/20/06 4:30	0.0	04/21/06 10:30	0.0	07/21/06 16:30	0.0	10/20/06 22:30	0.0

01/20/06 7:30	0.0	04/21/06 13:30	0.0	07/21/06 19:30	0.0	10/21/06 1:30	0.0
01/20/06 10:30	0.0	04/21/06 16:30	0.0	07/21/06 22:30	0.0	10/21/06 4:30	0.0
01/20/06 13:30	0.0	04/21/06 19:30	0.0	07/22/06 1:30	0.0	10/21/06 7:30	0.0
01/20/06 16:30	0.0	04/21/06 22:30	0.0	07/22/06 4:30	0.0	10/21/06 10:30	0.0
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01/20/06 22:30	0.0	04/22/06 4:30	0.0	07/22/06 10:30	3.7	10/21/06 16:30	0.0
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01/21/06 10:30	0.0	04/22/06 16:30	0.0	07/22/06 22:30	0.0	10/22/06 4:30	0.0
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01/21/06 22:30	0.0	04/23/06 4:30	0.0	07/23/06 10:30	1.5	10/22/06 16:30	0.0
01/22/06 1:30	0.0	04/23/06 7:30	0.0	07/23/06 13:30	0.0	10/22/06 19:30	0.0
01/22/06 4:30	0.0	04/23/06 10:30	0.0	07/23/06 16:30	0.0	10/22/06 22:30	0.0
01/22/06 7:30	0.0	04/23/06 13:30	0.0	07/23/06 19:30	0.0	10/23/06 1:30	0.0
01/22/06 10:30	0.0	04/23/06 16:30	0.0	07/23/06 22:30	0.0	10/23/06 4:30	0.0
01/22/06 13:30	0.0	04/23/06 19:30	0.0	07/24/06 1:30	0.0	10/23/06 7:30	0.0
01/22/06 16:30	0.0	04/23/06 22:30	0.0	07/24/06 4:30	0.0	10/23/06 10:30	0.0
01/22/06 19:30	0.0	04/24/06 1:30	0.0	07/24/06 7:30	0.0	10/23/06 13:30	0.0
01/22/06 22:30	0.0	04/24/06 4:30	0.0	07/24/06 10:30	0.0	10/23/06 16:30	0.0
01/23/06 1:30	0.0	04/24/06 7:30	0.0	07/24/06 13:30	0.0	10/23/06 19:30	0.0
01/23/06 4:30	0.0	04/24/06 10:30	0.0	07/24/06 16:30	0.0	10/23/06 22:30	0.0
01/23/06 7:30	0.0	04/24/06 13:30	0.0	07/24/06 19:30	0.0	10/24/06 1:30	0.0
01/23/06 10:30	0.0	04/24/06 16:30	0.0	07/24/06 22:30	0.0	10/24/06 4:30	0.0
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01/23/06 16:30	0.0	04/24/06 22:30	0.0	07/25/06 4:30	0.0	10/24/06 10:30	0.0
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01/23/06 22:30	0.0	04/25/06 4:30	0.0	07/25/06 10:30	0.0	10/24/06 16:30	0.0
01/24/06 1:30	0.0	04/25/06 7:30	0.0	07/25/06 13:30	0.0	10/24/06 19:30	0.0
01/24/06 4:30	0.0	04/25/06 10:30	0.0	07/25/06 16:30	0.0	10/24/06 22:30	0.0
01/24/06 7:30	0.0	04/25/06 13:30	0.0	07/25/06 19:30	0.0	10/25/06 1:30	0.0
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01/24/06 22:30	0.0	04/26/06 4:30	0.0	07/26/06 10:30	0.0	10/25/06 16:30	0.0
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01/25/06 4:30	0.0	04/26/06 10:30	0.0	07/26/06 16:30	0.0	10/25/06 22:30	0.0
01/25/06 7:30	0.0	04/26/06 13:30	0.0	07/26/06 19:30	0.0	10/26/06 1:30	0.0
01/25/06 10:30	0.0	04/26/06 16:30	0.0	07/26/06 22:30	0.0	10/26/06 4:30	0.0
01/25/06 13:30	0.0	04/26/06 19:30	0.0	07/27/06 1:30	0.0	10/26/06 7:30	0.0
01/25/06 16:30	0.0	04/26/06 22:30	0.0	07/27/06 4:30	0.0	10/26/06 10:30	0.0
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01/25/06 22:30	0.0	04/27/06 4:30	0.0	07/27/06 10:30	1.0	10/26/06 16:30	0.0

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01/26/06 4:30	0.0	04/27/06 10:30	0.0	07/27/06 16:30	0.0	10/26/06 22:30	0.0
01/26/06 7:30	0.0	04/27/06 13:30	0.0	07/27/06 19:30	0.0	10/27/06 1:30	0.0
01/26/06 10:30	0.0	04/27/06 16:30	0.0	07/27/06 22:30	1.9	10/27/06 4:30	0.0
01/26/06 13:30	0.0	04/27/06 19:30	0.0	07/28/06 1:30	0.0	10/27/06 7:30	0.0
01/26/06 16:30	0.0	04/27/06 22:30	0.0	07/28/06 4:30	7.4	10/27/06 10:30	0.0
01/26/06 19:30	0.0	04/28/06 1:30	0.0	07/28/06 7:30	3.7	10/27/06 13:30	0.0
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01/27/06 1:30	0.0	04/28/06 7:30	0.0	07/28/06 13:30	2.9	10/27/06 19:30	0.0
01/27/06 4:30	0.0	04/28/06 10:30	0.0	07/28/06 16:30	1.7	10/27/06 22:30	0.0
01/27/06 7:30	0.0	04/28/06 13:30	0.0	07/28/06 19:30	0.0	10/28/06 1:30	0.0
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01/27/06 22:30	0.0	04/29/06 4:30	0.0	07/29/06 10:30	2.4	10/28/06 16:30	0.0
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01/28/06 16:30	0.0	04/29/06 22:30	0.0	07/30/06 4:30	0.0	10/29/06 10:30	0.0
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01/28/06 22:30	0.0	04/30/06 4:30	0.0	07/30/06 10:30	0.0	10/29/06 16:30	0.0
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01/30/06 13:30	0.0	05/01/06 19:30	0.0	08/01/06 1:30	0.0	10/31/06 7:30	0.0
01/30/06 16:30	0.0	05/01/06 22:30	0.0	08/01/06 4:30	0.0	10/31/06 10:30	0.0
01/30/06 19:30	0.0	05/02/06 1:30	0.0	08/01/06 7:30	0.0	10/31/06 13:30	0.0
01/30/06 22:30	0.0	05/02/06 4:30	0.0	08/01/06 10:30	0.0	10/31/06 16:30	0.0
01/31/06 1:30	0.0	05/02/06 7:30	0.0	08/01/06 13:30	0.0	10/31/06 19:30	0.0
01/31/06 4:30	0.0	05/02/06 10:30	0.0	08/01/06 16:30	0.0	10/31/06 22:30	0.0
01/31/06 7:30	0.0	05/02/06 13:30	0.0	08/01/06 19:30	0.0	11/01/06 1:30	0.0
01/31/06 10:30	0.0	05/02/06 16:30	0.0	08/01/06 22:30	0.0	11/01/06 4:30	0.0
01/31/06 13:30	0.0	05/02/06 19:30	0.0	08/02/06 1:30	0.0	11/01/06 7:30	0.0
01/31/06 16:30	0.0	05/02/06 22:30	0.0	08/02/06 4:30	0.0	11/01/06 10:30	0.0

01/31/06 19:30	0.0	05/03/06 1:30	0.0	08/02/06 7:30	0.0	11/01/06 13:30	0.0
01/31/06 22:30	0.0	05/03/06 4:30	0.0	08/02/06 10:30	0.0	11/01/06 16:30	0.0
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02/01/06 16:30	0.0	05/03/06 22:30	0.0	08/03/06 4:30	0.0	11/02/06 10:30	1.6
02/01/06 19:30	0.0	05/04/06 1:30	0.0	08/03/06 7:30	0.0	11/02/06 13:30	4.3
02/01/06 22:30	0.0	05/04/06 4:30	0.0	08/03/06 10:30	0.0	11/02/06 16:30	0.0
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02/02/06 4:30	0.0	05/04/06 10:30	0.0	08/03/06 16:30	0.8	11/02/06 22:30	0.0
02/02/06 7:30	0.0	05/04/06 13:30	0.0	08/03/06 19:30	0.0	11/03/06 1:30	0.0
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02/03/06 10:30	0.0	05/05/06 16:30	0.0	08/04/06 22:30	19.0	11/04/06 4:30	0.0
02/03/06 13:30	0.0	05/05/06 19:30	0.0	08/05/06 1:30	1.0	11/04/06 7:30	0.0
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02/05/06 22:30	0.0	05/08/06 4:30	0.0	08/07/06 10:30	8.2	11/06/06 16:30	0.0
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02/06/06 7:30	0.0	05/08/06 13:30	0.0	08/07/06 19:30	0.0	11/07/06 1:30	0.0
02/06/06 10:30	0.0	05/08/06 16:30	0.0	08/07/06 22:30	2.2	11/07/06 4:30	0.0

02/06/06 13:30	0.0	05/08/06 19:30	0.0	08/08/06 1:30	1.7	11/07/06 7:30	0.0
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02/07/06 1:30	0.0	05/09/06 7:30	0.0	08/08/06 13:30	0.0	11/07/06 19:30	0.0
02/07/06 4:30	0.0	05/09/06 10:30	0.0	08/08/06 16:30	1.9	11/07/06 22:30	0.0
02/07/06 7:30	0.0	05/09/06 13:30	0.0	08/08/06 19:30	20.8	11/08/06 1:30	0.0
02/07/06 10:30	0.0	05/09/06 16:30	0.0	08/08/06 22:30	0.4	11/08/06 4:30	0.0
02/07/06 13:30	0.0	05/09/06 19:30	0.0	08/09/06 1:30	0.0	11/08/06 7:30	0.0
02/07/06 16:30	0.0	05/09/06 22:30	0.0	08/09/06 4:30	0.0	11/08/06 10:30	2.4
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02/07/06 22:30	0.0	05/10/06 4:30	0.0	08/09/06 10:30	0.0	11/08/06 16:30	0.0
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02/08/06 4:30	0.0	05/10/06 10:30	0.0	08/09/06 16:30	0.0	11/08/06 22:30	0.0
02/08/06 7:30	0.0	05/10/06 13:30	0.0	08/09/06 19:30	0.0	11/09/06 1:30	0.0
02/08/06 10:30	0.0	05/10/06 16:30	0.0	08/09/06 22:30	0.0	11/09/06 4:30	0.0
02/08/06 13:30	0.0	05/10/06 19:30	0.0	08/10/06 1:30	0.0	11/09/06 7:30	0.0
02/08/06 16:30	0.0	05/10/06 22:30	0.0	08/10/06 4:30	0.0	11/09/06 10:30	0.0
02/08/06 19:30	0.0	05/11/06 1:30	0.0	08/10/06 7:30	0.0	11/09/06 13:30	0.0
02/08/06 22:30	0.0	05/11/06 4:30	0.0	08/10/06 10:30	0.0	11/09/06 16:30	0.0
02/09/06 1:30	0.0	05/11/06 7:30	0.0	08/10/06 13:30	0.0	11/09/06 19:30	0.0
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02/10/06 4:30	0.0	05/12/06 10:30	0.0	08/11/06 16:30	0.0	11/10/06 22:30	0.0
02/10/06 7:30	0.0	05/12/06 13:30	0.0	08/11/06 19:30	0.0	11/11/06 1:30	0.0
02/10/06 10:30	0.0	05/12/06 16:30	0.0	08/11/06 22:30	0.0	11/11/06 4:30	0.0
02/10/06 13:30	0.0	05/12/06 19:30	0.0	08/12/06 1:30	0.0	11/11/06 7:30	0.0
02/10/06 16:30	0.0	05/12/06 22:30	0.0	08/12/06 4:30	0.0	11/11/06 10:30	0.0
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02/10/06 22:30	0.0	05/13/06 4:30	0.0	08/12/06 10:30	0.0	11/11/06 16:30	0.0
02/11/06 1:30	0.0	05/13/06 7:30	0.0	08/12/06 13:30	0.0	11/11/06 19:30	0.0
02/11/06 4:30	0.0	05/13/06 10:30	0.0	08/12/06 16:30	0.0	11/11/06 22:30	0.0
02/11/06 7:30	0.0	05/13/06 13:30	0.0	08/12/06 19:30	0.0	11/12/06 1:30	0.0
02/11/06 10:30	0.0	05/13/06 16:30	0.0	08/12/06 22:30	0.0	11/12/06 4:30	0.0
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02/12/06 4:30	0.0	05/14/06 10:30	0.0	08/13/06 16:30	0.0	11/12/06 22:30	0.0

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02/12/06 10:30	0.0	05/14/06 16:30	0.0	08/13/06 22:30	0.0	11/13/06 4:30	0.0
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02/15/06 7:30	0.0	05/17/06 13:30	0.0	08/16/06 19:30	0.0	11/16/06 1:30	0.0
02/15/06 10:30	0.0	05/17/06 16:30	0.0	08/16/06 22:30	1.4	11/16/06 4:30	0.0
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02/17/06 22:30	0.0	05/20/06 4:30	0.0	08/19/06 10:30	0.0	11/18/06 16:30	0.0

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02/18/06 4:30	0.0	05/20/06 10:30	0.0	08/19/06 16:30	0.0	11/18/06 22:30	0.0
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02/18/06 10:30	0.0	05/20/06 16:30	0.0	08/19/06 22:30	0.0	11/19/06 4:30	0.0
02/18/06 13:30	0.0	05/20/06 19:30	0.0	08/20/06 1:30	0.0	11/19/06 7:30	0.0
02/18/06 16:30	0.0	05/20/06 22:30	0.0	08/20/06 4:30	0.0	11/19/06 10:30	0.0
02/18/06 19:30	0.0	05/21/06 1:30	0.0	08/20/06 7:30	0.0	11/19/06 13:30	0.0
02/18/06 22:30	0.0	05/21/06 4:30	0.0	08/20/06 10:30	0.0	11/19/06 16:30	0.0
02/19/06 1:30	0.0	05/21/06 7:30	0.0	08/20/06 13:30	0.0	11/19/06 19:30	0.0
02/19/06 4:30	0.0	05/21/06 10:30	0.0	08/20/06 16:30	0.0	11/19/06 22:30	0.0
02/19/06 7:30	0.0	05/21/06 13:30	0.0	08/20/06 19:30	0.0	11/20/06 1:30	0.0
02/19/06 10:30	0.0	05/21/06 16:30	0.0	08/20/06 22:30	0.0	11/20/06 4:30	0.0
02/19/06 13:30	0.0	05/21/06 19:30	0.0	08/21/06 1:30	0.0	11/20/06 7:30	0.0
02/19/06 16:30	0.0	05/21/06 22:30	0.0	08/21/06 4:30	0.0	11/20/06 10:30	0.0
02/19/06 19:30	0.0	05/22/06 1:30	0.0	08/21/06 7:30	0.0	11/20/06 13:30	0.0
02/19/06 22:30	0.0	05/22/06 4:30	0.0	08/21/06 10:30	0.0	11/20/06 16:30	0.0
02/20/06 1:30	0.0	05/22/06 7:30	0.0	08/21/06 13:30	0.0	11/20/06 19:30	0.0
02/20/06 4:30	0.0	05/22/06 10:30	0.0	08/21/06 16:30	0.0	11/20/06 22:30	0.0
02/20/06 7:30	0.0	05/22/06 13:30	0.0	08/21/06 19:30	0.0	11/21/06 1:30	0.0
02/20/06 10:30	0.0	05/22/06 16:30	0.0	08/21/06 22:30	0.0	11/21/06 4:30	0.0
02/20/06 13:30	0.0	05/22/06 19:30	0.0	08/22/06 1:30	0.0	11/21/06 7:30	0.0
02/20/06 16:30	0.0	05/22/06 22:30	0.0	08/22/06 4:30	0.0	11/21/06 10:30	0.0
02/20/06 19:30	0.0	05/23/06 1:30	0.0	08/22/06 7:30	0.0	11/21/06 13:30	0.0
02/20/06 22:30	0.0	05/23/06 4:30	0.0	08/22/06 10:30	0.0	11/21/06 16:30	0.0
02/21/06 1:30	0.0	05/23/06 7:30	0.0	08/22/06 13:30	0.0	11/21/06 19:30	0.0
02/21/06 4:30	0.0	05/23/06 10:30	0.0	08/22/06 16:30	0.0	11/21/06 22:30	0.0
02/21/06 7:30	0.0	05/23/06 13:30	0.0	08/22/06 19:30	0.0	11/22/06 1:30	0.0
02/21/06 10:30	0.0	05/23/06 16:30	0.0	08/22/06 22:30	0.0	11/22/06 4:30	0.0
02/21/06 13:30	0.0	05/23/06 19:30	0.0	08/23/06 1:30	0.0	11/22/06 7:30	0.0
02/21/06 16:30	0.0	05/23/06 22:30	0.0	08/23/06 4:30	0.0	11/22/06 10:30	0.0
02/21/06 19:30	0.0	05/24/06 1:30	0.0	08/23/06 7:30	0.0	11/22/06 13:30	1.5
02/21/06 22:30	0.0	05/24/06 4:30	0.0	08/23/06 10:30	0.0	11/22/06 16:30	0.0
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02/22/06 7:30	0.0	05/24/06 13:30	0.0	08/23/06 19:30	0.0	11/23/06 1:30	0.0
02/22/06 10:30	0.0	05/24/06 16:30	0.0	08/23/06 22:30	0.0	11/23/06 4:30	0.0
02/22/06 13:30	0.0	05/24/06 19:30	0.0	08/24/06 1:30	0.0	11/23/06 7:30	0.0
02/22/06 16:30	0.0	05/24/06 22:30	0.0	08/24/06 4:30	0.0	11/23/06 10:30	0.0
02/22/06 19:30	0.0	05/25/06 1:30	0.0	08/24/06 7:30	0.0	11/23/06 13:30	1.0
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02/23/06 4:30	0.0	05/25/06 10:30	0.0	08/24/06 16:30	0.0	11/23/06 22:30	0.0
02/23/06 7:30	0.0	05/25/06 13:30	0.0	08/24/06 19:30	0.0	11/24/06 1:30	0.0
02/23/06 10:30	0.0	05/25/06 16:30	0.0	08/24/06 22:30	0.0	11/24/06 4:30	0.0
02/23/06 13:30	0.0	05/25/06 19:30	0.0	08/25/06 1:30	0.0	11/24/06 7:30	0.0
02/23/06 16:30	0.0	05/25/06 22:30	0.0	08/25/06 4:30	0.0	11/24/06 10:30	2.0

02/23/06 19:30	0.0	05/26/06 1:30	0.0	08/25/06 7:30	0.0	11/24/06 13:30	0.0
02/23/06 22:30	0.0	05/26/06 4:30	0.0	08/25/06 10:30	0.0	11/24/06 16:30	0.0
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02/24/06 4:30	0.0	05/26/06 10:30	0.0	08/25/06 16:30	0.0	11/24/06 22:30	0.0
02/24/06 7:30	0.0	05/26/06 13:30	0.0	08/25/06 19:30	0.0	11/25/06 1:30	0.0
02/24/06 10:30	0.0	05/26/06 16:30	0.0	08/25/06 22:30	0.0	11/25/06 4:30	0.0
02/24/06 13:30	0.0	05/26/06 19:30	0.0	08/26/06 1:30	0.0	11/25/06 7:30	0.0
02/24/06 16:30	0.0	05/26/06 22:30	0.0	08/26/06 4:30	0.0	11/25/06 10:30	0.0
02/24/06 19:30	0.0	05/27/06 1:30	0.0	08/26/06 7:30	0.0	11/25/06 13:30	0.0
02/24/06 22:30	0.0	05/27/06 4:30	0.0	08/26/06 10:30	0.0	11/25/06 16:30	0.0
02/25/06 1:30	0.0	05/27/06 7:30	0.0	08/26/06 13:30	0.0	11/25/06 19:30	0.0
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02/25/06 7:30	0.0	05/27/06 13:30	0.0	08/26/06 19:30	0.0	11/26/06 1:30	0.0
02/25/06 10:30	0.0	05/27/06 16:30	0.0	08/26/06 22:30	0.0	11/26/06 4:30	0.0
02/25/06 13:30	0.0	05/27/06 19:30	0.0	08/27/06 1:30	0.0	11/26/06 7:30	0.0
02/25/06 16:30	0.0	05/27/06 22:30	0.0	08/27/06 4:30	0.0	11/26/06 10:30	0.0
02/25/06 19:30	0.0	05/28/06 1:30	0.0	08/27/06 7:30	0.0	11/26/06 13:30	0.0
02/25/06 22:30	0.0	05/28/06 4:30	0.0	08/27/06 10:30	0.0	11/26/06 16:30	0.0
02/26/06 1:30	0.0	05/28/06 7:30	0.0	08/27/06 13:30	0.0	11/26/06 19:30	0.0
02/26/06 4:30	0.0	05/28/06 10:30	0.0	08/27/06 16:30	0.0	11/26/06 22:30	0.0
02/26/06 7:30	0.0	05/28/06 13:30	0.0	08/27/06 19:30	0.0	11/27/06 1:30	0.0
02/26/06 10:30	0.0	05/28/06 16:30	0.0	08/27/06 22:30	0.0	11/27/06 4:30	0.0
02/26/06 13:30	0.0	05/28/06 19:30	0.0	08/28/06 1:30	0.0	11/27/06 7:30	0.0
02/26/06 16:30	0.0	05/28/06 22:30	0.0	08/28/06 4:30	0.0	11/27/06 10:30	0.0
02/26/06 19:30	0.0	05/29/06 1:30	0.0	08/28/06 7:30	0.0	11/27/06 13:30	0.0
02/26/06 22:30	0.0	05/29/06 4:30	0.0	08/28/06 10:30	0.0	11/27/06 16:30	0.0
02/27/06 1:30	0.0	05/29/06 7:30	0.0	08/28/06 13:30	0.0	11/27/06 19:30	0.0
02/27/06 4:30	0.0	05/29/06 10:30	0.0	08/28/06 16:30	0.0	11/27/06 22:30	0.0
02/27/06 7:30	0.0	05/29/06 13:30	0.0	08/28/06 19:30	0.0	11/28/06 1:30	0.0
02/27/06 10:30	0.0	05/29/06 16:30	0.0	08/28/06 22:30	0.0	11/28/06 4:30	0.0
02/27/06 13:30	0.0	05/29/06 19:30	1.4	08/29/06 1:30	0.0	11/28/06 7:30	0.0
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02/27/06 22:30	0.0	05/30/06 4:30	0.0	08/29/06 10:30	0.0	11/28/06 16:30	0.0
02/28/06 1:30	0.0	05/30/06 7:30	0.0	08/29/06 13:30	0.0	11/28/06 19:30	0.0
02/28/06 4:30	0.0	05/30/06 10:30	0.0	08/29/06 16:30	0.0	11/28/06 22:30	0.0
02/28/06 7:30	0.0	05/30/06 13:30	0.0	08/29/06 19:30	0.0	11/29/06 1:30	0.0
02/28/06 10:30	0.0	05/30/06 16:30	0.0	08/29/06 22:30	0.0	11/29/06 4:30	0.0
02/28/06 13:30	0.0	05/30/06 19:30	0.0	08/30/06 1:30	0.0	11/29/06 7:30	0.0
02/28/06 16:30	0.0	05/30/06 22:30	0.0	08/30/06 4:30	0.0	11/29/06 10:30	0.0
02/28/06 19:30	0.0	05/31/06 1:30	0.0	08/30/06 7:30	0.0	11/29/06 13:30	0.0
02/28/06 22:30	0.0	05/31/06 4:30	1.3	08/30/06 10:30	0.0	11/29/06 16:30	0.0
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03/01/06 7:30	0.0	05/31/06 13:30	0.0	08/30/06 19:30	0.0	11/30/06 1:30	0.0
03/01/06 10:30	0.0	05/31/06 16:30	0.0	08/30/06 22:30	0.0	11/30/06 4:30	0.0

03/01/06 13:30	0.0	05/31/06 19:30	0.0	08/31/06 1:30	0.0	11/30/06 7:30	0.0
03/01/06 16:30	0.0	05/31/06 22:30	0.0	08/31/06 4:30	0.0	11/30/06 10:30	0.0
03/01/06 19:30	0.0	06/01/06 1:30	0.0	08/31/06 7:30	0.0	11/30/06 13:30	0.0
03/01/06 22:30	0.0	06/01/06 4:30	4.3	08/31/06 10:30	0.0	11/30/06 16:30	0.0
03/02/06 1:30	0.0	06/01/06 7:30	0.0	08/31/06 13:30	0.0	11/30/06 19:30	0.0
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03/02/06 7:30	0.0	06/01/06 13:30	0.0	08/31/06 19:30	0.0	12/01/06 1:30	0.0
03/02/06 10:30	0.0	06/01/06 16:30	0.0	08/31/06 22:30	0.0	12/01/06 4:30	0.0
03/02/06 13:30	0.0	06/01/06 19:30	0.0	09/01/06 1:30	0.0	12/01/06 7:30	0.0
03/02/06 16:30	0.0	06/01/06 22:30	0.0	09/01/06 4:30	0.0	12/01/06 10:30	0.0
03/02/06 19:30	0.0	06/02/06 1:30	0.0	09/01/06 7:30	0.0	12/01/06 13:30	0.0
03/02/06 22:30	0.0	06/02/06 4:30	0.0	09/01/06 10:30	0.0	12/01/06 16:30	0.0
03/03/06 1:30	0.0	06/02/06 7:30	0.0	09/01/06 13:30	0.0	12/01/06 19:30	0.0
03/03/06 4:30	0.0	06/02/06 10:30	0.2	09/01/06 16:30	0.0	12/01/06 22:30	0.0
03/03/06 7:30	0.0	06/02/06 13:30	0.0	09/01/06 19:30	0.0	12/02/06 1:30	0.0
03/03/06 10:30	0.0	06/02/06 16:30	0.0	09/01/06 22:30	0.0	12/02/06 4:30	0.0
03/03/06 13:30	0.0	06/02/06 19:30	0.0	09/02/06 1:30	0.0	12/02/06 7:30	0.0
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03/03/06 19:30	0.0	06/03/06 1:30	0.0	09/02/06 7:30	0.0	12/02/06 13:30	0.0
03/03/06 22:30	0.0	06/03/06 4:30	0.0	09/02/06 10:30	0.0	12/02/06 16:30	0.0
03/04/06 1:30	0.0	06/03/06 7:30	0.0	09/02/06 13:30	0.0	12/02/06 19:30	0.0
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03/04/06 10:30	0.0	06/03/06 16:30	0.0	09/02/06 22:30	0.0	12/03/06 4:30	0.0
03/04/06 13:30	0.0	06/03/06 19:30	0.0	09/03/06 1:30	0.0	12/03/06 7:30	0.0
03/04/06 16:30	0.0	06/03/06 22:30	0.0	09/03/06 4:30	0.0	12/03/06 10:30	0.0
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03/05/06 1:30	0.0	06/04/06 7:30	0.0	09/03/06 13:30	0.0	12/03/06 19:30	0.0
03/05/06 4:30	0.0	06/04/06 10:30	0.0	09/03/06 16:30	0.0	12/03/06 22:30	0.0
03/05/06 7:30	0.0	06/04/06 13:30	0.0	09/03/06 19:30	0.0	12/04/06 1:30	0.0
03/05/06 10:30	0.0	06/04/06 16:30	0.0	09/03/06 22:30	0.0	12/04/06 4:30	0.0
03/05/06 13:30	0.0	06/04/06 19:30	0.0	09/04/06 1:30	0.0	12/04/06 7:30	0.0
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03/05/06 19:30	0.0	06/05/06 1:30	0.0	09/04/06 7:30	0.0	12/04/06 13:30	0.0
03/05/06 22:30	0.0	06/05/06 4:30	0.0	09/04/06 10:30	0.0	12/04/06 16:30	0.0
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03/06/06 7:30	0.0	06/05/06 13:30	0.0	09/04/06 19:30	0.0	12/05/06 1:30	0.0
03/06/06 10:30	0.0	06/05/06 16:30	0.0	09/04/06 22:30	0.0	12/05/06 4:30	0.0
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03/06/06 19:30	0.0	06/06/06 1:30	0.0	09/05/06 7:30	0.0	12/05/06 13:30	0.0
03/06/06 22:30	0.0	06/06/06 4:30	0.0	09/05/06 10:30	0.0	12/05/06 16:30	0.0
03/07/06 1:30	0.0	06/06/06 7:30	0.0	09/05/06 13:30	0.0	12/05/06 19:30	0.0
03/07/06 4:30	0.0	06/06/06 10:30	0.0	09/05/06 16:30	0.0	12/05/06 22:30	0.0

03/07/06 7:30	0.0	06/06/06 13:30	0.0	09/05/06 19:30	0.0	12/06/06 1:30	0.0
03/07/06 10:30	0.0	06/06/06 16:30	0.0	09/05/06 22:30	0.0	12/06/06 4:30	0.0
03/07/06 13:30	0.0	06/06/06 19:30	0.0	09/06/06 1:30	0.0	12/06/06 7:30	0.0
03/07/06 16:30	0.0	06/06/06 22:30	0.0	09/06/06 4:30	0.0	12/06/06 10:30	0.0
03/07/06 19:30	0.0	06/07/06 1:30	0.0	09/06/06 7:30	0.0	12/06/06 13:30	0.0
03/07/06 22:30	0.0	06/07/06 4:30	0.0	09/06/06 10:30	0.0	12/06/06 16:30	0.0
03/08/06 1:30	0.0	06/07/06 7:30	0.0	09/06/06 13:30	0.0	12/06/06 19:30	0.0
03/08/06 4:30	0.0	06/07/06 10:30	0.0	09/06/06 16:30	0.0	12/06/06 22:30	0.0
03/08/06 7:30	0.0	06/07/06 13:30	0.0	09/06/06 19:30	0.0	12/07/06 1:30	0.0
03/08/06 10:30	0.0	06/07/06 16:30	0.0	09/06/06 22:30	0.0	12/07/06 4:30	0.0
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03/09/06 4:30	0.0	06/08/06 10:30	0.0	09/07/06 16:30	0.0	12/07/06 22:30	0.0
03/09/06 7:30	0.0	06/08/06 13:30	0.0	09/07/06 19:30	0.0	12/08/06 1:30	0.0
03/09/06 10:30	0.9	06/08/06 16:30	0.0	09/07/06 22:30	0.0	12/08/06 4:30	0.0
03/09/06 13:30	1.7	06/08/06 19:30	0.0	09/08/06 1:30	0.0	12/08/06 7:30	0.0
03/09/06 16:30	3.2	06/08/06 22:30	0.0	09/08/06 4:30	0.0	12/08/06 10:30	0.0
03/09/06 19:30	0.0	06/09/06 1:30	0.0	09/08/06 7:30	0.0	12/08/06 13:30	0.0
03/09/06 22:30	0.0	06/09/06 4:30	0.0	09/08/06 10:30	3.0	12/08/06 16:30	0.0
03/10/06 1:30	0.0	06/09/06 7:30	0.0	09/08/06 13:30	1.0	12/08/06 19:30	0.0
03/10/06 4:30	0.0	06/09/06 10:30	0.0	09/08/06 16:30	0.0	12/08/06 22:30	0.0
03/10/06 7:30	0.0	06/09/06 13:30	0.0	09/08/06 19:30	23.0	12/09/06 1:30	0.0
03/10/06 10:30	0.0	06/09/06 16:30	0.0	09/08/06 22:30	0.6	12/09/06 4:30	0.0
03/10/06 13:30	0.0	06/09/06 19:30	0.0	09/09/06 1:30	0.0	12/09/06 7:30	0.0
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03/10/06 19:30	0.0	06/10/06 1:30	0.0	09/09/06 7:30	0.0	12/09/06 13:30	0.0
03/10/06 22:30	0.0	06/10/06 4:30	0.0	09/09/06 10:30	0.0	12/09/06 16:30	0.0
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03/11/06 10:30	0.0	06/10/06 16:30	0.0	09/09/06 22:30	0.0	12/10/06 4:30	0.0
03/11/06 13:30	0.0	06/10/06 19:30	0.0	09/10/06 1:30	0.0	12/10/06 7:30	0.0
03/11/06 16:30	0.0	06/10/06 22:30	0.0	09/10/06 4:30	0.0	12/10/06 10:30	0.0
03/11/06 19:30	0.0	06/11/06 1:30	0.0	09/10/06 7:30	6.8	12/10/06 13:30	0.0
03/11/06 22:30	0.0	06/11/06 4:30	0.0	09/10/06 10:30	0.6	12/10/06 16:30	0.0
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03/12/06 7:30	0.0	06/11/06 13:30	0.0	09/10/06 19:30	0.7	12/11/06 1:30	0.0
03/12/06 10:30	0.0	06/11/06 16:30	0.0	09/10/06 22:30	0.0	12/11/06 4:30	0.0
03/12/06 13:30	0.0	06/11/06 19:30	0.0	09/11/06 1:30	0.0	12/11/06 7:30	0.0
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03/12/06 19:30	0.0	06/12/06 1:30	0.0	09/11/06 7:30	0.0	12/11/06 13:30	0.0
03/12/06 22:30	0.0	06/12/06 4:30	0.0	09/11/06 10:30	0.0	12/11/06 16:30	0.0

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03/13/06 4:30	0.0	06/12/06 10:30	0.0	09/11/06 16:30	3.9	12/11/06 22:30	0.0
03/13/06 7:30	0.0	06/12/06 13:30	0.0	09/11/06 19:30	0.0	12/12/06 1:30	0.0
03/13/06 10:30	0.0	06/12/06 16:30	0.0	09/11/06 22:30	0.0	12/12/06 4:30	0.0
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03/14/06 7:30	0.0	06/13/06 13:30	0.0	09/12/06 19:30	0.0	12/13/06 1:30	0.0
03/14/06 10:30	0.0	06/13/06 16:30	0.0	09/12/06 22:30	0.0	12/13/06 4:30	0.0
03/14/06 13:30	0.0	06/13/06 19:30	0.0	09/13/06 1:30	0.0	12/13/06 7:30	0.0
03/14/06 16:30	0.0	06/13/06 22:30	0.0	09/13/06 4:30	0.0	12/13/06 10:30	0.0
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03/15/06 4:30	0.0	06/14/06 10:30	0.0	09/13/06 16:30	0.9	12/13/06 22:30	0.0
03/15/06 7:30	0.0	06/14/06 13:30	0.0	09/13/06 19:30	0.0	12/14/06 1:30	0.0
03/15/06 10:30	0.0	06/14/06 16:30	0.0	09/13/06 22:30	0.0	12/14/06 4:30	0.0
03/15/06 13:30	0.0	06/14/06 19:30	0.0	09/14/06 1:30	0.0	12/14/06 7:30	0.0
03/15/06 16:30	0.0	06/14/06 22:30	0.0	09/14/06 4:30	0.0	12/14/06 10:30	0.0
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03/15/06 22:30	0.0	06/15/06 4:30	0.0	09/14/06 10:30	6.1	12/14/06 16:30	0.0
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03/16/06 4:30	0.0	06/15/06 10:30	0.7	09/14/06 16:30	0.6	12/14/06 22:30	0.0
03/16/06 7:30	0.0	06/15/06 13:30	0.7	09/14/06 19:30	1.6	12/15/06 1:30	0.0
03/16/06 10:30	0.0	06/15/06 16:30	0.0	09/14/06 22:30	0.0	12/15/06 4:30	0.0
03/16/06 13:30	0.0	06/15/06 19:30	0.0	09/15/06 1:30	0.0	12/15/06 7:30	0.0
03/16/06 16:30	0.0	06/15/06 22:30	0.0	09/15/06 4:30	0.0	12/15/06 10:30	0.0
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03/16/06 22:30	0.0	06/16/06 4:30	0.0	09/15/06 10:30	3.5	12/15/06 16:30	0.0
03/17/06 1:30	0.0	06/16/06 7:30	0.0	09/15/06 13:30	2.5	12/15/06 19:30	0.0
03/17/06 4:30	0.0	06/16/06 10:30	9.5	09/15/06 16:30	0.7	12/15/06 22:30	0.0
03/17/06 7:30	0.0	06/16/06 13:30	1.8	09/15/06 19:30	0.0	12/16/06 1:30	0.0
03/17/06 10:30	0.0	06/16/06 16:30	0.0	09/15/06 22:30	0.0	12/16/06 4:30	0.0
03/17/06 13:30	0.0	06/16/06 19:30	0.0	09/16/06 1:30	0.0	12/16/06 7:30	0.0
03/17/06 16:30	0.0	06/16/06 22:30	0.0	09/16/06 4:30	0.0	12/16/06 10:30	0.0
03/17/06 19:30	0.0	06/17/06 1:30	0.0	09/16/06 7:30	2.5	12/16/06 13:30	0.0
03/17/06 22:30	0.0	06/17/06 4:30	0.0	09/16/06 10:30	2.7	12/16/06 16:30	0.0
03/18/06 1:30	0.0	06/17/06 7:30	3.0	09/16/06 13:30	0.7	12/16/06 19:30	0.0
03/18/06 4:30	0.0	06/17/06 10:30	2.2	09/16/06 16:30	0.0	12/16/06 22:30	0.0
03/18/06 7:30	0.0	06/17/06 13:30	0.0	09/16/06 19:30	0.0	12/17/06 1:30	0.0
03/18/06 10:30	0.0	06/17/06 16:30	0.0	09/16/06 22:30	0.0	12/17/06 4:30	0.0
03/18/06 13:30	0.0	06/17/06 19:30	0.0	09/17/06 1:30	0.0	12/17/06 7:30	0.0
03/18/06 16:30	0.0	06/17/06 22:30	0.0	09/17/06 4:30	0.0	12/17/06 10:30	0.0

03/18/06 19:30	0.0	06/18/06 1:30	0.0	09/17/06 7:30	0.0	12/17/06 13:30	0.0
03/18/06 22:30	0.0	06/18/06 4:30	0.0	09/17/06 10:30	0.4	12/17/06 16:30	0.0
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03/19/06 4:30	0.0	06/18/06 10:30	0.5	09/17/06 16:30	0.0	12/17/06 22:30	0.0
03/19/06 7:30	0.0	06/18/06 13:30	7.2	09/17/06 19:30	0.0	12/18/06 1:30	0.0
03/19/06 10:30	0.0	06/18/06 16:30	2.1	09/17/06 22:30	0.0	12/18/06 4:30	0.0
03/19/06 13:30	0.0	06/18/06 19:30	0.0	09/18/06 1:30	0.0	12/18/06 7:30	0.0
03/19/06 16:30	0.0	06/18/06 22:30	0.0	09/18/06 4:30	0.0	12/18/06 10:30	0.0
03/19/06 19:30	0.0	06/19/06 1:30	0.0	09/18/06 7:30	0.0	12/18/06 13:30	0.0
03/19/06 22:30	0.0	06/19/06 4:30	0.0	09/18/06 10:30	0.6	12/18/06 16:30	0.0
03/20/06 1:30	0.0	06/19/06 7:30	1.7	09/18/06 13:30	0.2	12/18/06 19:30	0.0
03/20/06 4:30	0.0	06/19/06 10:30	2.5	09/18/06 16:30	0.0	12/18/06 22:30	0.0
03/20/06 7:30	0.0	06/19/06 13:30	0.0	09/18/06 19:30	0.0	12/19/06 1:30	0.0
03/20/06 10:30	0.0	06/19/06 16:30	0.6	09/18/06 22:30	0.0	12/19/06 4:30	0.0
03/20/06 13:30	0.0	06/19/06 19:30	0.0	09/19/06 1:30	0.0	12/19/06 7:30	0.0
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03/20/06 19:30	0.0	06/20/06 1:30	0.0	09/19/06 7:30	0.0	12/19/06 13:30	0.0
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03/21/06 7:30	0.0	06/20/06 13:30	0.0	09/19/06 19:30	1.2	12/20/06 1:30	0.0
03/21/06 10:30	0.0	06/20/06 16:30	1.2	09/19/06 22:30	0.0	12/20/06 4:30	0.0
03/21/06 13:30	0.0	06/20/06 19:30	0.0	09/20/06 1:30	0.0	12/20/06 7:30	0.0
03/21/06 16:30	0.0	06/20/06 22:30	0.0	09/20/06 4:30	0.0	12/20/06 10:30	0.0
03/21/06 19:30	0.0	06/21/06 1:30	0.0	09/20/06 7:30	0.0	12/20/06 13:30	0.0
03/21/06 22:30	0.0	06/21/06 4:30	0.0	09/20/06 10:30	0.0	12/20/06 16:30	0.0
03/22/06 1:30	0.0	06/21/06 7:30	0.0	09/20/06 13:30	2.4	12/20/06 19:30	0.0
03/22/06 4:30	0.0	06/21/06 10:30	0.5	09/20/06 16:30	0.0	12/20/06 22:30	0.0
03/22/06 7:30	0.0	06/21/06 13:30	0.0	09/20/06 19:30	0.0	12/21/06 1:30	0.0
03/22/06 10:30	0.0	06/21/06 16:30	6.0	09/20/06 22:30	0.0	12/21/06 4:30	0.0
03/22/06 13:30	0.0	06/21/06 19:30	0.0	09/21/06 1:30	0.0	12/21/06 7:30	0.0
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03/22/06 19:30	0.0	06/22/06 1:30	0.0	09/21/06 7:30	0.0	12/21/06 13:30	0.0
03/22/06 22:30	0.0	06/22/06 4:30	0.0	09/21/06 10:30	0.6	12/21/06 16:30	0.0
03/23/06 1:30	0.0	06/22/06 7:30	0.0	09/21/06 13:30	0.0	12/21/06 19:30	0.0
03/23/06 4:30	0.0	06/22/06 10:30	6.0	09/21/06 16:30	0.0	12/21/06 22:30	0.0
03/23/06 7:30	0.0	06/22/06 13:30	7.6	09/21/06 19:30	0.0	12/22/06 1:30	0.0
03/23/06 10:30	0.0	06/22/06 16:30	9.5	09/21/06 22:30	0.0	12/22/06 4:30	0.0
03/23/06 13:30	0.0	06/22/06 19:30	3.5	09/22/06 1:30	0.0	12/22/06 7:30	0.0
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03/24/06 4:30	0.0	06/23/06 10:30	0.0	09/22/06 16:30	0.0	12/22/06 22:30	0.0
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03/24/06 10:30	0.0	06/23/06 16:30	0.0	09/22/06 22:30	0.0	12/23/06 4:30	0.0

03/24/06 13:30	0.0	06/23/06 19:30	3.0	09/23/06 1:30	0.0	12/23/06 7:30	0.0
03/24/06 16:30	0.0	06/23/06 22:30	1.7	09/23/06 4:30	0.0	12/23/06 10:30	0.0
03/24/06 19:30	0.0	06/24/06 1:30	0.0	09/23/06 7:30	0.0	12/23/06 13:30	0.0
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03/25/06 7:30	0.0	06/24/06 13:30	0.0	09/23/06 19:30	0.0	12/24/06 1:30	0.0
03/25/06 10:30	0.0	06/24/06 16:30	0.0	09/23/06 22:30	0.0	12/24/06 4:30	0.0
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03/27/06 10:30	0.0	06/26/06 16:30	0.0	09/25/06 22:30	0.0	12/26/06 4:30	0.0
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03/28/06 10:30	0.0	06/27/06 16:30	0.0	09/26/06 22:30	0.0	12/27/06 4:30	0.0
03/28/06 13:30	0.0	06/27/06 19:30	0.0	09/27/06 1:30	0.0	12/27/06 7:30	0.0
03/28/06 16:30	0.0	06/27/06 22:30	0.0	09/27/06 4:30	0.0	12/27/06 10:30	0.0
03/28/06 19:30	0.0	06/28/06 1:30	0.0	09/27/06 7:30	0.0	12/27/06 13:30	0.0
03/28/06 22:30	0.0	06/28/06 4:30	0.0	09/27/06 10:30	0.0	12/27/06 16:30	0.0
03/29/06 1:30	0.0	06/28/06 7:30	0.4	09/27/06 13:30	0.0	12/27/06 19:30	0.0
03/29/06 4:30	0.0	06/28/06 10:30	0.0	09/27/06 16:30	0.0	12/27/06 22:30	0.0
03/29/06 7:30	0.0	06/28/06 13:30	0.0	09/27/06 19:30	0.0	12/28/06 1:30	0.0
03/29/06 10:30	0.0	06/28/06 16:30	0.0	09/27/06 22:30	0.0	12/28/06 4:30	0.0
03/29/06 13:30	0.0	06/28/06 19:30	0.0	09/28/06 1:30	0.0	12/28/06 7:30	0.0
03/29/06 16:30	0.0	06/28/06 22:30	0.0	09/28/06 4:30	0.0	12/28/06 10:30	0.0
03/29/06 19:30	0.0	06/29/06 1:30	0.0	09/28/06 7:30	0.0	12/28/06 13:30	0.0
03/29/06 22:30	0.0	06/29/06 4:30	0.0	09/28/06 10:30	0.0	12/28/06 16:30	0.0
03/30/06 1:30	0.0	06/29/06 7:30	0.0	09/28/06 13:30	0.0	12/28/06 19:30	0.0
03/30/06 4:30	0.0	06/29/06 10:30	0.0	09/28/06 16:30	0.0	12/28/06 22:30	0.0

03/30/06 7:30	0.0	06/29/06 13:30	0.0	09/28/06 19:30	0.0	12/29/06 1:30	0.0
03/30/06 10:30	0.0	06/29/06 16:30	0.3	09/28/06 22:30	0.0	12/29/06 4:30	0.0
03/30/06 13:30	0.0	06/29/06 19:30	1.2	09/29/06 1:30	0.0	12/29/06 7:30	0.0
03/30/06 16:30	0.0	06/29/06 22:30	0.6	09/29/06 4:30	0.0	12/29/06 10:30	0.0
03/30/06 19:30	0.0	06/30/06 1:30	0.0	09/29/06 7:30	0.0	12/29/06 13:30	0.0
03/30/06 22:30	0.0	06/30/06 4:30	0.0	09/29/06 10:30	0.0	12/29/06 16:30	0.0
03/31/06 1:30	0.0	06/30/06 7:30	0.0	09/29/06 13:30	0.0	12/29/06 19:30	0.0
03/31/06 4:30	0.0	06/30/06 10:30	0.0	09/29/06 16:30	0.0	12/29/06 22:30	0.0
03/31/06 7:30	0.0	06/30/06 13:30	0.0	09/29/06 19:30	0.0	12/30/06 1:30	0.0
03/31/06 10:30	0.0	06/30/06 16:30	0.0	09/29/06 22:30	0.0	12/30/06 4:30	0.0
03/31/06 13:30	0.0	06/30/06 19:30	0.4	09/30/06 1:30	0.0	12/30/06 7:30	0.0
03/31/06 16:30	0.0	06/30/06 22:30	0.0	09/30/06 4:30	0.0	12/30/06 10:30	0.0
03/31/06 19:30	0.0	07/01/06 1:30	1.1	09/30/06 7:30	0.0	12/30/06 13:30	0.0
03/31/06 22:30	0.0	07/01/06 4:30	3.7	09/30/06 10:30	0.0	12/30/06 16:30	0.0
04/01/06 1:30	0.0	07/01/06 7:30	0.5	09/30/06 13:30	0.0	12/30/06 19:30	0.0
04/01/06 4:30	0.0	07/01/06 10:30	0.0	09/30/06 16:30	3.2	12/30/06 22:30	0.0
04/01/06 7:30	0.0	07/01/06 13:30	0.0	09/30/06 19:30	0.6	12/31/06 1:30	0.0
04/01/06 10:30	0.0	07/01/06 16:30	0.0	09/30/06 22:30	0.0	12/31/06 4:30	0.0
04/01/06 13:30	0.0	07/01/06 19:30	0.0	10/01/06 1:30	0.0	12/31/06 7:30	0.0
04/01/06 16:30	0.0	07/01/06 22:30	0.0	10/01/06 4:30	0.0	12/31/06 10:30	0.0
04/01/06 19:30	0.0	07/02/06 1:30	0.0	10/01/06 7:30	0.0	12/31/06 13:30	0.0
04/01/06 22:30	0.0	07/02/06 4:30	0.1	10/01/06 10:30	0.0	12/31/06 16:30	0.0
04/02/06 1:30	0.0	07/02/06 7:30	3.3	10/01/06 13:30	0.0	12/31/06 19:30	0.0
04/02/06 4:30	0.0	07/02/06 10:30	2.5	10/01/06 16:30	0.0	12/31/06 22:30	0.0

Similarly, TRMM rainfall data was obtained for all grids for the year 1998 to 2012.

## APPENDIX – F

This appendix represents the three different cropping patterns used for study of irrigation water demand- deficit and water allocation scenarios under MIKE HYDRO Basin model

1. Multicrop Cropping Pattern
2. Major Crops Cropping Pattern
3. Sugarcane only Cropping Pattern

**Table F.1 Multicrop Cropping Pattern**

Season	Crops	Area (%)
Kharif	Jowar	10
	Bajara	5
	Soybean	3
	Groundnut	5
Rabi	Jowar	25
	Wheat	8
	Gram	5
Summer	Sunflower	20
	Cotton	2
	Maize	5
Perennial	Sugarcane	12

**Table F.2 Major Crops Cropping Pattern**

Season	Crops	Area (%)
Kharif	Bajara	50
Rabi	Jowar	50
Summer	Maize	50
Perennial	Sugarcane	50

**Sugarcane only Cropping Pattern = Total Area 100%**

## APPENDIX – G

### Crop data used as input for the MIKE HYDRO Basin model for estimation of irrigation water demand

		% Area	Sowing Dates	Crop period	Day length				Kcb			Root Depth	
					Initial	Development	Mid	Late	Initial	Mid	Late	Initial	Mid
<b>Kharif</b>	<b>Jowar</b>	13	16-Jun	125	20	35	40	30	0.1	0.95	0.35	100	1200
	<b>Bajara</b>	5	16-Jun	105	15	25	40	25	0.15	0.95	0.2	100	1000
	<b>Soybean</b>	5	20-Jun	150	20	25	75	30	0.5	1.15	0.5	100	1000
	<b>Cotton</b>	7	01-May	195	30	50	60	55	0.3	0.9	0.65	200	1300
<b>Rabi</b>	<b>Jowar</b>	22	01-Sep	105	15	25	40	25	0.1	0.95	0.35	100	1200
	<b>Wheat</b>	13	01-Nov	160	15	25	90	30	0.15	1.1	0.3	100	900
	<b>Gram</b>	5	10-Oct	100	20	30	30	20	0.15	1	0.55	50	500
<b>Summer</b>	<b>Sunflower</b>	8	20-Feb	130	25	35	45	25	0.15	1.1	0.25	80	1000
	<b>Groundnut</b>	5	16-Jan	120	20	30	45	25	0.35	1.1	0.5	100	600
	<b>Maize</b>	5	01-Jan	130	25	35	40	30	0.15	1.15	0.5	100	1200
<b>Perennial</b>	<b>Sugarcane</b>	12	10-Jan	320	30	50	180	60	0.15	1.2	0.7	150	1500

		Depletion	Crop height (m)	Ky				Potential yield kg/ha
				Initial	Development	Mid	Late	
<b>Kharif</b>	<b>Jowar</b>	0.55	1.5	0.2	0.55	0.45	0.2	1500
	<b>Bajara</b>	0.55	1.5	0.2	0.55	0.45	0.2	1500
	<b>Soybean</b>	0.5	0.8	0.2	0.8	0.1	0.2	1400
	<b>Cotton</b>	0.5	1.2	0.2	0.5	0.45	0.2	500
<b>Rabi</b>	<b>Jowar</b>	0.55	1.5	0.2	0.55	0.45	0.2	2500
	<b>Wheat</b>	0.5	1	0.2	0.6	0.5	0.2	2400
	<b>Gram</b>	0.45	0.4	0.2	1.1	0.75	0.2	1200
<b>Summer</b>	<b>Sunflower</b>	0.45	2	0.4	0.1	0.8	0.2	1200
	<b>Groundnut</b>	0.4	0.4	0.2	0.8	0.6	0.2	1000
	<b>Maize</b>	0.55	2	0.4	1.5	0.5	0.2	2400
<b>Perennial</b>	<b>Sugarcane</b>	0.65	3	0.75	0.5	0.5	0.1	125000









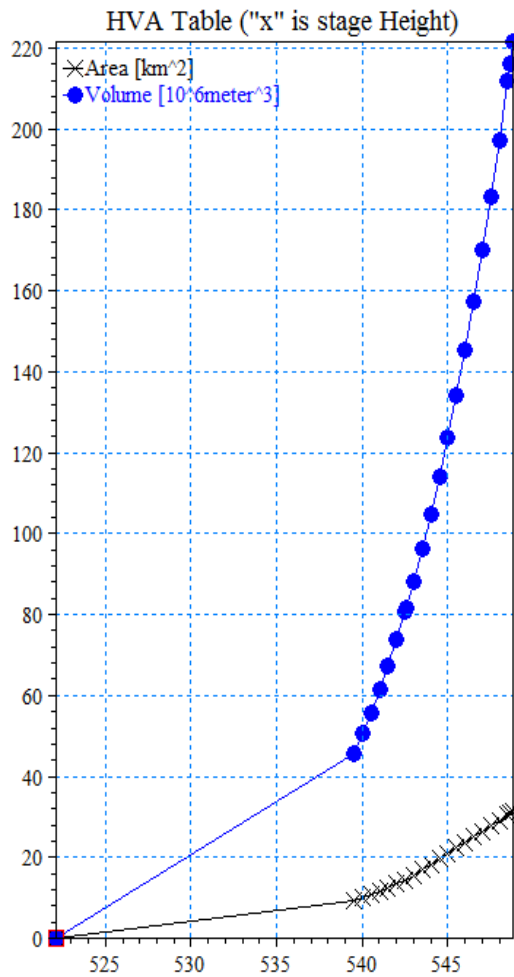






## APPENDIX - I

This appendices represents timeseries of Level-Area-Volume of Ghod reservoir



	x [meter]	1:Area [km <sup>2</sup> ]	2:Volume [10 <sup>6</sup> meter <sup>3</sup> ]
0	522.12	0	0
1	539.5	9.32	45.53
2	540	10.1091	50.4797
3	540.5	10.8983	55.6916
4	541.02	11.719	61.5248
5	541.5	12.5601	67.333
6	542	13.4362	73.7831
7	542.5	14.3124	80.821
8	542.55	14.4	81.545
9	543	15.6208	88.2282
10	543.5	16.9773	96.1684
11	544	18.3338	104.719
12	544.5	19.6903	114.023
13	545	21.0468	123.842
14	545.5	22.4033	134.296
15	546	23.7598	145.4
16	546.5	25.1162	157.17
17	547	26.4727	169.961
18	547.5	27.8292	183.197
19	548	29.1857	197.182
20	548.5	30.5422	211.982
21	548.64	30.922	216.31

**Table I.1 Characteristic levels of different reservoirs.**

Sr. No.	Reservoir	Bottom level (m)	Top of dead storage (m)	Dam crest level (m)
1	Chilewadi	687	703.17	739
2	Dimbhe	655	682.75	719.645
3	Ghod	535	541.02	548.61
4	Manikdoh	667.51	688.75	711.25
5	Pimpalgaonjoga	661.54	682	686.8
6	Wadaj	697.5	704.7	717.53
7	Yedgaon	621.25	634.3	641

**Table I.2 Flood control levels of different reservoir**

Chilewadi		Dimbhe		Ghod		Manikdoh		Pimpalgaonjoga	
1 Jan.	739	1 Jan.	719.145	1 Jan.	548.64	1 Jan.	711.25	1 Jan.	686.8
1 Feb.	739	1 Feb.	719.145	1 Feb.	548.64	1 Feb.	711.25	1 Feb.	686.8
1 March	739	1 March	719.145	1 March	548.64	1 March	711.25	1 March	686.8
1 April	739	1 April	719.145	1 April	548.64	1 April	711.25	1 April	686.8
1 May	739	1 May	719.145	1 May	548.64	1 May	711.25	1 May	686.8
1 June	709	1 June	719.145	1 June	548.64	1 June	708.41	1 June	686.8
16 June	711.96	15 June	714.95	15 June	546.9	15 June	708.41	15 June	685.16
1 July	735.5	30 June	714.95	30 June	546.92	1 July	708.54	30 June	685.21
16 July	735.85	15 July	714.95	15 July	546.96	15 July	708.67	15 July	685.4
1 Aug.	736.3	31 July	714.95	31 July	547.11	1 Aug.	709.67	31 July	685.88
16 Aug.	737.2	15 Aug.	715.7	15 Aug.	547.48	15 Aug.	710.36	15 Aug.	686.5
1 Sept.	738.4	31 Aug.	717.7	31 Aug.	547.84	1 Sept.	710.88	31 Aug.	686.65
16 Sept.	739	15 Sept.	718.8	1 Sept.	548.39	15 Sept.	711.16	15 Sept.	686.77
1 Oct.	739	30 Sept.	719.1	15 Sept.	548.54	30 Sept.	711.23	30 Sept.	686.79
15 Oct.	739	15 Oct.	719.145	1 Oct.	548.64	15 Oct.	711.25	15 Oct.	686.8

<b>Wadaj</b>		<b>Yedgaon</b>	
1 Jan.	717.53	1 Jan.	641
1 Feb.	717.53	1 Feb.	641
1 March	717.53	1 March	641
1 April	717.53	1 April	641
1 May	717.53	1 May	641
1 June	712.5	1 June	641
15 June	712.5	15 June	636
30 June	712.5	30 June	636
15 July	712.5	15 July	636
31 July	712.5	31 July	638.4
15 Aug.	714.93	15 Aug.	639.8
31 Aug.	716.67	31 Aug.	640.3
15 Sept.	717.3	15 Sept.	640.7
30 Sept.	717.53	30 Sept.	640.9
30 Sept.	717.53	30 Sept.	641
15 Oct.	717.53	15 Oct.	641
30 Oct.	717.53	30 Oct.	641

## APPENDIX – J

This appendix presents sample data of the daily values of the climatological parameters used for the present study.

**Table J.1 Shirur weather station data for year 2008**

Date	No. of day in year	Tmax (°C)	Tmin (°C)	RHmax (%)	RHmin (%)	ASSH (hr)	WS (km/hr)	Rainfall (mm)	PE (mm)
1-Jan-09	1	28.8	6.2	92	31	10	0.9	0	NA
2-Jan-09	2	28.5	7.3	95	47	9.7	1.8	0	NA
3-Jan-09	3	28.3	10.3	91	42	9.3	2.9	0	NA
4-Jan-09	4	29.5	11.5	93	50	9.2	3.6	0	NA
5-Jan-09	5	29	12	94	45	8.2	1.4	0	NA
6-Jan-09	6	29	11.6	91	46	8.5	1.9	0	NA
7-Jan-09	7	26.4	10.8	93	43	8.5	2	0	NA
8-Jan-09	8	27.6	12.4	91	45	7.6	2.8	0	NA
9-Jan-09	9	29.2	13	92	43	8.3	5.4	0	NA
10-Jan-09	10	29.4	13.2	92	44	9.2	6.9	0	NA
11-Jan-09	11	29.3	12.6	89	43	8.2	2.4	0	NA
12-Jan-09	12	29.6	13.5	92	42	9	5.1	0	NA
13-Jan-09	13	30.7	14.8	88	40	8.5	6.6	0	NA
14-Jan-09	14	29.8	13.3	89	34	8.8	4.9	0	NA
15-Jan-09	15	29.6	12.8	94	36	9.1	3.7	0	NA
16-Jan-09	16	29.2	13.6	92	35	9.4	8.1	0	NA
17-Jan-09	17	29.6	11.5	93	42	9	3	0	NA
18-Jan-09	18	29.2	11.7	91	40	8.8	3.6	0	NA
19-Jan-09	19	29.6	10.8	87	43	9.2	2.9	0	NA
20-Jan-09	20	29.2	10.3	91	44	8.4	1.3	0	NA
21-Jan-09	21	29.4	10	93	40	9.6	2.1	0	NA
22-Jan-09	22	29.6	9.9	91	39	9.9	1.5	0	NA
23-Jan-09	23	30	9.2	88	39	9.4	1.3	0	NA
24-Jan-09	24	29.8	10.4	91	37	10	0.8	0	NA
25-Jan-09	25	29.6	12.9	93	38	6	1.2	0	NA
26-Jan-09	26	32.1	11.6	89	33	10	2.7	0	NA
27-Jan-09	27	32.6	12	91	33	10.1	2.3	0	NA
28-Jan-09	28	32.8	11.8	87	32	9.8	1.4	0	NA
29-Jan-09	29	32.6	13	87	33	10	1.8	0	NA
30-Jan-09	30	33	14.2	92	32	6.2	1.2	0	NA
31-Jan-09	31	32.8	14.5	88	35	6.1	1.6	0	NA
1-Feb-09	32	32.6	13.2	92	30	9.6	2.1	0	NA
2-Feb-09	33	33.6	11.1	91	30	10.1	1.9	0	NA
3-Feb-09	34	33.4	10.3	89	28	10.3	2.4	0	NA
4-Feb-09	35	33.2	11	87	26	10.2	1.9	0	NA
5-Feb-09	36	34.2	10.8	91	28	10.1	4.2	0	NA
6-Feb-09	37	32	11.2	89	32	10.1	1.9	0	NA
7-Feb-09	38	31.8	10.7	91	35	10.2	2.1	0	NA

8-Feb-09	39	30.8	12.2	89	33	9.9	3.1	0	NA
9-Feb-09	40	33	13.3	88	30	9.8	2.2	0	NA
10-Feb-09	41	33.1	12.8	92	34	9.2	2.1	0	NA
11-Feb-09	42	29.9	8.7	90	42	9.3	2.6	0	NA
12-Feb-09	43	28.2	9.3	93	38	10	2.6	0	NA
13-Feb-09	44	29.2	10.4	91	34	10.3	2.6	0	NA
14-Feb-09	45	31.5	9.3	36	22	10	2.3	0	NA
15-Feb-09	46	30.4	11.8	89	34	10	2.3	0	NA
16-Feb-09	47	31	12.2	87	37	10	2.4	0	NA
17-Feb-09	48	31.7	14.3	88	34	9.4	3.3	0	NA
18-Feb-09	49	33.6	15.4	86	31	8.5	4.4	0	NA
19-Feb-09	50	34	13.8	88	33	9.3	2	0	NA
20-Feb-09	51	33.1	15.2	86	32	9.4	3	0	NA
21-Feb-09	52	34	16.8	87	31	9	3.5	0	NA
22-Feb-09	53	34.4	15.4	86	29	9.3	3.2	0	NA
23-Feb-09	54	35.1	15.7	87	27	9.4	1.3	0	NA
24-Feb-09	55	34.8	14.2	88	28	9.8	3.1	0	NA
25-Feb-09	56	35.2	11.4	91	29	10.4	3.5	0	NA
26-Feb-09	57	33.6	12.2	87	27	10.5	2.3	0	NA
27-Feb-09	58	35	13.1	88	28	10.7	2.2	0	NA
28-Feb-09	59	35.6	13.5	86	27	10.4	2.4	0	NA
1-Mar-09	60	35.4	13	85	26	10.6	3.8	0	NA
2-Mar-09	61	34.8	14.2	86	25	10.1	2.1	0	NA
3-Mar-09	62	35.6	14	86	24	10.2	2.3	0	NA
4-Mar-09	63	36.6	13.4	88	26	10.7	2.5	0	NA
5-Mar-09	64	36.4	13	89	25	10.2	2.6	0	NA
6-Mar-09	65	36.6	14.3	86	26	10	4.3	0	NA
7-Mar-09	66	35.2	15.1	88	28	9.8	2.9	0	NA
8-Mar-09	67	34.4	14.6	84	26	10.1	3.9	0	NA
9-Mar-09	68	35.6	15	90	30	8.8	2.3	0	NA
10-Mar-09	69	35.1	17.5	93	28	9.5	4.5	0	NA
11-Mar-09	70	35.5	18.3	91	26	7.9	91	0	NA
12-Mar-09	71	35.6	17.8	89	26	10.1	4.3	0	NA
13-Mar-09	72	36.4	16.6	92	35	8.3	3	0	NA
14-Mar-09	73	34.6	14.3	94	37	0.9	5.1	0	NA
15-Mar-09	74	33.4	15.1	92	39	8	10	0	NA
16-Mar-09	75	32.6	14.7	88	29	9.5	3.8	0	NA
17-Mar-09	76	33.6	14	90	24	9.8	3.7	0	NA
18-Mar-09	77	34.7	15.6	86	25	10.1	3	0	NA
19-Mar-09	78	35	15.2	88	23	10	4.3	0	NA
20-Mar-09	79	34.8	15.4	86	24	9.9	3.4	0	NA
21-Mar-09	80	35.1	14.7	88	24	10	4.6	0	NA
22-Mar-09	81	34.4	15	86	25	10.5	4.5	0	NA
23-Mar-09	82	34.8	15.6	85	27	10.4	4.9	0	NA
24-Mar-09	83	35	16.8	82	25	9.7	5.2	0	NA
25-Mar-09	84	35.7	17	82	25	9.7	5.2	0	NA
26-Mar-09	85	35.6	15.7	86	24	10.1	3.9	0	NA

27-Mar-09	86	35.4	14.7	88	24	10.3	4.3	0	NA
28-Mar-09	87	35.5	15	88	23	10.1	3.3	0	NA
29-Mar-09	88	36.4	17.1	87	22	9.6	3.7	0	NA
30-Mar-09	89	36.6	16.4	85	22	10.4	3.5	0	NA
31-Mar-09	90	37.2	17.6	85	20	10.4	3.3	0	8.8
1-Apr-09	91	37.6	17.4	87	19	10.6	4	0	8.2
2-Apr-09	92	38.1	17.8	86	18	10.1	3.6	0	9.1
3-Apr-09	93	38.6	19.4	84	19	10	3.4	0	9.8
4-Apr-09	94	39.4	19.8	85	20	8.9	3.6	0	8
5-Apr-09	95	38.6	20.3	90	22	8.9	2.8	0	9.4
6-Apr-09	96	38.2	20.6	91	21	8.2	5.2	0	9.5
7-Apr-09	97	37.3	20.1	88	24	10.3	5.1	0	8.6
8-Apr-09	98	37.4	21.2	93	25	8.4	5.6	0	8
9-Apr-09	99	37	15.6	92	22	10.6	7.2	0	9.6
10-Apr-09	100	36.8	16.4	89	20	11.2	4.3	0	8.4
11-Apr-09	101	37.6	17.2	89	20	10.9	5	0	9.8
12-Apr-09	102	38.2	18.5	87	24	10.7	4.2	0	9.1
13-Apr-09	103	38.8	19.6	88	23	7.9	3.5	0	9.9
14-Apr-09	104	39.2	20	90	20	10.6	3.8	0	8.8
15-Apr-09	105	38.7	19.4	86	22	10.6	6.6	0	8.2
16-Apr-09	106	38.4	20.2	88	23	10.7	7	0	10.9
17-Apr-09	107	37.2	22.7	90	23	9.4	8.4	0	8.4
18-Apr-09	108	37.5	20.4	86	19	9.4	4.9	0	10.6
19-Apr-09	109	39.6	19.8	91	18	9.7	4.9	0	9.6
20-Apr-09	110	40	20.1	85	21	10.9	3.8	0	8.8
21-Apr-09	111	40.2	22.4	90	22	10.6	7.6	0	9.9
22-Apr-09	112	39.9	21.5	93	14	8.9	6.9	0	10.3
23-Apr-09	113	38.8	20	93	20	9.1	7.3	0	10.1
24-Apr-09	114	37.8	20.2	88	19	10.5	5.7	0	11.6
25-Apr-09	115	37.6	20.5	85	17	8.3	5.7	0	9.8
26-Apr-09	116	38.5	21	86	21	10	5.9	0	10.6
27-Apr-09	117	39.2	21.3	83	17	10.8	3.7	0	10
28-Apr-09	118	40.6	21.7	87	18	10.7	5	0	10.2
29-Apr-09	119	41.1	20.8	86	16	10.9	3.7	0	10.6
30-Apr-09	120	41.6	21	85	16	9.4	4.8	0	9.8
1-May-09	121	41.2	21.4	85	20	9.7	7.5	0	11.6
2-May-09	122	40.6	20.9	85	21	10.1	8.7	0	11.4
3-May-09	123	40.7	21.5	87	18	10.9	9.5	0	11.2
4-May-09	124	40.4	21	80	17	11	9.5	0	11.4
5-May-09	125	40.2	21.3	82	19	11.1	7.5	0	11
6-May-09	126	39.6	21.8	48	21	10.3	8.2	0	10.6
7-May-09	127	38.8	22.3	81	19	10.6	8.1	0	10.8
8-May-09	128	39.2	22.4	79	21	10.7	6.2	0	9.8
9-May-09	129	39.3	20.7	80	17	10.9	5.5	0	9.6
10-May-09	130	39.7	21.4	79	16	11.2	7.9	0	11.6
11-May-09	131	40.1	20	41	17	11.3	9.6	0	11.3
12-May-09	132	39.6	19.9	84	13	11.5	9.8	0	12

13-May-09	133	40.7	20.6	82	18	11.6	8.1	0	11.6
14-May-09	134	40.4	22	81	18	11.1	9.4	0	10.8
15-May-09	135	40.2	22.6	78	17	10.4	8.8	0	10.9
16-May-09	136	40.5	21.8	79	19	9.2	10.5	0	9.7
17-May-09	137	40.2	22.7	76	21	10.3	9.9	0	10.6
18-May-09	138	40.3	23.2	80	21	10.8	12.3	0	11.9
19-May-09	139	39.4	24	81	28	8.7	6.6	0	8.6
20-May-09	140	39.4	24.2	80	29	8.6	10.7	0	9.8
21-May-09	141	36.8	22.1	89	31	5.5	16.1	0	7.4
22-May-09	142	37	24.2	80	32	10.4	9.9	0	9.2
23-May-09	143	37.6	22.3	87	30	8.2	11.7	0	8.3
24-May-09	144	38.5	22.8	85	26	9.6	12.7	0	9.8
25-May-09	145	38	21.4	88	24	9.2	12.5	0	9.4
26-May-09	146	37.8	22.5	82	24	12.3	10.7	0	10.7
27-May-09	147	38.6	22.8	85	26	9.7	11.1	0	9.6
28-May-09	148	38.8	21.7	87	22	10.4	8.1	0	8.4
29-May-09	149	39	21.3	90	23	10.5	9.8	0	9.3
30-May-09	150	38.6	21.8	87	24	10.7	10.1	0	10.5
31-May-09	151	38.5	22.2	88	26	11.3	11.9	0	9.1
1-Jun-09	152	37.6	23.4	87	25	10.3	12.2	0	9.8
2-Jun-09	153	37.4	22.9	86	31	11	12.9	0	10
3-Jun-09	154	37.1	22.5	89	34	9.9	11.1	0	10.6
4-Jun-09	155	36.6	22.8	90	38	10.7	10.7	0	9.1
5-Jun-09	156	36.4	23.2	92	35	10.7	12.2	0	9.6
6-Jun-09	157	37.4	22.5	93	36	10.2	8.9	0	9.4
7-Jun-09	158	36.8	21.8	95	52	8.1	10.3	31	6.4
8-Jun-09	159	32.4	20.7	93	34	0.9	6.9	10	2.4
9-Jun-09	160	34.8	21.4	93	30	11.1	9.6	0	2.1
10-Jun-09	161	36.4	22.1	90	33	10.9	7.6	0	4.3
11-Jun-09	162	36.8	23.3	94	32	10.2	9.5	0	10.1
12-Jun-09	163	37.2	23.5	90	41	10.1	13.2	2	9.2
13-Jun-09	164	35.4	21.8	93	34	10.5	10	0	10
14-Jun-09	165	36.8	23.1	95	31	10.1	8.2	0	9.6
15-Jun-09	166	37.2	22.8	93	29	9.2	9.9	0	10.2
16-Jun-09	167	37.5	22.2	95	32	9.4	11.3	0	9.3
17-Jun-09	168	36.7	21.8	93	33	10.6	8.1	0	9.8
18-Jun-09	169	37.2	24	94	41	10.2	8.9	0	10.6
19-Jun-09	170	37	22.9	97	49	9.5	8.9	2	7.8
20-Jun-09	171	33.2	21.6	93	44	8.4	6.7	2	3.8
21-Jun-09	172	35.4	22	97	41	5.9	4.8	56	5.4
22-Jun-09	173	35.8	22.2	95	44	5	9.3	0	5
23-Jun-09	174	32.7	21.8	93	52	4.1	6.5	0	8.6
24-Jun-09	175	33.4	22.1	95	52	4	12.3	0	9.4
25-Jun-09	176	32.8	21.6	93	51	5.4	12.6	0	10.8
26-Jun-09	177	33.8	22.5	95	54	4.8	9.9	0	10
27-Jun-09	178	33.4	22	97	50	4.4	11.6	0	8.2
28-Jun-09	179	34.2	23.6	94	59	4.5	10.6	0	7.8

29-Jun-09	180	31.5	23.2	95	55	4.3	10.8	0	6.8
30-Jun-09	181	32.4	23.4	94	50	4.6	9.3	0	9.6
1-Jul-09	182	33.6	22.7	92	50	4.4	6.4	0	7.2
2-Jul-09	183	34	22.8	83	50	4.7	7.7	0	0
3-Jul-09	184	32.8	22.5	89	57	4.3	15	0	0
4-Jul-09	185	31.2	22.8	97	62	3.3	13.5	0	0
5-Jul-09	186	30.2	22	95	58	4.3	13.3	0	0
6-Jul-09	187	31.2	21.5	95	72	4.7	6.2	10	0
7-Jul-09	188	29.8	23.4	94	64	4.8	4.1	0	0
8-Jul-09	189	31	21.9	95	76	3.5	5.7	62	0
9-Jul-09	190	31.6	22.1	93	75	3.3	5.2	0	4.1
10-Jul-09	191	27.8	22	95	65	3.9	6.9	0	1.9
11-Jul-09	192	30.5	22.2	93	63	4.7	12.4	0	5.3
12-Jul-09	193	30.2	22.5	90	61	3.6	13.2	0	6.2
13-Jul-09	194	31	22.6	95	62	3.5	15.1	0	7.3
14-Jul-09	195	31.3	23	90	71	3.7	15.2	0	5.9
15-Jul-09	196	29.6	22.2	95	85	2.7	11.5	3	5.1
16-Jul-09	197	27	22.1	93	70	3	12.4	0	1.9
17-Jul-09	198	28.8	21.8	90	64	3	12.4	2	3.8
18-Jul-09	199	31.2	22.9	95	62	3.5	17.9	0	5.6
19-Jul-09	200	31.4	22.5	93	66	3.8	18.1	0	4.8
20-Jul-09	201	30.9	23	95	91	3.3	16	0	4.2
21-Jul-09	202	29.4	22.4	97	75	4.1	10.2	2	2.8
22-Jul-09	203	28.8	22	97	95	4.2	11.6	6	1.9
23-Jul-09	204	25	21.7	93	75	3.3	11.7	9	1.2
24-Jul-09	205	28.8	21.9	95	74	3.3	19.8	0	5.3
25-Jul-09	206	29.7	22.1	95	94	4.7	18.4	0	5.9
26-Jul-09	207	30	22.3	92	71	3.9	14.1	0	6.4
27-Jul-09	208	30.1	22	93	63	3.5	15.1	0	5.9
28-Jul-09	209	31.2	22.3	95	73	3.5	16.2	0	5.7
29-Jul-09	210	29.8	21.5	93	64	3.8	13.4	0	6.4
30-Jul-09	211	31	21.6	98	66	4.3	11.4	0	4.8
31-Jul-09	212	30.4	21	97	66	3.9	8.5	0	3.6
1-Aug-09	213	31.4	21.2	95	71	3.6	10.2	0	4
2-Aug-09	214	29.6	20.9	93	62	3.3	9.4	0	3.2
3-Aug-09	215	30.8	20.4	90	62	3	10	0	3.9
4-Aug-09	216	31.6	20.8	95	63	3.2	11.2	0	4.4
5-Aug-09	217	31.4	21.5	93	62	4.2	15	0	5.6
6-Aug-09	218	31.5	21.7	92	63	4.1	14.5	0	5.1
7-Aug-09	219	31.2	22	95	61	3.4	14.4	0	4.3
8-Aug-09	220	31.4	22.4	97	60	4.1	13.7	0	3.2
9-Aug-09	221	32.2	21.6	93	59	3.4	11	0	4
10-Aug-09	222	32.3	21.8	92	58	3.6	9.4	0	3.8
11-Aug-09	223	32.5	22.1	95	63	3.3	9	0	3.1
12-Aug-09	224	30.2	22.4	93	60	2.9	6.5	3	2.9
13-Aug-09	225	32	22.2	95	61	3.1	8.9	10	1.8
14-Aug-09	226	33.2	20.9	93	59	4.1	8.9	0	3.9

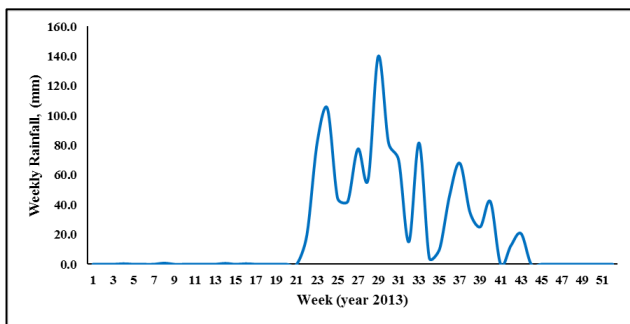
15-Aug-09	227	32.4	23.2	94	62	4.2	10.2	0	3.6
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17-Aug-09	229	32.8	21.7	95	57	4.6	7.3	0	3.4
18-Aug-09	230	31.6	22.1	93	61	5	4.1	15	3.6
19-Aug-09	231	31.4	21.8	97	58	3.8	5.3	5	5.4
20-Aug-09	232	32.6	22	95	73	5	3.2	0	4.2
21-Aug-09	233	29.7	21.5	97	71	5.3	2.9	40	0.8
22-Aug-09	234	29.4	21.8	95	68	4	2	7	2.6
23-Aug-09	235	30.2	21	97	70	4.8	2.9	68	2.8
24-Aug-09	236	30.1	21.7	95	77	5.2	2.8	46	3
25-Aug-09	237	29.1	20.8	93	71	6.6	3.3	0	0.5
26-Aug-09	238	29.1	20.8	93	71	5.5	2.7	2	3.8
27-Aug-09	239	29.8	21.3	92	68	4.9	9.3	0	3.9
28-Aug-09	240	27.4	21	98	93	4.3	1.3	0	2.6
29-Aug-09	241	28.9	21.4	93	67	3.9	7.3	5	3
30-Aug-09	242	30.2	22.1	95	64	4.6	11.7	2	2.6
31-Aug-09	243	30.4	21.2	92	60	3.5	9.3	0	3.2
1-Sep-09	244	31.1	22	90	71	4.4	4.9	0	2.8
2-Sep-09	245	29.8	22.2	95	73	5.2	3.5	5	4.2
3-Sep-09	246	28.4	21.6	93	75	5	5.3	4	2.1
4-Sep-09	247	28.6	21.8	95	90	4.4	4.9	26	2.9
5-Sep-09	248	26.2	22	95	71	5	6.4	3	1.7
6-Sep-09	249	29.6	21.1	93	81	6	5.8	2	2.4
7-Sep-09	250	30.8	20.6	91	69	5.1	5.3	0	2.3
8-Sep-09	251	29.8	20.2	93	64	5.7	5.7	0	2.9
9-Sep-09	252	31.2	21.4	92	53	6	6	0	3.6
10-Sep-09	253	32.4	20.8	90	56	5.4	5.8	0	4.6
11-Sep-09	254	31.6	21.1	95	79	5.3	2.7	0	3.4
12-Sep-09	255	30.2	20.8	97	69	5.3	2.9	9	2.6
13-Sep-09	256	29.4	21	95	58	5.4	2.4	0	3.2
14-Sep-09	257	32.2	21.6	95	58	6.5	2.8	6	4.8
15-Sep-09	258	32.4	20.7	93	60	6.1	4	0	4
16-Sep-09	259	31.8	21.4	92	59	5.8	7.2	0	4.4
17-Sep-09	260	30.6	20.5	91	60	5.6	1.7	0	3.6
18-Sep-09	261	31	20.1	93	59	10.3	3	0	5.3
19-Sep-09	262	31.6	20.4	91	50	10.3	2.4	0	5.8
20-Sep-09	263	33	20	93	55	9.2	2.6	0	6.2
21-Sep-09	264	33.3	20.2	90	56	7.1	2.3	0	6.6
22-Sep-09	265	32.5	21.7	90	53	6.2	2.8	0	4.2
23-Sep-09	266	33.4	21	90	48	8.9	5.5	0	5.6
24-Sep-09	267	33.5	20.9	90	50	9.1	2.6	0	6.4
25-Sep-09	268	33.7	20.5	90	52	8.8	3.2	0	6.1
26-Sep-09	269	32.9	20.5	90	47	9.5	3.5	0	6.5
27-Sep-09	270	33.5	21	97	52	9.7	4.5	0	6.3
28-Sep-09	271	32.4	21.4	93	51	9.3	5.5	0	4.8
29-Sep-09	272	33.2	21.7	90	49	3.9	7.4	0	4.2
30-Sep-09	273	34.1	23.8	92	54	7.3	9.6	0	4.4

1-Oct-09	274	32.4	21.8	95	50	2.4	6.2	11	5.6
2-Oct-09	275	33	23.2	94	48	6.4	7.8	0	3.8
3-Oct-09	276	34.1	23.4	94	50	7.4	5.8	0	3.4
4-Oct-09	277	34.2	20.8	97	79	4.7	5.1	79	0.9
5-Oct-09	278	27.4	22	93	68	3.1	11.2	0	3.1
6-Oct-09	279	29.6	22.4	95	59	2.7	10	0	3.6
7-Oct-09	280	31.6	20.6	91	81	9.2	7.4	0	4.1
8-Oct-09	281	31.4	20.3	93	52	7.1	3.9	5	4
9-Oct-09	282	31.2	19.4	95	45	10.1	3.5	0	4.4
10-Oct-09	283	31.4	18.2	93	51	10.1	1.8	0	4.8
11-Oct-09	284	31	20	93	48	8	1.9	0	4.2
12-Oct-09	285	31.6	21.1	92	49	9.8	2.1	0	5.2
13-Oct-09	286	32.2	21.4	88	47	9.1	3	0	5.6
14-Oct-09	287	32.4	21	90	44	4.9	2.8	0	4.8
15-Oct-09	288	33	21.2	90	43	8.6	2.3	0	5.1
16-Oct-09	289	32.6	19.8	89	40	9.3	2.4	0	5.6
17-Oct-09	290	32.2	20.4	88	44	9.3	2	0	5.2
18-Oct-09	291	32.8	18.6	91	41	8.2	2.6	0	5.8
19-Oct-09	292	31.8	17.5	89	35	9.7	1.9	0	4.8
20-Oct-09	293	33.2	18.1	93	38	9.9	2	0	5
21-Oct-09	294	33.4	18.5	93	34	10.1	2	0	5.6
22-Oct-09	295	33.6	19.2	89	36	9.9	1.7	0	5.4
23-Oct-09	296	32.4	15.4	90	33	9.7	2.3	0	4.8
24-Oct-09	297	32	14.2	92	30	10	2.5	0	5.2
25-Oct-09	298	32.2	13.4	88	31	10.3	1.8	0	4.9
26-Oct-09	299	31.8	12.7	91	30	10.3	1.8	0	6
27-Oct-09	300	31	11.5	93	28	10.3	2.3	0	5.2
28-Oct-09	301	30.8	11.6	91	27	10.5	3.7	0	5.8
29-Oct-09	302	31.6	12.4	91	27	10.3	3.9	0	5.6
30-Oct-09	303	31.5	12	93	29	9.5	3.3	0	5.3
31-Oct-09	304	32.4	10.5	91	28	9.3	4.9	0	6.1
1-Nov-09	305	32	9.6	86	27	10	3.3	0	6.4
2-Nov-09	306	32.2	9.6	88	26	10.2	2.7	0	5.9
3-Nov-09	307	32	10.4	86	25	10	4.2	0	6
4-Nov-09	308	31.4	10.3	89	27	10.3	4.7	0	6.4
5-Nov-09	309	30.8	12.7	87	28	10.1	3.6	0	6.2
6-Nov-09	310	31.1	16.2	92	29	9.8	4.5	0	6.6
7-Nov-09	311	32.4	16.4	89	29	9.4	3.8	0	6.9
8-Nov-09	312	32	17	91	51	9.6	4.1	0	6.5
9-Nov-09	313	30	20.3	95	87	3.8	4.2	12	4.4
10-Nov-09	314	24.8	20	96	90	3	5.6	16	2.2
11-Nov-09	315	23.2	20	96	95	3.2	13.2	34	0.4
12-Nov-09	316	22.5	21	93	63	2.9	19.7	31	0.2
13-Nov-09	317	28	21.2	96	72	2.8	5.1	0	1.4
14-Nov-09	318	28.2	21	96	70	2.8	1.8	3	2.8
15-Nov-09	319	28	18.2	89	69	3.8	2.4	0	2
16-Nov-09	320	29.5	18.5	95	85	5.4	3.6	34	2.3

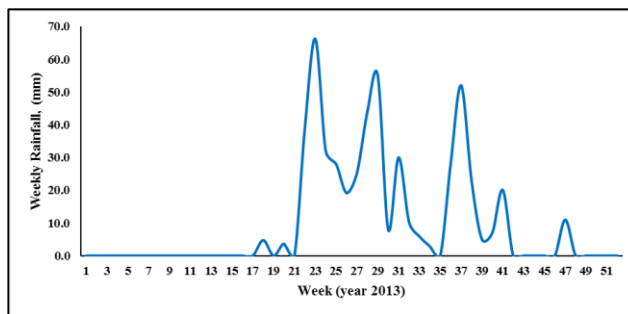
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18-Nov-09	322	25.4	20	93	55	0.3	2	0	2.2
19-Nov-09	323	29	16.3	92	70	8	2	0	2.6
20-Nov-09	324	28	13.4	88	43	7.8	1.8	0	2.9
21-Nov-09	325	28.6	13.5	84	44	10.2	2	0	3.4
22-Nov-09	326	28.2	12.6	87	48	10	1.7	0	3.1
23-Nov-09	327	28	12	93	43	9.9	1.6	0	3.8
24-Nov-09	328	29	12.6	89	39	9.8	2.1	0	3.6
25-Nov-09	329	30.4	13.8	88	37	19.2	1.2	0	3.4
26-Nov-09	330	30.2	14.6	92	38	9.3	1.3	0	3.1
27-Nov-09	331	31.2	15.8	88	39	9.1	1.1	0	3.8
28-Nov-09	332	30.2	14.5	92	39	8.7	2	0	3.6
29-Nov-09	333	28.6	11.2	91	35	9.2	2.1	0	3.3
30-Nov-09	334	27.4	10.7	86	34	9.2	2	0	3.2
1-Dec-09	335	27.3	9.2	88	35	9.6	2.1	0	3.8
2-Dec-09	336	27	8.9	90	34	0.4	2.4	0	3
3-Dec-09	337	28.6	9.8	86	32	9.2	1.6	0	3.3
4-Dec-09	338	30.4	12.7	87	37	8.5	1.9	0	2.9
5-Dec-09	339	30.1	8.7	90	36	8.1	1.9	0	3.4
6-Dec-09	340	30.2	11.4	87	33	6.9	2.5	0	3.6
7-Dec-09	341	30.8	13.2	86	39	8.6	2.7	0	3.7
8-Dec-09	342	30.2	13.8	84	37	8.1	2.1	0	3.9
9-Dec-09	343	30.6	13.5	88	33	9.3	4	0	4.1
10-Dec-09	344	30.8	12.4	87	34	9.6	3.8	0	4.3
11-Dec-09	345	29.8	12	91	40	9.1	2.5	0	3.7
12-Dec-09	346	28.6	11.8	91	41	8.5	3.4	0	3.2
13-Dec-09	347	27.8	11	93	34	8.6	2.9	0	3.8
14-Dec-09	348	30.4	11.6	89	39	8.5	1.8	0	3.3
15-Dec-09	349	30.2	13.8	88	42	8.3	1.9	0	3.5
16-Dec-09	350	30.4	14.2	88	40	7.6	3.3	0	3
17-Dec-09	351	29.8	14.7	86	48	8.1	4	0	3.6
18-Dec-09	352	28.6	13.5	92	50	7.2	3.4	0	3.1
19-Dec-09	353	28.2	13.8	90	43	7.4	3.3	0	2.9
20-Dec-09	354	29.2	13	92	45	7	2.7	0	2.6
21-Dec-09	355	27	13.4	90	52	7.4	3.7	0	2.5
22-Dec-09	356	27	11.8	91	46	5.4	3.5	0	3.2
23-Dec-09	357	27.2	9.9	91	41	8.4	4	0	3.6
24-Dec-09	358	27.6	7.8	90	37	9.2	2	0	3.1
25-Dec-09	359	27	6.6	92	35	9.3	3.2	0	3
26-Dec-09	360	27.4	7.9	88	33	9.7	3.1	0	3.4
27-Dec-09	361	28.4	8.5	90	39	9.2	2.5	0	3.2
28-Dec-09	362	28.6	9.1	90	45	7.3	3.7	0	3.4
29-Dec-09	363	28.8	12.6	91	40	7.7	3	0	3.5
30-Dec-09	364	19	10.3	93	36	6.3	3.6	0	3.3
31-Dec-09	365	27.2	7.1	92	37	9.8	2.6	0	2.9

## APPENDIX – K

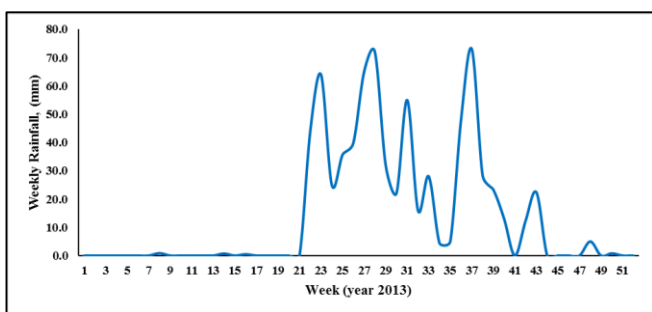
This appendix presents the weekly rainfall forecasted by using ANN 4-10-1 model for different rain gauge stations



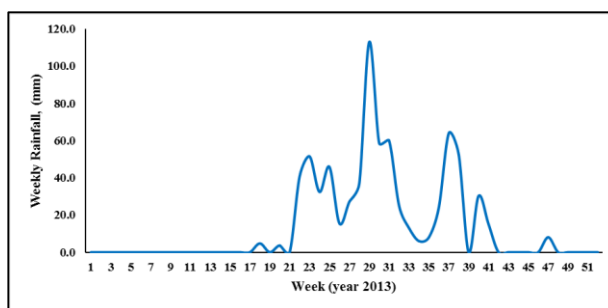
**Figure K.1 Weekly forecasted rainfall of Pimpalgaonjoga for the year 2013**



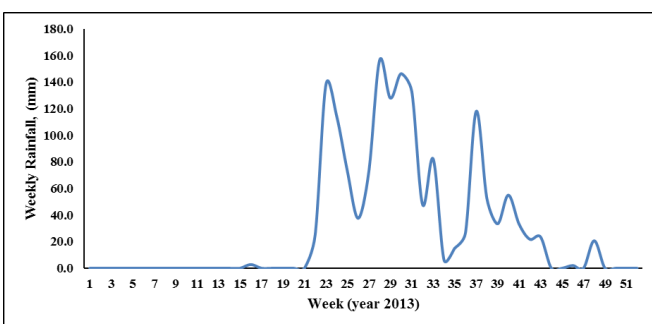
**Figure K.2 Weekly forecasted rainfall of Shirur for the year 2013**



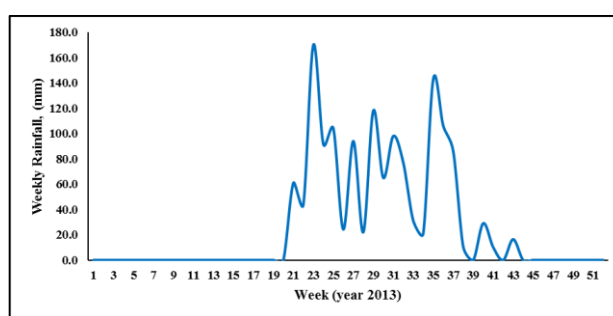
**Figure K.3 Weekly forecasted rainfall of Pimpalwandi for the year 2013**



**Figure K.4 Weekly forecasted rainfall of Kurwandi for the year 2013**



**Figure K.5 Weekly forecasted rainfall of Aundhe for the year 2013**



**Figure K.6 Weekly forecasted rainfall of Savale for the year 2013**

## APPENDIX – L

This appendix presents the daily ETr forecasted by using ANN 4-11-1 model for Shirur station.

01-Jan-13	2.12	05-Feb-13	3.91	12-Mar-13	2.59	16-Apr-13	5.08	21-May-13	6.6
02-Jan-13	2.24	06-Feb-13	3.37	13-Mar-13	2.86	17-Apr-13	5.27	22-May-13	5.86
03-Jan-13	2.41	07-Feb-13	3.3	14-Mar-13	3.91	18-Apr-13	5.53	23-May-13	5.83
04-Jan-13	2.37	08-Feb-13	3.4	15-Mar-13	3.53	19-Apr-13	5.6	24-May-13	6.32
05-Jan-13	2.35	09-Feb-13	3.42	16-Mar-13	3.45	20-Apr-13	5.72	25-May-13	6.1
06-Jan-13	2.32	10-Feb-13	3.83	17-Mar-13	4.09	21-Apr-13	4.31	26-May-13	6.25
07-Jan-13	2.44	11-Feb-13	3.56	18-Mar-13	4.21	22-Apr-13	4.71	27-May-13	6.11
08-Jan-13	2.41	12-Feb-13	3.47	19-Mar-13	4.4	23-Apr-13	4.76	28-May-13	5.83
09-Jan-13	2.49	13-Feb-13	3.69	20-Mar-13	4.56	24-Apr-13	5.48	29-May-13	5.18
10-Jan-13	2.52	14-Feb-13	3.75	21-Mar-13	3.75	25-Apr-13	5	30-May-13	5.3
11-Jan-13	2.37	15-Feb-13	3.36	22-Mar-13	4.14	26-Apr-13	4.99	31-May-13	5.52
12-Jan-13	2.4	16-Feb-13	3.49	23-Mar-13	3.82	27-Apr-13	4.77	01-Jun-13	5.38
13-Jan-13	2.87	17-Feb-13	3.56	24-Mar-13	3.99	28-Apr-13	4.83	02-Jun-13	5.06
14-Jan-13	2.48	18-Feb-13	3.64	25-Mar-13	4.4	29-Apr-13	5.56	03-Jun-13	5.45
15-Jan-13	2.63	19-Feb-13	3.54	26-Mar-13	4.44	30-Apr-13	5.38	04-Jun-13	2.17
16-Jan-13	2.37	20-Feb-13	3.39	27-Mar-13	4.13	01-May-13	5.51	05-Jun-13	4.17
17-Jan-13	2.72	21-Feb-13	4.26	28-Mar-13	4.69	02-May-13	4.9	06-Jun-13	5.54
18-Jan-13	2.46	22-Feb-13	3.84	29-Mar-13	4.41	03-May-13	5.15	07-Jun-13	5.08
19-Jan-13	2.48	23-Feb-13	4.67	30-Mar-13	4.84	04-May-13	5.01	08-Jun-13	6.17
20-Jan-13	2.68	24-Feb-13	4.41	31-Mar-13	5.04	05-May-13	4.32	09-Jun-13	5.97
21-Jan-13	2.57	25-Feb-13	3.82	01-Apr-13	4.71	06-May-13	5.39	10-Jun-13	5.72
22-Jan-13	2.58	26-Feb-13	4.29	02-Apr-13	4.36	07-May-13	5.97	11-Jun-13	5.95
23-Jan-13	3	27-Feb-13	4.3	03-Apr-13	4.73	08-May-13	6.97	12-Jun-13	6.24
24-Jan-13	2.56	28-Feb-13	3.95	04-Apr-13	4.59	09-May-13	4.79	13-Jun-13	5.98
25-Jan-13	2.77	01-Mar-13	3.89	05-Apr-13	6.12	10-May-13	6.42	14-Jun-13	5.62
26-Jan-13	2.58	02-Mar-13	4.05	06-Apr-13	3.97	11-May-13	6.16	15-Jun-13	5.35
27-Jan-13	2.56	03-Mar-13	4	07-Apr-13	4.76	12-May-13	6.04	16-Jun-13	3.3
28-Jan-13	2.56	04-Mar-13	4.04	08-Apr-13	3.67	13-May-13	5.5	17-Jun-13	3.48
29-Jan-13	2.45	05-Mar-13	4.15	09-Apr-13	4.25	14-May-13	6.32	18-Jun-13	3.47
30-Jan-13	2.71	06-Mar-13	4.01	10-Apr-13	4.93	15-May-13	4.38	19-Jun-13	2.9
31-Jan-13	2.67	07-Mar-13	3.71	11-Apr-13	4.66	16-May-13	4.32	20-Jun-13	3.49
01-Feb-13	3.47	08-Mar-13	3.63	12-Apr-13	5.1	17-May-13	3.23	21-Jun-13	4.15
02-Feb-13	4.16	09-Mar-13	3.75	13-Apr-13	4.97	18-May-13	4.03	22-Jun-13	4.5
03-Feb-13	3.25	10-Mar-13	3.66	14-Apr-13	6.01	19-May-13	6.06	23-Jun-13	2.82
04-Feb-13	4.55	11-Mar-13	3.46	15-Apr-13	6.18	20-May-13	4.86	24-Jun-13	3.68

25-Jun-13	3.55	09-Aug-13	3.93	23-Sep-13	2.84	07-Nov-13	3.06	22-Dec-13	2.92
26-Jun-13	3.53	10-Aug-13	4.07	24-Sep-13	3.11	08-Nov-13	3.28	23-Dec-13	3.11
27-Jun-13	3.48	11-Aug-13	4.07	25-Sep-13	3.09	09-Nov-13	2.48	24-Dec-13	2.7
28-Jun-13	4.2	12-Aug-13	3.13	26-Sep-13	3.17	10-Nov-13	1.42	25-Dec-13	2.93
29-Jun-13	3.2	13-Aug-13	3.51	27-Sep-13	3.4	11-Nov-13	2.22	26-Dec-13	2.77
30-Jun-13	2.49	14-Aug-13	4.16	28-Sep-13	3.79	12-Nov-13	2.84	27-Dec-13	2.78
01-Jul-13	2.68	15-Aug-13	3.08	29-Sep-13	3.01	13-Nov-13	2.28	28-Dec-13	3.45
02-Jul-13	3.11	16-Aug-13	2.21	30-Sep-13	3.44	14-Nov-13	2.83	29-Dec-13	3.29
03-Jul-13	2.7	17-Aug-13	3.11	01-Oct-13	2.71	15-Nov-13	1.68	30-Dec-13	3.07
04-Jul-13	2.46	18-Aug-13	2.05	02-Oct-13	2.61	16-Nov-13	1.92		
05-Jul-13	1.69	19-Aug-13	1.54	03-Oct-13	2.46	17-Nov-13	2.85		
06-Jul-13	1.84	20-Aug-13	2.56	04-Oct-13	2.2	18-Nov-13	3.11		
07-Jul-13	2.1	21-Aug-13	1.79	05-Oct-13	1.94	19-Nov-13	3.24		
08-Jul-13	2.37	22-Aug-13	1.85	06-Oct-13	2.06	20-Nov-13	3.21		
09-Jul-13	3.07	23-Aug-13	1.81	07-Oct-13	2.13	21-Nov-13	3.21		
10-Jul-13	3.67	24-Aug-13	3.05	08-Oct-13	2.02	22-Nov-13	3		
11-Jul-13	2.22	25-Aug-13	2.71	09-Oct-13	3.37	23-Nov-13	3.27		
12-Jul-13	1.71	26-Aug-13	2.71	10-Oct-13	3.47	24-Nov-13	3.18		
13-Jul-13	2.46	27-Aug-13	2.71	11-Oct-13	2.84	25-Nov-13	3.38		
14-Jul-13	2.77	28-Aug-13	2.71	12-Oct-13	3.18	26-Nov-13	3.22		
15-Jul-13	4.65	29-Aug-13	3.61	13-Oct-13	3.01	27-Nov-13	3.37		
16-Jul-13	4	30-Aug-13	3.61	14-Oct-13	2.71	28-Nov-13	3.35		
17-Jul-13	2.64	31-Aug-13	3.24	15-Oct-13	2.63	29-Nov-13	3.26		
18-Jul-13	2.33	01-Sep-13	3.06	16-Oct-13	2.82	30-Nov-13	3.29		
19-Jul-13	1.66	02-Sep-13	3.14	17-Oct-13	2.49	01-Dec-13	2.85		
20-Jul-13	1.8	03-Sep-13	1.96	18-Oct-13	3.01	02-Dec-13	2.84		
21-Jul-13	2.62	04-Sep-13	1.64	19-Oct-13	2.99	03-Dec-13	2.5		
22-Jul-13	3.73	05-Sep-13	2.31	20-Oct-13	3.44	04-Dec-13	2.74		
23-Jul-13	3.03	06-Sep-13	1.9	21-Oct-13	3.24	05-Dec-13	2.6		
24-Jul-13	3.68	07-Sep-13	2.3	22-Oct-13	3.65	06-Dec-13	2.88		
25-Jul-13	3.03	08-Sep-13	3.07	23-Oct-13	3.86	07-Dec-13	2.7		
26-Jul-13	3.3	09-Sep-13	3.42	24-Oct-13	3.25	08-Dec-13	2.8		
27-Jul-13	2.6	10-Sep-13	3.44	25-Oct-13	2.11	09-Dec-13	2.78		
28-Jul-13	3.47	11-Sep-13	3.77	26-Oct-13	3.56	10-Dec-13	2.59		
29-Jul-13	3.8	12-Sep-13	3.95	27-Oct-13	3.86	11-Dec-13	2.66		
30-Jul-13	3.44	13-Sep-13	2.46	28-Oct-13	3.74	12-Dec-13	2.82		
31-Jul-13	2.71	14-Sep-13	2.31	29-Oct-13	3.68	13-Dec-13	2.84		
01-Aug-13	3.73	15-Sep-13	1.92	30-Oct-13	3.17	14-Dec-13	2.55		
02-Aug-13	3.06	16-Sep-13	2.93	31-Oct-13	5.13	15-Dec-13	2.83		
03-Aug-13	3.66	17-Sep-13	2.71	01-Nov-13	2.65	16-Dec-13	2.96		
04-Aug-13	3.03	18-Sep-13	3.48	02-Nov-13	3.67	17-Dec-13	2.69		
05-Aug-13	2.91	19-Sep-13	1.95	03-Nov-13	3.47	18-Dec-13	2.59		
06-Aug-13	2.3	20-Sep-13	3.51	04-Nov-13	3.18	19-Dec-13	2.7		
07-Aug-13	4.19	21-Sep-13	3.76	05-Nov-13	3.26	20-Dec-13	3.02		
08-Aug-13	2.32	22-Sep-13	2.54	06-Nov-13	3.15	21-Dec-13	2.82		

## VITAE

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**DOCTOR OF PHILOSOPHY (AGRICULTURAL ENGINEERING)**  
**IN**  
**IRRIGATION AND DRAINAGE ENGINEERING**  
**2020**

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