

# **Design and Implementation of a Generic Methodology for Scenario Development with Assessment over Water Resources**

**THESIS**

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## **CERTIFICATE**

This is to certify that the thesis entitled “**Design and Implementation of a Generic Methodology for Scenario Development with Assessment over Water Resources**” and submitted by **Mr. Gaurav Kumar**, ID No. **2014PHXF0004P** for award of Ph.D. of the Institute embodies original work done by him under my supervision.

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## **ABSTRACT**

Application of scenario planning in various areas of research has undergone a significant evolution in terms of management of the resources. It helps resources be available in future with least complexities. Scenario development for water resources, the most vital source of life, has been considered in the thesis. Water resources are getting extinct gradually due to excessive usage and limited replenishment generating worries for its future availability. Scenarios have been planned considering different possibilities incorporating prediction and simulation with various water balance and climate models. Application of GIS (Geographical Information System) adds another dimension to such models.

Methods encountered in literature are found focusing on either prediction techniques of input variables or derivation of outputs with respect to predicted/defined inputs or both. A proper classification can be done to check which method is used for prediction or derivation. Prediction techniques encountered are found complex having rigorous calculation procedures and difficult to understand. Simpler and easier to apply techniques of prediction can be developed since scenarios can be considered as approximations. Derivation techniques/models determined the states of few of the water resources with respect to predefined scenarios. An integrated state variable model can be developed deriving states of all water resources within a watershed for a random number of scenarios accounting various combinations of predicted input variables. Application of GIS has been found limited to analysis and presentation of the spatial data for water resource scenarios and devoid of prediction. Vector/one-dimensional data prediction techniques employed in scenario development can be employed to predict 2D/3D data.

Focusing primarily on the prediction techniques, a simpler and easier to apply technique for prediction has been developed using systems Input-Output approach of time domain analysis derived from moving average method of forecasting. A case study for the water resource management in semi-arid region of nine villages in the Chirawa block of Rajasthan has been considered to evaluate the method developed with respect to the reasonable results of ground water recharge and demand affected by the climatic variables of rainfall and evaporation. Real data for rainfall, temperature, population, and crop land has been collected for the previous years to validate the model. Normally, scenarios are difficult to validate and primarily generate

reasonable data over a wide range. Cost-benefit analysis has been conducted to suggest the best option from the noticed solutions to compensate water requirement with recharge over the region. The best option is judged in terms of highest volume of water saved and lowest implementation cost incurred from the suggested list of solutions. Prediction of future input variables of rainfall, evaporation, crop water requirement, and population by the generalized equations is found reasonable with an error close to 6%, 7.5%, 7%, and 1% respectively in the business as usual scenario over the nine villages in Chirawa.

Embedded to the prediction technique developed, a state variable model has been designed in MATLAB Simulink that determines the time-invariant states of different water storage components within a watershed for a random number of scenarios. The major storage components comprise of soil, aquifers, reaches, and ponds/reservoirs. Parameters affecting the hydrological system are inputs to the model. The generalized equations developed for prediction are used to predict the input parameters at every time step providing a dynamism in the execution of the model. The model is validated over a village area named Ardawta, Rajasthan (India). Scenarios for the state of ground water level up to the year 2030 have been generated and five among them have been selected from worst to best case situation. The prediction error for the ground water level in business as usual (BAU) scenario using the state variable model developed is found 0.64% with respect to the ground water level data for the year 2016.

Further the prediction technique has been deployed over the raster data in GIS to predict future rainfall and evaporation maps from their historical interpolated maps. State variable approach has been applied to predict the future state of ground water level in the form of ground water level maps affected by predicted rainfall, evaporation and ground water draft parameters from pixel to pixel. Other inputs defining the characteristics of the hydrological region comprise curve number, digital elevation, hydraulic conductivity, and reach distance maps. A dynamic state variable GIS model to generate such scenarios has been developed in python of ArcGIS 10.1. An error of 0.013% between means of predicted and actual interpolated ground water level map of the year 2016 reflects a good estimation. Outputs for the drought, surplus, and business as usual scenarios present that ground water draft has 99% effect while rainfall and evaporation have the effect of 1% only on the ground water level.

Prediction technique developed has proved its significance in the forecast of future input variables for hydrological system observed on the basis of results obtained for the change in ground water level within a lumped state variable model and GIS based distributed model developed covering the physical relations defined for hydrology.

Keywords: *Scenario development, Water resource management, Time series extrapolation, State variable modeling, Geographical information system.*

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# **CHAPTER 1: INTRODUCTION**

## **1.1 Problem statement**

Future estimation and planning is the basic nature of a human being. Generally, people forecast with their intuition for near and far future with respect to various factors affecting any system of their interest. Since seeking for a sustainable future is the fundamental right of every person, one needs to evaluate the future aspects of his environment either quantitatively or qualitatively. Engineering, technology, and management have formulated or coded human future estimation intuitions by many statistical, probabilistic, and artificial intelligence techniques which are based on certain mathematical functions intending to model the nature. Such mathematical functions to model the nature are getting complex enough to be understood and applied by a novice user. In light of the complexity of mathematical functions incorporated, their easier to apply counterparts with lesser technical parameters of consideration will be more suitable and user-friendly. The technical term used for the process of future estimation is known as scenario development.

Scenario development plays a challenging role in identifying the possible circumstances and their impact in the future instances (Schoemaker, 1995). A scenario is not a forecast instead a possible future outcome (Porter, 1985). Although future cannot be predicted yet forecasts are required to manage the possible future conditions. Scenarios force organizational planners to consider paradigms that challenge their current thinking focusing on long term and short term stories about the future (Chermack et al., 2001). It articulates mental models to help managers to make better decisions (Martelli, 2001). It is widely applied in different areas of research for estimating the outcomes of the system in different conditions used for strategic planning and policy making (Yoe, 2004).

### **1.1.1 Scenario and water resources**

Over-exploitation of water resources compared to their replenishment draws attention towards water management for future generations. Rapid economic development coupled with other human activities cause this transition of water resources (Kulshreshtha, 1998). Therefore, water resource planning can be described as a guiding resource to achieve desired goals of water

management (Huaicheng and Beanlands, 1994). Sustainable water resource management requires ideally accurate estimations on per capita consumption and a good understanding of the factors influencing the consumption (Hussein et al., 2016). Insufficient water resources with respect to demands from different agents may cause water conflicts (Oftadeh et al., 2016). Balancing human demands for water with environmental requirements to maintain functioning ecosystems requires the quantification of ecological water requirements (Yuan et al., 2016). A watershed, a ground water or a river basin can be focused for scenario planning and management (Barrow, 1998).

Scenario planning is primarily based on a prediction process to generate the possible outcomes in future. Various prediction techniques have been used with respect to one or more number of factors affecting a hydrological system. A hydrological system for scenario planning requires certain prediction and derivation methods. Prediction is required to derive the input variables for any system in future time steps. Predictions are carried out through certain soft techniques like ANN (Artificial Neural Network), Fuzzy logic, Markov model, GAMLSS (Generalized Additive Model for Location, Scale, and Shape), genetic programming, etc.

Besides prediction of input variables for a hydrological system, it is required to get the proper estimation of resources affected by them in future. It requires hard techniques (derivation methods) or hydrological models (Bejjeman et al., 2009). Hard techniques are the techniques employing the physical relations of any system deriving the outputs with respect to the inputs, e.g. rainfall runoff models, evapotranspiration models, water balance models, etc. in the context of water resources. Potential of water resources is dropping due to various factors which include socioeconomic, anthropogenic and climatic variables (Wang et al., 2011; Mao et al., 2014). It is required to identify future states of these resources to plan for the possibilities that may arise. Certain defined/designed water balance models have been used to predict the states of various water storage elements (Jiang et al., 2007). Such hard systems consider a watershed as a lumped system with no distributed characteristics. Few other researchers have taken watershed as a spatially distributed system. Distributed system for water resources employed GIS (Geographical Information System) as a very effective tool for widespread analysis and presentation.

Application of SWAT (Soil and Water Assessment Tool) model, a GIS extension is highly significant in most of the literature taking watershed as a distributed system.

## **1.2 Outline of the thesis**

The thesis work is divided and organized into seven different chapters.

### Chapter 2 Literature Review

This chapter provides a thorough review of the literature covering the concept of scenario development for water resources. Different methods of prediction and derivation are focused to identify the research gaps.

### Chapter 3 Fundamental Techniques Employed in Scenario Development of Water Resources

This chapter provides a classification of the fundamental techniques employed for scenario development of water resources into predictive and derivative classes. Besides, fundamentals of the techniques taken forward for implementation of the research are also presented.

### Chapter 4 Scenario Planning for Water Resource Management in Semi Arid Zone

This chapter introduces the newly developed methodology based on the Input-Output system of time domain analysis identified from moving average method of extrapolation. A case study of nine villages in Chirawa block of district Jhunjhunu, Rajasthan (India) has been considered to examine the technique. This technique has been used to predict various input factors affecting the ground water resources. Later ground water recharge and demand has been evaluated with respect to predicted variables and certain methods of water conservation have been evaluated to compensate the demand. Cost benefit analyses have been conducted to determine the best method for water conservation.

### Chapter 5 Development of a State Variable Model for Generating Hydrological Scenarios

This chapter introduces the newly developed hydrological state variable model taking inputs as per the method developed in Chapter 4 which can derive the future states of water storage

elements within a watershed for various scenarios. A case study of Ardawta village in Chirawa block of district Jhunjhunu, Rajasthan (India) has been considered to validate the model.

#### Chapter 6 GIS Modeling for Scenario Development of Water Resources

This chapter introduces a newly developed GIS model to evaluate the future state of water resources over a region as per the methodologies applied in Chapter 4 and Chapter 5. A case study of Chirawa block of district Jhunjhunu, Rajasthan (India) has been used to validate the modeling approach.

#### Chapter 7 Conclusions and Future Scope

This chapter concludes the findings of the research work with strong theoretical bases for accepting and rejecting the methodologies developed. Following the concluding discussions, the chapter outlines major findings, contributions, implications, limitations and future scope of the study.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Chapter overview

The literature review in this chapter defines the different perspectives of scenario development and the importance of the factors required to be considered for any system. Further need, cause, and approaches to scenario development of the water resources are discussed. Finally, research gaps and thereafter research objectives of the thesis are mentioned at the end of the chapter.

## 2.2 Introduction

Scenario development is a prediction process to judge the future aspects of any system. There are various types of scenarios with respect to the different important factors within a system. Description of the types of scenarios with respect to the approach of their development, merits, and demerits are presented in section 2.2.1. Further, section 2.2.2 presents a brief overview of the factors to be considered for scenario development.

### 2.2.1 Scenario types

Scenarios can be categorized into the following groups as shown in Figure 2.1.

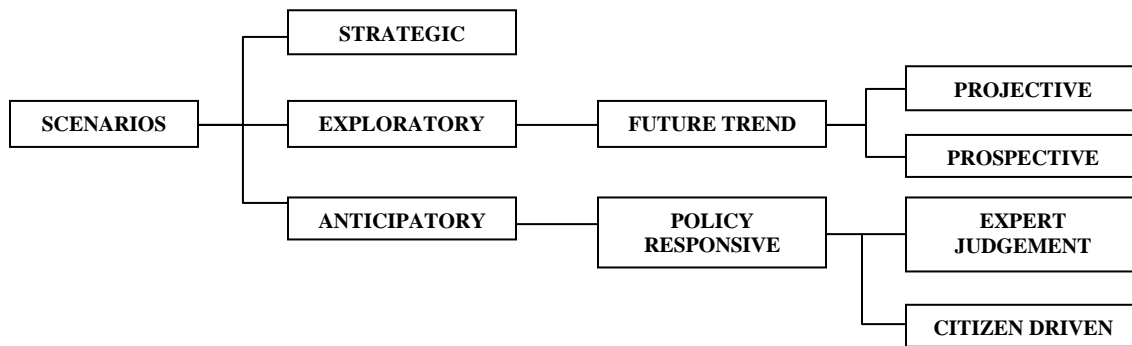


Figure 2.1. Types of scenarios (Mahmoud, 2008)

Modelers and researchers are primarily interested in strategic scenarios aimed to identify the inconsistent behavior of a complex system with respect to various disciplines and their approaches where explicit assumptions, patterns, and data selected by the disciplines are emphasized (Mahmoud, 2008). Exploratory scenarios portray the future based on identified courses of change and predictions from past observations (McCarthy et al., 2001). Scenarios such as future trend are based on extrapolations of trends, projections, and patterns. Application

of such trends is simple but lack to see the future effects of any relevant policy (Godet and Roubelat, 1996; Steinitz, 2003). They can either be projective or prospective. Forward projections in the future based on the past trends observed is implemented in projective scenarios while prospective scenarios anticipate upcoming changes varying significantly from the past (Hulse and Gregory, 2001). When the situations for the desired or feared visions to attain or avoid are judged with respect to certain events or actions if occur, then the scenarios are termed as anticipatory. There is high subjectivity in such scenarios based on the conditions observed in past and likely to arise in future (Godet and Roubelat, 1996; McCarthy et al., 2001). An anticipatory approach is followed in policy responsive scenarios where serious issues are targeted to outline the policy decisions and then the scenarios corresponding to policy are developed to achieve the desired future effects. Governmental and organizational decision makers follow the anticipatory approach frequently in order to identify and manage risks in better ways (Schwartz, 2000; Steinitz 2003; Baker et al., 2004). Policy responsive scenarios again have two dimensions as expert judgment and stakeholders view. When scenarios are modeled with respect to scientific facts gained from the conclusions, laws, goals, and principles found by scientists and subject experts, then the scenarios are considered as expert judgment. Such type of scenarios is based on current thinking projecting future changes incorporating a varied significant information and building a scientific agreement. Such scenarios are very subjective and lack political reasonability putting them into the biased frame (Houghton et al., 2001; McCarthy et al., 2001; Hulse et al., 2004). Scenarios involving the stakeholders are citizen-driven where there is greater political reasonability and public acknowledgment than expert judgment due to the active involvement of the stakeholders in scenario planning and development processes (Hulse et al., 2004). However, it is potentially biased as only the most committed citizens are usually involved.

### **2.2.2 Factors affecting scenarios**

A term referred to as STEEPV (Social, Technological, Economic (macro), Environment, Political, and Values) includes all the variables for any type of scenario building (Tankersley, 2006). These factors include socioeconomic, anthropogenic and climatic variables (Wong et al., 2011; Mao et al., 2014; Yuan et al., 2016). All these factors are categorized as predictable, unpredictable, important and unimportant as shown in Figure 2.2. The factors which are

unimportant and predictable must be excluded from the scenario planning. The factors which are important and unpredictable are always considered. All the factors considered will inhibit the property of evolution and definitely evolve after a time period. It is required to simulate the evolution pattern of these factors in future to analyze their effects on the resources of any system. For instance with respect to water resources, population as an anthropogenic factor determines the pattern of demand which may arise in future. Land use and land cover as socioeconomic factor determine the pattern of ground water recharge based on the impervious cover of any region. Temperature and rainfall as climatic factors determine the future condition of water availability. All such factors are variable with respect to time as verified by the historic review. More or less all these factors are affecting each other in different perspectives.

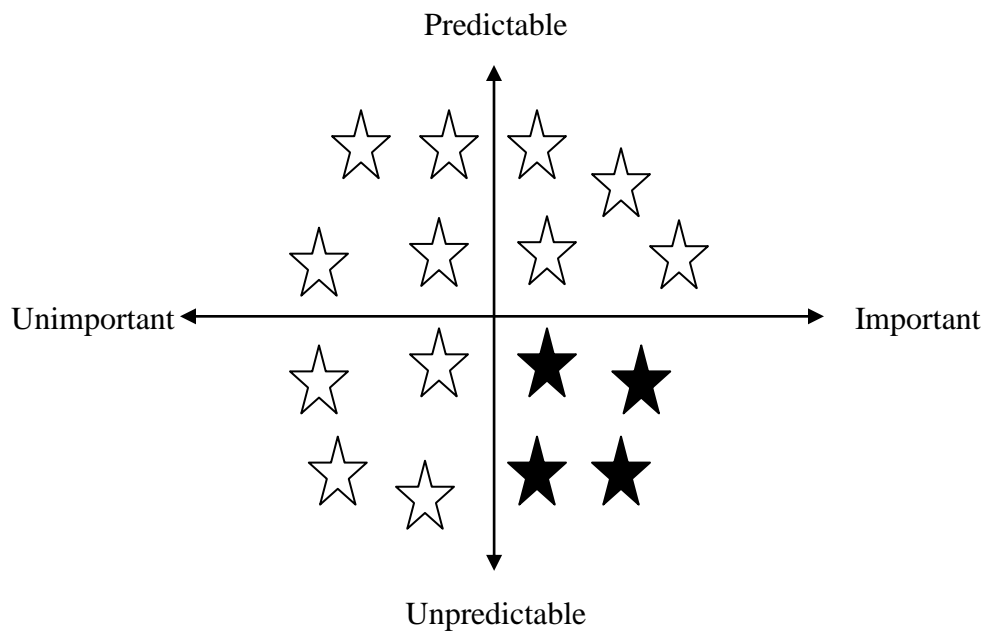


Figure 2.2. Selection chart of factors for scenario development

### 2.3 Need for scenario development for water resource management

Water resource management is required for future generations as all sources of water are getting exploited more in comparison to their replenishment due to various factors in the environment. Kulshreshtha (1998) stated that the exploitation of water resources is the effect of socioeconomic development. A proper balance between social and environmental water requirements is necessary for sustainability (Yuan et al., 2016; Oftadeh et al., 2016). This can be achieved by

quantification of the water consumption for different factors (Hussein et al., 2016). Scenarios are found useful to account for uncertainties related to climatic, demographic, economic, social, technical and political conditions affecting the performance of water resource systems, future water availability, demand and management strategies (Gallopín and Rijsberman, 2000; Alcamo and Gallopín, 2009). It helps to explore and analyze future water related issues to support water managers and decision makers to find solutions for potential problems (Mahmoud, 2008). Water resource planners have learned to plan, design, build and operate structures that increase the benefits people can obtain from the water resources (Cooper and Bottcher, 1993).

#### **2.4 Causes of scenario development for water management**

Water being one of the important resources for sustainable life on the planet is required to be preserved for the future generations. Water for various purposes of mankind is obtained from the underground aquifers (ground water), meteorological rainfall (precipitation) and river flows (surface water). These resources are getting scarce in their potential due to their excessive usage and limited replenishment, climate change, increasing demands and changing land use scenarios (Klove et al., 2014). Climate change with high temperature and altered precipitation patterns impacts water resource availability and irrigation water demand directly (Chung et al., 2011; Falloon and Betts, 2010; Zhu and Ringler, 2012) along with water quality and ecosystem stability. The pavement of the land by urban infrastructures generates more runoff instead of ground water recharge. Therefore, urban planning and development is suggested based upon the microclimatic conditions which are used to plan the further development (Wong et al., 2011). Evaporation is increasing relatively due to increasing temperature. This may evolve the condition of drought due to multiple climatological and hydrological parameters (Mishra and Singh, 2010; Vicente-Serrano et al., 2012). It is required to identify the parameters and their effects on the water resources which are causing them to diminish. Hence scenarios are required to be planned to identify alternative future states of the water system which facilitate water managers to make robust decisions and strategies. This may help to achieve planning objectives such as alleviating water stress, improving water quality, maintaining the ecosystem services, etc. (Lempert et al., 2006; Groves, 2006).



## **2.5 Approaches for scenario development for water management**

There are various approaches for scenario development with respect to the granularity of data and stages being considered. It can be bottom up, top down or multistage. Bottom up approach focuses on socioeconomic vulnerabilities while top down approach often results into an explosion of uncertainties and therefore complicate decision making (Kalaugher et al., 2013). Wang et al. (2011) developed a simulation model for change in land use patterns under drought scenarios combining top down system dynamics model, bottom up cellular automaton model and the artificial neural network model. The multistage approach is like scenario development rules to be applied at every time step with respect to the state of the system at that time step. Pallottino et al. (2005) devised a Decision Support System (DSS) for water resource management incorporating demand and supply as the nodes connected by a junction at some time step as one stage. For multiple consecutive time steps, there are multiple similar stages. These stages have been optimized for sustainability with respect to various predefined scenarios of demand and supply. Li et al. (2008) applied IMSIP (Inexact Multistage Stochastic Integer Programming) for analyses of the multiple policy scenarios that are associated with economic penalties when the promised targets are violated as well as the economics of surplus water diversion. Li et al. (2009) applied Multistage Fuzzy-Stochastic Quadratic Programming (MFSQP) approach within a multilayered scenario tree for agricultural sustainability under uncertainty. Fan et al. (2015) developed a generalized fuzzy two-stage stochastic programming (GFTSP) method for planning water resources management systems under uncertainty.

Top down, bottom up, and multistage approaches can be considered as viewpoints to solve the problem more efficiently and effectively. Ultimately, these viewpoints require certain methods including prediction techniques and derivative models to solve the problem. Input variables for future time steps require prediction while derivative models generate desired outputs at those time steps. It requires a system approach to derive outputs with respect to the supplied inputs. These systems can be classified into soft systems and hard systems. Soft systems are the flexible tools for describing a system (Checkland and Poulter, 2010) while hard systems integrate the physical aspects of the system (Beijeman et al., 2009). Soft systems include various soft computing techniques like Artificial Neural Network (ANN), Markov model, Fuzzy logic, GAMLSS (Generalized Additive model for location, scale, and shape), etc., while hard systems

include system models like hydrological models in the context of water resources. It is observed that the integration of soft techniques to predict inputs in future and hard techniques to derive outputs corresponding to the predicted inputs can help in the scenario development of any system.

A few of the researches performed with *prima facie* soft techniques of prediction are presented here. Suen and Lai (2013) projected the future salinity concentration in rivers using soft computing technique of ANN (Artificial Neural Network) with respect to the precipitation and stream flow. Kourgialas et al. (2015) forecasted river flows using ANN on an hourly basis resolving accurate estimation of extreme flows. Zhang et al. (2017) applied back propagation ANN (BP-ANN) method to predict ground water level using 180 monthly GWD (Ground Water Depth) data records in districts of Beijing Plain, China. Song et al. (2018) used ELM (extreme learning machine (a variant of ANN with high learning rate and single hidden layer)) to forecast the ground water flow and salinity level patterns in the coastal aquifers of Baldwin County, Alabama. Deo et al. (2017) used ELM over wavelet transformed data of Drought indices (a weighted function of rainfall time series to analyze drought risk) to forecast drought indices in three hydrological stations in Australia. Lopez and Frances (2013) used another soft technique called GAMLSS (Generalized Additive model for location, scale, and shape) for flood frequency analysis modeling the non stationary climatic time series data. Serinaldi and Kilsby (2012) modeled the monthly log transformation based deseasonalized data of rainfall and stream flow using GAMLSS. Candela et al. (2009) used Markov chain to model the rainfall occurrences and a probabilistic model for modeling the rainfall amounts. Markov chain method of soft computing has been integrated with other soft method called fuzzy logic in few of the studies. Fu et al. (2012) developed a fuzzy-Markov-chain based stochastic dynamic programming (FM\_SDP) method for tackling uncertainties expressed as fuzzy sets and distributions with fuzzy probabilities (DFPs) in reservoir operation. Halmy et al. (2015) predicted land use change using Markov-CA (Markov Cellular Automaton) method. Ravansalar et al. (2017) used linear genetic programming over the DWT (discrete wavelet transformed) time series data of streamflow to predict future streamflow in two gauging stations of Beshar River, Iran. Shamaei and Kaedi (2016) used an ensemble of genetic programming and neuro-fuzzy prediction models for higher accuracy in the prediction of suspended sediments at two stations Rio Valenciano and Quebrada

Blanca in the USA. Mehr and Nourani (2018) forecasted stream flow through genetic programming with respect to the rainfall data preprocessed by the seasonal algorithm (breaking time series into its trend, seasonality and irregularity components) in the Haldizen catchment, Trabzon, Turkey.

Above soft computing techniques have been used but not limited to predict future inputs for the different variables incorporated within a system with respect to their historical time series data. Somewhere these methods have been used to forecast future inputs with respect to historical inputs elsewhere they are used to model outputs with respect to predefined future inputs/scenarios. Such predefined scenarios are obtained from other sources or models.

With reference to water resource management, input climatic data of rainfall, temperature, etc. for various predefined scenarios has been obtained from the climate models referred as GCMs (Global climate models) and RCMs (Regional climate models). Global Climate Models are commonly used in large scale climate change studies which have been downscaled to Regional Climate Models to obtain fine scale studies (Bozkurt and Sen, 2013). Suen and Lai (2013) generated future daily precipitation data by statistically downscaling results from seven GCMs: CGCM3.1, CSIRO-Mk3.5, ECHAM5, GFDL-CM2.0, GFDLCM2.1, MRI-CGCM2.3.2, and MIROC3.2. Average of the downscaled rainfall from seven GCMs had been used to project the salinity concentration at several locations in Taiwanese river. Candela et al. (2009) coupled the temperature and precipitation data from GCM HadCM3 to a ground water model to estimate impacts of climate change on ground water.

Besides the soft prediction techniques there is other class of system specific hard derivative techniques. With reference to water resources various water balance models, potential evapotranspiration models (PETs) and rainfall runoff models lie in this category. Griffin et al. (2013) implemented USGS Thornthwaite water balance model with estimates of climate change and land use change parameters to assess future water resources based on predicted monthly fluxes of the water balance. Jiang et al. (2007) compared the results produced by different water models such as Vrije Universitet Brussel (VJB), Xinanjiang (XAJ), Guo (GM), WatBal (WM) and Schaake (SM) along with Thornthwaite. Bae et al. (2011) compared differences of response

for climate change in the Chungju Dam basin of Korea for seven different PET (Potential Evapotranspiration) computation methods incorporated in the three distributed hydrological models called PRMS (Precipitation-Runoff Modeling System), SLURP (Semi-distributed Land Use-based Processes), and SWAT (Soil and Water Assessment Tool). The seven PET methods are Hamon and Jensen-Haise methods for PRMS, Penman-Monteith, Granger and Spittlehouse-Black for SLURP, Penman-Monteith, Priestley-Taylor and Hargreaves for SWAT. Simulations by the hydrological models for different PET methods induce major differences in the runoff for the same climate change projections. Siberstein et al. (2012) used certain rainfall runoff models such as SIMHYD, Sacramento, IHACRES, AWBM and SMARG to estimate runoff in catchments. Water balance, rainfall runoff, and PET models act as systems or subsystems for any hydrological problem. A system dynamic approach can be applied integrating these models to simulate the hydrology of a catchment area. System dynamics is a technique to simulate time variant state change of different stock variables within a problem specific system. Wang et al. (2011) applied system dynamic approach to simulate land use patterns under a drought transition to account for the complexity of driving factors behind land use change and micro level changes in land use patterns. Sahin et al. (2016) integrated supply, demand, and asset management processes in system dynamics model simulating the proposed changes to water governance. These hard systems being applied are the lumped systems. Certain distributed systems for water resources have been applied to obtain the distributed outputs over a geographical area. Here comes the role of GIS (Geographical Information System). Few of the distributed GIS models being studied are ISAT (Impervious Surface Analysis Tool), PRMS, SLURP, and SWAT. Yang et al. (2011) applied ISAT to identify the effective impervious area (EIA) based upon the proper networking of sewer for better analysis of the runoff. Bae et al. (2011) used and compared hydrological responses of PRMS, SLURP, and SWAT with respect to their PET computation techniques. Application of SWAT model is highly significant in the hydrological studies conducted by the researchers. Huang and Li (2010) used SWAT to simulate the water cycle components associated with crop production, i.e. precipitation, evapotranspiration, available soil moisture, deep drainage, and runoff, in breadbasket basins (river basins of Songliao, Hai, Huang, Huai, Chang, Dongnan, and Zhu) of China. Yang et al. (2016) used SWAT to examine the water quality effects like sediments, total nitrogen and total phosphorus loadings in Black River watershed, Southern Ontario, Canada. Pradhanang et al. (2011) used SWAT to simulate

snowpack and snowmelt at different elevation bands considering daily precipitation and temperature data in the region of Cannonsville watershed, New York, USA. Awotwi et al. (2015) applied SWAT to investigate the hydrological impact of possible future climate change in White Volta catchment, West Africa. Setegn et al. (2010) tested SWAT for predicting sediment yield with respect to subbasin and slope discretization in Anjenigauged watershed, Ethiopia.

Few of the scenario techniques reviewed were based on certain indices related to water management system. Pulido-Velazquez et al. (2011) applied a systematic methodology of indices like demand satisfaction index, demand reliability index, withdrawal index and withdrawal use index to analyze the outcomes in future. Goodarzi et al. (2016) used GRDI (Ground water Recharge Drought Index) which could predict the drought in ground water. Kwak et al. (2016) applied Standardized Precipitation Index (SPI) time series calculated from Representative Control Pathways (RCPs) scenarios and HADGEM3-RA (Hadley Centre Global Environment Model version 3) regional climate model to analyze the effect of climate change and spatial distribution of the drought in future. Ashofteh et al. (2017) analyzed the reservoir system by efficiency indices (EIs) affected by climate change with respect to the demand in Gharanghu multi-purpose reservoir system (East Azerbaijan, Iran).

Beyond the modelling for scenario development sensitivity analysis plays an important role in defining the robustness of the model. It is the study of how the uncertainty in the output of a mathematical model or system (numerical or otherwise) can be apportioned to different sources of uncertainty in its inputs (Saltelli et al., 2008). Sensitivity analysis can be useful for a range of purposes (Pannell, 1997) including testing the robustness of the results of a model or system in the presence of uncertainty; increased understanding of the relationships between input and output variables in a system or model; uncertainty reduction: identifying model inputs that cause significant uncertainty in the output (Mahmoud et al., 2009; Bishop et al., 2007); searching for errors in the model (by encountering unexpected relationships between inputs and outputs); model simplification – fixing model inputs that have no effect on the output, or identifying and removing redundant parts of the model structure; finding regions in the space of input factors for which the model output is either maximum or minimum or meets some optimum criterion. Sensitivity Analysis (SA) may serve validation, optimization, and risk analysis of simulation

models (Kleijnen, 2005). An SA technique based on local or global methodologies has been applied to assess the effect of climate change and water management interactions on ground water dependent ecosystems (Candela et al., 2009). SA defines the robustness of the methods which would be based on exploratory bottom up approaches identifying vulnerable scenarios prior to assigning likelihoods (Herman et al., 2015). Variance based global sensitivity analysis method, eFAST (extended Fourier Amplitude Sensitivity Testing) has been used to diagnose a complex social-ecological system under deep uncertainty in scenarios (Gao et al., 2016).

## **2.6 Research gaps identified**

- a) Time series prediction methods like Markov Model, ANN, Fuzzy logic, GAMLSS, genetic programming, etc. are found complex and have a rigorous process of prediction with various parameters of consideration. GAMLSS simulation involves various functional dependencies on mean, standard deviation, and other shape defining parameters in the probability distribution of future data. Markov Model requires determination of the probabilities for the change in states and derives the probability of any state to occur in future instead of any approximate value. ANN may requires a number of iterations to come up to a reliable system to forecast starting with certain arbitrary weights to the inputs and incorporating few other parameters like learning rate and bias. Fuzzy logic determines the predictions in future for a variable with less or no historical data based on the rules defined by experts with respect to other associated data forecasted and derives the fuzzy predictions. Genetic programming involves a number of random solutions to evolve into the best solution to a problem and does not follow any set of predefined mathematical functions.
- b) Hydrological models used have been simulated with respect to predefined scenarios; and been specific to a few state variables of a hydrological system. Normally, system behaviour is not considered in the development of scenarios and only future input variables are predicted.
- c) Application of GIS in the area of scenario development for water resources is restricted to visual representation of the predicted results over a map of some region. Prediction should not only visualize the data in GIS but also estimate its evolution (Castrillón et al., 2011).

## **2.7 Research objectives**

- a. Study of the various methodologies implemented in scenario development.
- b. Designing of a generic methodology for the scenario development of the water resources for future scenarios.
- c. Development of a hydrological state variable model for the methodology designed.
- d. Development of a GIS model for the simulation of the methodology over the spatial data.
- e. Validation and comparison of the results obtained using the methodology developed.

# **CHAPTER 3: FUNDAMENTAL TECHNIQUES EMPLOYED IN SCENARIO DEVELOPMENT OF WATER RESOURCES**

## **3.1 Chapter overview**

Fundamentals of various techniques employed in scenario planning of water resources from prediction of future inputs to derivation of corresponding outputs has been presented and classified into a broad spectrum of soft and hard techniques. Accuracy and ease of prediction for all prediction techniques have been discussed. GIS based techniques employed in scenario development of the water resources have also been mentioned and identified whether they have been used for the prediction or derivation. Later fundamentals of the techniques employed in the thesis have been presented.

## **3.2 Prediction methods**

Various prediction tools like ANN, Markov chains, GAMLSS, Fuzzy logic, and genetic programming are used for estimating the future conditions of different parameters of consideration (rainfall, evaporation, land use, stream flow, etc.) within a hydrological system. A brief summary of the methods employed in different methodologies is required to understand their applications in the context of different data of various factors at diverse scales. Complexity and ease of use of the prediction methods are the main focus in the thesis. It is required to understand the basic components of the developed methods in isolation. The prediction methods are the soft systems to estimate the future values of various input variables (Checkland and Poulter, 2010). The list of such soft systems encountered in the literature of scenario planning for water resources is presented as:

### **3.2.1 Markov model**

The Markov model deals problems under a probabilistic or statistical framework (Rabinder and Juang, 1986; Robertson et al., 2004; Mehrotra and Sharma, 2010). It produces plausible predictions (Charles et al., 1999) based on the transition probabilities of a system from one state to another state in discrete time steps such that all the states are finite and belong to a defined set. The product of the transition probabilities (chain) as per the changes observed at consecutive time steps historically will determine the probability of all the states considered one by one at the



next time step. The most suitable state as per the analysis can be assumed a future state of the system. Land use maps can be predicted using Markov modelling approach to determine surface runoff characteristics in future in the context of water resource management (Candela et al., 2009; Fu et al., 2012; Halmy et al., 2015). The complexity of the method depends upon the order of the chain or the number of discrete previous events to be considered for prediction. The accuracy of the predictions is judged by hit and trial over different chain orders.

### **3.2.2 GAMLSS**

GAMLSS (Generalized Additive Model for Location, Scale, and Shape) generates data for the future time steps as per the distribution function of the observed data at previous consecutive time steps incorporating more parameters besides mean and standard deviation of the distribution function. Rigby and Stasinopoulos (2005) extended GAMs (Generalized Additive Models) and GLMs (Generalized Linear Models) generating data with respect to mean and standard deviation (replicating the historical data for future or assuming the observed distribution stationary) to GAMLSS providing the scope for more parameters. Mean and standard deviation corresponds to location and scale of the distribution respectively while other parameters will determine the shape of the simulated distribution. All such parameters are modeled as monotonic link functions relating to the explanatory variable. These functions can be linear or non-linear with or without additive random/noise terms. The coupled effect of all the functions will provide distributed simulations of the data in future. The distribution for the response variables in GAMLSS can be selected from a very general family of distributions including highly skew or kurtotic continuous and discrete distributions (Stasinopoulos and Rigby, 2007) for long term survival models (De Castro et al., 2010). Modeling of the rainfall data (climatic variables) in the future is performed using GAMLSS to generate different scenarios incorporating climate indices and social indices as shape parameters other than location and scale. The larger volume of previous data and model fitting with appropriate functions will help to provide better accuracy although the modeling approach is very complex.

### **3.2.3 Fuzzy Logic**

Fuzzy logic can be used when there is no sufficient historical data and experience for the variables to be predicted (Zadeh, 1973). Various scenarios can be constructed on the subjective

and linguistic description of the expected conditions in the future based on the experts' knowledge (Nguyen et al., 2007). It predicts based on certain rules defined by the scenario team such as low temperature and high humidity may cause high rainfall. It involves the process of fuzzification (classification of the input and output data into linguistic descriptive classes); definition of rules (to define the class in which output may fall with respect to the classes in which inputs will lie); and defuzzification (giving an exact value to the output class based on different methods). As the name suggests the predictions are always fuzzy and may deviate from the reality. Since scenarios can be considered as approximations, fuzzy logic fits well for the purpose of scenario development. In the context of water resource scenarios fuzzy logic has been used to judge the future sustainability under uncertainty (Li et al., 2009; Fu et al., 2012). Accuracy in the fuzzy logic depends on the knowledge of the scenario team (Nguyen et al., 2007).

#### **3.2.4 ANN**

Artificial neural networks are motivated by the biological neural network system within a human brain attempting to learn the process of predicting the outputs of some system with respect to its inputs iteratively. ANN approach evolves into an approximate function dependent on various inputs to the system (Haykin, 1999). These networks are generally distributed, adaptive, and nonlinear comprising of various nodes/processing elements (Principe et al., 2000). Processing elements are classified into three types of layers as one input, one or many hidden, and one output layers connected with the links carrying certain weights to scale the inputs from one layer to another layer. Input layer processing elements just forward the inputs to its succeeding layer while other layers' processing elements process the weighted sum of inputs from its preceding layer and produce outputs either for its succeeding layer or output layer. Output layer produces the required outputs. If the evaluated outputs do not match the desired outputs then the weights are adjusted by applying certain functions in various iterations and this process is termed as the learning process of ANN. Training data is used to adjust the weights and it does not follow any physical laws governing any system or the statistical distribution of the data observed (Hertz et al., 1991; Hagan et al., 1996). ANN in the context of water resources has been applied to predict river flows, ground water level, and river salinity concentration with respect to the other associated inputs like rainfall, stream flow, etc. (Suen and Lai, 2013; Kourgialas et al., 2015;

Zhang et al., 2017). Application of ANN is observed as a very rigorous and complex practice implementing an iterative process to adjust weights until the convergence which may lead to the better accuracy.

### **3.2.5 Genetic Programming**

Genetic programming (GP) is a technique of solving a problem through evolution over a population of computer programs. It transforms the population of computer programs into a new population with a hope to find better and fitter programs by the process of crossover and mutation (Poli et al., 2008; Guven, 2009). It automatically solves a problem without any user intervention to specify domain specific functions instead a high-level objective is required. Every program in GP comprises of a sequence of variable length instructions which operates on one or more constants provided as inputs from the user. Various functions in a program are composed of arithmetic operators (+, -, \*, /), conditional statements, and function calls (ex, x, sin, cos, tan, log, sqrt, ln, power). Any program can be represented by a tree/graph like structure where inner nodes in the tree represent functions/operators and leaf nodes represent the constants/variables. Crossover and mutation are the processes of exchange of subtrees between two trees and change of function/operator at some inner node of a tree respectively. This way GP can provide a highly nonlinear solution to a problem (Brameier, 2004). The complexity of the GP method is part of computer processing and accuracy is a matter of iterations.

### **3.3 Derivation methods**

Hard derivative systems are required to identify the effects of the input variables within a system. For scenario development future input variables are predicted using the soft techniques. With reference to water resources various water balance models, potential evapotranspiration models (PETs) and rainfall runoff models must lie under derivative category (Kalaugher et al., 2013). They can be classified as lumped system and distributed systems. Lumped systems assume any watershed as a system with no variation over space while distributed systems consider a watershed as a spatially distributed system (Vieux, 2001). Application of GIS has proven an efficient and effective process for simulating hydrology in distributed environment.

### **3.3.1 Lumped systems**

#### **3.3.1.1 Water balance models**

These are certain hydrological models which can estimate the future scenarios on some predicted climatic possibilities under a variety of hydrological conditions (Xu and Singh, 1998). The water balance models account the distribution of water among the different modules within a hydrologic system. Thornthwaite and Mather (1955) is a simple model relating climate and runoff in one equation while other complex models such as Stanford Watershed model (1966) and Sacramento model (1973) are termed as soil moisture accounting models (Schaake and Liu, 1989). Simple water balance models assist in understanding complex land surface processes with available data to estimate model parameters (Schaake et al., 1996). Monthly temperature and rainfall are the inputs to the model and the outputs comprises of evapotranspiration, soil moisture storage, snow accumulation, runoff, and surplus. Predicted variables are incorporated in water balance models to derive the results to be considered for scenario planning of water resources.

#### **3.3.1.2 Potential Evapotranspiration (PET) Models**

This is another set of hydrological models that contribute to the analysis of estimated potential evaporation (mm/month) (Thornthwaite, 1948). It is used to estimate actual evapotranspiration in rainfall-runoff and ecosystem modeling considering the soil moisture status (Lu et al., 2005; Bormann, 2011). PET can be defined as the water demand by the atmosphere (Rind et al., 1990) or the quantity of evaporation which may occur from the unit area of water body surface having sufficient water stored. PET can be considered as the fulfilment of moisture requirement of atmosphere by the earth surface affected by surface and air temperatures, insolation, and wind. For brevity, any place where annual PET exceeds annual precipitation is considered as dry land. Therefore, PET models also help in deriving the final outcomes for scenario planning of water resources taking evaporation into account.

#### **3.3.1.3 Rainfall Runoff Models**

Any mathematical hydrological model illustrating the relations of surface runoff to rainfall within a catchment/basin/watershed and to estimate the river discharge is considered as a rainfall-runoff model (Sun et al., 2010). Various runoff models have several parameters for consideration (Vaze et al., 2010). Generally, such models produce runoff hydrograph as a

function of the rainfall hydrograph. Runoff models are linear as well as non-linear where linear models like linear reservoir have limited applicability in practice. Non-linear models are more applicable universally with an assumption that rainfall will be more or less uniformly distributed over the area and the size of the watershed to be dependent on the rainfall behaviour within the region. Larger the catchment area of the study region, more the number of sub-catchments considered to combine various runoff hydrographs using flood routing methods (Reddy, 2005). As rainfall hydrographs are seasonal, surface runoff hydrographs can predict runoff in rainfall season only. Certain runoff models can derive runoff with respect to rainfall value over a time period, say annual/monthly rainfall, and can be used in short/long term scenario planning.

### **3.3.2 Distributed Systems**

#### **3.3.2.1 ISAT**

Man-made features like concrete pavements and building rooftops which replace the naturally pervious soil and hinder precipitation permeation into the soil and evapotranspiration to the atmosphere are termed as impervious surfaces (Chabaeva et al., 2009). ISAT (Impervious Surface Analysis Tool) is a GIS (Geographical Information System) extension which is used to evaluate the percentage of impervious area within the geographical regions like watershed, municipalities, etc. (Carter et al., 2005). A correlation between water quality and the impervious area is well established within the small watersheds such that increase in impervious area cause a decrease in the water quality. ISAT has been applied to predict the impact of different management scenarios with respect to the impervious area on local water quality. Here GIS is used for impervious area-water quality analysis instead of prediction.

#### **3.3.2.2 SWAT**

SWAT (Soil and Water Assessment Tool) is a distributed model applied on large and complex watersheds to measure the impacts of land use practices. It is a publicly available model developing and supported by the USDA Agricultural Research Service, Grassland, Soil and Water Research Laboratory, Temple, Texas, USA. SWAT is considered as a watershed hydrological transport model with the various components like weather data generator, surface runoff, base flow, infiltration, evapotranspiration, river transmission losses, ponds and reservoir storage, return flow, and reach routing in the context of water resources estimation. There are

other components like crop growth and irrigation, nutrient and pesticide loadings in the context of effects of the estimated water resources. This model is used worldwide (Gassman et al., 2007) and is continuously under development. It is an analysis tool incorporating various possible factors concerned with water and can be classified under a derivative tool rather than a predictive one. GIS application of SWAT is to define HRUs (Hydrological Response Units) with respect to the elevation, soil, and slope of the region (Neitsch et al., 2011). Time variable states of the water storage elements and other hydrological processes are generated for each HRU with respect to some weather data generators.

### **3.3.2.3 PRMS**

PRMS (Precipitation-Runoff Modelling System) evaluates the response of various combinations of climate and land use over the river and watershed hydrology incorporating the physical processes involved based on various distributed parameters (LaFontaine et al., 2013; Leavesley et al., 1983; Leavesley and Stannard, 1995). Its primary goals include (1) simulating hydrological procedures covering transpiration, evaporation, infiltration, runoff, and interflow based on energy and water budgeting of the plant canopy, snowpack, and soil layers with respect to the distributed climatic variables (precipitation, temperature, and solar radiation); (2) simulating temporal hydrological water budgets for the watersheds within the ranges lying from days to centuries; (3) integrating itself with other models intended for management of the natural resources or other scientific discipline models; and (4) providing a library of modules to opt alternative hydrologic-process algorithms (Markstrom et al., 2015). It must also be classified under the derivative kind of GIS system rather than predictive.

### **3.3.2.4 SLURP**

Semi-distributed Land Use-based Runoff Processes (SLURP), is a model that simulates the hydrological cycle within a basin from rainfall to runoff with its effects on the reservoirs, dams, water extractions and irrigation schemes (Kite, 1997; Kite and Droogers, 2000; Wu et al. 2012). The model can be used to examine the effects of predicted/proposed climate change or change in land cover on different water resource consumers within a basin. It can be simulated with respect to the locally available climatic data or public domain data available on the internet. The model has the provisions to use satellite images in order to obtain land cover, vegetation index (for leaf

area index and evaporation), cloud cover (for distribution of rainfall), and snow extent. Windows-based graphical user interface makes the model user-friendly. It is also a kind of derivative GIS system incorporating proposed defined/predicted variables.

Based upon the discussions above, the methods are classified as predictive, derivative and being a GIS/distributive application as presented in Table 3.1 and Figure 3.1.

Table 3.1. Classification of scenario development methods under predictive, derivative, and GIS applications

<b>Tools</b>	<b>Predictive</b>	<b>Derivative</b>	<b>GIS Application/Distributed model</b>
Markov Model	√	×	×
GAMLSS	√	×	×
Fuzzy Logic	√	√	×
ANN	√	√	×
Genetic Programming	√	√	×
Water Balance Models	×	√	×
PET Models	×	√	×
Rainfall Runoff Models	×	√	×
ISAT	×	√	√
SWAT	×	√	√
PRMS	×	√	√
SLURP	×	√	√

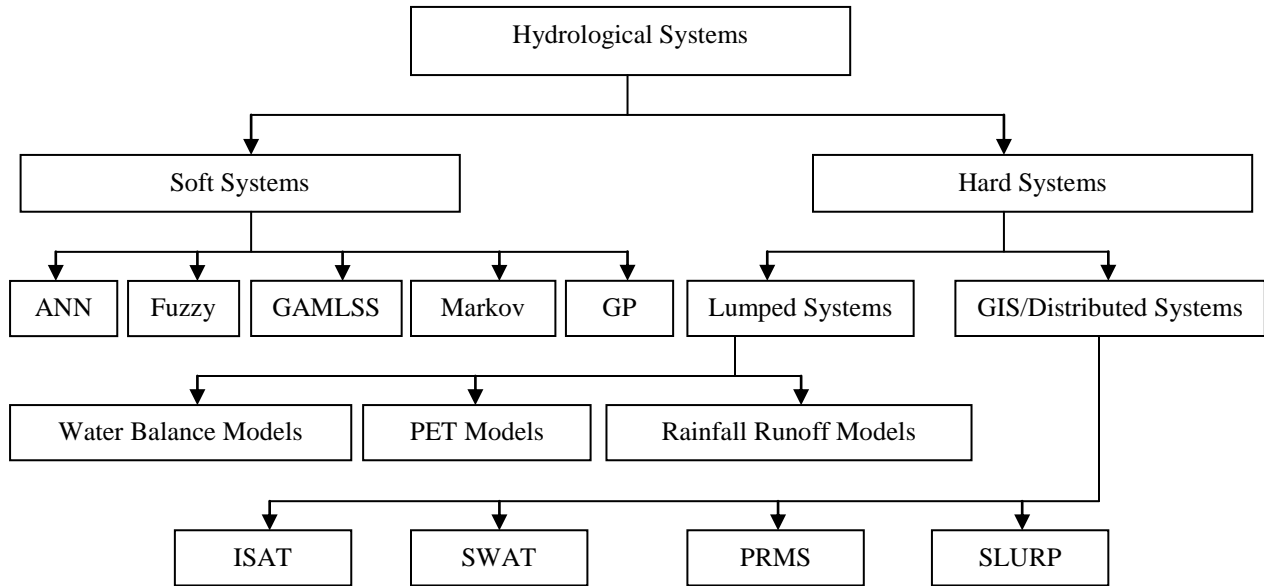


Figure 3.1. Classification of techniques employed in scenario development of water resources

### 3.4 Water Indices

Indices are used for analysis of the system over a scale, somewhere defined and somewhere developed. Water indices have been used by the researchers to present the state of a hydrological system evaluating one input/output variable with respect to other input/output variable or variables as found suitable by them with respect to their study. For example, Pulido-Velazquez et al. (2011) developed a systematic methodology of indices like demand satisfaction index, demand reliability index, withdrawal index and withdrawal use index presenting the results of a water management system under expected future scenarios. Other indices developed include GRDI (Ground water Recharge Drought Index) predicting ground water drought (Goodarzi et al., 2016), EIs (Efficiency indices) of a reservoir system (Ashofteh et al., 2017), etc.

### 3.5 Climate Models

Climate models are used to simulate and characterize the transfer of energy in different parts of the ocean, atmosphere, and land. They partition the Earth's surface into a 3-D grid of cells where each cell executes process of energy interaction and transfer to its neighbouring cells. Computation time for the climate models is inversely proportional to the resolution of grid cells. Such models calculate wind, heat transfer, radiation, relative humidity, etc. in each cell based on the basic laws of physics and fluid motion. Besides spatial resolution, climate models also



include elements of time in minutes, hours, days, and year which also affects the computation time. (<https://www.climate.gov/maps-data/primer/climate-models> dated 22/04/2018).

### **3.6 Sensitivity Analysis**

Sensitivity analysis is the process to determine the effect of various inputs employed within a system on the outputs derived by a model. It helps to make a model robust by a check how the uncertainty in the output can be apportioned to different sources of uncertainty in its inputs (Saltelli et al., 2008). Sensitivity analysis may serve validation, optimization, and risk analysis of simulation models (Kleijnen, 2005).

### **3.7 System Dynamics**

System dynamics (SD) is an approach to understand the behaviour of complex systems over time (Vlachos et al., 2007). It deals with internal feedback loops and time delays that influence the performance of the entire system (Sterman, 2001). It is capable of representing information flows through the physical components of the system enabling to understand its non linear dynamic behaviour in uncertain conditions (Suryani et al., 2010; Stave, 2003).

### **3.8 Techniques used in the thesis**

In the thesis, the prima facie components applied are required to be explained to get a clear picture of the work. Serial description of the techniques and tools used for the design and development of the methodology is given in the following subsections:

#### **3.8.1 Moving average prediction**

Moving average is one among various time series techniques of prediction that can be viewed as representation of the outcomes of a random variable of concern over a fixed period of time, usually taken at equally spaced intervals (Gupta and Nagrath, 2005). Since, a time series is a description of the past, a logical procedure for forecasting the future is to make use of the historical data. If history is to repeat itself, i.e., if the past data are indicative of what could be expected in future, many underlying mathematical models like moving average can be postulated. Moving average method of forecasting uses only recent history and represents

multiple observations. It places more weight on the most recent observation (Gupta and Nagrath, 2005). The steps performed in the method are shown from Equation (3.1) to Equation (3.3).

$$M(t) = \frac{X(t) + X(t-1) + \dots + X(t-n+1)}{n} \quad (3.1)$$

$$M^2(t) = \frac{M(t) + M(t-1) + \dots + M(t-n+1)}{n} \quad (3.2)$$

$$Y(t + T) = a(t) + b(t) * T \quad (3.3)$$

where;  $a(t) = 2M(t) - M^2(t)$  and  $b(t) = \frac{2(M(t) - M^2(t))}{n-1}$

In the above equations  $M(t)$  and  $M^2(t)$  are SMA (Single Moving Average) and DMA (Double Moving Average) respectively.  $X(t) + X(t-1) + \dots + X(t-n+1)$  is the sum of values of historical data from  $t \dots t-n+1$ , where  $t$  is the time step and  $X(t)$  is the data value at time step  $t$ .  $Y(t+T)$  is the forecasted value of data at time step  $T$  ahead of  $t$ .

There are various variants of moving average method of forecasting like simple moving average (SMA), cumulative moving average (CMA), and exponential moving average (EMA) defined as per the weights assigned to the historical data used. SMA and CMA assign equal weights to all the preceding data used in forecasting such that SMA limits the data values whereas CMA increases the data values by one to forecast further. EMA method of forecasting assigns weights  $\alpha$  and  $(1 - \alpha)$  to one previous value and one forecasted value respectively, such that  $(0 < \alpha < 1)$ . The moving average method incorporated in the thesis is the two-step moving average (simple moving average of simple moving average) which will assign more weights to the recent terms among the previous terms, since the incident occurred previously has the highest probability to reoccur (Gupta and Nagrath, 2005).

### 3.8.2 Recurrence/Input-Output relation

Linear recurrence relations is a class of discrete mathematics where in a set data its every element follows a relation with respect to its certain previous terms constrained by some initial conditions (Liu, 1986). A recurrence relation of the form in Equation (3.4), where  $c_i$ 's are constants and  $a_r$ 's are terms at time step  $r$ , is called a linear recurrence relation with constant coefficients. It is also termed as the linear difference equation.

$$c_0 a_r + c_1 a_{r-1} + c_2 a_{r-2} + \dots + c_k a_{r-k} = f(r) \quad (3.4)$$

Such a recurrence relation is known as  $k$ th order recurrence relation provided that both  $c_0$  and  $c_k$  are non zero. The total solution of a linear difference equation with constant coefficients is the sum of two parts, the homogeneous solution, which satisfies the difference equation when the right hand side of the equation is set to 0, and the particular solution, which satisfies the equation with  $f(r)$  on the right hand side.

A homogeneous solution of a linear difference equation with constant coefficients is of the form  $A\alpha_1^r$  where  $\alpha_1$  is called a characteristic root and  $A$  is a constant to be determined by the initial condition/term; i.e.  $a_0$ . For  $n$  number of coefficients to be determined  $n$  initial terms; i.e.  $a_0 \dots a_n$  are required. Substituting  $A\alpha^r$  for  $a_r$  in the difference equation with the right hand side of the equation set to 0, we obtain Equation (3.5), which can be simplified to Equation (3.6).

$$C_0A\alpha^r + C_1A\alpha^{r-1} + C_2A\alpha^{r-2} + \dots + C_kA\alpha^{r-k} = 0 \quad (3.5)$$

$$C_0\alpha^k + C_1\alpha^{k-1} + C_2\alpha^{k-2} + \dots + C_k = 0 \quad (3.6)$$

Equation (3.6) is the characteristic equation of the difference equation. A characteristic equation of  $k$ th degree has  $k$  characteristic roots, providing the homogeneous solution to the difference equation (Equation (3.7)), where  $\alpha_1, \alpha_2, \dots, \alpha_k$  are the distinct characteristic roots and  $A_1, A_2, \dots, A_k$  are constants which are to be determined by the initial conditions.

$$a_r(h) = A_1\alpha_1^r + A_2\alpha_2^r + \dots + A_k\alpha_k^r \quad (3.7)$$

There is no general procedure for determining the particular solution ( $p(r)$ ) of a difference equation. However, in simple cases, this solution can be obtained by the method of inspection as presented from Equation (3.8) to Equation (3.10).

$$p(r) = P\beta^r \quad (3.8)$$

Subject to:  $f(r) = \beta^r$  and  $\beta \neq \alpha_1, \alpha_2, \dots, \alpha_k$

$$p(r) = (P_1r^t + P_2r^{t-1} + \dots + P_t r + P_{t+1})\beta^r \quad (3.9)$$

Subject to:  $f(r) = (F_1r^t + F_2r^{t-1} + \dots + F_t r + F_{t+1})\beta^r$  and  $\beta \neq \alpha_1, \alpha_2, \dots, \alpha_k$

$$p(r) = r^{m-1}(P_1r^t + P_2r^{t-1} + \dots + P_t r + P_{t+1})\beta^r \quad (3.10)$$

Subject to:  $f(r) = (F_1r^t + F_2r^{t-1} + \dots + F_t r + F_{t+1})\beta^r$  and  $\beta = \alpha$  occurring  $m - 1$  times

The terms  $F_1, F_2, \dots, F_{t+1}$  are the constants and  $t$  is the degree associated with any time step  $r$ .  $P_1, P_2, \dots, P_{t+1}$  are the coefficients to be determined for obtaining the particular solution.

Substituting the particular form equation into the original difference equation, the different values from  $P_1 \dots P_{t+1}$  can be derived. Placing the values of P's obtained back into corresponding forms of  $f(r)$ , the particular solution for the difference equation will be obtained.

Finally, homogeneous solution and the particular solution are added to obtain the total solution. Therefore for the  $k$ th order difference equation, the  $k$  undetermined coefficients  $A_1, A_2, \dots, A_k$  in the homogeneous solution can be determined by the initial conditions,  $a_{r_0}, a_{r_0+1}, \dots, a_{r_0+k-1}$ , for any  $r_0$ . For a difference equation having all roots distinct, the total solution is of the form of Equation (3.11), where  $p(r)$  is the particular solution. This equation will derive the term at any time step  $r$ .

$$a_r = A_1\alpha_1^r + A_2\alpha_2^r + \dots + A_k\alpha_k^r + p(r) \quad (3.11)$$

### 3.8.3 State variable model

A dynamic system is described by a set of variables called state variables. Models that consist of coupled first-order differential equations are said to be in a state-variable form (William, 2010). The state variable model of an  $n$ th-order linear, time-invariant, discrete-time system comprises of state and output equations (3.12) and (3.13) respectively.

$$\text{State Equation} \quad x(k+1) = Ax(k) + Br(k) \quad (3.12)$$

$$\text{Output Equation} \quad y(k) = Cx(k) + Dr(k) \quad (3.13)$$

where  $x(k)$  =  $n$ -dimensional state vector,  $r(k)$  =  $m$ -dimensional input vector,  $y(k)$  =  $p$ -dimensional output vector,  $A$  = ( $n \times n$ ) matrix of constants,  $B$  = ( $n \times m$ ) matrix of constants,  $C$  = ( $p \times n$ ) matrix of constants,  $D$  = ( $p \times m$ ) matrix of constants, and  $k$  is a discrete time step (Nagrath and Gopal, 1982). Matrices of constants define the various characteristics of the system.

## 3.9 Software Systems used

The techniques comprising of moving average prediction, linear recurrence relation, and state variable model have been implemented within the environment of the software systems MATLAB, Simulink, and GIS (Geographical Information System) given in the subsections 3.9.1 to 3.9.3.

### **3.9.1 MATLAB**

MATLAB can be used for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. It provides an interactive environment for iterative exploration, design and problem solving. It incorporates mathematical functions of linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration, and solving ordinary differential equations ([https://www.tutorialspoint.com/matlab/matlab\\_overview.htm](https://www.tutorialspoint.com/matlab/matlab_overview.htm) dated 22/04/2018).

### **3.9.2 MATLAB-Simulink**

Simulink is a simulation and model-based design environment for dynamic and embedded systems, integrated with MATLAB. It is a data flow graphical programming language tool with customizable set of libraries for modelling, simulating, and analyzing multi-domain dynamic systems. It allows to incorporate MATLAB algorithms into models as well as export the simulation results into MATLAB for further analysis ([https://www.tutorialspoint.com/matlab/matlab\\_simulink.htm](https://www.tutorialspoint.com/matlab/matlab_simulink.htm) dated 22/04/2018).

### **3.9.3 Geographical Information System (GIS)**

GIS is a computer based information system that enables capturing, modeling, manipulation, retrieval, analysis and presentation of geographically referenced data (Burrough and McDonnel, 1998). There are different formats to store the data in GIS. The two primary data types are vector and raster. Points, lines and polygons are used to represent the vector data (data that has an exact location or hard boundaries) whereas data with no hard boundaries or exact location is represented by raster data (<https://researchguides.library.wisc.edu/GIS> dated 22/04/2018). Raster data is pixel oriented presented as series of grid cells with values representing the feature being observed. Raster data is appropriate to model surfaces like elevation, temperature, precipitation, etc. Certain interpolation techniques like IDW (Inverse Distance Weighted), splines, kriging, etc. are used to generate continuous raster data over a surface with respect to distribute point feature values ([http://www.gisresources.com/types-interpolation-methods\\_3/](http://www.gisresources.com/types-interpolation-methods_3/) dated 22/04/2018). GIS systems include a lot of analytical tools and provide environment to develop such tools (<http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?id=618&pid=616&topicname=ArcToolbo>

x\_window\_basics dated 22/04/2018). Tools can be developed by the hybridization of given tools or else can be coded using the python and other programming systems provided by the GIS systems.

# **CHAPTER 4: SCENARIO PLANNING FOR WATER RESOURCE MANAGEMENT IN SEMI ARID ZONE**

## **4.1 Chapter overview**

Scenario planning for water resource management in semi arid zone is performed using systems Input-Output approach of time domain analysis. This approach derived the future values of input variables of the hydrological system from their preceding values. Input variables considered here are precipitation, evaporation, population and crop irrigation. Ingles & De Souza's method (Jha and Smakhtin, 2008) and Thornthwaite model (Wang et al., 2011) have been used to estimate runoff and evaporation respectively. Difference between precipitation inflow and the sum of runoff and evaporation has been approximated as ground water recharge. Population and crop irrigation derived the total water demand. Compensation of total water demand by groundwater recharge has been analyzed. Further compensation has been evaluated by proposing efficient methods of water conservation. The best measure to be adopted for water conservation is suggested based on the cost benefit analysis. A case study for nine villages in Chirawa region of district Jhunjhunu, Rajasthan (India) validates the model.

## **4.2 Approach for scenario development**

The encountered methods of prediction like Markov Model, ANN, Fuzzy logic, GAMLSS, and Genetic programming are found complex and have a rigorous process of prediction. Here the idea is to generalize such methods so one can apply them with lesser and general information (Liu, 1986); e.g. using historical data and time step to forecast. Keeping this in mind a generalized method of prediction has been developed using Systems Input-Output approach (Nagrath and Gopal, 1982) from a traditional moving average method of forecasting (Gupta and Nagrath, 2005).

## **4.3 Forecasting technique**

The technique used for forecasting of the variables is the resultant of two methods, one traditional moving average method of forecasting and other generalization of the recurrence

relation/Input-Output equation of time domain analysis. The steps involved in moving average method of forecasting and generalization of a recursive relation are mentioned in section 3.8.1 and section 3.8.2 respectively. The term N in moving average method corresponds to the number of previous consecutive terms at equal time intervals.

In the thesis, it is assumed that various values of N will take the forecasts to different dimensions leading to numerous scenarios. Input-Output/recurrence relations are generalized for different values of N. Forecasts obtained using the complete set of historical data is considered under Business As Usual (BAU), while forecasts with minimum and maximum averages are reserved to be considered for worst and best cases respectively.

#### 4.4 Methodology developed using generalized recursive relation

Data for social, environmental and economic factors in previous years has been collected from the region of nine selected villages in Chirawa block. Such chronological data of these factors are used to predict their values in future years using time series analyses on annual basis. Here the time horizon up to the year 2025 has been forecasted. All data used for prediction ranges from years 2007 to 2014. Since the method requires certain initial conditions, hence generalized equations are derived considering limitations imposed by the availability of data.

Considering the moving average method of forecasting for  $N = 2, 3,$  and  $4$  as per the section 3.8.1 and keeping the value of  $T = 1$  in Equation (3.3) recurrence/difference equations obtained are (4.1), (4.2), and (4.3) respectively.

$$4a_r - 5a_{r-1} - 2a_{r-2} + 3a_{r-3} = 0 \quad (4.1)$$

$$9a_r - 7a_{r-1} - 5a_{r-2} - 3a_{r-3} + 4a_{r-4} + 2a_{r-5} = 0 \quad (4.2)$$

$$48a_r - 27a_{r-1} - 22a_{r-2} - 17a_{r-3} - 12a_{r-4} + 15a_{r-5} + 10a_{r-6} + 5a_{r-7} = 0 \quad (4.3)$$

All three of the above equations have 0 on their right hand side, and hence their generalized solutions to obtain the  $r$ th term will be equal to their homogeneous solutions. Corresponding to the difference equations (4.1) to (4.3) their characteristic equations are (4.4) to (4.6) respectively.

$$4\alpha^3 - 5\alpha^2 - 2\alpha + 3 = 0 \quad (4.4)$$

$$9\alpha^5 - 7\alpha^4 - 5\alpha^3 - 3\alpha^2 + 4\alpha + 2 = 0 \quad (4.5)$$



$$48\alpha^7 - 27\alpha^6 - 22\alpha^5 - 17\alpha^4 - 12\alpha^3 + 15\alpha^2 + 10\alpha + 5 = 0 \quad (4.6)$$

The roots of a characteristic equation are obtained through MATLAB command prompt using 'roots' function with its argument as  $1 \times (n+1)$  matrix storing  $(n+1)$  coefficients of an  $n$ th degree polynomial equation (<https://www.mathworks.com/help/matlab/ref/roots.html> dated 22/04/2018).

Therefore, the roots for the characteristic equations (4.4) to (4.6) are obtained as:

N=2	N=3	N=4
1	1	1
1	1	1
-0.75	-0.3955	-0.7436
	-0.4134 + 0.6253i	-0.0593 + 0.7712i
	-0.4134 - 0.6253i	-0.0593 - 0.7712i
		-0.2877 + 0.3891i
		-0.2877 - 0.3891i

The roots obtained are real as well as complex numbers with their conjugates which provide the generalized solution as Equation (4.7).

$$a_r(h) = a_r(h)_{\text{real}} + a_r(h)_{\text{comp}} \quad (4.7)$$

where,

$$a_r(h)_{\text{real}} = A_1\alpha_1^r + A_2\alpha_2^r + \dots + A_k\alpha_k^r \quad (4.8)$$

$$\text{and } a_r(h)_{\text{comp}} = B_1s_1^r \cos(r\phi_1) + B_2s_1^r \sin(r\phi_1) + B_3s_2^r \cos(r\phi_2) + B_4s_2^r \sin(r\phi_2) + \dots + B_{2n-1}s_n^r \cos(r\phi_n) + B_{2n}s_n^r \sin(r\phi_n) \quad (4.9)$$

$\alpha_1, \alpha_2, \dots, \alpha_k$  are the real roots.

$s_n = \sqrt{a_n^2 + b_n^2}$ ,  $\phi_n = \text{atan2}(b_n, a_n)$  for  $n$ th pair of complex conjugate roots  $a_n + b_n i$  and  $a_n - b_n i$ ,  $r$  corresponds to the  $r$ th term,  $A_1, A_2, \dots, A_k$ , and  $B_1, B_2, \dots, B_{2n}$  are the associated coefficients to be determined with respect to  $(k + 2n)$  initial conditions.

Since, the current study is performed in time domain the term  $r$  is substituted by  $z\Delta t$  and the generalized equations derived for the three cases of recursive relations above (i.e.,  $N = 2, 3$ , and  $4$ ) are presented as Equation (4.10) to Equation (4.12) respectively as per section 3.8.2. Here  $X(z\Delta t)$  is the value of a variable at  $z$ th time interval  $\Delta t$ .

$$X(z\Delta t) = A.z + B + C.(-0.75)^z \quad (4.10)$$

$$X(z\Delta t) = A.z + B + C.(-0.3955)^z + (0.7496)^z .(D \cos(2.155z) + E \sin(2.155z)) \quad (4.11)$$

$$X(z\Delta t) = A.z + B + C.(-0.7436)^z + (0.7735)^z (D \cos(1.6475z) + E \sin(1.6475z)) \\ + (0.4839)^z (F \cos(2.2075z) + G \sin(2.2075z)) \quad (4.12)$$

Coefficients (A - G) in above equations will be derived using latest 2N-1 historical data set as their initial conditions. Since for the study the past observed data for eight years was available, so generalized equations are developed up to N=4. Here it is assumed that Equation (4.12) referring the largest set of chronological data will develop BAU scenario. Forecasts obtained by any of the above three equations having maximum and minimum means are reserved to be considered for best and worst scenarios respectively. The global matrix of scenarios selected is defined in Figure 4.1. Six scenarios considered are Business As Usual (BAU), High Demand and High Recharge (HDHR), Low Demand and High Recharge (LDHR), Low Demand and Low Recharge (LDLR), High Demand and Low Recharge (HDLR) and Drought (DRT). High Demand corresponds to scenarios having maximum water requirement and vice versa. High Recharge corresponds to scenarios having maximum ground water recharge and inverse for scenarios corresponding to Low Recharge. DRT is based on lowest recharge and highest demand occurred in historical/predicted data observed/generated by any of the equations from Equation (4.10) to Equation (4.12).

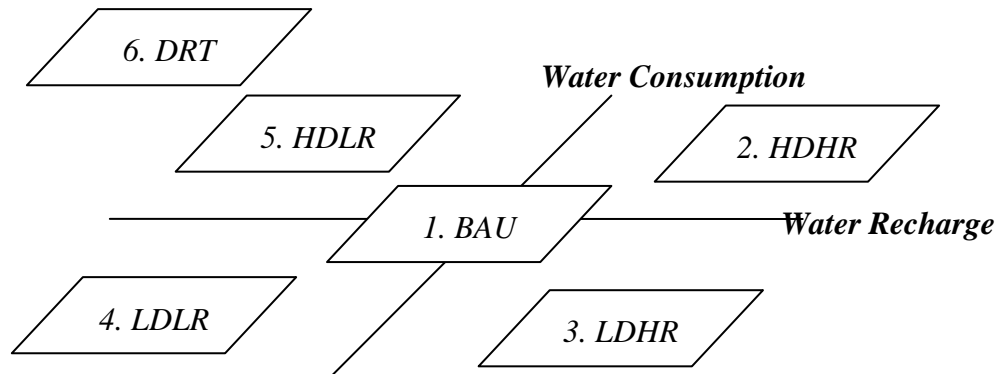


Figure 4.1. Global business matrix of scenarios considered

This study is focused on scenario planning for water resource management in a semi arid zone, attempting to check and devise solution for the compensation of total water requirement with natural ground water recharge. Development of a time series forecasting technique using generalized input-output/recurrence relation identified from moving average method of

forecasting is the highlight of the proposed methodology. A flowchart of the methodology is shown in Figure 4.2 presenting the successive phases of data collection, modeling and prediction, analysis/evaluation, design, and optimization. Bulleted list attached with each phase presents a set of its feasible factors/techniques, where bold items of the list are incorporated in the study and further illustrated in section 4.5.

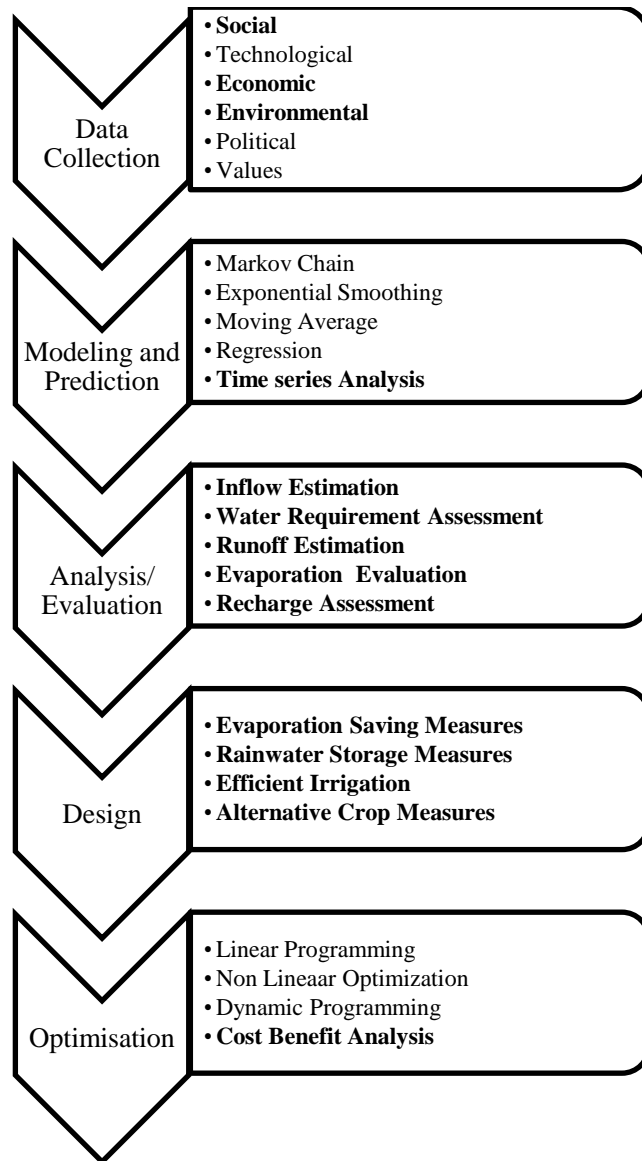


Figure 4.2. Methodology flowchart for scenario planning of water resources

#### **4.5 Case study**

A region comprising of nine villages in Chirawa tehsil of district Jhunjhunu in the Rajasthan state of India has been analyzed. Scenarios have been generated and planned with respect to the ground water utilization and replenishment. Name of the villages are Narhar, Ardawata, Gidaniya, Swamisei, Lakhu, Gothri Lamba, Gothri, Kidwana and Nuniya Gothra. These villages fall under the semi-arid zone of Chirawa. The situation of the study area in Chirawa has been declared as ‘DARK ZONE’ due to over-exploitation of ground water and has been restricted for new irrigation wells and increasing depth of existing wells. The cause of ground water depletion and pollution is rooted in population growth, economic expansion, decline in ground water recharge and over-abstraction caused by rapid increase in the number of wells, tube wells, and progress in pumping technology.

The total catchment area of the region is 5086629 square meters obtained using hydrology tool of ArcGIS 10.1 applied under its boundary. The digital elevation model (DEM) data for the region has been taken from USGS (United States Geological Survey) Earth Explorer. Fill → flow direction → flow accumulation → pour point selection → watershed area delineation are the successive steps followed in ArcGIS 10.1 to obtain the total catchment area. The total watershed area identified along with all possible pour points (sinks) is shown in Figure 4.3. The boundaries of the villages are obtained from village boundary database collected from Survey of India.

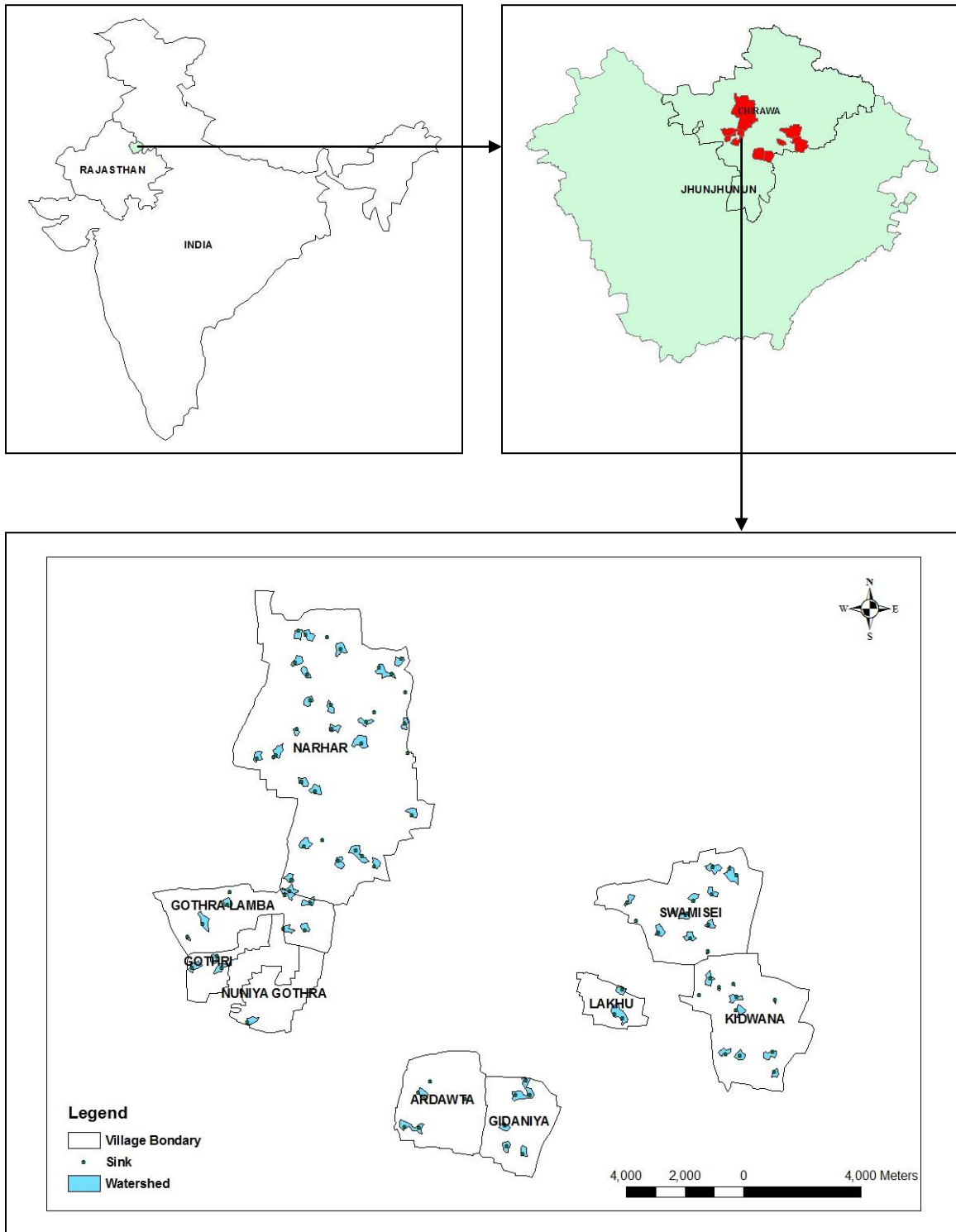


Figure 4.3. Total watershed area of the selected villages in Chirawa region

#### 4.5.1 Data collection

Primary data for population, rainfall, temperature, and crops from years 2007 to 2014 have been collected by field survey from the region. Rainfall and temperature data have been collected from the administrative center of Chirawa as shown in Table 4.1 and Table 4.2 respectively. Population data has been collected from the courtyard shelters in villages as shown in Table 4.3 and its distribution village wise is presented in Figure 4.4. Crop data has also been collected from the administrative center of Chirawa. Five major crops being cultivated in the region are wheat, oat, gram, mustard, and fenugreek. Figure 4.5 and Figure 4.6 present the village wise and crop wise distribution of cultivated land in hectares within the region respectively. Cultivation area and watering per unit area for every crop is collected, which led to forecast of crop water requirement. Locally surveyed economic data associated with the five major crops is shown in Table 4.4.

Table 4.1. Rainfall in the Chirawa region from the year 2007 to 2014 (mm)

Month/Year	2007	2008	2009	2010	2011	2012	2013	2014
January	0	0	0	4	0	0	19	0
February	74	0	1	10	42	0	29	34
March	33	0	15	4	6	0	0	40
April	20	31	0	0	0	16	10	10
May	43	78	25	0	45	11	16	21
June	68	114	41	21	48	3	39	81
July	62	87	136	84	45	68	138	67
August	26	233	35	203	182	177	134	155
September	150	138	44	186	183	39	117	33
October	0	0	0	10	0	0	15	26
November	0	0	2	20	0	0	12	0
December	0	0	0	24	0	4	0	0
<b>Total</b>	<b>476</b>	<b>681</b>	<b>299</b>	<b>566</b>	<b>551</b>	<b>318</b>	<b>529</b>	<b>467</b>

Table 4.2. Average temperature in the Chirawa region from the year 2007 to 2014 (°C)

Month/Year	2007	2008	2009	2010	2011	2012	2013	2014
January	13.54	13.61	14.62	11.90	11.40	12.50	12.50	13.00
February	17.96	17.59	17.95	15.95	16.75	14.80	16.40	15.80
March	20.91	27.62	23.55	22.10	22.80	22.35	23.15	21.25
April	30.78	30.32	28.08	29.20	27.90	27.95	28.30	27.65
May	32.98	30.39	33.57	32.50	34.20	32.70	33.90	31.35
June	34.14	30.86	33.00	34.20	28.80	23.15	34.55	33.95
July	31.76	31.23	31.68	31.10	31.10	33.00	32.10	32.65
August	30.55	29.27	31.30	29.85	29.40	29.40	29.55	30.75
September	29.13	28.26	28.97	29.65	28.35	30.60	29.70	29.65
October	26.06	28.23	25.92	26.05	25.90	25.65	26.90	25.40
November	22.56	21.87	21.50	19.84	22.10	20.20	19.75	21.25
December	14.47	15.36	18.46	13.30	14.75	15.05	15.95	14.45

Table 4.3. Population in the selected villages of Chirawa region from the year 2007 to 2014

2007	2008	2009	2010	2011	2012	2013	2014
29751	30241	30788	31387	31859	32346	32766	33253

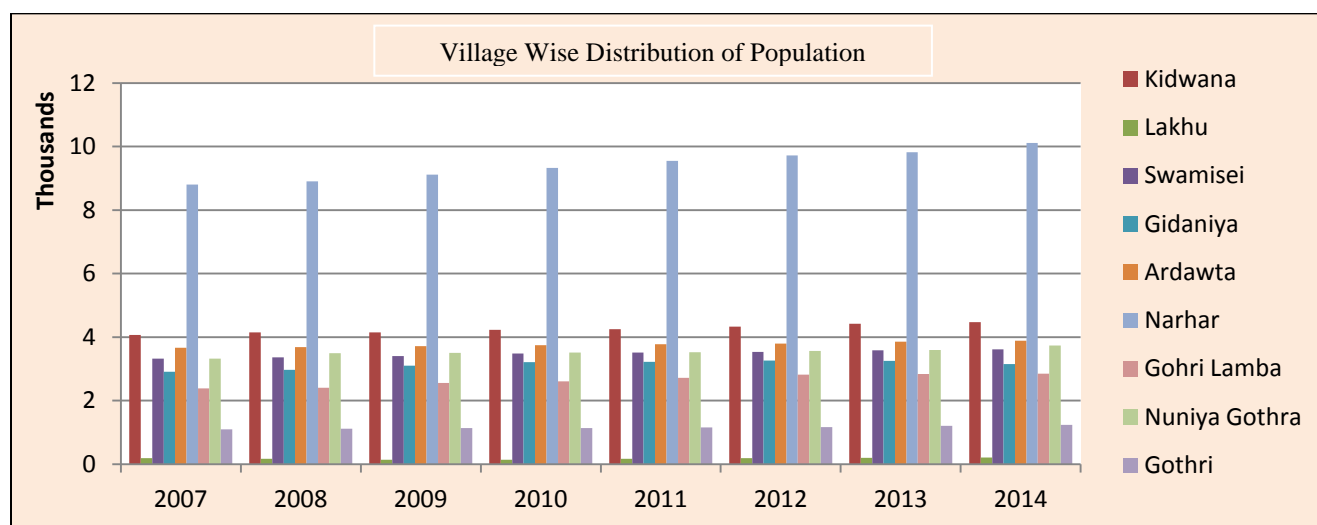


Figure 4.4. Yearly village wise distribution of population in selected villages of Chirawa

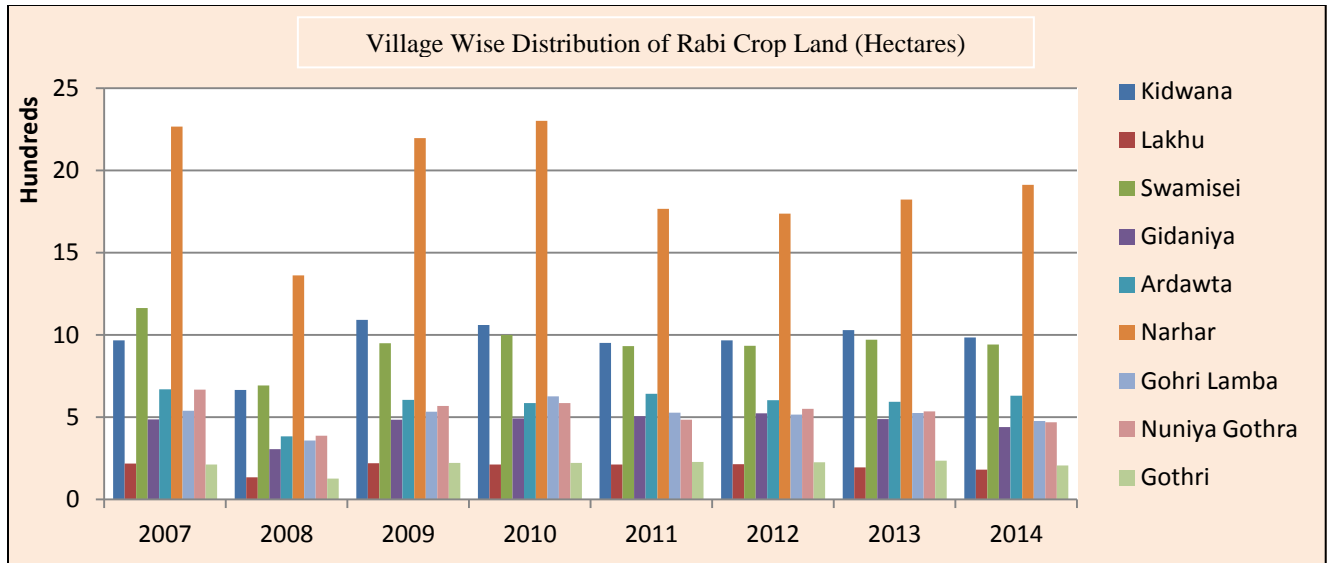


Figure 4.5. Yearly village wise distribution of rabi crop area in selected villages of Chirawa

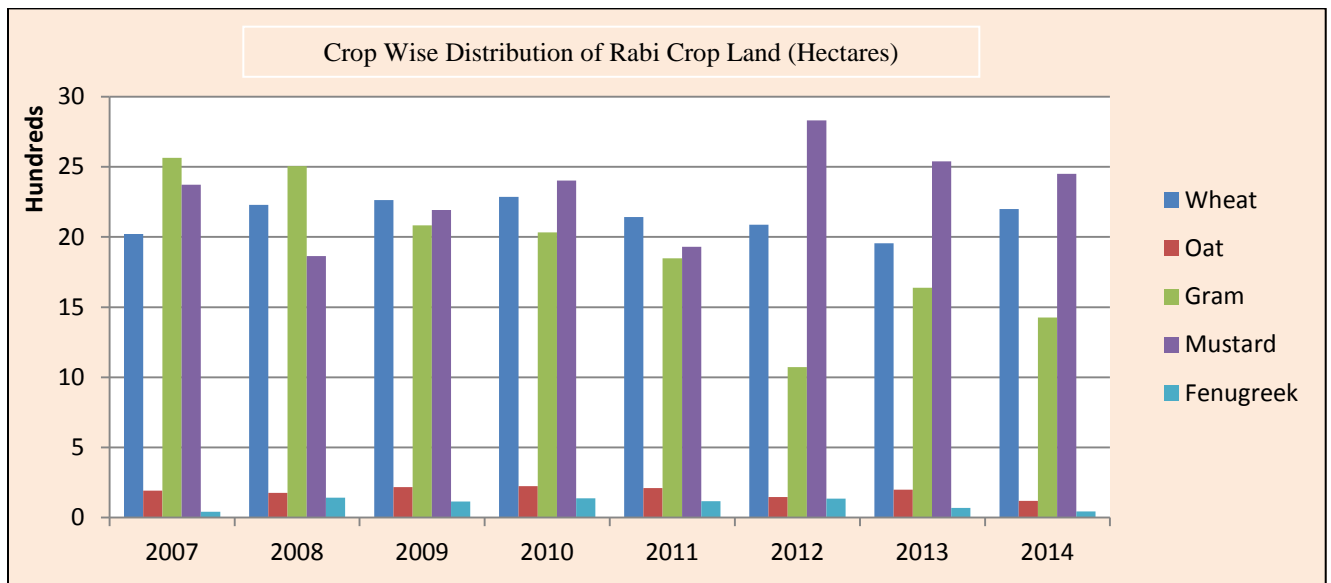


Figure 4.6. Crop wise distribution of rabi crop area sown in selected villages of Chirawa



Table 4.4. Economic statistics of the food crops produced in the selected villages of Chirawa

Crop Name	Water Used Per Hectare (Kilolitres)	Investment Per Hectare (Rs.)	Production Per Hectare(Quintals)	Revenue Per Hectare (Rs.)
Wheat	17028	10000	40-45	55000-60000
Oat	17028	8000	45-50	50000-55000
Gram	12096	9000	18-20	45000-50000
Mustard	12096	12000	18-20	55000-60000
Fenugreek	12096	8000	18-20	45000-50000

#### 4.5.2 Experimental analysis

Further the prediction of data has been conducted for every selected variable using Equation (4.10) to Equation (4.12). MATLAB codes to extrapolate data corresponding to the equations are presented in Appendix A. The three equations will take predictions into three directions. Time series analyses have been performed on few parameters (rainfall, population, evaporation, and water requirement for crops) while and other parameters (runoff and water requirement for population) have been derived with respect to forecasted values obtained for rainfall and population. Water requirement for the population is estimated by an average value of 40 liters of water used per person per day given by IS code for communities with population up to 20000. Inflow is evaluated by multiplication of total catchment area ( $m^2$ ) into rainfall (m). Runoff is derived from rainfall using the Ingles & De Souza's method (Jha and Smakhtin, 2008) presented by Equation (4.13) and Equation (4.14).

$$\text{For hilly area, } R = 0.85 P - 30.5 \quad (4.13)$$

$$\text{For plains, } R = (P - 17.8) P / 254 \quad (4.14)$$

where, R (cm) and P (cm) are runoff and precipitation respectively. The value obtained, being converted to meters, is multiplied by total catchment area ( $m^2$ ) to estimate total runoff (KL). Evaporation has been obtained as the product of catchment area by potential evapotranspiration (m). Potential evapotranspiration ( $P_e$ ) has been evaluated using Thornthwaite model presented by Equation (4.15) (Wang et al., 2011).

$$P_e = 1.6 d (10 T / I)^a \quad (4.15)$$

where, T is the monthly average temperature ( $^{\circ}C$ ), d is a correction factor that accounts for the length of each month obtained by dividing the number of days in a month by 30, I is the total heating index in a year such that  $I = \sum_{i=1}^{12} i$ , where i is the monthly average heating index for

months January ( $i = 1$ ) to December ( $i = 12$ ) such that,  $i = (T / 5)^{1.514}$ , the value of 'a' corresponds to the expression,  $a = 0.49239 + 1.792 * 10^{-2} I - 7.71 * 10^{-5} I^2 + 6.75 * 10^{-7} I^3$ . Recharge has been estimated as the difference between inflow and the sum of runoff and evaporation, although it may also happen due to the region outside the boundary of the study area and other hydrological characteristics due to ground water inflow. Total demand has been evaluated as the sum total of water requirement for population and crop water requirement.

Results of predictions for population, rainfall (mm), water requirements for population (KL (kiloliters)) and irrigating crops (KL), evaporation (KL), and runoff (KL) under six scenarios (S1 to S6) are presented from Figure 4.7 to Figure 4.12 over y-axis with respect to years over the x-axis. S1, S2, S3, S4, S5, and S6 corresponds to the scenarios BAU, HDHR, LDHR, LDLR, HDLR, and DRT respectively as shown in Figure 4.1. Observed and predicted data partitioned by a vertical line has been plotted before and after the year 2014 respectively for all the scenarios in their respective charts. Methods of prediction are shown in Table 4.5. Historical values from the year 2007 to the year 2014 and forecasted values from the year 2015 to the year 2025 are shown in green, blue, and yellow colored cells for all the scenarios in Table 4.6, where blue colored cells are used for validation with respect to actual values of the year 2015. Forecasts are generated assuming that within the time frame to evaluate; i.e. until the year 2025, there will be no saturation of population over the region. Figure 4.7 and Figure 4.9 are reflecting a rising trend for the population and water requirement for the population in all six scenarios with slight deviations after the year 2014 since the population data is following an increasing trend every year. Figure 4.8 and Figure 4.12 are presenting irregular rainfall and its dependent runoff respectively, where both after the year 2014 are declining for the scenarios S1, S4, and S5, inclining for the scenarios S2 and S3, and flat at the bottom for scenario S6 (lowest rainfall continued ahead). Figure 4.10 is reflecting a decline in crop water requirement for scenarios S1, S3, and S4, an incline in scenarios S2 and S5, and flat at the top for scenario S6 (highest water requirement for crop taken ahead). Figure 4.11 is presenting slight inclination in evaporation for the scenarios S1, S2, and S3, high inclination in scenarios S4 and S5, and flat at the top for scenario S6 (highest evaporation continued ahead).

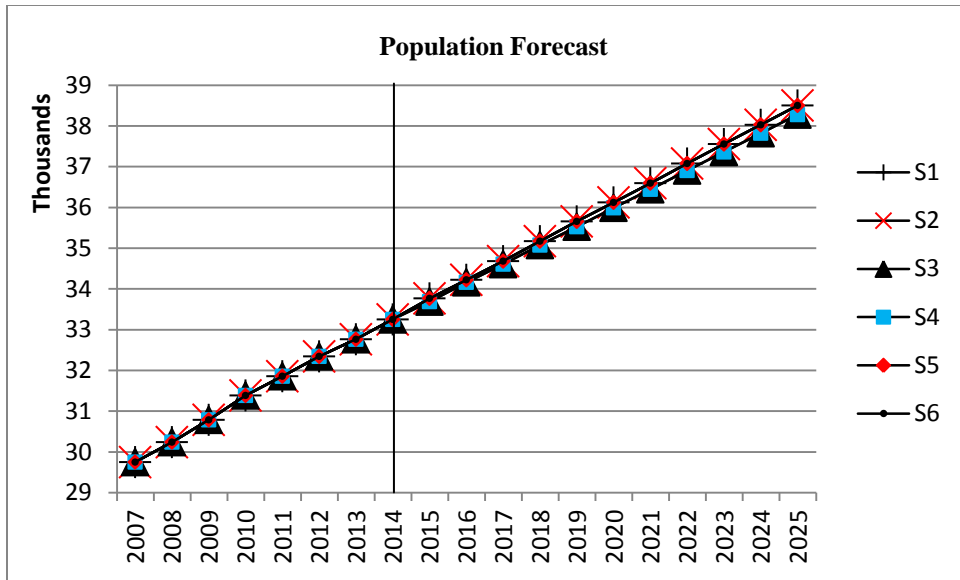


Figure 4.7. Forecast graph of population for selected villages in Chirawa

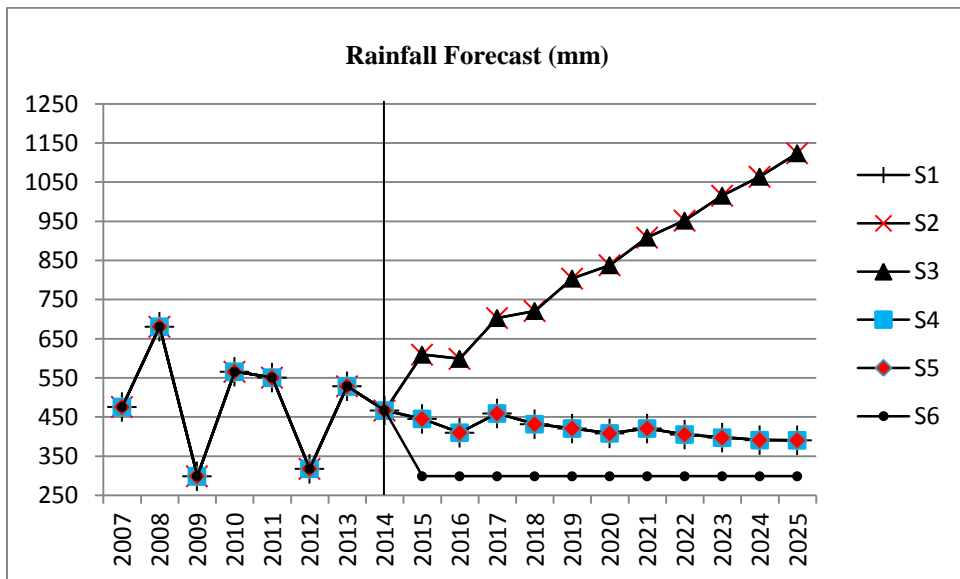


Figure 4.8. Forecast graph of rainfall in Chirawa region

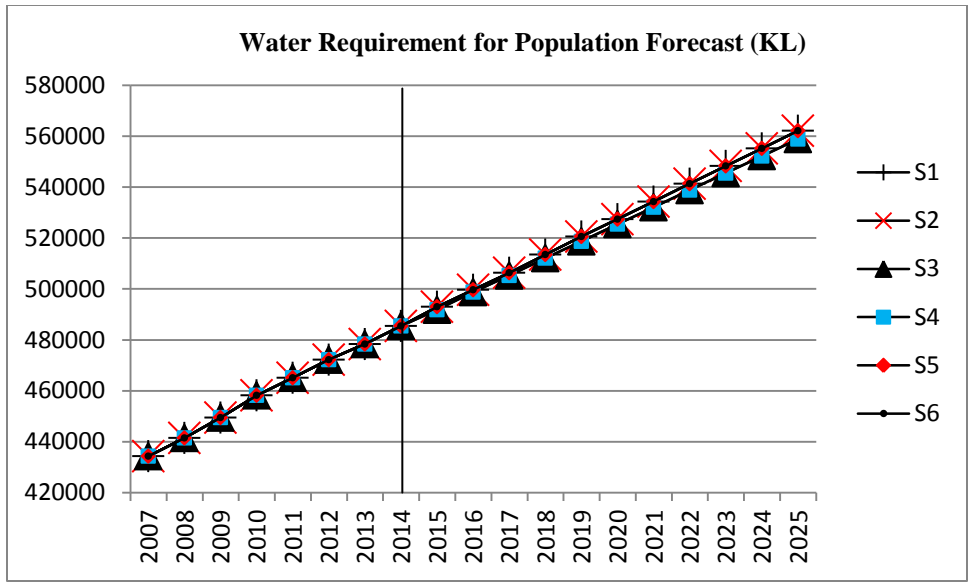


Figure 4.9. Forecast graph of water usage for human consumption in selected villages of Chirawa

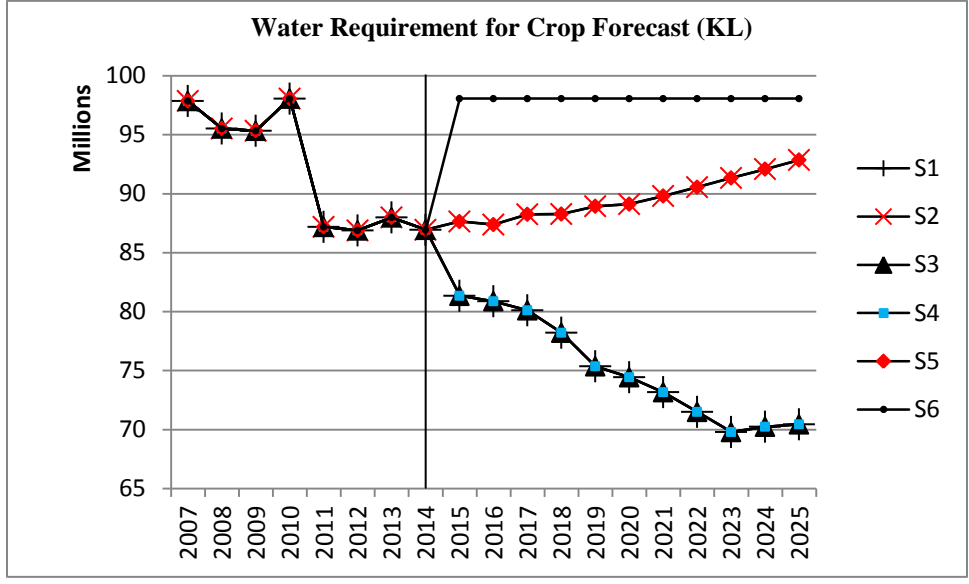


Figure 4.10. Forecast graph of crop water use in selected villages of Chirawa

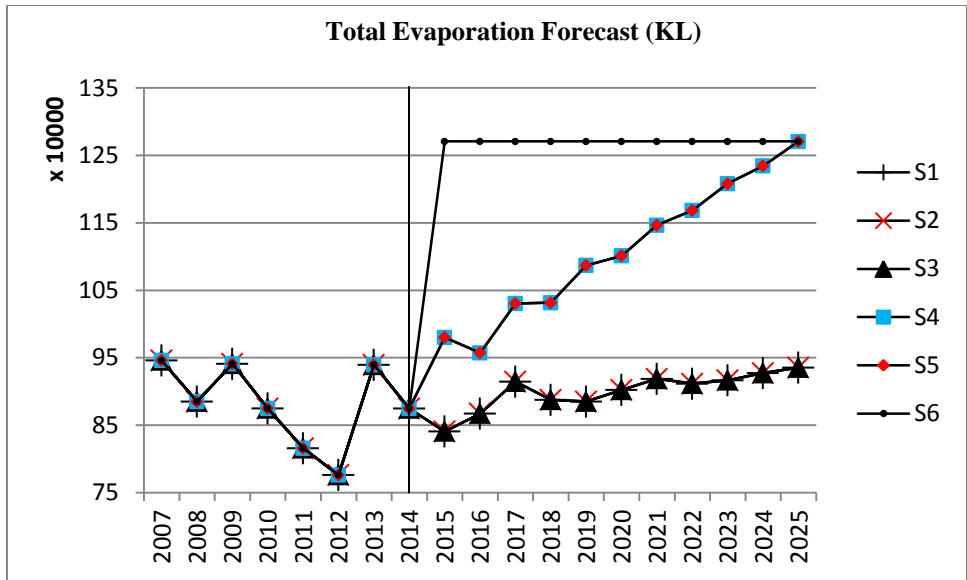


Figure 4.11. Forecast graph of evaporation over Chirawa region

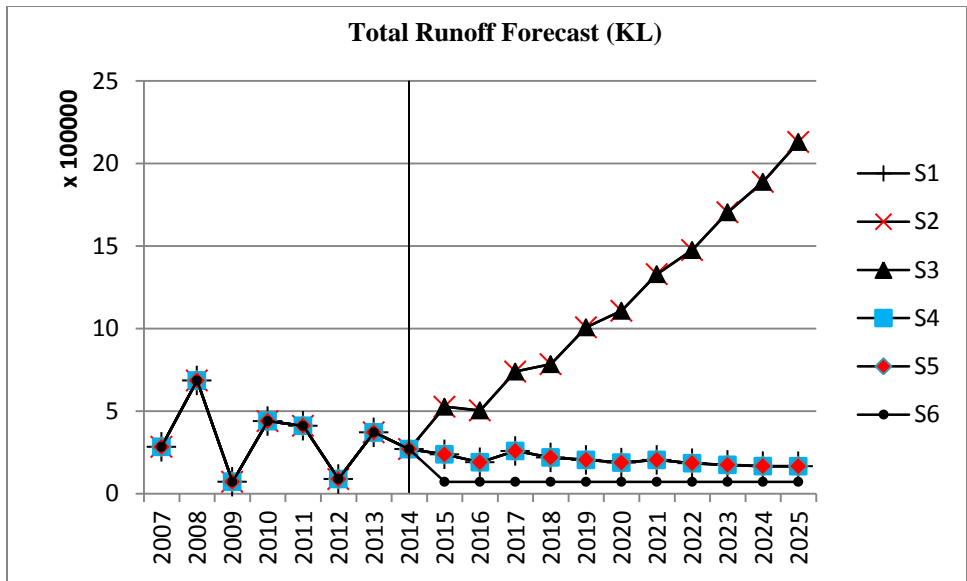


Figure 4.12. Forecast graph of runoff from selected villages of Chirawa

Table 4.5. Scenarios considered and their methods of prediction

Scenario 1 (BAU)	Scenario 2 (HDHR)	Scenario 3 (LDHR)	Scenario 4 (LDLR)	Scenario 5 (HDLR)	Scenario 6 (DRT)
Population - RR (N=4)	Population - Max (Mean (RR (N=2,3,4)))	Population - Min (Mean (RR (N=2,3,4)))	Population - Min (Mean (RR (N=2,3,4)))	Population - Max (Mean (RR (N=2,3,4)))	Population - Max (Mean (RR (N=2,3,4)))
Precipitation - RR (N=4)	Precipitation - Max (Mean (RR (N=2,3,4)))	Precipitation - Max (Mean (RR (N=2,3,4)))	Precipitation - Min (Mean (RR (N=2,3,4)))	Precipitation - Min (Mean (RR (N=2,3,4)))	Precipitation - Min (Observed, Forecasted (RR (N=2,3,4) in year 2015))
Water for Crops - RR (N=4)	Water for Crops - Max (Mean (RR (N=2,3,4)))	Water for Crops - Min (Mean (RR (N=2,3,4)))	Water for Crops - Min (Mean (RR (N=2,3,4)))	Water for Crops - Max (Mean (RR (N=2,3,4)))	Water for Crops Max (Observed, Forecasted (RR (N=2,3,4) in year 2015))
Evaporation - RR (N=4)	Evaporation - Min (Mean (RR (N=2,3,4)))	Evaporation - Min (Mean (RR (N=2,3,4)))	Evaporation - Max (Mean (RR (N=2,3,4)))	Evaporation - Max (Mean (RR (N=2,3,4)))	Evaporation - Max (Observed, Forecasted (RR (N=2,3,4) in year 2015))

**Note:** RR(Recurrence Relation); Max(Maximum); Min(Minimum)

**RR:** Generalized recurrence relation identified from moving average method of forecasting

**RR(N = 4):** Forecasts obtained with values of previous seven years, i.e. from the year 2008 to the year 2014

**RR(N = 3):** Forecasts obtained with values of previous five years, i.e. from the year 2010 to the year 2014

**RR(N = 2):** Forecasts obtained with values of previous three years, i.e. from the year 2012 to the year 2014

**Mean (RR (N = 2, 3, 4)):** Mean of forecasts and historical values for RR(N=2), RR(N=3), and RR(N=4)

**Max (Mean (RR (N = 2, 3, 4))):** Forecasts and historical values with maximum mean for RR(N=2), RR(N=3), and RR(N=4)

**Min (Mean (RR (N = 2, 3, 4))):** Forecasts and historical values with minimum mean for RR(N=2), RR(N=3), and RR(N=4)

**Min(Observed, Forecasted(RR (N = 2, 3, 4) in year 2015)):** Forecasts after the year 2015 taking minimum of the value from the historical values or forecasted value of the year 2015.

**Max(Observed, Forecasted(RR (N = 2, 3, 4) in year 2015)):** Forecasts after the year 2015 taking maximum of the value from the historical values or forecasted value of the year 2015.

Table 4.6. Forecast statistics for the influencing parameters considered

Year	Population						Rainfall (mm)						Evaporation (KL)						Water for Crops (KL)					
	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6	S1	S2	S3	S4	S5	S6
2007	29751	29751	29751	29751	29751	29751	476	476	476	476	476	476	946113	946113	946113	946113	946113	946113	97867728	97867728	97867728	97867728	97867728	97867728
2008	30241	30241	30241	30241	30241	30241	681	681	681	681	681	681	885073	885073	885073	885073	885073	885073	95534424	95534424	95534424	95534424	95534424	95534424
2009	30788	30788	30788	30788	30788	30788	299	299	299	299	299	299	941026	941026	941026	941026	941026	941026	95342976	95342976	95342976	95342976	95342976	95342976
2010	31387	31387	31387	31387	31387	31387	566	566	566	566	566	566	874900	874900	874900	874900	874900	874900	98067384	98067384	98067384	98067384	98067384	98067384
2011	31859	31859	31859	31859	31859	31859	551	551	551	551	551	551	815839	815839	815839	815839	815839	815839	87192900	87192900	87192900	87192900	87192900	87192900
2012	32346	32346	32346	32346	32346	32346	318	318	318	318	318	318	776262	776262	776262	776262	776262	776262	86891364	86891364	86891364	86891364	86891364	86891364
2013	32766	32766	32766	32766	32766	32766	529	529	529	529	529	529	939544	939544	939544	939544	939544	939544	87996708	87996708	87996708	87996708	87996708	87996708
2014	33253	33253	33253	33253	33253	33253	467	467	467	467	467	467	874827	874827	874827	874827	874827	874827	86945472	86945472	86945472	86945472	86945472	86945472
2015	33770	33770	33690	33690	33770	33770	445	610	610	445	445	299	840820	840820	840820	980193	980193	1270640	81349620	87646295	81349620	81349620	87646295	98067384
2016	34226	34226	34164	34164	34226	34226	410	599	599	410	410	299	867270	867270	867270	957304	957304	1270640	80886063	87388887	80886063	80886063	87388887	98067384
2017	34684	34684	34610	34610	34684	34684	459	703	703	459	459	299	914576	914576	914576	1030551	1030551	1270640	80117923	88258749	80117923	80117923	88258749	98067384
2018	35174	35174	35078	35078	35174	35174	432	721	721	432	432	299	887617	887617	887617	1031568	1031568	1270640	78218303	88282858	78218303	78218303	88282858	98067384
2019	35659	35659	35529	35529	35659	35659	421	804	804	421	421	299	885073	885073	885073	1087013	1087013	1270640	75371778	88941225	75371778	75371778	88941225	98067384
2020	36126	36126	35993	35993	36126	36126	408	838	838	408	408	299	902368	902368	902368	1101255	1101255	1270640	74445254	89124078	74445254	74445254	89124078	98067384
2021	36598	36598	36447	36447	36598	36598	421	909	909	421	421	299	918645	918645	918645	1146526	1146526	1270640	73176942	89814438	73176942	73176942	89814438	98067384
2022	37080	37080	36908	36908	37080	37080	406	952	952	406	406	299	911524	911524	911524	1168399	1168399	1270640	71503996	90559681	71503996	71503996	90559681	98067384
2023	37558	37558	37364	37364	37558	37558	398	1016	1016	398	398	299	916611	916611	916611	1208074	1208074	1270640	69796681	91340741	69796681	69796681	91340741	98067384
2024	38030	38030	37824	37824	38030	38030	391	1064	1064	391	391	299	927292	927292	927292	1234525	1234525	1270640	70247495	92094512	70247495	70247495	92094512	98067384
2025	38505	38505	38281	38281	38505	38505	391	1124	1124	391	391	299	935431	935431	935431	1270640	1270640	1270640	70447428	92867843	70447428	70447428	92867843	98067384
Avg.	34200	34200	34120	34120	34200	34200	446	696	696	446	446	378	892674	892674	892674	1014191	1014191	1106875	82178970	90639909	82178970	82178970	90639909	95504220

- Historical values
- Predicted values to be compared with its real
- Predicted values



Situations over the study area have been judged with respect to recharge and demand for the six scenarios. Overall recharge is very less in all scenarios with respect to demand. Scenario 2 and 3 reflect rise in recharge while other scenarios 1, 4, 5, and 6, all reflect decline in recharge. There is fall in demand in scenario 1, 3 and 4 while scenarios 2, 5 and 6 reflect rise in demand. Figure 4.13 and Figure 4.14 present conditions of demand and recharge under six scenarios denoting the volume of water in KL over y-axis with respect to years over the x-axis.

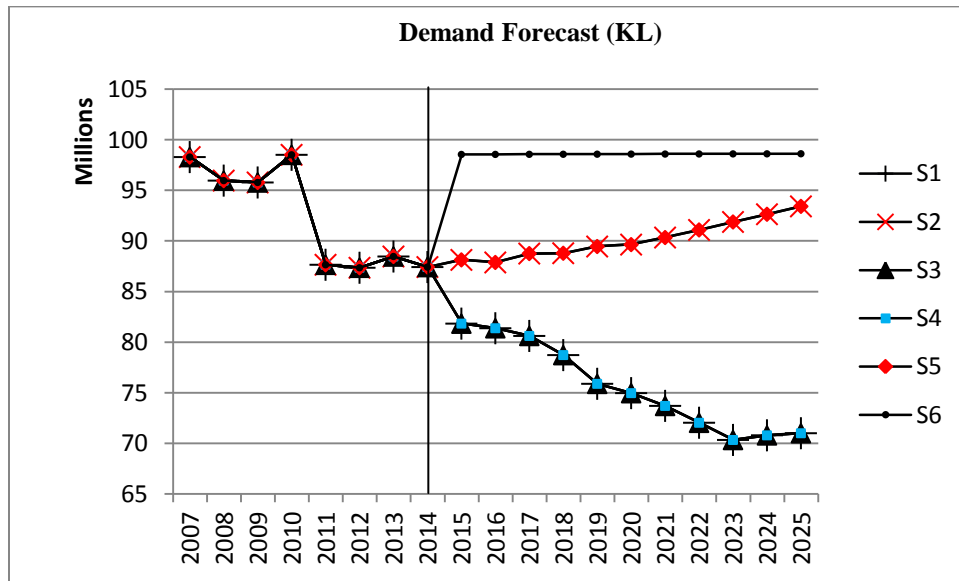


Figure 4.13. Forecast for water demand in selected villages of Chirawa

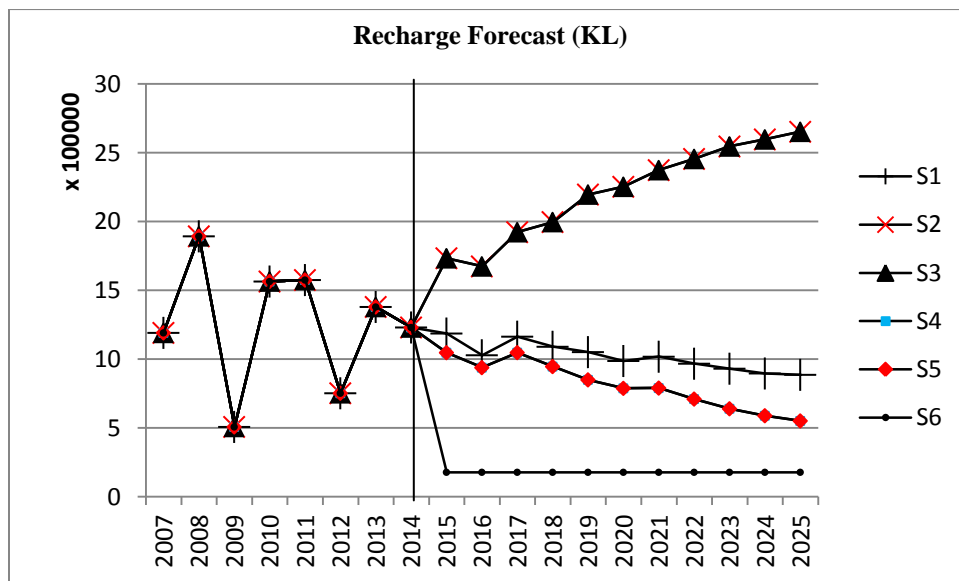


Figure 4.14. Forecast for ground water recharge in selected villages of Chirawa

It has been assumed that for sustainability an average water demand for all six scenarios must be compensated by average recharge and water conservation measures. Certain water conservation methods are explored as:

- Reduction of evaporation losses using continuous floating covers, modular systems, shade structures and chemical covers.
- Recharge of water table using rain water harvesting such as creating percolation wells for surface runoff & household and village tanks for roof top runoff.
- Production of alternative crops consuming lesser water and providing same revenue as the crops being practiced.
- Efficient methods of irrigation like the sprinkler and drip irrigation.

Benefits with respect to various alternatives have been analyzed to identify the best set of alternatives to be adopted. It has been explored that evaporation can be reduced by 90%, 90%, 75%, and 30% by using continuous floating covers, modular systems, shade structures and chemical covers respectively (Reddy, 2005). Rain water harvesting can save about 30% of drinking and cooking water (Rahman et al., 2014). Water required for drinking and cooking purposes is about 8 liters per day per head (Ministry of Drinking Water & Health, Government of India, 2013). Alternative food crops can save about 30% of water in our study region. Sprinkler irrigation can save about 40% (<http://www.agrifarming.in/drip-irrigation-vs-sprinkler> dated 17/08/2016) and drip irrigation can save about 70% of water (<http://vikaspedia.in/agri-inputs/farm-machinery/drip-irrigation-system> dated 17/08/2016). Therefore the benefit of any system can be generalized as:

$$\text{Total water saved} = \text{water saved from evaporation} + \text{water saved using rain water harvesting} + \text{water saved using efficient irrigation}$$

Considering average values for all predicted variables from the year 2015 to the year 2025 in scenarios S1 to S6 amount of water that can be saved using generalized water saving scheme is presented in Table 4.7. Benefits associated with the twelve combinations of above water savings schemes in the six scenarios are presented in Table 4.8.

Table 4.7. Expected saving of water using different measures in Scenarios S1 to S6

Water Saving Measures	Types of Measures	S1	S2	S3	S4	S5	S6
Water Saved from Evaporation (KL)	Continuous Floating Covers	808655	808655	808655	981816	981816	1113890
	Modular Systems	808655	808655	808655	981816	981816	1113890
	Shade Structures	673879	673879	673879	818180	818180	928242
	Chemical Covers	269552	269552	269552	327272	327272	371297
Water saved using rain water harvesting(K.L.)		29959	29959	29889	29889	29959	29959
Water saved using efficient irrigation(K.L.)	Alternative Crop	24653691	27191973	24653691	24653691	27191973	28651266
	Sprinkle Irrigation	32871588	36255963	32871588	32871588	36255963	38201688
	Drip Irrigation	57525279	63447936	57525279	57525279	63447936	66852954

Table 4.8. Total water which can be saved using the twelve possible water conservation combinations

S. No.	Combinations of Alternatives	Water saved (KL)					
		S1	S2	S3	S4	S5	S6
1	C, R, A	25492305	28030586	25492234	25665396	28203747	29795116
2	C, R, Sp	33710202	37094577	33710131	33883293	37267738	39345538
3	C, R, D	58363893	64286550	58363823	58536984	64459711	67996804
4	M, R, A	25492305	28030586	25492234	25665396	28203747	29795116
5	M, R, Sp	33710202	37094577	33710131	33883293	37267738	39345538
6	M, R, D	58363893	64286550	58363823	58536984	64459711	67996804
7	S, R, A	25357529	27895811	25357459	25501760	28040112	29609467
8	S, R, Sp	33575426	36959801	33575356	33719657	37104102	39159889
9	S, R, D	58229117	64151774	58229047	58373348	64296075	67811155
10	Ch, R, A	24953202	27491483	24953132	25010852	27549204	29052522
11	Ch, R, Sp	33171099	36555474	33171029	33228749	36613195	38602944
12	Ch, R, D	57824790	63747447	57824720	57882440	63805167	67254210

**Note: C(Continuous floating covers); M(Modular systems); S(Shade structures); Ch(Chemical covers); R(Rain water harvesting); A(Alternative crop); Sp(Sprinkle irrigation); D(Drip irrigation)**

Cost benefit analysis with respect to the above solutions has been conducted to select a solution with higher benefit in terms of water saved and lower cost in terms of its implementation. It has been explored that the lowest implementation cost of floating covers, modular covers, and shade structures is about Rs. 234, Rs. 167 and Rs. 500 per square meter respectively covering total catchment area. The lowest cost of chemical covers is Rs. 334 per kg, with an application rate of

1.5 kg per hectare once in every four days (Craig, 2008). Implementation of rainwater harvesting system costs on an average Rs. 2 per liter of water saved (<http://www.rainwaterharvesting.org/urban/costs.htm> dated 18/08/2016). Implementation of drip and sprinkler irrigation methods cost about Rs. 45000 per hectare and Rs. 15000 per hectare respectively covering average cultivated land since the year 2007 to the year 2025 for all scenarios (<http://www.ncpahindia.com/applications/pressurisedirrigation/application13.php> dated 18/08/2016). Alternate crops like gram, mustard, and fenugreek which require 12096 Kiloliters of water with an average investment of Rs. 9666 per hectare can be produced instead of wheat and oat demanding 17028 Kiloliters of water with an average investment of Rs. 9000 per hectare. It needs an investment of Rs. 666 per hectare. Hence comparative graphs for all scenarios covering water saved and cost incurred by implementing all the alternatives (given in Table 4.8) are shown in Figure 4.15 and Figure 4.16 respectively. The graphs are observed for all scenarios leading to a common solution for all with the highest benefit and lowest implementation cost. Alternatives 3, 6, 9 and 12 have higher benefits where alternative 12 has the least implementation cost. Hence alternative 12, implementing chemical covers for saving evaporation, rainwater harvesting system for household purposes and drip irrigation method for crop production is well suited for the region in all the six scenarios.

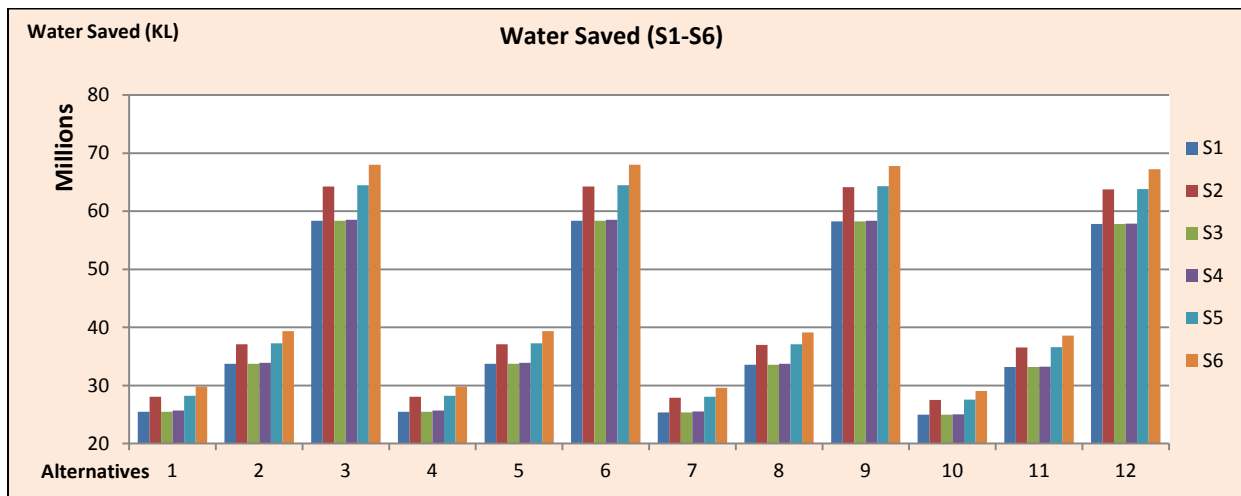


Figure 4.15. Water Saved Graph for S1-S6 in selected villages of Chirawa

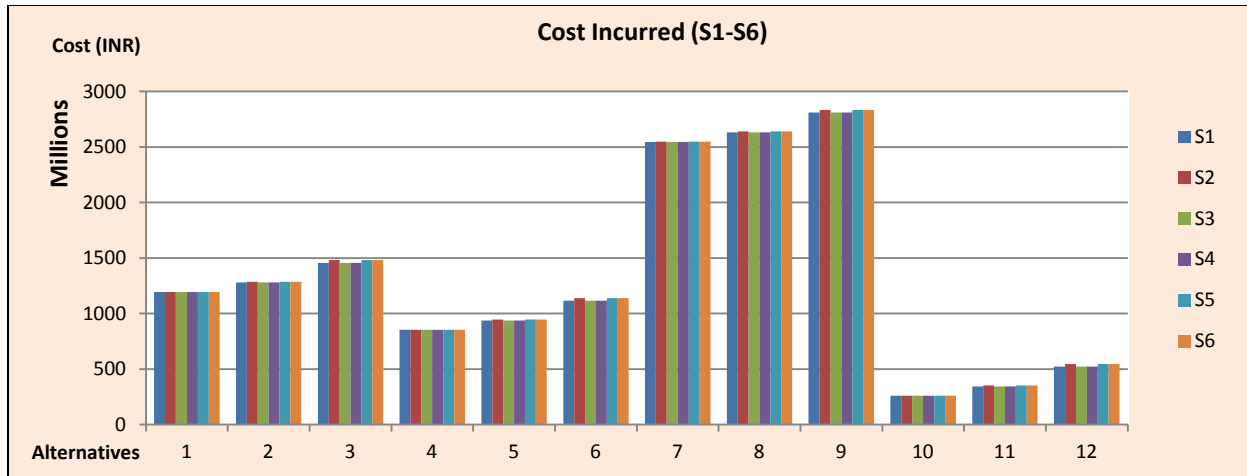


Figure 4.16. Cost Incurred Graph for S1-S6 in selected villages of Chirawa

## 4.6 Methodology investigation

The methodology applied over the study area has been investigated with respect to the resulting difference between predicted and observed values and sensitivity analysis of the driving factors (rainfall, evaporation, population and crop water requirement) in developed scenarios.

### 4.6.1 Results

Normally scenarios are difficult to validate since it predicts the future with no available records. Besides, the accuracy of the predicted values can be judged by dividing the historical data into two parts, one used for prediction and another for validation. Forecasts evaluated for population, rainfall, potential evaporation, and water requirement for crops generated using their respective data from the year 2008 to the year 2014 are validated with their actual data obtained for the year 2015. Errors found in the predicted data with respect to actual data for the variables are presented in Table 4.9. Rainfall and evaporation being the natural processes are highly uncertain as compared to the population which is more or less in control of the human beings. Crop water requirement is also uncertain in the study region due to changing patterns of the cultivated area crop wise and year wise as shown in Figure 4.4 and Figure 4.5.

Table 4.9. Percent Error of prediction of variables in Scenarios S1 to S6 for the year 2015

Variables	Error (%)					
	S1	S2	S3	S4	S5	S6
Population	0.94	0.94	0.71	0.71	0.94	0.94
Rainfall	5.92	28.96	28.96	5.92	5.92	36.79
Evaporation	7.65	7.65	7.65	7.65	7.65	39.66
Crop water	7.00	0.19	7.00	7.00	0.19	12.11

#### 4.6.2 Sensitivity analysis

Sensitivity analysis aims to describe how much model output values are affected by changes in model input values. It is the investigation of the importance of imprecision or uncertainty in model inputs in a decision-making or modeling process (Loucks, et al., 2005). Sensitivity analysis for the four parameters (rainfall ( $P_1$ ), evaporation ( $P_2$ ), population ( $P_3$ ), and crop water ( $P_4$ )) considered in developed methodology is conducted in terms of water scarcity taken as the performance indicator ( $I$ ). Sum of the products of squares of sensitivity coefficients ( $\frac{\Delta I_i}{\Delta P_i}$ ) and variances ( $var(P_i)$ ) of input parameters ( $P_i$ 's) determine the total variance ( $var(I)$ ) of the performance indicator in the system as per Equation (4.16). Sensitivity coefficient of indicator  $I$  for parameter  $P_i$  is the ratio of the difference of lowest ( $I_L$ ) and highest ( $I_H$ ) values of  $I$  and difference of lower ( $P_{iL}$ ) and higher ( $P_{iH}$ ) values of  $P_i$  for corresponding lowest and highest values of  $I$ , as per Equation (4.17). Percentage of every parameter's product of the square of sensitivity coefficient and variance with respect to the total variance of indicator derives its uncertainty contribution ( $U_{\%}(P_i)$ ) as per Equation (4.18) and presented in Table 4.10 for the input parameters considered in the study. Here rainfall has the significant contribution of about 10 and 26 percent for uncertainty in water deficit for scenarios S2 and S3 respectively. Evaporation has significant contribution in scenario S6 where the population has negligible effect. Crop water requirement is highly significant in all scenarios considered.

$$var(I) = \sum_{i=1}^n \left( \frac{\Delta I_i}{\Delta P_i} \right)^2 * var(P_i) \quad (4.16)$$

$$\left( \frac{\Delta I_i}{\Delta P_i} \right) = \frac{I_H - I_L}{P_{iH} - P_{iL}} \quad (4.17)$$

$$U_{\%}(P_i) = \frac{\left(\frac{\Delta I}{\Delta P_i}\right)^2 * var(P_i)}{var(I)} * 100 \quad (4.18)$$

Table 4.10. Percent uncertainty of input parameters in scenarios S1 to S6

Parameters	S1	S2	S3	S4	S5	S6
Rainfall	0.05	10.05	25.61	0.05	0.57	0.37
Evaporation	0.06	0.44	0.03	0.07	0.75	57.19
Population	43.64	22.28	32.61	43.40	12.72	0.43
Crop Water	56.24	67.23	41.75	56.49	85.96	42.01

### 4.6.3 Inference of the study

Scenario development of the water resources till the year 2025 in the selected villages falling under semi arid zone of Chirawa block reflects the decline in the availability of water reserves and rise in demand with respect to varying statistics of precipitation, evaporation, population and crop water requirement. To make the system sustainable, it is required to adopt efficient methods of irrigation and production of crops which requires lesser water for their growth. Certain other measures which can be adopted are the reduction of evaporation from open surface water bodies and replenishment of the ground water table using artificial recharge methods. The benefit in terms of total water saved suggests implementing chemical covers to save water from evaporation, to create rain water harvesting structures at homes for household purposes and to apply drip method of irrigation in crops. About half of the water requirement can be compensated by implementing the solution identified and it will cost on an average of Rs. 8.75 per Kiloliter of water saved. Plans to store surface runoff can also be implemented, developing a large community tank which can be networked to household tanks channelizing their overflows. Above all water should be used wisely and safely considering its every drop precious.

### 4.7 Summary of the Chapter

Summary of the chapter includes the following points:

- Development of a generic methodology for scenario development of any time series data based on the generalized recurrence relation identified from moving average method of forecasting for three different sets of historical data (three, five, and seven).

- Forecasting the time series data of rainfall, evaporation, population, and crop water requirement into their respective three directions and assigning their forecasted statistics to the six scenarios (BAU (business as usual), HDHR (high demand high recharge), LDHR (low demand low recharge), LDLR (low demand high recharge), HDLR (high demand low recharge), and DRT (drought)) as per the rules defined in Table 4.5. The study is carried over a region comprising of nine villages in Chirawa, Rajasthan (India).
- Derivation of demand for water (total of population and crop water demand) and ground water recharge (difference of rainfall and sum of evaporation and runoff) in forthcoming years for the six scenarios to derive their expected scarcity of water.
- Identification of water conservation techniques like evaporation reduction (continuous floating covers, modular covers, shade structures, and chemical covers), rain water harvesting, and efficient irrigation practices (alternative crops, sprinkler irrigation, and drip irrigation) to compensate mean annual forecasted water demand for the six scenarios. Twelve combinations of the water saving schemes are presented in Table 4.8.
- Evaluating the cost of implementation for the twelve alternatives of water saving scheme with respect to their benefits (water saved) resulting that alternative implementing chemical covers for evaporation reduction, rain water harvesting at households, and drip method of irrigation for crops is identified as the low cost-high benefit solution.



# **CHAPTER 5: DEVELOPMENT OF A STATE VARIABLE MODEL FOR GENERATING HYDROLOGICAL SCENARIOS**

## **5.1 Chapter overview**

Extinction of water resources is a serious concern for sustainability. Their uncertain replenishment and over exploitation are the root causes for such situation. It is required to predict the future states of water resources in order to devise plans for sustainable prospects. Various models have been developed and applied to generate scenarios for future states of water resources (Griffin et al., 2013; Bae et al., 2011; Silberstein et al., 2012). Most of the models are following either state variable or system dynamics approach; both following the similar fundamental concept (Jiang et al., 2007; Neitsch et al., 2011; Wang et al., 2011; Sahin et al., 2016). Such models have been simulated with respect to the predefined scenarios and were specific to a few state variables. This study has developed a hydrological model based on state variable approach of time domain analysis, that determines the time invariant states of different water storage components for a random number of scenarios. Later few among the generated random scenarios are selected fitting/reflecting best to the considered scenario definitions. The model has been developed and simulated in MATLAB Simulink ([https://www.tutorialspoint.com/matlab/matlab\\_simulink.htm](https://www.tutorialspoint.com/matlab/matlab_simulink.htm) dated 22/04/2018). It is validated over a village area named Ardawta, Rajasthan (India). Scenarios for the state of ground water level up to the year 2030 have been generated and five among them have been selected from worst to best case situation.

## **5.2 State variable modeling approach**

The modeling approach to develop a hydrological state variable system determining the future states of various water resources within a watershed includes the prediction of input variables affecting the system and designing stocks and flows as per certain defined equations for different water resources (soil, aquifers, reaches, and ponds). The basic fundamental of state variable model is given in section 3.8.3. Input variables predicted for forthcoming incidents will help to derive the states of water storage elements of a hydrological system in future.

### 5.2.1 Prediction of input variables

A set of generalized equations generated from recurrence relation found in moving average method of forecasting are used for predicting inputs (Equation (4.10) to Equation (4.12)). These equations have been developed as per the availability of the historical data. The method to obtain the generalized equations is mentioned in section 3.8.2. In this chapter first  $2N-1$  values for the input variables are taken for prediction with respect to moving average technique as described in section 3.8.1.

### 5.2.2 Development of the hydrological model

A state variable model has been developed incorporating the input variables to produce outputs. Model design is based on the water balance hypotheses given by Neitsch et al. (2011) which is illustrated further. Precipitation inflow after surface runoff moves to the soil layer. Excess water above field capacity of soil percolates to the aquifers. There are two types of aquifers; i.e. shallow unconfined and deep confined aquifers. A certain fraction of percolated water goes to deep aquifer while remaining stays into the shallow aquifer. Ground water flow from the aquifers, surface runoff, and precipitation over the areal extent of reaches and ponds generates additional inflow to them (reaches and ponds). There are other losses from aquifers in form of evaporation water demand by the soil and water consumption. Reaches lose water in form of outflow, transmission losses, and evaporation, while ponds lose water in form of seepage and evaporation from their respective surface areas. Transmission losses from reaches and seepage from ponds route to aquifer recharge.

Paraphrasing Neitsch et al. (2011), surface runoff within a region is the inherent property of its soil, land use and slope. Water percolation will occur over the whole region. The areal extent which routes surface runoff to the main channel is called watershed area. Watershed area over a region depends upon the selection of a number of reach outlets. State change relations for soil water, shallow and deep aquifers, ground water level, reach and pond storage are given from Equation (5.1) to Equation (5.6).

$$S_{SW}(k+1) = C_{field} (S_{SW}(k) + I_{SW}(k) + B_{revap} \cdot E(k) - E(k)) \quad (5.1)$$

where,  $S_{SW}(k)$  (m): soil water storage at time step  $k$ .

- $I_{SW}(k)$  (m): soil water intake at time step  $k$ .
- $E(k)$  (m): evapotranspiration at time step  $k$ .
- $C_{field}$ : field capacity as a fraction of total soil water volume.
- $B_{revap}$ : revap coefficient, a fractional value ranging from 0 (no evaporation demand of soil from aquifer) to 1 (direct evaporation from aquifer).

Equation (5.1) describes the water balance for soil with certain intermediate equations:

- to derive soil water intake ( $I_{SW}(k)$  (m)) in meters with precipitation ( $P(k)$  (m)) and surface runoff ( $R(k)$  (m)), both expressed in meters as per Equation (5.1a); and
- to derive surface runoff ( $R(k)$  (mm)) in millimetres as per Equation (5.1b) and Equation (5.1c) where precipitation ( $P(k)$  (mm)), and soil retention parameter ( $S(k)$  (mm)) are expressed in millimetres.

$$I_{SW}(k) = P(k) - R(k) \quad (5.1a)$$

where,  $P(k)$  (m): precipitation at time step  $k$ .

$R(k)$  (m): surface runoff at time step  $k$ .

$$R(k) = \frac{(P(k) - 0.2S)^2}{P(k) + 0.8S} \quad (5.1b)$$

where,  $R(k)$  (mm): runoff in mm at time step  $k$ .

$P(k)$  (mm): precipitation at time step  $k$ .

$S$ (mm): soil retention parameter.

$$S = 25.4 \left( \frac{1000}{CN} - 10 \right) \quad (5.1c)$$

where,  $CN$ : a specific curve number for some land use and soil.

$$V_{SA}(k+1) = V_{SA}(k) + (1 - B_{deep}) \cdot R_{aq}(k) \quad (5.2)$$

where,  $V_{SA}(k)$  (m<sup>3</sup>): shallow aquifer volume at time step  $k$ .

$R_{aq}(k)$  (m<sup>3</sup>): aquifer recharge volume at time step  $k$ .

$B_{deep}$ : fractional deep aquifer percolation coefficient.

Equation (5.2) describes the water balance for the shallow aquifer with certain intermediate equations:

- to derive aquifer recharge volume ( $R_{aq}(k)$  (m<sup>3</sup>)) in cubic meters with soil water percolation ( $P_{SW}(k)$  (m<sup>3</sup>)), ground water flow ( $Q_{gw}(k)$  (m<sup>3</sup>)), water usage ( $U(k)$  (m<sup>3</sup>)), and evaporation ( $E(k)$  (m<sup>3</sup>)) expressed in cubic meters as per Equation (5.2a);

- to derive soil water percolation volume ( $P_{SW}(k)$  ( $m^3$ )) in cubic meters with watershed area ( $A_{total}$  ( $m^2$ )), reach area ( $A_{reach}$  ( $m^2$ )), and pond area ( $A_{pond}$  ( $m^2$ )) expressed in square meters, and soil water storage ( $S_{SW}(k)$  ( $m$ )) and soil water intake ( $I_{SW}(k)$  ( $m$ )) expressed in meters as per Equation (5.2b); and
- to derive ground water flow ( $Q_{gw}(k)$  ( $mm$ )) as per Equation (5.2c) where ground water flow has been evaluated in millimetres with respect to the hydraulic conductivity of the aquifer ( $K_{sat}$  ( $mm/day$ )) expressed in millimetres per day, height of water table ( $h_{wtbl}$  ( $m$ )) and distance from sub basin divide to reach ( $L_{gw}$  ( $m$ )) both expressed in meters.

$$R_{aq}(k) = P_{SW}(k) - Q_{gw}(k) - U(k) - B_{revap} \cdot E(k) \quad (5.2a)$$

where,  $P_{SW}(k)$  ( $m^3$ ): soil water percolation at time step  $k$ .

$Q_{gw}(k)$  ( $m^3$ ): ground water flow at time step  $k$ .

$U(k)$  ( $m^3$ ): water use at time step  $k$ .

$$P_{SW}(k) = (A_{total} - A_{reach} - A_{pond}) (I - C_{field}) (S_{SW}(k) + I_{SW}(k)) \quad (5.2b)$$

where,  $A_{total}$  ( $m^2$ ): total area of watershed.

$A_{reach}$  ( $m^2$ ): reach area in watershed.

$A_{pond}$  ( $m^2$ ): pond area in watershed.

$$Q_{gw}(k) = \frac{8000 \cdot K_{sat}}{L_{gw}^2} h_{wtbl} \text{ (Hooghoudt, 1940)} \quad (5.2c)$$

where,  $K_{sat}$  ( $mm/day$ ): hydraulic conductivity of aquifer.

$L_{gw}$  ( $m$ ): distance from sub basin divide to reach.

$h_{wtbl}$  ( $m$ ): height of water table.

$Q_{gw}(k)$  ( $mm$ ): ground water flow into main channel at time step  $k$ .

$$V_{DA}(k+1) = V_{DA}(k) + B_{deep} \cdot R_{aq}(k) + R_{tloss}(k) \quad (5.3)$$

where,  $V_{DA}(k)$  ( $m^3$ ): deep aquifer volume at time step  $k$ .

$R_{tloss}(k)$  ( $m^3$ ): reach transmission losses at time step  $k$ .

Equation (5.3) describes the water balance for the deep aquifer with certain intermediate equations:

- to derive reach transmission losses ( $R_{tloss}(k)$  ( $m^3$ )) in cubic meters with wetted perimeter of reach ( $P_{ch}$  ( $m$ )) expressed in meters, length of reach ( $L_{ch}$  ( $km$ )) expressed in kilometres, effective hydraulic conductivity of the reach alluvium ( $K_{ch}$  ( $mm/hr$ )) expressed in millimetres per hour, and reach flow travel time ( $T(k)$  ( $hr$ )) expressed in hours as per Equation (5.3a); and

– to derive reach flow travel time ( $T(k)$  (s)) in seconds as per Equation (5.3b) with respect to the reach storage ( $S_{reach}(k)$  ( $m^3$ )) expressed in cubic meters and reach discharge rate ( $q_{out}(k)$  ( $m^3/s$ )) expressed in cubic meters per second.

$$R_{tloss}(k) = K_{ch} \cdot T(k) \cdot P_{ch} \cdot L_{ch} \quad (5.3a)$$

where,  $P_{ch}$  (m): wetted perimeter of reach.  
 $L_{ch}$  (km): length of reach.  
 $K_{ch}$  (mm/hr): effective hydraulic conductivity of the reach alluvium.  
 $T(k)$  (hr): reach flow travel time at time step  $k$  in hours.

$$T(k) = \frac{S_{reach}(k)}{q_{out}(k)} \quad (5.3b)$$

where,  $S_{reach}(k)$  ( $m^3$ ): reach storage at time step  $k$ .  
 $q_{out}(k)$  ( $m^3/s$ ): reach discharge rate at time step  $k$ .  
 $T(k)$  (s): reach flow travel time at time step  $k$  in seconds.

$$S_{reach}(k+1) = S_{reach}(k) + V_{reachin}(k) - V_{reachout}(k) \quad (5.4)$$

where,  $S_{reach}(k)$  ( $m^3$ ): reach storage at time step  $k$ .  
 $V_{reachin}(k)$  ( $m^3$ ): total volume of water inflow to reach at time step  $k$ .  
 $V_{reachout}(k)$  ( $m^3$ ): total volume of reach water outflow from reach at time step  $k$ .

Equation (5.4) describes the water balance for the reach with certain intermediate equations:

– to derive total volume of water inflow to reach ( $V_{reachin}(k)$  ( $m^3$ )) in cubic meters with reach inflow volume ( $I_{reach}(k)$  ( $m^3$ )) expressed in cubic meters, area of watershed ( $A_{wshed}$  ( $m^2$ )) and area of reach ( $A_{reach}$  ( $m^2$ )) expressed in meters square, and runoff ( $R(k)$  (m)), ground water flow ( $Q_{gw}(k)$  (m)), and precipitation ( $P(k)$  (m)) expressed in meters as per Equation (5.4a); and  
– to derive total volume of water outflow from reach ( $V_{reachout}(k)$  ( $m^3$ )) in cubic meters with reach outflow volume ( $O_{reach}(k)$  ( $m^3$ )) and reach transmission losses ( $R_{tloss}(k)$  ( $m^3$ )) expressed in cubic meters, evaporation ( $E(k)$  (m)) expressed in meters, and area of reach ( $A_{reach}$  ( $m^2$ )) expressed in meters square as per Equation (5.4b).

$$V_{reachin}(k) = I_{reach}(k) + A_{wshed}(R(k) + Q_{gw}(k)) + A_{reach} \cdot P(k) \quad (5.4a)$$

where,  $I_{reach}(k)$  ( $m^3$ ): reach inflow volume derived by product of time interval (s) between two consecutive time steps and average of reach inflow rate ( $m^3/s$ ) at start and end of time interval.

$A_{wshed}$  ( $m^2$ ): watershed area routing to the reach.

$A_{reach}$  ( $m^2$ ): reach area.  
 $R(k)$  (m): surface runoff at time step  $k$ .  
 $Q_{gw}(k)$  (m): ground water flow at time step  $k$ .  
 $P(k)$  (m): precipitation at time step  $k$ .

$$V_{reachout}(k) = O_{reach}(k) + R_{tloss}(k) + A_{reach} \cdot E(k) \quad (5.4b)$$

where  $O_{reach}(k)$  ( $m^3$ ): reach outflow volume derived by the product of time interval (s) between two consecutive time steps and average of reach outflow rate ( $m^3/s$ ) at the start and end of time interval.

$R_{tloss}(k)$  ( $m^3$ ): reach transmission losses at time step  $k$ .  
 $E(k)$  (m): evapotranspiration at time step  $k$ .  
 $A_{reach}$  ( $m^2$ ): reach area.

$$S_{pond}(k+1) = S_{pond}(k) + V_{pondin}(k) - V_{pondout}(k) \quad (5.5)$$

where,  $S_{pond}(k)$  ( $m^3$ ): pond storage at time step  $k$ .

$V_{pondin}(k)$  ( $m^3$ ): total volume of water inflow to pond at time step  $k$ .  
 $V_{pondout}(k)$  ( $m^3$ ): total volume of water outflow from pond at time step  $k$ .

Equation (5.5) describes the water balance for the pond with certain intermediate equations:

- to derive total volume of water inflow to pond ( $V_{pondin}(k)$  ( $m^3$ )) in cubic meters with runoff ( $R(k)$  (m)), ground water flow ( $Q_{gw}(k)$  (m)), and precipitation ( $P(k)$  (m)) expressed in meters and surface area of pond ( $A_{pond}$  ( $m^2$ )) and fraction of watershed area routing to pond ( $F_{wshed}$  ( $m^2$ )) expressed in meters square as per Equation (5.5a);
- to derive total volume of water outflow from pond ( $V_{pondout}(k)$  ( $m^3$ )) in cubic meters with pond seepage ( $O_{seep}(k)$  ( $m^3$ )) and pond overflow ( $O_{of}(k)$  ( $m^3$ )) expressed in cubic meters, and evaporation ( $E(k)$  (m)) expressed in meters as per Equation (5.5b);
- to derive seepage losses ( $O_{seep}(k)$  ( $m^3/day$ )) in cubic meters per day with effective hydraulic conductivity of the reservoir/pond ( $K_{sat}$  (mm/hr)) expressed in millimetres per hour and surface area of the pond ( $A_{pond}$  (ha)) expressed in hectares as per Equation (5.5c); and
- to derive pond overflow ( $O_{of}(k)$  ( $m^3$ )) in cubic meters with total volume of water inflow to pond ( $V_{pondin}(k)$  ( $m^3$ )) and volume of pond ( $V_{pond}$  ( $m^3$ )) both expressed in cubic meters as per Equation (5.5d).

$$V_{pondin}(k) = A_{pond} \cdot P(k) + F_{wshed}(R(k) + Q_{gw}(k)) \quad (5.5a)$$

where,  $A_{pond}$  ( $m^2$ ): pond surface area.

$F_{wshed}$  (m<sup>2</sup>): fraction of watershed area routing to pond.

$R(k)$  (m): surface runoff at time step  $k$ .

$Q_{gw}(k)$  (m): ground water flow at time step  $k$ .

$P(k)$  (m): precipitation at time step  $k$ .

$$V_{pondout}(k) = A_{pond} \cdot E(k) + O_{seep}(k) + O_{of}(k) \quad (5.5b)$$

where,  $E(k)$  (m): evapotranspiration at time step  $k$ .

$O_{seep}(k)$  (m<sup>3</sup>): pond seepage at time step  $k$ .

$O_{of}(k)$  (m<sup>3</sup>): pond overflow at time step  $k$ .

$$O_{seep}(k) = 240 \cdot A_{pond} \cdot K_{sat} \quad (5.5c)$$

where,  $K_{sat}$  (mm/hr): effective saturated hydraulic conductivity of the reservoir/pond.

$A_{pond}$  (ha): surface area of the reservoir/pond.

$$O_{of}(k) = V_{pondin}(k) - V_{pond} \quad (5.5d)$$

where,  $V_{pond}$  (m<sup>3</sup>): volume of the reservoir/pond.

$$D_{WL}(k+1) = D_{WL}(k) - \frac{R_{aq}(k)}{A_{total}} \quad (5.6)$$

where,  $D_{WL}(k)$  (m): depth of water level below ground at time step  $k$ .

$R_{aq}(k)$  (m<sup>3</sup>): aquifer recharge at time step  $k$ .

$A_{total}$  (m<sup>2</sup>): area of the geographical region.

Equation (5.6) describes the water balance of depth of ground water level ( $D_{WL}(k)$  (m)) in meters with aquifer recharge ( $R_{aq}(k)$  (m<sup>3</sup>)) expressed in cubic meters and area of the region ( $A_{total}$  (m<sup>2</sup>)) expressed in meters square.

Few of the output variables that can be evaluated using the state variables are presented from Equation (5.7) to Equation (5.10).

$$S_{SWC}(k) = (C_{field} - C_{wilt}) \cdot S_{SW}(k) \quad (5.7)$$

$$V_{aq}(k) = V_{SA}(k) + V_{DA}(k) \quad (5.8)$$

$$S_{surf}(k) = S_{reach}(k) + S_{pond}(k) \quad (5.9)$$

$$P_{SW}(k) = (1 - C_{field}) (S_{SW}(k) + I_{SW}(k)) \quad (5.10)$$

where  $S_{SWC}(k)$  (m<sup>3</sup>): soil water available for crop at time step  $k$ .

$V_{aq}(k)$  (m<sup>3</sup>): total aquifer water at time step  $k$ .

$S_{surf}(k)$  (m<sup>3</sup>): surface water storage at time step  $k$ .

$P_{SW}(k)$  (m<sup>3</sup>): soil water percolation at time step  $k$ .

$C_{wilt}$  : wilting point as a fraction of total soil water volume.

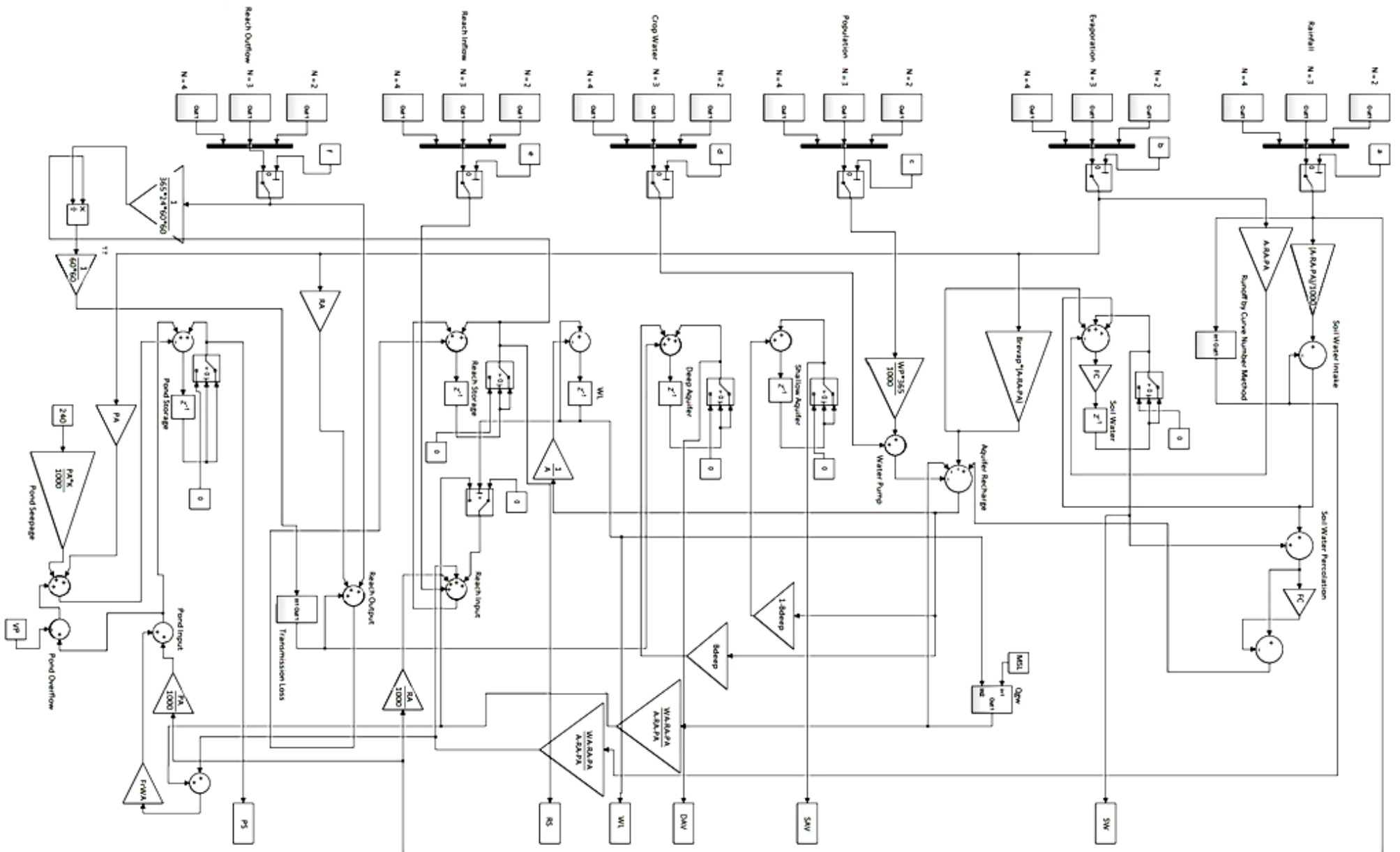
Output variables can either be derived from state variables, state variables themselves or can be used as input for state variables. However, it is required to be judged that which variables are of considerable interest and scenarios with respect to those variables should be generated. Initial states of various state variables are mandatory to generate the outputs, if not available, a null value can be used. Later meaningful outputs can be used to analyze the scenarios. Simulink model developed in MATLAB is presented in Figure 5.1. Matrix representation of the state variable model developed as defined by Equation (3.12) is given as Equation (5.11). Similarly, a matrix for few of the defined output variables (Equation (5.7) to Equation (5.10)) as per Equation (3.13) is given as Equation (5.12).



$$\begin{bmatrix} S_{SW}(k+1) \\ V_{SA}(k+1) \\ V_{DA}(k+1) \\ S_{reach}(k+1) \\ S_{pond}(k+1) \\ D_{WL}(k+1) \end{bmatrix} = \begin{bmatrix} C_{field} & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} S_{SW}(k) \\ V_{SA}(k) \\ V_{DA}(k) \\ S_{reach}(k) \\ S_{pond}(k) \\ D_{WL}(k) \end{bmatrix} + \begin{bmatrix} C_{field} & C_{field}(B_{revap} - 1) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 - B_{deep} & 0 & 0 & 0 & 0 \\ 0 & 0 & B_{deep} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & -1/A_{total} & 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} I_{SW}(k) \\ E(k) \\ R_{aq}(k) \\ R_{tloss}(k) \\ V_{reachin}(k) \\ V_{reachout}(k) \\ V_{pondin}(k) \\ V_{pondout}(k) \end{bmatrix} \quad (5.11)$$

$$\begin{bmatrix} S_{SWc}(k) \\ V_{aq}(k) \\ S_{surf}(k) \\ P_{SW}(k) \end{bmatrix} = \begin{bmatrix} C_{field} - C_{wilt} & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 1 - C_{field} & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} S_{SW}(k) \\ V_{SA}(k) \\ V_{DA}(k) \\ S_{reach}(k) \\ S_{pond}(k) \\ D_{WL}(k) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 - C_{field} \end{bmatrix} \times [I_{SW}(k)] \quad (5.12)$$

Figure 5.1. State variable hydrological model developed in MATLAB Simulink



In Figure 5.1, starting from the extreme left six blocks are developed to supply forecasted input data for the variables rainfall, evaporation, population, crop water requirement, reach inflow, and reach outflow at discrete equal interval time steps. The complete input block of any variable comprises of three subsystems generating forecasted data as per Equation (4.10) ( $N = 2$ ), Equation (4.11) ( $N = 3$ ), and Equation (4.12) ( $N = 4$ ) respectively, one bus creator carrying the signals from the three subsystems, and one block of index vector to select input signals from any one of the three blocks selected by the index variable associated with it. Complete input block and the three subsystems to supply input signals for one variable are shown from Figure 5.2 to Figure 5.5. Various constants presented in the corresponding block diagrams can be referred from Appendix B. Figure 5.3 to Figure 5.5 correspond to the subsystems forecasting the rainfall data. Similar subsystems are incorporated for the other input factors in the state variable model.

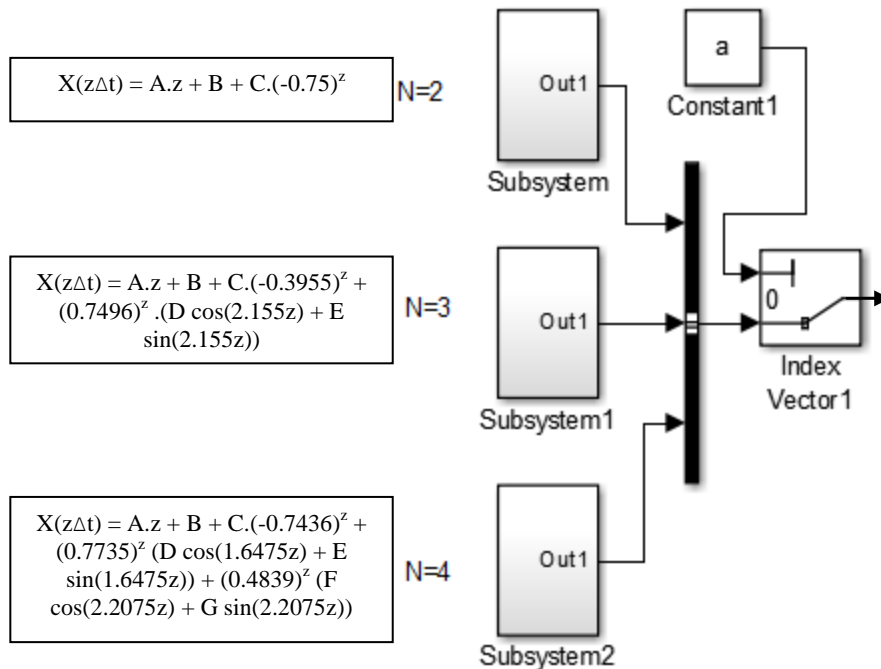


Figure 5.2. Block diagram to provide forecasted inputs to the state variable model

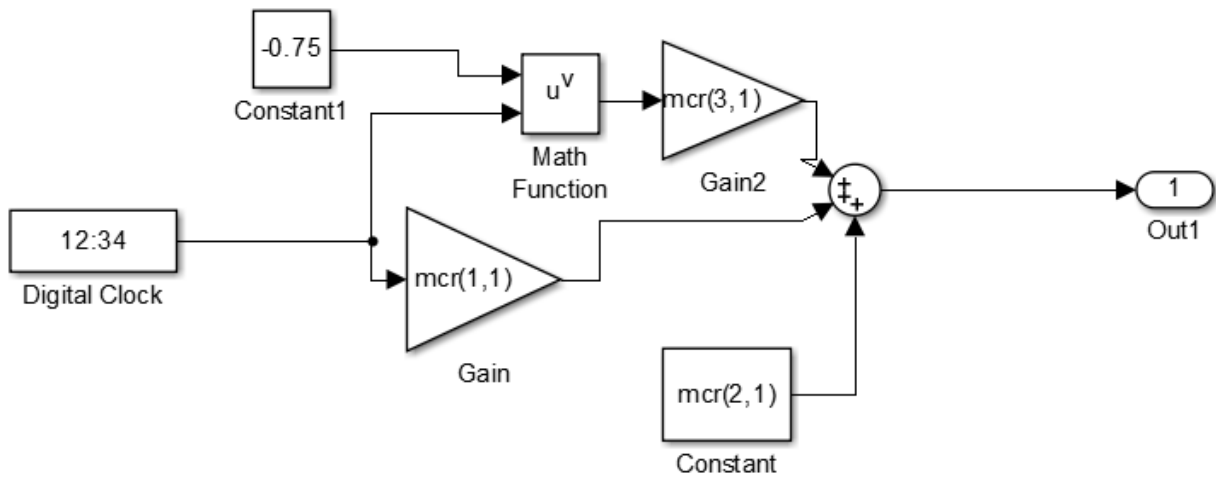


Figure 5.3. Block diagram to generate forecasts as per Equation (4.10) (N = 2)

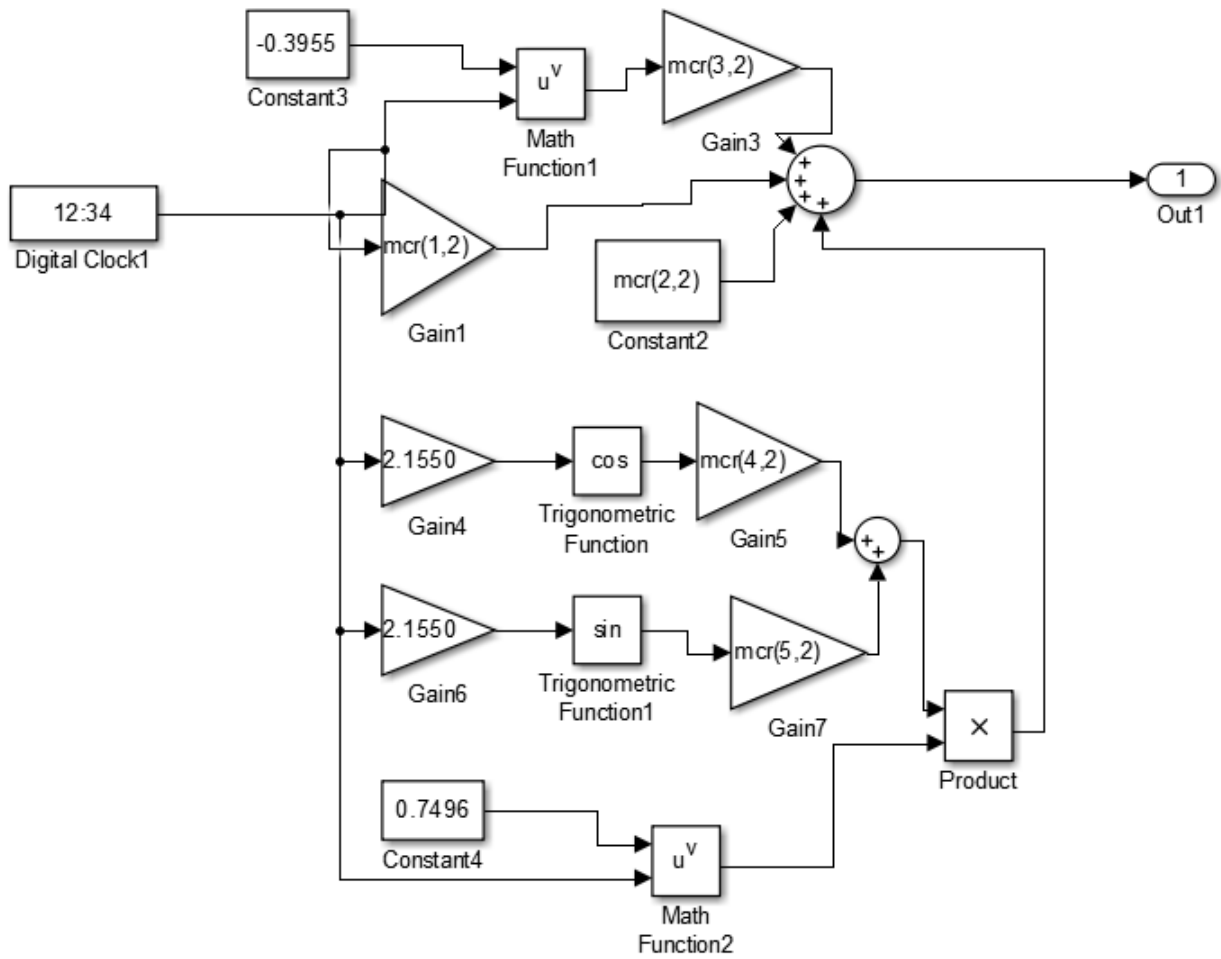


Figure 5.4. Block diagram to generate forecasts as per Equation (4.11) (N = 3)

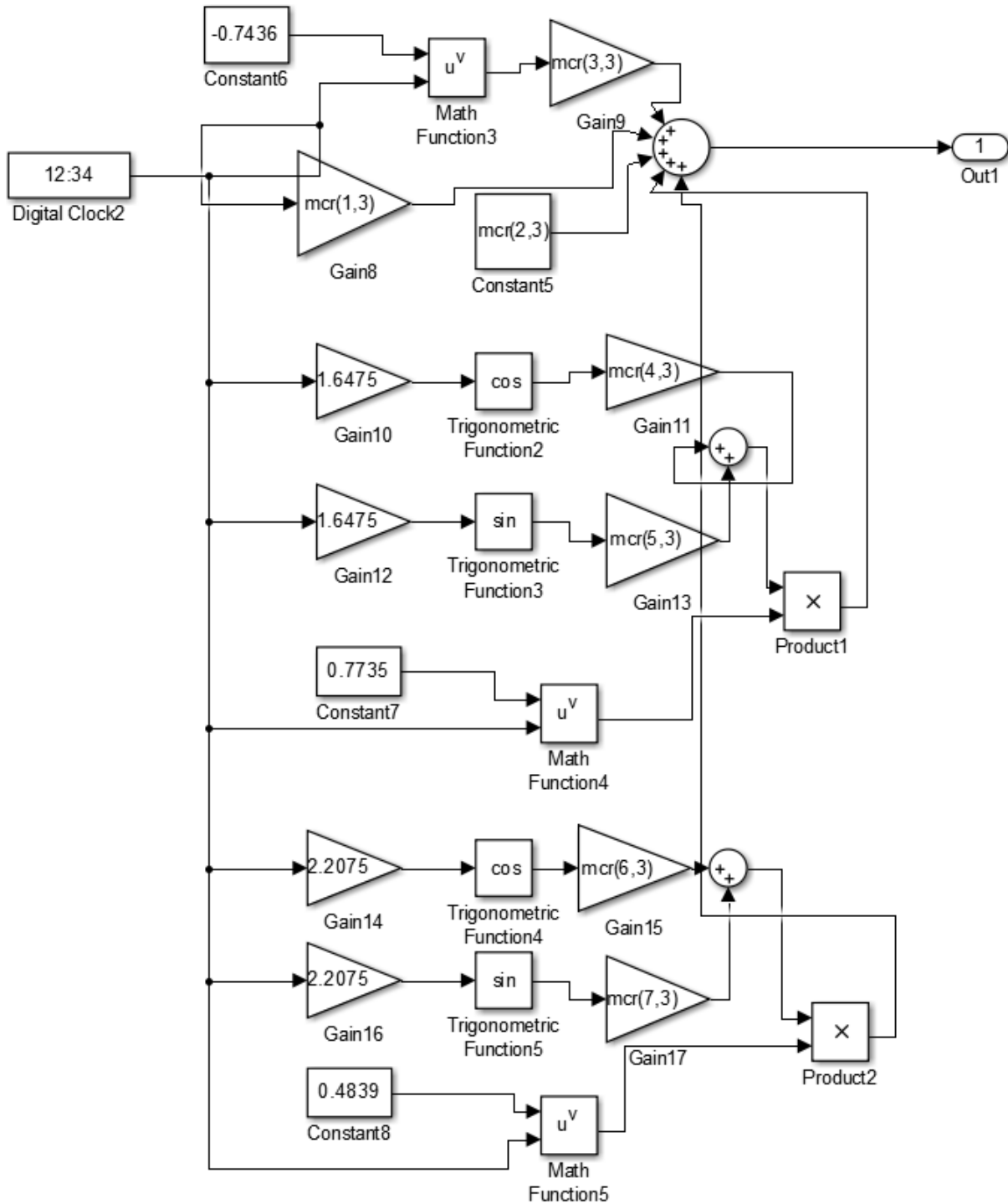


Figure 5.5. Block diagram to generate forecasts as per Equation (4.12) (N = 4)

Further there are six state variables in Figure 5.1 entitled soil water, shallow aquifer, deep aquifer, water level (WL), reach storage, and pond storage shown with a block called 'delay' which stores the previous state of a state variable and supplies it to determine next state as per

the effect of input variables. Other elements found in the model are operators like sum to add, gain to multiply, switches to avoid negative values of water storages for various state variables, and constants defined by the user. Blocks on the extreme right are the outputs in the form of states of various state variables defined in the model at every time step. There are certain other subsystems defined in the model for deriving rainfall runoff by curve number method, ground water flow, and reach transmission losses as presented from Figure 5.6 to Figure 5.8.

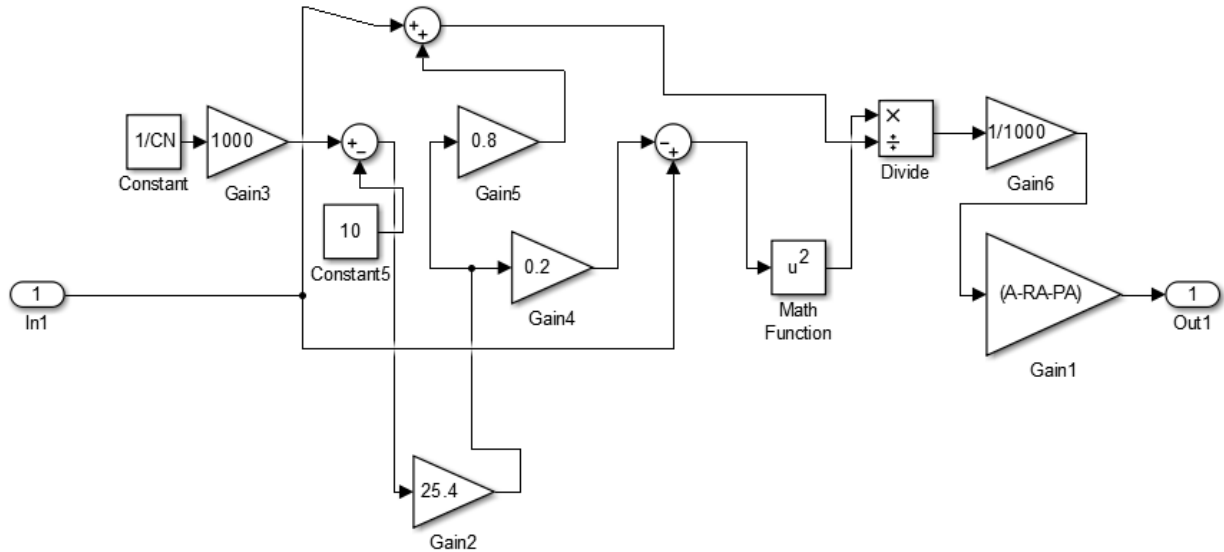


Figure 5.6. Block diagram to evaluate rainfall runoff by curve number (CN) method

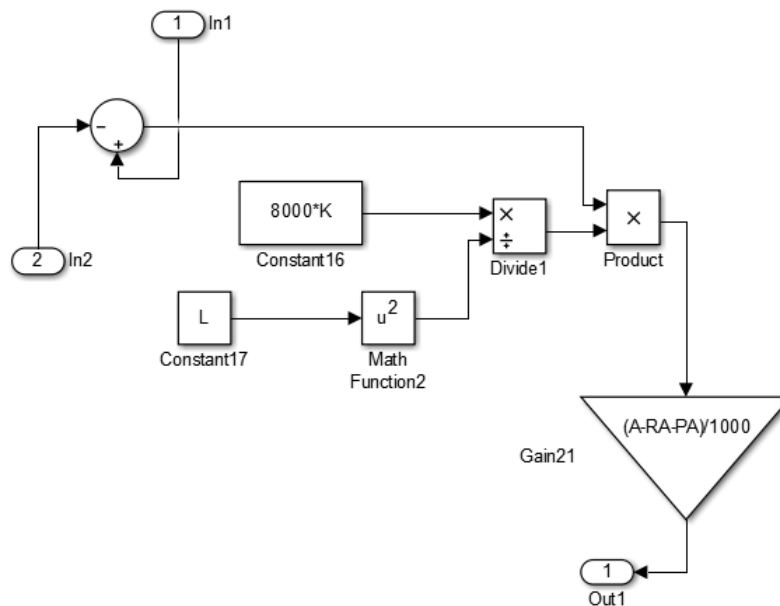


Figure 5.7. Block diagram to evaluate ground water flow

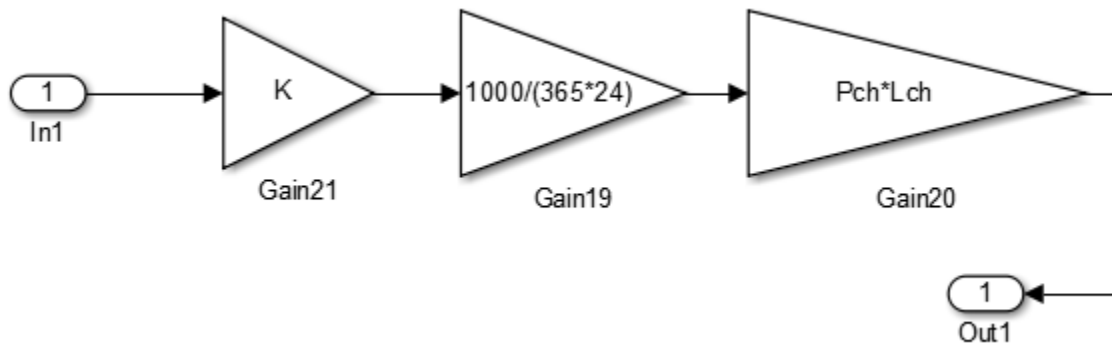


Figure 5.8. Block diagram to evaluate reach transmission loss

### 5.3 Simulation of state variable model

The methodology has been implemented over a village region named Ardawta, Rajasthan (India). This village has been declared under dark zone due to over exploitation of ground water and restricted for new irrigation wells and increasing depth of existing wells. It is attempted to identify the future state of various water storage elements with respect to the influence of forecasted inputs (rainfall, evaporation, population, crop water, reach inflow, and reach outflow) over the topography within the village boundary. The topography of a region can be represented by its digital elevation model (DEM). DEM with 10 meter spatial resolution for the village Ardawta has been collected from NRSC (National Remote Sensing Centre), India. Later DEM-based watershed area delineation has been performed using the SWAT extension of ArcGIS 10.1. A single DEM-based stream (reach) has been defined for the entire watershed area collecting its runoff water and ground water flow. Rainfall runoff will be routed through the stream to its outlet while ground water flow will be routed only if the depth of the stream is more than the depth of water table (Neitsch et al., 2011). There is no pond within the village area, hence pond statistics are presumed as null. Input data of the factors influencing hydrology of the village from the year 2008 to the year 2014 is used to forecast inputs at future time steps. Reach inflow and outflow is considered null since there is no such source of inflow and sink for outflow like perennial rivers. The hydrological profile of the village is shown in Figure 5.9. It comprises of a single stream of length 4.6 kilometers and depth and width of 0.23 meters and 3.14 meters respectively. Watershed area with respect to stream is 4415395 meters square. Total area of the village is 9124448 meters square. The principal aquifer system over the region is single unconfined schist aquifer having thickness of 10-80 meters and transmissivity of 5-84 square

meters per day (<http://www.india-wris.nrsc.gov.in/LithologApp.html> dated 09/03/2018). Using average value of thickness and transmissivity, hydraulic conductivity is taken as 365 meters/year as per Equation (5.13) ([http://www.aqtesolv.com/aquifer-tests/aquifer\\_properties.htm](http://www.aqtesolv.com/aquifer-tests/aquifer_properties.htm) dated 09/03/2018).

$$T = K \cdot b \quad (5.13)$$

where  $T$  ( $\text{m}^2/\text{day}$ ),  $K$  ( $\text{m}/\text{day}$ ), and  $b$  ( $\text{m}$ ) are transmissivity, hydraulic conductivity, and aquifer thickness respectively. There is no deep aquifer in the region so deep aquifer percolation coefficient has been taken as null. The curve number corresponding to the sandy soil over the region has been considered as 64 (SCS Engineering Division, 1986). Field capacity of the sandy soil in the region is taken 0.06 (Neitsch et al., 2011). Revap coefficient has been taken as 1 to allow evaporation water requirement from the aquifer. The precipitation, temperature and population data over the region are presented from Table 5.1 to Table 5.3. Crop water use has been evaluated by the area of various crops cultivated multiplied by their water requirement. The height of water table has been considered as the difference between mean sea level and depth of ground water table as the configuration of the water table commonly is a replica of the land surface topography on a regional scale ([http://www.pubs.usgs.gov/circ/circ1186/html/gen\\_facts.html](http://www.pubs.usgs.gov/circ/circ1186/html/gen_facts.html) dated 09/03/2018). The distance from basin divide to reach has been taken as 2100 meters (square root of the total watershed area).



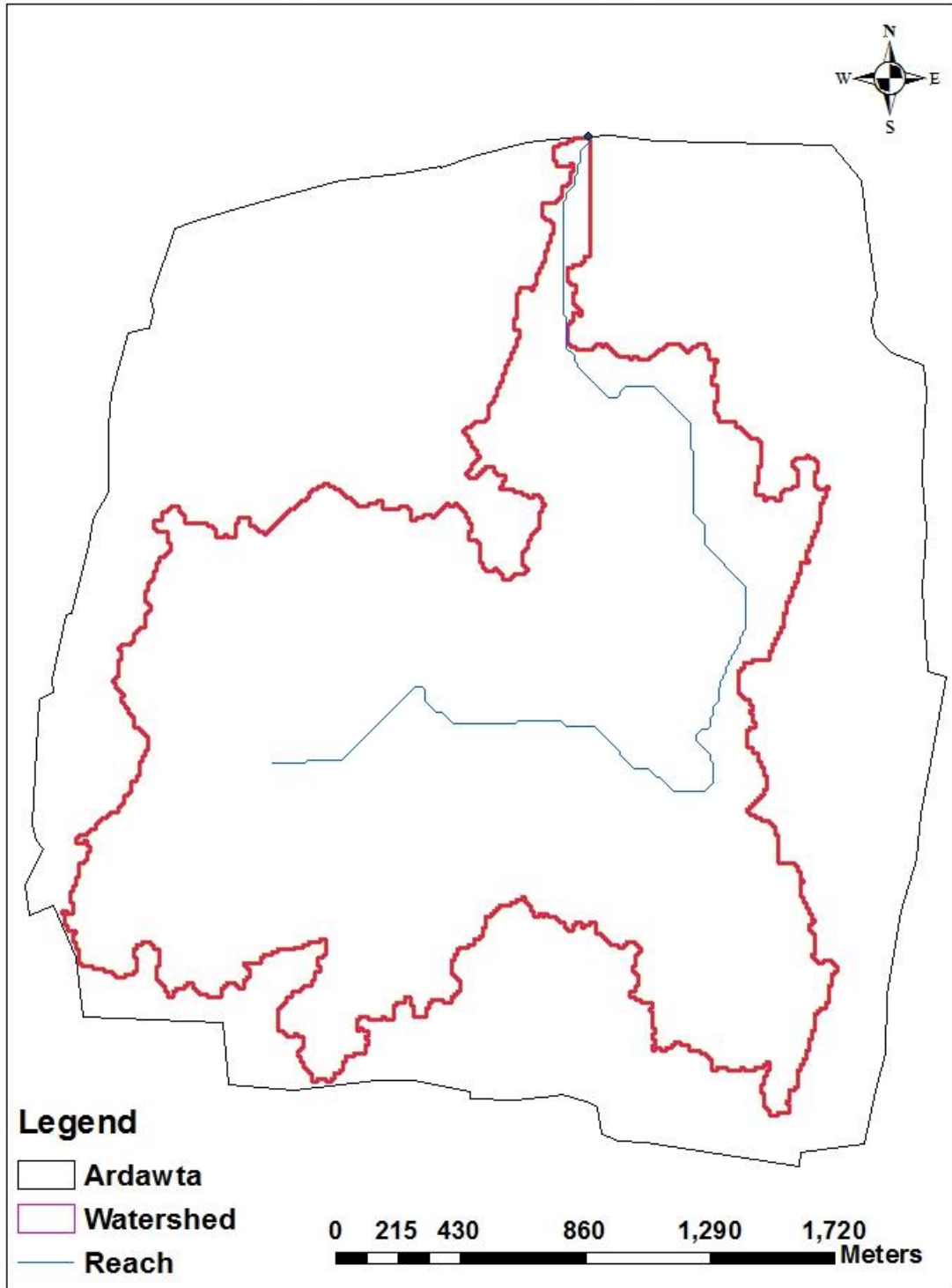


Figure 5.9. Hydrological profile of village Ardawta

Table 5.1. Rainfall in the Ardawta region from the year 2007 to 2014 (mm)

Month/Year	2007	2008	2009	2010	2011	2012	2013	2014
January	0	0	0	4	0	0	19	0
February	74	0	1	10	42	0	29	34
March	33	0	15	4	6	0	0	40
April	20	31	0	0	0	16	10	10
May	43	78	25	0	45	11	16	21
June	68	114	41	21	48	3	39	81
July	62	87	136	84	45	68	138	67
August	26	233	35	203	182	177	134	155
September	150	138	44	186	183	39	117	33
October	0	0	0	10	0	0	15	26
November	0	0	2	20	0	0	12	0
December	0	0	0	24	0	4	0	0
<b>Total</b>	<b>476</b>	<b>681</b>	<b>299</b>	<b>566</b>	<b>551</b>	<b>318</b>	<b>529</b>	<b>467</b>

Table 5. 2. Average temperature in the Ardawta region from the year 2007 to 2014 (°C)

Month/Year	2007	2008	2009	2010	2011	2012	2013	2014
January	13.54	13.61	14.62	11.90	11.40	12.50	12.50	13.00
February	17.96	17.59	17.95	15.95	16.75	14.80	16.40	15.80
March	20.91	27.62	23.55	22.10	22.80	22.35	23.15	21.25
April	30.78	30.32	28.08	29.20	27.90	27.95	28.30	27.65
May	32.98	30.39	33.57	32.50	34.20	32.70	33.90	31.35
June	34.14	30.86	33.00	34.20	28.80	23.15	34.55	33.95
July	31.76	31.23	31.68	31.10	31.10	33.00	32.10	32.65
August	30.55	29.27	31.30	29.85	29.40	29.40	29.55	30.75
September	29.13	28.26	28.97	29.65	28.35	30.60	29.70	29.65
October	26.06	28.23	25.92	26.05	25.90	25.65	26.90	25.40
November	22.56	21.87	21.50	19.84	22.10	20.20	19.75	21.25
December	14.47	15.36	18.46	13.30	14.75	15.05	15.95	14.45

Table 5.3. Population in the Ardawta region from the year 2007 to 2014

2007	2008	2009	2010	2011	2012	2013	2014
3663	3685	3714	3746	3770	3793	3851	3884

Data for all the input variables at annual time steps has been supplied to the state variable model as per the MATLAB ([https://www.tutorialspoint.com/matlab/matlab\\_overview.htm](https://www.tutorialspoint.com/matlab/matlab_overview.htm) dated 22/04/2018) code presented in Appendix B. Consecutive data for seven years from 2008 to 2014 has been used to extrapolate data for future years. Equation (4.10), Equation (4.11), and Equation (4.12) will extrapolate data for future years for all the input variables using their first three, five and seven consecutive data values respectively. There will be three scenarios generated by three extrapolations of any one input variable and keeping extrapolation of other input variables fixed. Various extrapolated combinations of all the six input variables would generate 36 scenarios. Since there is no significance of reach inflow and outflow in the region under study, there were 34 scenarios generated as shown in Appendix C.

Water requirement for the population is estimated by an average value of 40 liters of water used per person in a day for communities with population up to 20000 given by IS code. Precipitation inflow is evaluated by multiplication of total area of the region into precipitation. Potential evapotranspiration ( $P_e$ ) has been evaluated using Thornthwaite model presented by Equation (5.14) (Wang et al., 2011), earlier used in Chapter 4 as Equation (4.15).

$$P_e = 1.6 d (10 T / I)^a \quad (5.14)$$

Initial soil water for the region has been taken as the product of soil depth (150 cm) and soil moisture ( $0.05 \text{ m}^3/\text{m}^3$ ) at the end of the year 2007 (<http://bhuvan.nrsc.gov.in/data/download/index.php> dated 10/01/2018). Initial shallow aquifer and deep aquifer volumes are taken null due to unavailability of data. Initial reach storage and pond storage are also taken null due to their shallow structures and rainfall fed behavior. The initial ground water level is taken 57.29 meters below ground level in the year 2007, from the well located in Khudana near Ardawta (<http://india-wris.nrsc.gov.in/GWL/GWL.html> dated 14/09/2017).

Later scenarios are generated to predict the water level in the region until the year 2030. Three of the generated scenarios are selected as best, worst and business as usual (BAU). Closest, least,

and highest predicted values of ground water level for the year 2016 with respect to its true level corresponds to BAU, best, and worst case scenarios respectively among the 3<sup>4</sup> scenarios generated as per Appendix C. Two more scenarios have been generated termed as drought and surplus. Step functions have been used over the input data after the time step from where data is unavailable; i.e. from the year 2015 to the year 2030. For drought scenario, rainfall and evaporation are stepped to lowest and highest of their observed values respectively. Conversely for surplus scenario rainfall and evaporation are stepped highest and lowest of their observed values respectively. Population and crop water use have been predicted as per Equation (4.10) to Equation (4.12). Among the nine scenarios generated for both the cases, scenarios corresponding to lowest and highest value of ground water level in 2030 are selected as drought and surplus respectively. The strategic diagram for the scenarios is presented in Figure 5.10.

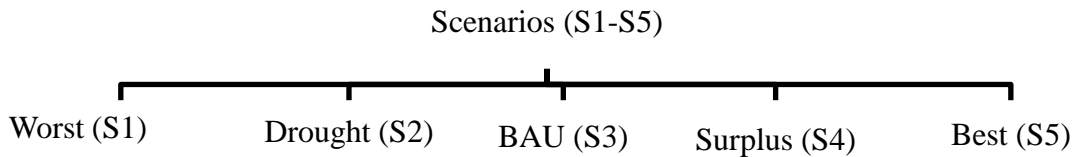


Figure 5.10. Strategic diagram of the scenarios considered for state variable model

### 5.3.1 Results

The predicted input variables are shown in Table 5.5 where, green and yellow colored cells represent historical data used for prediction and predicted data respectively as per the corresponding equations defined in Table 5.4. The predicted values are back tracked as per the outputs obtained for ground water level in the five scenarios (S1 - S5) defined and presented in Table 5.6 along with the observed ground water level from the year 2007 to the year 2016. Figure 5.11 is figuring out the level of ground water for the observed scenario from the year 2007 to the year 2016 and for the five scenarios from the year 2007 to the year 2030. Blue colored cells in Table 5.6 are used to check the divergence of results with respect to observed ground water level of the year 2016. All the scenarios are projecting a decline of ground water level until the year 2030. The error in prediction for the respective scenarios is verified with respect to the observed value of ground water level in the year 2016 and presented in Table 5.7.

Table 5.4. Scenarios and their methods of prediction as per Equation (4.10) to Equation (4.12) and step function for input variables

Scenario 1 (Worst)	Scenario 2 (Drought)	Scenario 3 (BAU)	Scenario 4 (Surplus)	Scenario 5 (Best)
Population - Equation (4.12)	Population - Equation (4.12)	Population - Equation (4.11)	Population - Equation (4.11)	Population - Equation (4.11)
Precipitation - Equation (4.11)	Precipitation - step to lowest observed value	Precipitation - Equation (4.12)	Precipitation - step to highest observed value	Precipitation - Equation (4.12)
Water for Crops - Equation (4.10)	Water for Crops - Equation (4.10)	Water for Crops - Equation (4.10)	Water for Crops - Equation (4.12)	Water for Crops - Equation (4.12)
Evaporation - Equation (4.12)	Evaporation - step to highest observed value	Evaporation - Equation (4.11)	Evaporation - step to lowest observed value	Evaporation - Equation (4.11)

Table 5.5. Historical and predicted input variables for the scenarios S1 to S5 supplied to the state variable model

Year	Population					Rainfall (mm)					Evaporation (m)					Water for Crops (KL)				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
2007	3663	3663	3663	3663	3663	476	476	476	476	476	0.186	0.186	0.186	0.186	0.186	9103284	9103284	9103284	9103284	9103284
2008	3685	3685	3685	3685	3685	681	681	681	681	681	0.174	0.174	0.174	0.174	0.174	5579712	5579712	5579712	5579712	5579712
2009	3714	3714	3714	3714	3714	299	299	299	299	299	0.185	0.185	0.185	0.185	0.185	8467236	8467236	8467236	8467236	8467236
2010	3746	3746	3746	3746	3746	566	566	566	566	566	0.172	0.172	0.172	0.172	0.172	8488944	8488944	8488944	8488944	8488944
2011	3770	3770	3770	3770	3770	551	551	551	551	551	0.160	0.160	0.160	0.160	0.160	10660000	10660000	10660000	9097272	9097272
2012	3793	3793	3793	3793	3793	318	318	318	318	318	0.153	0.153	0.153	0.153	0.153	11219000	11219000	11219000	8457840	8457840
2013	3851	3851	3824	3824	3824	458	529	529	529	529	0.185	0.185	0.144	0.185	0.144	12987000	12987000	12987000	8250336	8250336
2014	3884	3884	3848	3848	3848	398	467	467	467	467	0.172	0.172	0.133	0.172	0.133	13848000	13848000	13848000	8848548	8848548
2015	3907	3907	3873	3873	3873	300	299	445	681	445	0.165	0.186	0.125	0.153	0.125	15390000	15390000	15390000	9030500	9030500
2016	3945	3945	3901	3901	3901	343	299	410	681	410	0.171	0.186	0.116	0.153	0.116	16421000	16421000	16421000	8678300	8678300
2017	3987	3987	3926	3926	3926	292	299	459	681	459	0.180	0.186	0.106	0.153	0.106	17835000	17835000	17835000	8794300	8794300
2018	4019	4019	3952	3952	3952	239	299	432	681	432	0.175	0.186	0.097	0.153	0.097	18962000	18962000	18962000	9046900	9046900
2019	4051	4051	3979	3979	3979	241	299	421	681	421	0.174	0.186	0.088	0.153	0.088	20304000	20304000	20304000	9085900	9085900
2020	4088	4088	4005	4005	4005	198	299	408	681	408	0.177	0.186	0.079	0.153	0.079	21485000	21485000	21485000	9016700	9016700
2021	4125	4125	4031	4031	4031	162	299	421	681	421	0.181	0.186	0.070	0.153	0.070	22787000	22787000	22787000	9123800	9123800
2022	4159	4159	4057	4057	4057	145	299	406	681	406	0.179	0.186	0.060	0.153	0.060	23998000	23998000	23998000	9247500	9247500
2023	4193	4193	4083	4083	4083	108	299	398	681	398	0.180	0.186	0.051	0.153	0.051	25277000	25277000	25277000	9285100	9285100
2024	4229	4229	4110	4110	4110	77	299	391	681	391	0.182	0.186	0.042	0.153	0.042	26505000	26505000	26505000	9306600	9306600
2025	4265	4265	4136	4136	4136	53	299	391	681	391	0.184	0.186	0.033	0.153	0.033	27771000	27771000	27771000	9393800	9393800
2026	4299	4299	4162	4162	4162	20	299	381	681	381	0.184	0.186	0.023	0.153	0.023	29009000	29009000	29009000	9473800	9473800
2027	4334	4334	4188	4188	4188	0	299	374	681	374	0.185	0.186	0.014	0.153	0.014	30268000	30268000	30268000	9522000	9522000
2028	4370	4370	4214	4214	4214	0	299	369	681	369	0.187	0.186	0.005	0.153	0.005	31511000	31511000	31511000	9573300	9573300
2029	4405	4405	4240	4240	4240	0	299	364	681	364	0.188	0.186	0	0.153	0	32766000	32766000	32766000	9647000	9647000
2030	4440	4440	4267	4267	4267	0	299	357	681	357	0.189	0.186	0	0.153	0	34012000	34012000	34012000	9713400	9713400




 Historical values used for prediction  
 Predicted values for the subsequent years

Table 5.6. Observed and predicted ground water level in the Ardawta region from the year 2007 to 2030 (mbgl) for scenarios S1 to S5

Year/Scenarios	O	S1	S2	S3	S4	S5
2007	57.29	57.29	57.29	57.29	57.29	57.29
2008	58.96	58.02	58.02	58.02	58.02	58.02
2009	60.85	59.15	59.15	59.15	59.15	59.15
2010	62.30	60.26	60.26	60.26	60.26	60.26
2011	63.67	61.60	61.60	61.60	61.43	61.43
2012	67.05	63.00	63.00	63.00	62.53	62.53
2013	67.35	64.62	64.62	64.58	63.63	63.59
2014	67.11	66.33	66.32	66.24	64.78	64.70
2015	68.45	68.20	68.21	68.06	65.92	65.82
2016	69.54	70.19	70.22	69.99	67.02	66.90
2017		72.34	72.38	72.05	68.14	67.98
2018		74.62	74.66	74.23	69.28	69.08
2019		77.04	77.08	76.55	70.42	70.17
2020		79.61	79.64	78.99	71.56	71.25
2021		82.32	82.33	81.56	72.71	72.33
2022		85.17	85.16	84.25	73.87	73.41
2023		88.17	88.13	87.08	75.04	74.48
2024		91.33	91.22	90.02	76.20	75.55
2025		94.63	94.46	93.10	77.38	76.62
2026		98.10	97.83	96.30	78.56	77.69
2027		101.75	101.33	99.62	79.75	78.76
2028		105.60	104.97	103.07	80.94	79.82
2029		109.76	108.74	106.65	82.14	80.88
2030		114.85	112.65	110.36	83.34	81.94

**Note: mbgl (meters below ground level)**

 Observed ground water level for the year 2016


 Predicted ground water level for the year 2016

Table 5.7. Percent Error of prediction of ground water level (mbgl) in Scenarios S1 to S5 in Ardawta region

GWL (2016)	S1	S2	S3	S4	S5
Predicted	70.1858	70.2159	69.98512	67.023	66.90218
Observed	69.54	69.54	69.54	69.54	69.54
% Error	0.92	0.97	0.64	3.61	3.79

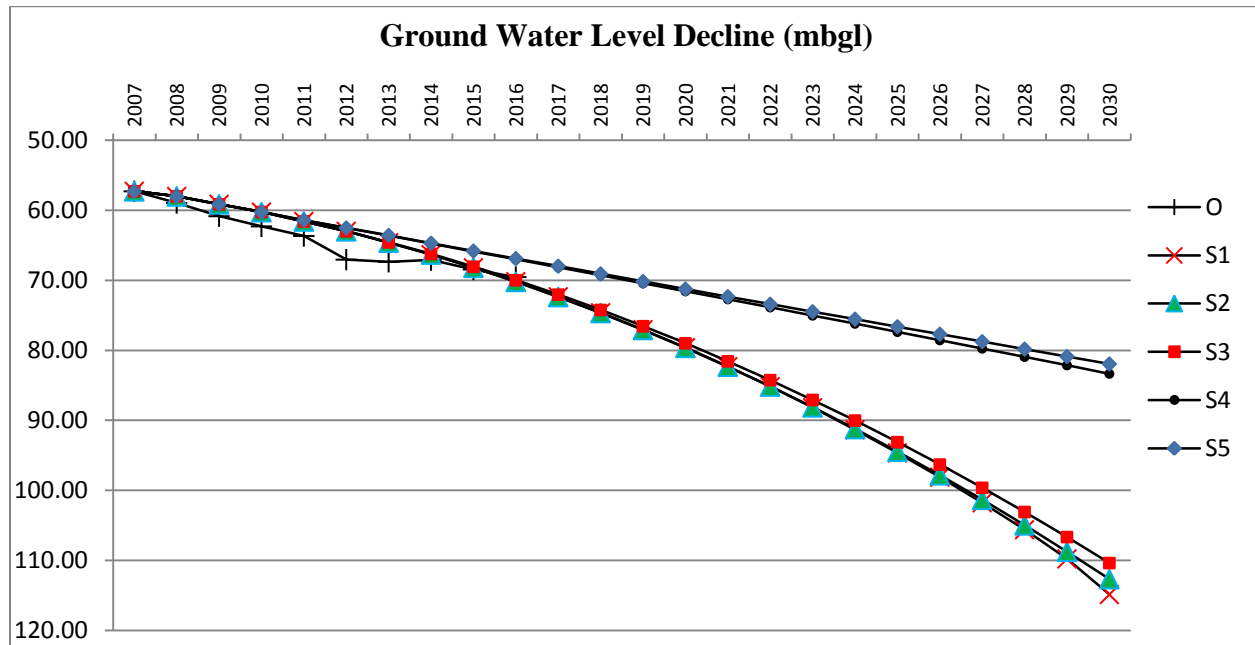


Figure 5.11. Decline of ground water level in Ardawta region from the year 2007 to 2030 in observed and predicted scenarios S1 to S5

### 5.3.2 Testing the model for defined predicted inputs

Although the model is generating reasonable predictions for the ground water level in various scenarios with respect to the combinations of the predicted input variables yet the predictions of rainfall in S1 and evaporation in S3 and S5 are not sensible at longer intervals. This can be attributed to the uncertain nature or ups and downs of such climatic variables. Either the state variable model integrated with input sets defined by Equation (4.10) to Equation (4.12) can be considered as a black box model or else the adjacent scenarios to the scenarios selected above can be chosen having reasonable predictions. The model is required to be tested whether it will go well with the normalized random inputs of higher uncertainty, i.e. rainfall and evaporation. Population and crop water requirement are certain in terms of their rising pattern. Equation (4.9)



incorporating largest volume of historical data and generating reasonable predictions for all input variables up to the time step of year 2030 has been used to forecast population and crop water requirement. Maximum difference in annual evaporation found in the data used to forecast (from the year 2007 to the year 2014) and the historical data since 1969 procured from IMD (Indian Meteorological Department), Pune is of 33 mm and 75 mm respectively. While maximum difference in annual rainfall in the data used to forecast and historical data since 1969 is of 382 mm and 700 mm respectively. Considering the most uncertain variable of rainfall, five rainfall scenarios (R1-R5) have been generated. The five rainfall scenarios are:

- R1(lowest rainfall of available data continued further with lowest rainfall once as observed from historical data; or drought with disaster);
- R2 (low rainfall evaluated by normalized random values lying in first one-third of the range of rainfall; or drought);
- R3 ( medium rainfall evaluated by normalized random values lying in second one-third of the range of rainfall; or average rainfall);
- R4 (high rainfall evaluated by normalized random values lying in the last one-third of the range of rainfall; or surplus); and
- R5 (highest rainfall of available data continued further with highest rainfall once as observed from historical data; or surplus with flood)

Scenarios R2 to R4 corresponds to the normalized random extrapolated values of rainfall from their corresponding ranges while scenarios R1 and R5 used impulse function providing lowest (165 mm in the year 2002) and highest (866 mm in the year 1971) rainfall from the historical data since 1969 assumed to occur once in the forecasted time frame (let's say in the year 2023) respectively. The model simulates the five rainfall extrapolations in combination with one normalized random extrapolated values of evaporation within the range of collected data, one population, and one crop water requirement, both extrapolated by Equation (4.12). The strategic diagram for the rainfall scenarios is presented in Figure 5.12.

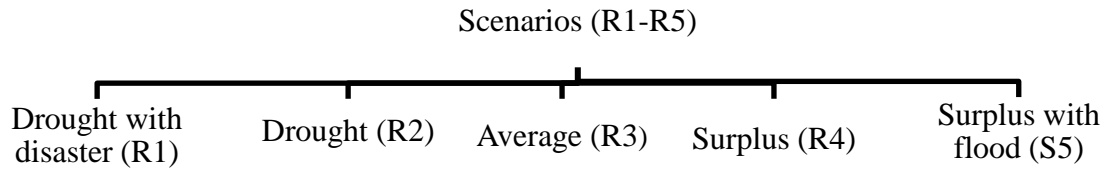


Figure 5.12. Strategic diagram for the rainfall scenarios considered for state variable model

With respect to the five scenarios defined above over the village Ardawta, results obtained for the ground water level are shown in Table 5.9 and linear diagram for the decline is shown in Figure 5.13. The overlapping pattern of the five rainfall scenarios are producing reasonable results for the ground water level but do not promise for generating scenarios in diverse directions or else signify that there is no major role of precipitation and evaporation in the decline of ground water level. To identify this sensitivity analysis has been conducted on the inputs generated by scenario R3 for all the input variables of rainfall, evaporation, population and crop water requirement. Inputs generated for all the scenarios R1 to R5 are presented in Table 5.8. The precipitation and evaporation are sensitive to the model by 1% while population and crop water requirement are sensitive by about 71% and 27% respectively as presented in Table 5.10. Sensitivity analysis method is defined in Chapter 4 and it presents how much the variation of input variables from their minimum to maximum values make variations to output variables (Loucks, et al., 2005). There is an average error of 4% in prediction of ground water level as compared to actual ground water level of the year 2016 for scenarios R1 to R5.

Table 5.8. Results of predicted inputs for the scenarios R1 to R5 supplied to the state variable model

Year	Population					Rainfall (mm)					Evaporation (m)					Water for Crops (KL)				
	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5
2007	3663	3663	3663	3663	3663	476	476	476	476	476	0.186	0.186	0.186	0.186	0.186	9103284	9103284	9103284	9103284	9103284
2008	3685	3685	3685	3685	3685	681	681	681	681	681	0.174	0.174	0.174	0.174	0.174	5579712	5579712	5579712	5579712	5579712
2009	3714	3714	3714	3714	3714	299	299	299	299	299	0.185	0.185	0.185	0.185	0.185	8467236	8467236	8467236	8467236	8467236
2010	3746	3746	3746	3746	3746	566	566	566	566	566	0.172	0.172	0.172	0.172	0.172	8488944	8488944	8488944	8488944	8488944
2011	3770	3770	3770	3770	3770	551	551	551	551	551	0.160	0.160	0.160	0.160	0.160	9097272	9097272	9097272	9097272	9097272
2012	3793	3793	3793	3793	3793	318	318	318	318	318	0.153	0.153	0.153	0.153	0.153	8457840	8457840	8457840	8457840	8457840
2013	3851	3851	3851	3851	3851	529	529	529	529	529	0.185	0.185	0.185	0.185	0.185	8250336	8250336	8250336	8250336	8250336
2014	3884	3884	3884	3884	3884	467	467	467	467	467	0.172	0.172	0.172	0.172	0.172	8848548	8848548	8848548	8848548	8848548
2015	3907	3907	3873	3873	3873	299	324	564	718	681	0.189	0.189	0.189	0.189	0.189	9030500	9030500	9030500	9030500	9030500
2016	3945	3945	3901	3901	3901	299	317	543	674	681	0.182	0.182	0.182	0.182	0.182	8678300	8678300	8678300	8678300	8678300
2017	3987	3987	3926	3926	3926	299	310	522	630	681	0.175	0.175	0.175	0.175	0.175	8794300	8794300	8794300	8794300	8794300
2018	4019	4019	3952	3952	3952	299	313	532	652	681	0.179	0.179	0.179	0.179	0.179	9046900	9046900	9046900	9046900	9046900
2019	4051	4051	3979	3979	3979	299	299	492	567	681	0.165	0.165	0.165	0.165	0.165	9085900	9085900	9085900	9085900	9085900
2020	4088	4088	4005	4005	4005	299	331	584	761	681	0.196	0.196	0.196	0.196	0.196	9016700	9016700	9016700	9016700	9016700
2021	4125	4125	4031	4031	4031	299	309	521	628	681	0.175	0.175	0.175	0.175	0.175	9123800	9123800	9123800	9123800	9123800
2022	4159	4159	4159	4159	4159	299	333	588	770	681	0.197	0.197	0.197	0.197	0.197	9247500	9247500	9247500	9247500	9247500
2023	4193	4193	4193	4193	4193	165	312	529	645	866	0.177	0.177	0.177	0.177	0.177	9285100	9285100	9285100	9285100	9285100
2024	4229	4229	4229	4229	4229	299	320	552	694	681	0.185	0.185	0.185	0.185	0.185	9306600	9306600	9306600	9306600	9306600
2025	4265	4265	4265	4265	4265	299	289	463	506	681	0.155	0.155	0.155	0.155	0.155	9393800	9393800	9393800	9393800	9393800
2026	4299	4299	4299	4299	4299	299	299	492	566	681	0.165	0.165	0.165	0.165	0.165	9473800	9473800	9473800	9473800	9473800
2027	4334	4334	4334	4334	4334	299	325	567	725	681	0.190	0.190	0.190	0.190	0.190	9522000	9522000	9522000	9522000	9522000
2028	4370	4370	4370	4370	4370	299	300	494	572	681	0.166	0.166	0.166	0.166	0.166	9573300	9573300	9573300	9573300	9573300
2029	4405	4405	4405	4405	4405	299	316	541	670	681	0.182	0.182	0.182	0.182	0.182	9647000	9647000	9647000	9647000	9647000
2030	4440	4440	4440	4440	4440	299	304	505	594	681	0.169	0.169	0.169	0.169	0.169	9713400	9713400	9713400	9713400	9713400

 Historical values used for prediction




 Predicted values for the subsequent years

Table 5.9. Observed and predicted ground water level in the Ardawta region from the year 2007 to 2030 (mbgl) for Scenarios R1 to R5

Year/Scenarios	O	R1	R2	R3	R4	R5
2007	57.29	57.29	57.29	57.29	57.29	57.29
2008	58.96	58.39	58.39	58.39	58.39	58.39
2009	60.85	59.31	59.31	59.31	59.31	59.31
2010	62.30	60.51	60.51	60.51	60.51	60.51
2011	63.67	61.53	61.53	61.53	61.53	61.53
2012	67.05	62.41	62.41	62.41	62.41	62.41
2013	67.35	63.44	63.44	63.44	63.44	63.44
2014	67.11	64.37	64.37	64.37	64.37	64.37
2015	68.45	65.51	65.50	65.49	65.48	65.48
2016	69.54	66.66	66.65	66.62	66.61	66.61
2017		67.82	67.81	67.77	67.75	67.75
2018		69.01	69.00	68.94	68.92	68.92
2019		70.19	70.18	70.10	70.08	70.07
2020		71.40	71.38	71.29	71.26	71.26
2021		72.59	72.58	72.47	72.43	72.43
2022		73.82	73.80	73.67	73.63	73.63
2023		75.05	75.01	74.87	74.82	74.82
2024		76.28	76.23	76.07	76.02	76.01
2025		77.48	77.44	77.26	77.21	77.19
2026		78.70	78.65	78.46	78.41	78.39
2027		79.94	79.90	79.69	79.63	79.61
2028		81.17	81.13	80.90	80.84	80.82
2029		82.43	82.38	82.14	82.07	82.04
2030		83.67	83.62	83.37	83.29	83.27

**Note: mbgl (meters below ground level)**

 Observed ground water level for the year 2016

 Predicted ground water level for the year 2016

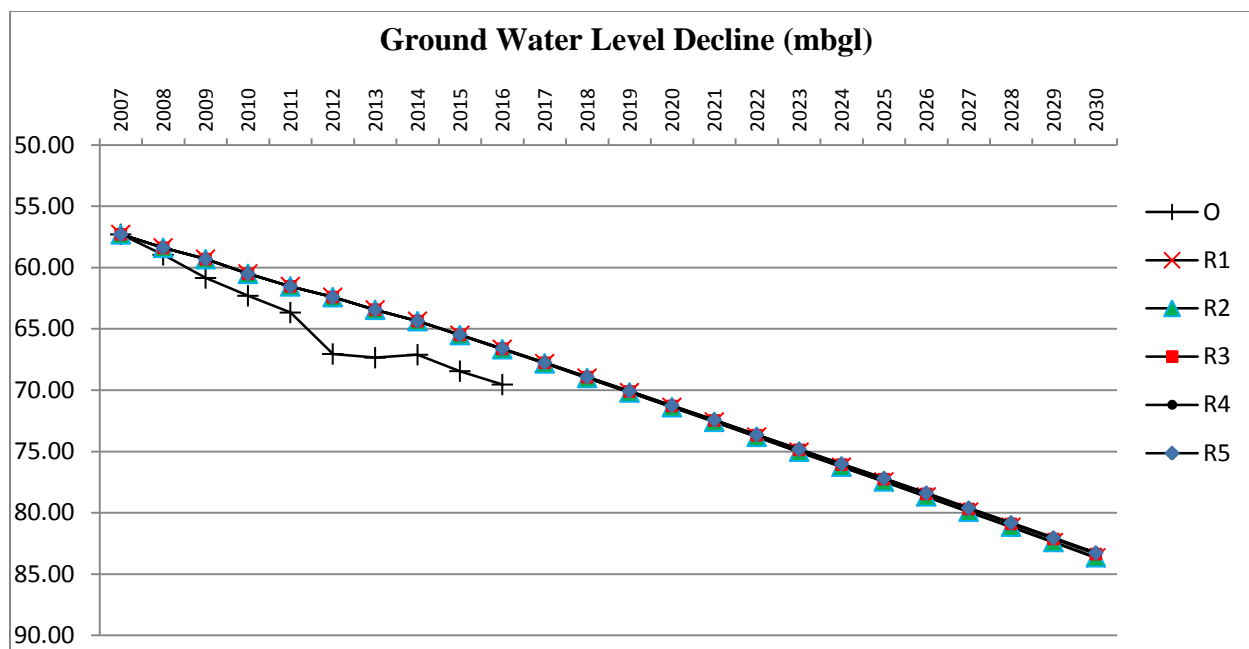


Figure 5.13. Decline of ground water level in Ardawta region from the year 2007 to 2030 in observed and predicted scenarios R1 to R5

Table 5.10. Percent sensitivity of input parameters for the ground water level obtained by state variable model

Parameters	Percent sensitivity
Rainfall	1.04
Evaporation	1.04
Population	71.34
Crop Water	26.58

### 5.3.3 Inference of the study

Scenario development of the water resources up to the year 2030 in the semi-arid region of village Ardawta reflects downfall in the level of ground water in all the scenarios from S1 to S5. Scenarios S1, S2, and S3 follow a trend of severe decline as per their nomenclature while S4 and S5 are also declining fairly opposed to their taxonomy. Similarly, scenarios R1 to R5 are also reflecting the decline of ground water level very close to each other. This declination of ground water level forces to develop certain solutions to deal with the problem of water scarcity. Surface runoff water should be stored and recharged artificially. This can be implemented by impounding a pond at the outlet of reach where all runoff water gets stored and recharged to the ground.

Rainfall harvesting and efficient methods of crop irrigation like drip and sprinkler irrigation can help to make the water resources sustainable over the region.

The model developed in this study has considered the watershed as a lumped system and valid for a small region where input values or characteristics of the watershed are not varying significantly. Calibration of the model in our study area assumed evapotranspiration as the evaporation, reach alluvium effective hydraulic conductivity and pond effective saturated hydraulic conductivity equal to aquifer hydraulic conductivity. For snow, its water equivalent can be added to the precipitation data. Hence for a large area model can be simulated by partitioning the area into regions of smaller area and can be evaluated with different properties of different regions.

Besides the equations (4.10) to (4.12) used to forecast the input variables to simulate the state variable model, certain analytical functions can also be used to generate future predictions based on the pattern/assumptions as per the historical data. Step and random functions have been used in section 5.3.2. Random function can be used for the type of data varying uncertainly within a range, e.g. climate data of rainfall, evaporation, etc. Step function can be used with certain assumptions for extreme forecasts further like minimum rainfall continued ahead (drought) or maximum rainfall continued ahead (surplus). Few of the variables like population can be forecasted using ramp function since it generally follows a rising trend. To simulate unexpected forecasts like disasters (flood or drought) at an instance of the forecasted data impulse function can be used. Table 5.8 shows the rainfall forecasts for scenarios R1 and R5 simulated by step function where an impulse function is introduced for the rainfall in year 2023 (assuming lowest and highest of previous recorded rainfall to occur once over scenario development timeframe) while scenarios R2, R3, and R4 are the random function simulated scenarios based on the division of range of historical data into three ranges for low, medium, and high rainfall. Although ramp function is not used in the study yet population can be simulated with respect to the slope of its observed data trend (Nagrath and Gopal, 1982).

#### **5.4 Summary of the Chapter**

Summary of the chapter includes the following points:

- Development of a state variable model for generating hydrological scenarios deriving the future state of water storage components (soil moisture, shallow aquifer, deep aquifer, reach storage, pond storage, and ground water level) with respect to their respective water balance equations (Equation (5.1) to Equation (5.6)) within a watershed influenced by various forecasted parameters (rainfall, evaporation, population, crop water requirement, reach inflow, and reach outflow).
- Simulation of the model for the various combinations of the forecasted statistics of the input parameters over the village region of Ardawta, Rajasthan (India). Forecasted statistics of the input parameters are generated by Equation (4.10) to Equation (4.12) with respect to their first three, five and seven consecutive historical data values. Few more combinations comprising of lowest rainfall and highest evaporation continued further with three forecasted statistics of other input parameters (drought) and highest rainfall and lowest evaporation continued further with three forecasted statistics of other input parameters (surplus) are generated.
- Model simulations are analyzed with respect to the ground water level since data for other hydrological components was not available for the region. Since there is no reach in the region, ground water level scenarios are generated with respect to the forecasted statistics of only four input parameters (rainfall, evaporation, population, and crop water requirement) till the year 2030. First 81 scenarios are generated for the ground water level corresponding to the 81 ( $3 \times 3 \times 3 \times 3$ ) combinations of forecasted statistics of input parameters. Three of them are selected as worst, business as usual, and best cases with respect to their forecasted ground water level deviation from the actual ground water level in the year 2016.
- 9 scenarios have been generated keeping one forecast direction for both rainfall and evaporation (lowest rainfall and highest evaporation from observed data continued ahead) and three forecasted statistics for other parameters ( $1 \times 1 \times 3 \times 3$ ). One with the lowest ground water level in the year 2016 is selected as drought scenario. Conversely, one more scenario has been selected as surplus scenario from the 9 scenarios generated for ground water level with respect to the combinations of highest rainfall and lowest evaporation continued further with three forecasted statistics of other parameters.
- Results of the study show that there will be declining state of ground water level in every scenario selected from worst to best concluding that there is very little effect of rainfall and

evaporation on the ground water level as compared to crop water requirement and human consumption.



# **CHAPTER 6: GIS MODELING FOR SCENARIO DEVELOPMENT OF WATER RESOURCES**

## **6.1 Chapter overview**

Various models have been incorporated to predict potential of water resources including rainfall runoff, potential evapotranspiration, and water balance systems (Jiang et al., 2007; Silberstein et al., 2012; Griffin et al., 2013; Sahin et al., 2016). Besides, application of GIS (Geographical Information System) based on such systems provided an interactive two/three dimensional medium to them where spatially distributed parameters within a large area can be simulated suitably (Setegn et al., 2010; Huang and Li, 2010; Bae et al., 2011; Yang et al., 2011; Pradhanang et al., 2011; Awotwi et al., 2015; Yang et al., 2016). Review of literature reflects that GIS has been restricted to analysis and presentation of the spatial data. This study is an approach to generate predicted maps taking inputs in the form of maps. The maps for potential of water resources have been generated in the year 2030 for the three scenarios i.e., one business as usual (BAU), and two extreme scenarios of drought and surplus. Input data considered include rainfall, evaporation, curve number, hydraulic conductivity, ground water draft, initial ground water level, digital elevation, and reach distance raster maps with the time step at which ground water level has to be predicted as output. Pixel by pixel state variable approach has been used to derive the future state of ground water level. Future input maps of rainfall and evaporation have been predicted using systems Input-Output approach of time domain analysis and step functions for BAU and extreme scenarios respectively. A dynamic state variable GIS model to generate such scenarios has been developed in Python (<http://desktop.arcgis.com/en/arcmap/latest/analyze/python/what-is-python-.htm> dated 22/04/2018). Its implementation over the study region of Chirawa block in the Jhunjhunu district of Rajasthan (India) reflects that stretch of ground water level decline is spreading towards south west from north east in the year 2030 as compared to the year 2006.

## **6.2 Scenario approach through GIS**

Interpolated maps of rainfall, evaporation and ground water draft for consecutive historical years have been used to forecast their maps for the succeeding years. Pixel value for future input maps has been forecasted using Equation (4.12) incorporating largest set of historical data (pixel

values of seven historical interpolated maps). Other maps defining the characteristics of the watershed are the maps for curve number, hydraulic conductivity, digital elevation, reach distance, and initial ground water level). Initial ground water level map acts as the initial condition, with respect to which ground water level map in future will be determined as per the effect of forecasted rainfall, evaporation and ground water draft maps.

### 6.2.1 Methodology

Point data of rainfall, temperature, and ground water level from rainfall recording stations, temperature recording stations, and observation wells respectively distributed over a geographical region at consecutive historical time steps have been used to generate interpolated maps of precipitation, evaporation, and ground water level at their respective time steps. As per the ground water level maps presented in India-WRIS (<http://www.india-wris.nrsc.gov.in/GWLevelApp.html> dated 9/03/2018) interpolation of the maps has used inverse distance weighted (IDW) method to predict data value at unvisited points derived from the data values at visited points using Equation (6.1) (Burrough & McDonnel, 1998). Since the methodology requires values of the variables of consideration at each pixel over the map, method of interpolation is not a matter of concern and any appropriate interpolation technique can be adopted.

$$\hat{z}(x_j) = \sum_{i=1}^n z(x_i) \cdot d_{ij}^{-r} / \sum d_{ij}^{-r} \quad (6.1)$$

where,  $x_j$ :  $j$ th point where the surface is to be interpolated.

$x_i$ :  $i$ th point with the observed data.

$d_{ij}$ : distance between points  $x_i$  and  $x_j$ .

$z$ : data value at point  $x_i$ .

$\hat{z}$ : data value at point  $x_j$ .

$r$ : an exponential term influencing the effect of known values over to unknown values.

An interpolated map is composed of a matrix of pixels distributed in rows and columns. IDW assigns a value to all the pixels within a map. These interpolated maps act as input to the state variable model determining the future state of ground water level. Precipitation, evaporation, and ground water draft maps have been forecasted in future time steps pixel by pixel using Equation (4.12).

## 6.2.2 Development of the model

Later a state variable approach has been applied to derive the future state of ground water level (Nagrath and Gopal, 1982). A Python toolbox has been designed based on certain water balance equations with respect to various hydrological components of watershed (Neitsch et al., 2011). Precipitation inflow after surface runoff percolates underground. There is an outflow from the ground water in form of ground water flow, ground water draft, and evaporation from the aquifers. The state change relation for ground water level has been defined in Equation (6.2).

$$D_{WL}(k + 1) = D_{WL}(k) - \frac{R_{aq}(k)}{A} \quad (6.2)$$

where,  $D_{WL}(k)$  (m): depth of water level in meters below ground level at time step  $k$ .

$R_{aq}(k)$  ( $m^3$ ): aquifer recharge at time step  $k$ .

$A$  ( $m^2$ ): area of a pixel.

Aquifer recharge has been evaluated over the area of a pixel using Equation (6.3).

$$R_{aq}(k) = I(k) - R(k) - Q_{gw}(k) - U(k) - E(k) \quad (6.3)$$

where,  $I(k)$  ( $m^3$ ): precipitation inflow at time step  $k$ .

$R(k)$  ( $m^3$ ): surface runoff at time step  $k$ .

$Q_{gw}(k)$  ( $m^3$ ): ground water flow at time step  $k$ .

$U(k)$  ( $m^3$ ): ground water draft at time step  $k$ .

$E(k)$  ( $m^3$ ): evaporation at time step  $k$ .

Precipitation inflow and evaporation have been derived from the product of precipitation and potential evapotranspiration with the area of the pixel respectively. Potential evapotranspiration ( $P_e$ ) has been obtained using Thornthwaite model presented by Equation (6.4) (Wang et al., 2011) earlier used in Chapters 4 and 5 as equations (4.15) and (5.14) respectively.

$$P_e = 1.6 d (10 T / I)^a \quad (6.4)$$

It is difficult to distribute the ground water draft over to different pixels over a region. Hence, distributed ground water draft has been assumed as per the Equation (6.5).

$$U(k) = A.D_{py} + (I(k) - R(k) - Q_{gw}(k) - E(k)) \quad (6.5)$$

where,  $D_{py}$  (m) is ground water level decline per year calculated from the ground water level difference of initial year and final year. Ground water flow and surface runoff per unit area have

been evaluated using Equation (6.6) (Hooghoudt, 1940) and Equation (6.7) earlier used in Chapter 5 as equations (5.2c) and (5.1c) respectively.

$$Q_{gw}(k) = \frac{8000.K_{sat}}{L_{gw}^2} h_{wtbl}(k) \quad (6.6)$$

$$R(k) = \frac{(P(k)-0.2S)^2}{P(k)+0.8S} \quad (6.7)$$

As per the availability of data for ground water level, Equation (6.2) is the only state variable equation developed for simulations in GIS and a number of output equations can be created for the variables dependent upon the state of ground water level.

### 6.3 Simulation of GIS model

Implementation of the model incorporates the execution of python toolboxes developed as per the code presented in Appendix D, taking precipitation and evaporation interpolated maps as climatic inputs. Other input maps representing characteristics of the study area under consideration are for hydraulic conductivity, curve number, digital elevation, and reach distance. Initial ground water level and ground water draft maps are the human induced inputs to the system. The model has been executed over a block Chirawa of district Jhunjhunu in the Rajasthan state of India. The hydrological profile of Chirawa is presented in Figure 6.1.

DEM (Digital Elevation Model) data with 30 meter spatial resolution for the district Jhunjhunu has been downloaded from Bhuvan, an Indian geo-platform of ISRO (Indian Space Research Organization) (<http://bhuvan.nrsc.gov.in/data/download/index.php> dated 10/01/2018). All other input maps developed have been set to similar spatial resolution as DEM. Data for rainfall and temperature have been procured from IMD (Indian Meteorological Department), India for the eight rainfall stations and one surface data station respectively located in district Jhunjhunu from the year 2007 to the year 2013 as presented in Table 6.1 and Table 6.2. Ground water level data from 16 observation well sites in Jhunjhunu from the year 2006 to the year 2016 is presented in Table 6.3 (<http://www.india-wris.nrsc.gov.in/GWLevelApp.html> dated 9/03/2018).

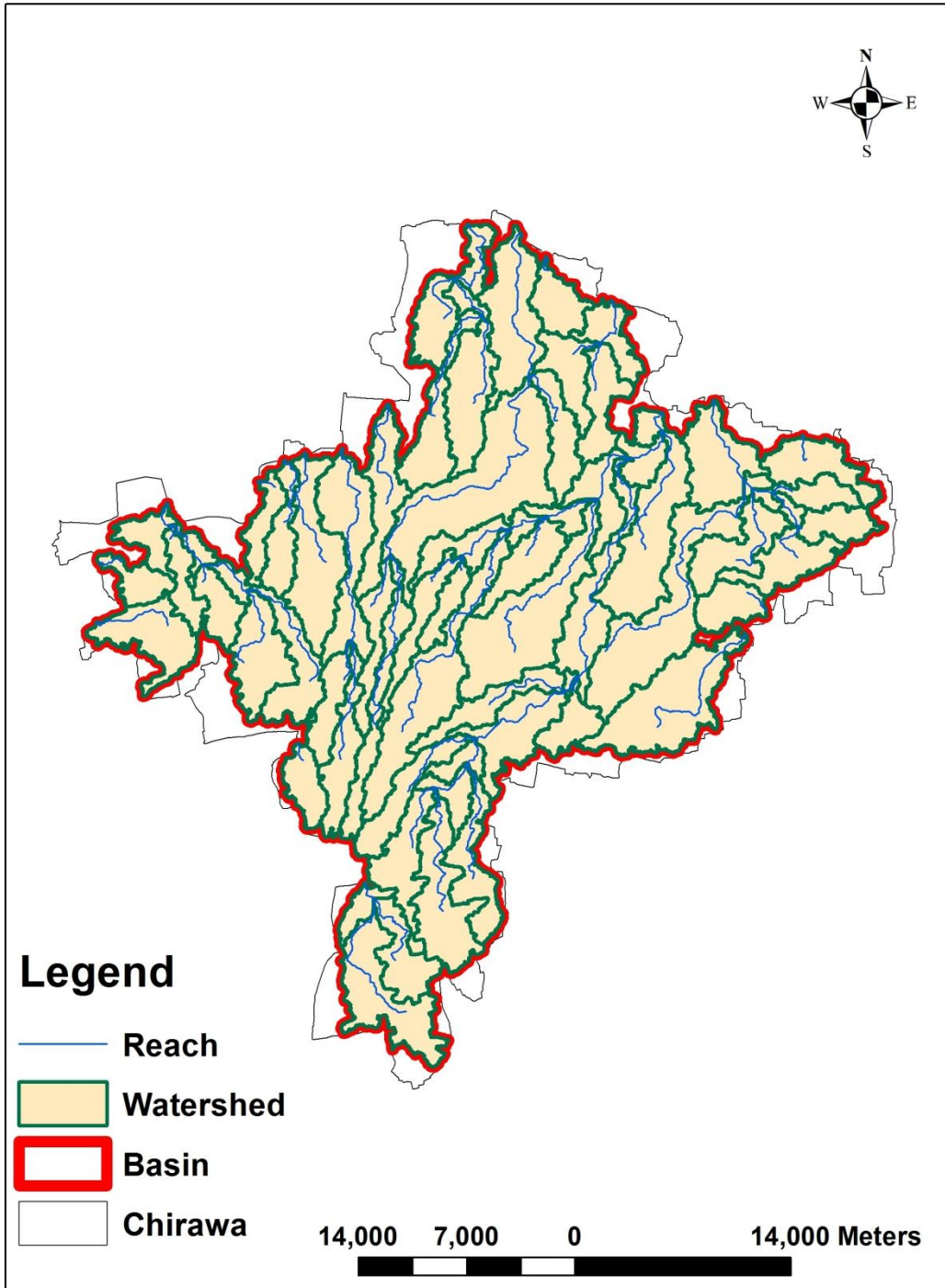


Figure 6.1. Hydrological profile of Chirawa

Table 6.1. Annual rainfall recorded at rainfall stations located in Jhunjhunu (mm)

Rainfall Station	2007	2008	2009	2010	2011	2012	2013
Chirawa	480	681	274	566	545	319	541
Buhana	561	679	231	578	520	480	476
Jhunjhunu	442	610	214	828	646	427	487
Khetri	413	800	547	944	645	519	652
Malsigar	633	521	295	991	981	503	722
Nawalgarh	351	550	284	655	752	838	423
Pilani	455	648	327	414	681	510	506
Udaipur/Shekha	538	595	187	813	643	540	593

Table 6.2. Average temperature recorded at only surface data station Pilani (°C)


Month/Year	2007	2008	2009	2010	2011	2012	2013
January	13.54	13.61	14.62	11.90	11.40	12.50	12.50
February	17.96	17.59	17.95	15.95	16.75	14.80	16.40
March	20.91	27.62	23.55	22.10	22.80	22.35	23.15
April	30.78	30.32	28.08	29.20	27.90	27.95	28.30
May	32.98	30.39	33.57	32.50	34.20	32.70	33.90
June	34.14	30.86	33.00	34.20	28.80	23.15	34.55
July	31.76	31.23	31.68	31.10	31.10	33.00	32.10
August	30.55	29.27	31.30	29.85	29.40	29.40	29.55
September	29.13	28.26	28.97	29.65	28.35	30.60	29.70
October	26.06	28.23	25.92	26.05	25.90	25.65	26.90
November	22.56	21.87	21.50	19.84	22.10	20.20	19.75
December	14.47	15.36	18.46	13.30	14.75	15.05	15.95

Table 6.3. Ground water level recorded at observation well sites in Jhunjhunu (mgbl)

Site Name	Site Type	Well Code	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Badagaon	Tube Well	W18362	36.2	37.5	38.85	40.5	41.6	44.42	44.5	46.05	46.25	51.89	50.44
Birmi	Tube Well	W18339	38.48	39.79	39	26.13	39.42	39.55	40.18	38.6	42.4	40.22	40.45
Chowara	Tube Well	W18363	23.6	25.34	26.58	27.98	30.26	36.41	33.77	42.35	37.1	41.82	43.89
Churela	Tube Well	W18340	41.47	41.86	42.25	42.66	43.1	43.39	45.62	44.32	44.8	48.63	46.67
Dighal	Tube Well	W18348	48.24	48.95	49.17	50.34	50.67	51.16	53.18	55.93	58.67	56.38	54.36
Jaisinghpura	Tube Well	W18349	43.7	44.25	44.55	45.9	45.85	46.11	47.15	47.1	47.69	48.27	48.92
Jhanjha	Tube Well	W18343	64.84	69.41	73.44	80.7	83.72	91.27	70.39	49.52	68.56	61.50	51.70
Jhunjhunu	Tube Well	W18350	58.15	59.55	60.25	61.55	62.85	64.46	68.1	69.9	65.70	65.69	65.12
Lakhu	Tube Well	W18347	58.07	59.7	61.65	62.93	70.45	66.09	68.2	65.55	70	74.45	77.48
Mandasi Sandasi	Tube Well	W18352	49.75	50.38	50.93	51.7	52.44	53.18	52.2	54.35	55.7	56.56	57.64
Mandrela	Tube Well	W20623	38.46	49.87	50.97	51.56	52.11	52.73	60.35	59.37	61.36	56.82	56.6
Meghpur	Tube Well	W18345	59.46	63.45	68.78	74.58	74.08	77.48	84.9	86.05	88.06	91.80	95.75
Mukundgarh	Tube Well	W18358	46.75	47.23	47.86	48.05	48.58	49.11	49.97	51.95	52.06	52.18	52.29
Paporana	Dug Well	W18357	20.43	23.29	18.02	22.14	22.04	15.64	17.82	20	23.6	26.62	21.65
Pilani	Tube Well	W18359	60.3	60.76	62.76	66.51	62.06	76.54	74.98	73.41	73.21	73.40	75.23
Pipli	Tube Well	W18360	60.06	61.34	62.58	63.23	54.5	67.32	69.2	65.65	72.24	78.82	97.1

**Note: mbgl (meters below ground level)**

 Missing value interpolated as average of its previous term and later term

 Missing value predicted as per Equation (4.12) with respect to previous seven terms

The entries of Table 6.3 highlighted in green and yellow were missing which have been interpolated and extrapolated respectively. Green cells correspond to the missing data which has been estimated as the average of its before and after terms. Yellow cells are the data extrapolated from the earlier seven data values as per Equation (4.12).

IDW Interpolated maps with  $r = 2$  (default in IDW interpolation tool of ArcGIS 10.1) for annual rainfall from the year 2007 to the year 2013 and ground water level from the year 2006 to the year 2016 have been developed. Since there is only one station in Jhunjhunu for temperature data, raster maps with same annual evaporation all over the region for the year 2007 to the year 2013 have been prepared as per Equation (6.4).

Later all the above maps prepared have been clipped within the boundary of Chirawa block extracted from the village boundary database of the district Jhunjhunu procured from Survey of India. To determine surface runoff as per Equation (6.7), a map for curve number (CN) has been generated. CN for the region corresponds to coarse texture soil (<http://india-wris.nrsc.gov.in/SoilApp.html> dated 9/03/2018) and weighted average land use. 88%, 3%, and 9% of the area fall

under crop land, built up, and forest respectively (<http://india-wris.nrsc.gov.in/LULCApp.html> dated 9/03/2018). For one soil group, one CN has been assigned. Therefore, a CN map having value as 73 has been used to evaluate surface runoff (SCS Engineering Division, 1986). Ground water flow as per Equation (6.6) has been characterized by a hydraulic conductivity map. The principal aquifer system over the region is alluvium having thickness of 40-800 meters and transmissivity of 200-400 square meters per day (<http://www.india-wris.nrsc.gov.in/LithologApp.html> dated 9/03/2018). Using average value of thickness and transmissivity, hydraulic conductivity is taken as 261 meters per year as per Equation (6.8) ([http://www.aqtesolv.com/aquifer-tests/aquifer\\_properties.htm](http://www.aqtesolv.com/aquifer-tests/aquifer_properties.htm) dated 9/03/2018) earlier used in Chapter 5 as Equation (5.13).

$$T = K \cdot b \quad (6.8)$$

The height of water table has been considered as the difference between DEM and depth of ground water table as the configuration of the water table commonly is a replica of the land surface topography on a regional scale ([http://www.pubs.usgs.gov/circ/circ1186/html/gen\\_facts.html](http://www.pubs.usgs.gov/circ/circ1186/html/gen_facts.html) dated 9/03/2018). Map for the reach distance has been developed by converting watershed area shape file to raster assigning a value of reach distance to every pixel within a sub basin since groundwater flow from a sub basin as per Equation (6.6) requires one value of reach distance from sub basin divide. The watershed area delineation has been performed by SWAT (Soil and Water Assessment Tool) extension of ArcGIS 10.1 (Neitsch et al., 2011). The final raster has been classified into sub basins with the values of their pixels equal to square root of their respective areas (reach distance) considering distance from sub basin divide to the reach equal to the side of a square equivalent in area to the area of sub basin. The reason for the consideration is that if the actual distance from pixels to reach would have been used then the ground water flow from the pixels closer to reach would tend to infinity as per Equation (6.6). Region which did not fall under watershed has been assigned reach distance value as null. Ground water draft raster maps for the year 2007 to the year 2013 have been evaluated as per Equation (6.5) where  $D_{py}$  (m) raster is calculated with respect to the interpolated ground water level maps of the year 2006 and the year 2016.

Three python toolboxes have been developed in ArcGIS 10.1 to derive ground water level in the year 2030 for three scenarios of drought (S1), BAU (S2), and surplus (S3) with respect to the



climate variables (rainfall and evaporation) as presented in Figure 6.2. It is considered that if the extreme cases can be monitored then all intermediate cases can be handled effectively whereas business as usual cases are necessary to determine the expected outcomes. Rainfall and evaporation have been predicted as per Equation (4.12) for BAU. For drought scenario minimum of the rainfall and maximum of the evaporation from the year 2007 to the year 2013 has been extrapolated till the time step at which ground water level is desired and vice versa for surplus. Ground water draft has been forecasted by Equation (4.12) for all the three scenarios since climate variables are considered for the development of scenarios.

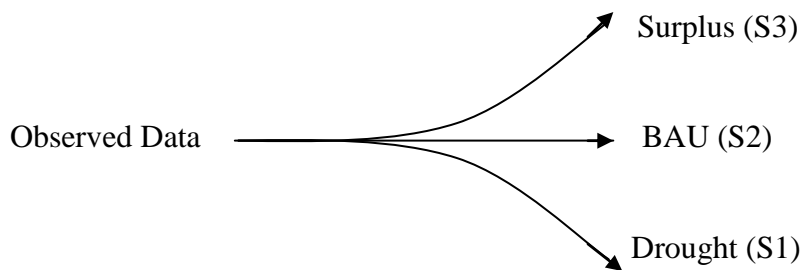


Figure 6.2. Schematic diagram of scenarios developed for GIS state variable model

### 6.3.1 Results

Interpolated maps of the rainfall for the scenario S2 (BAU), S1 (drought), and S3 (surplus) as per the criteria defined from the year 2007 to the year 2030 are shown in Figure 6.3, Figure 6.4, and Figure 6.5 respectively. Similarly the interpolated maps of ground water draft from the year 2007 to the year 2030 common to all scenarios S1, S2, and S3 are shown in Figure 6.6. The rainfall and ground water draft maps from the year 2007 to the year 2013 are the interpolated maps generated with the available data for their respective years while the maps from the year 2014 to the year 2030 are the maps predicted with respect to the generated maps as per Equation (4.12) for scenario S2 of rainfall and for all scenarios S1, S2, and S3 of ground water draft. Scenarios S1 and S2 of rainfall consider the minimum and the maximum value of rainfall for every pixel from the rainfall maps of the year 2007 to the year 2013 to be continued further from the year 2014 to the year 2030.

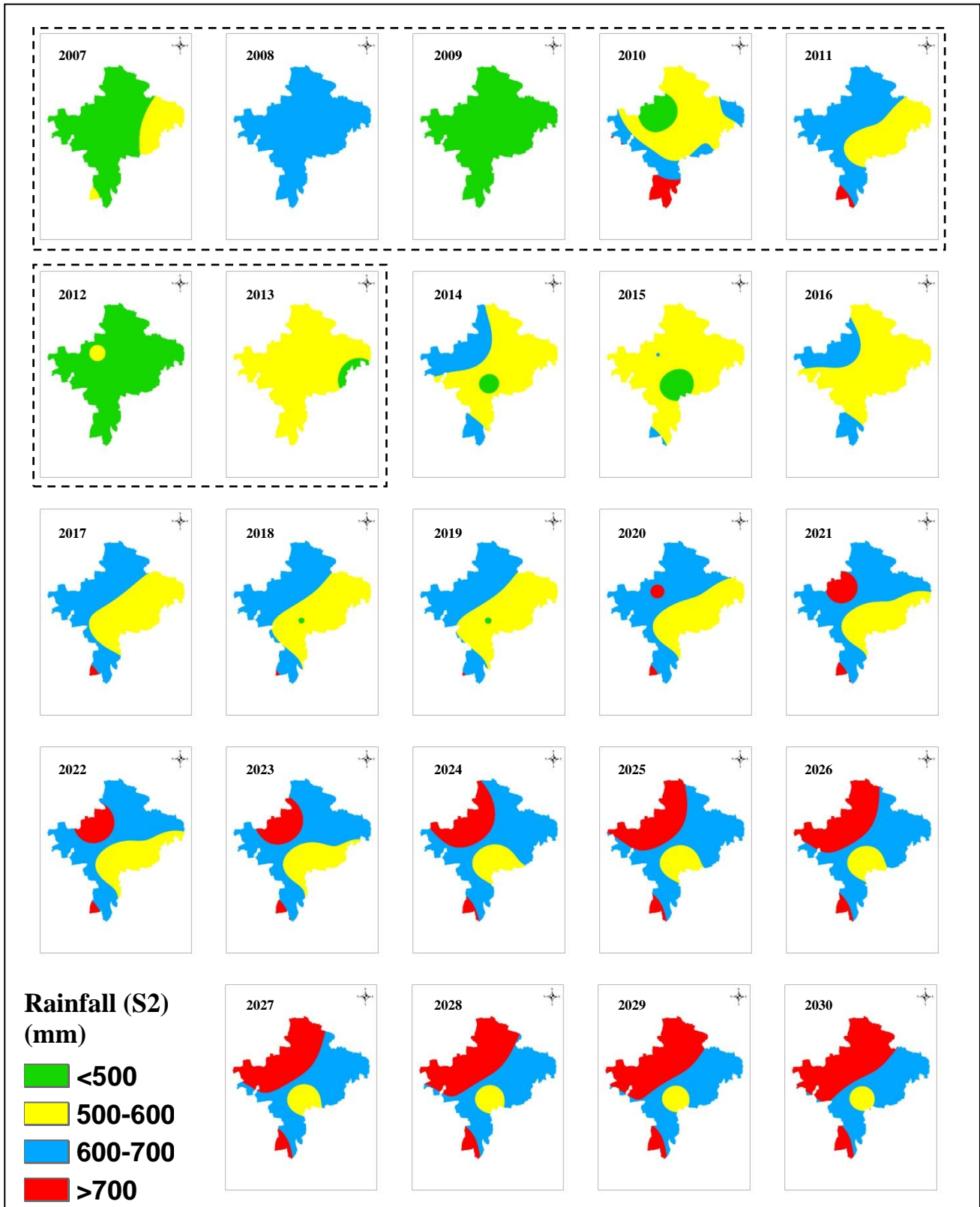


Figure 6.3. Interpolated maps of rainfall in Chirawa for scenario S2 from the year 2007 to the year 2030

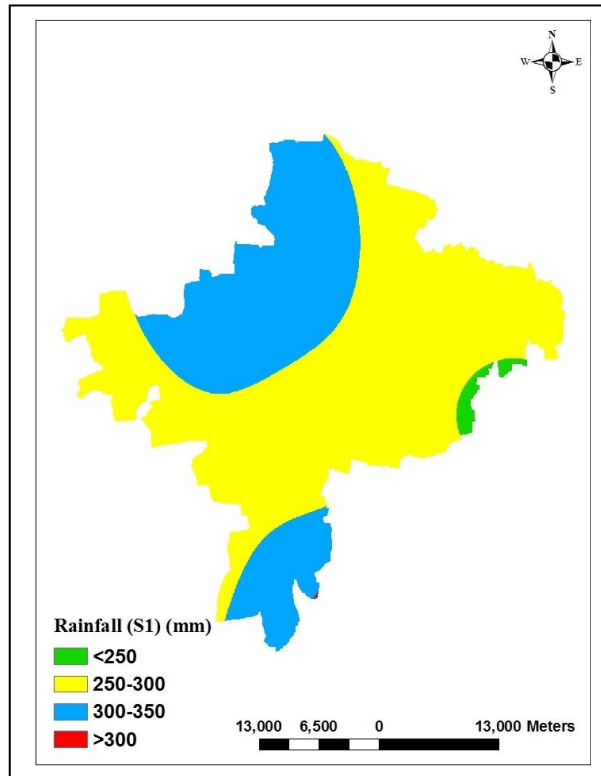


Figure 6.4. Rainfall map of Chirawa for the scenario S1 from the year 2014 to the year 2030

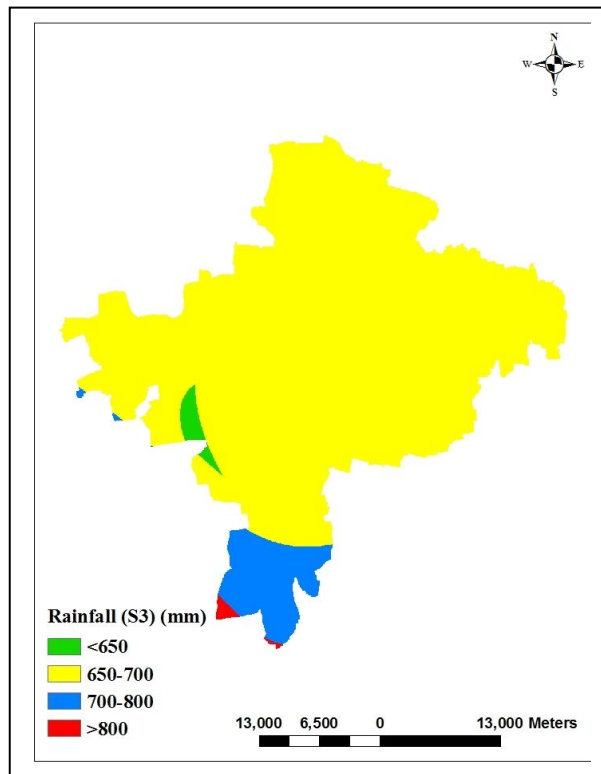


Figure 6.5. Rainfall map of Chirawa for the scenario S3 from the year 2014 to the year 2030

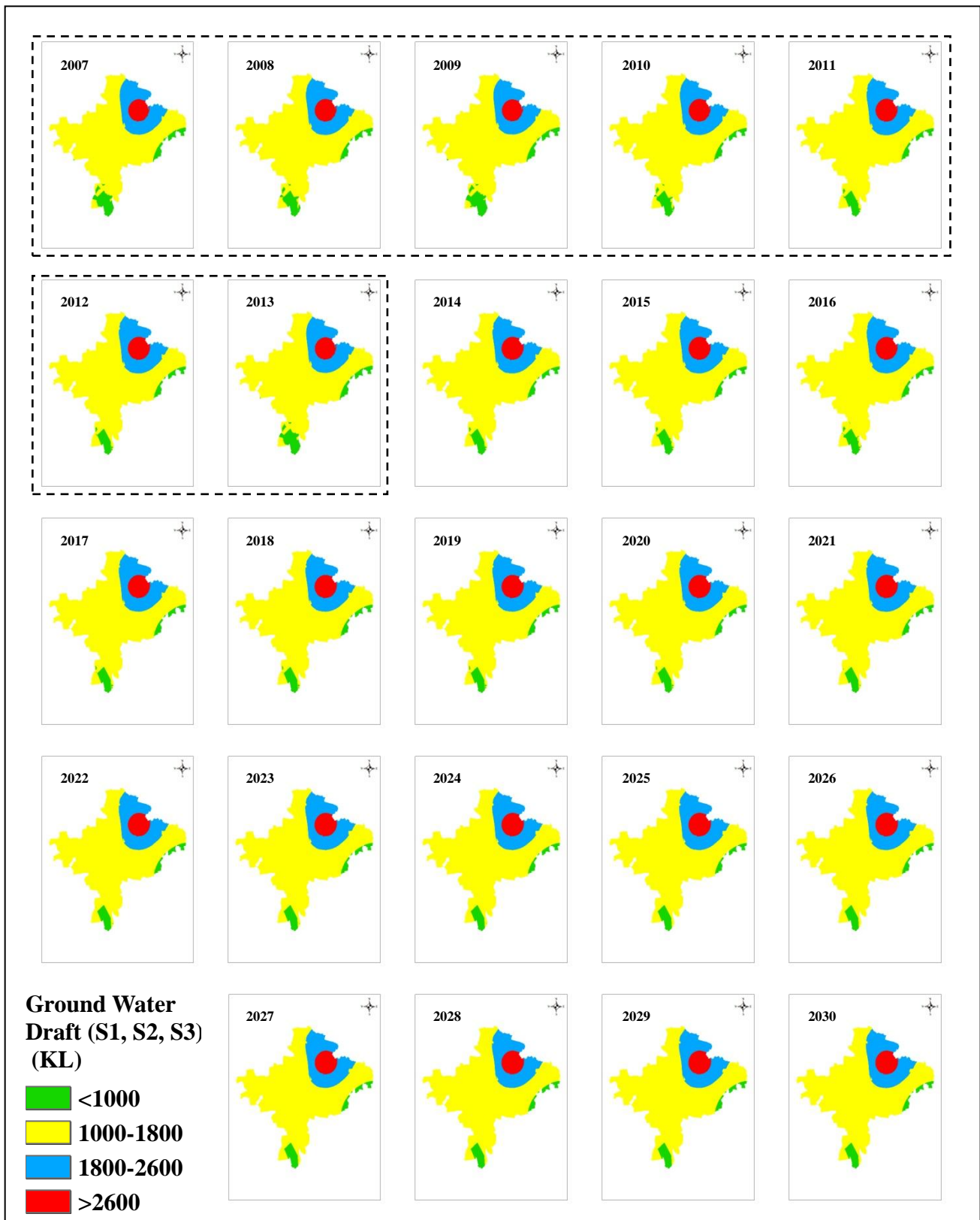


Figure 6.6. Ground water draft maps of Chirawa common for the scenarios S1, S2, and S3 from the year 2007 to the year 2030


Since the evaporation maps developed are the maps with the same value of evaporation at all pixels within a map due to the temperature data available from only one surface station (Pilani) in the Jhunjhunu district, the evaporation values for the three scenarios are presented in Table 6.4 (data points not fit for interpolation). Green cells represent the derived values of evaporation with respect to the observed temperature data from the year 2007 to the year 2013 while yellow cells are the extrapolated values of evaporation from the year 2014 to the year 2030. Evaporation in scenario S2 is forecasted as per the Equation (4.12) while in scenarios S1 and S3 maximum and minimum values of evaporation from the historical evaporation are continued further from the year 2014 to the year 2030.


Resultant maps for the ground water level (GWL) in the year 2030 for the three scenarios have been shown from Figure 6.13 to Figure 6.15. GWL is represented by the unit as mbgl (meters below ground level). The GWL maps have been classified into the regions having GWL less than 70 meters, 70 - 80 meters, 80 - 90 meters, and greater than 90 meters below ground level. It has been assumed that the region falling below 90 meters is most stressed while the region falling above 70 meters is sustainable. GWL in the year 2006 presented in Figure 6.12 reflects no traces of stressed region. Later stress started spreading outwards towards south-west direction with respect to north-east region as the centre, evident from GWL maps from the year 2007 to the year 2030 shown in Figure 6.7. Annual mean, standard deviation, and confidence interval (95%) of GWL maps from the year 2006 to the year 2030 are presented in Table 6.5.

In the year 2030, scenarios S2 and S3 are very close while S1 is slightly different from them and can be judged by very keen observation. Validation of the results has been carried out comparing predicted mean GWL in the three scenarios to mean GWL in the year 2016. Predicted and actual interpolated maps for the year 2016 are presented from Figure 6.8 to Figure 6.11 respectively. Percent error of GWL in the three scenarios with respect to actual GWL in 2016 is presented in Table 6.6. No significant difference for the three scenarios in the year 2016 and the year 2030 indicates that ground water draft is making the biggest contribution in declining GWL while the effect of rainfall and evaporation is only about 0.1%. Due to insignificant differences among the predicted GWL maps for the three scenarios maps corresponding to scenario S2 (BAU) only are presented in Figure 6.7. Maps of GWL corresponding to scenarios S1 and S3 are close to the lookalike of scenario S2.

Table 6.4. Predicted data of annual evapotranspiration (mm) in Chirawa from the year 2007 to the year 2030 for the scenarios S1 to S3

Year/Scenarios	S1	S2	S3
2007	186	186	186
2008	174	174	174
2009	185	185	185
2010	172	172	172
2011	160	160	160
2012	153	153	153
2013	185	185	185
2014	186	160	153
2015	186	159	153
2016	186	162	153
2017	186	168	153
2018	186	158	153
2019	186	158	153
2020	186	159	153
2021	186	160	153
2022	186	156	153
2023	186	155	153
2024	186	155	153
2025	186	154	153
2026	186	152	153
2027	186	152	153
2028	186	151	153
2029	186	150	153
2030	186	149	153

 Derived value of evaporation from the historical temperature data.

 Extrapolated value of evaporation with respect to the historical evaporation.

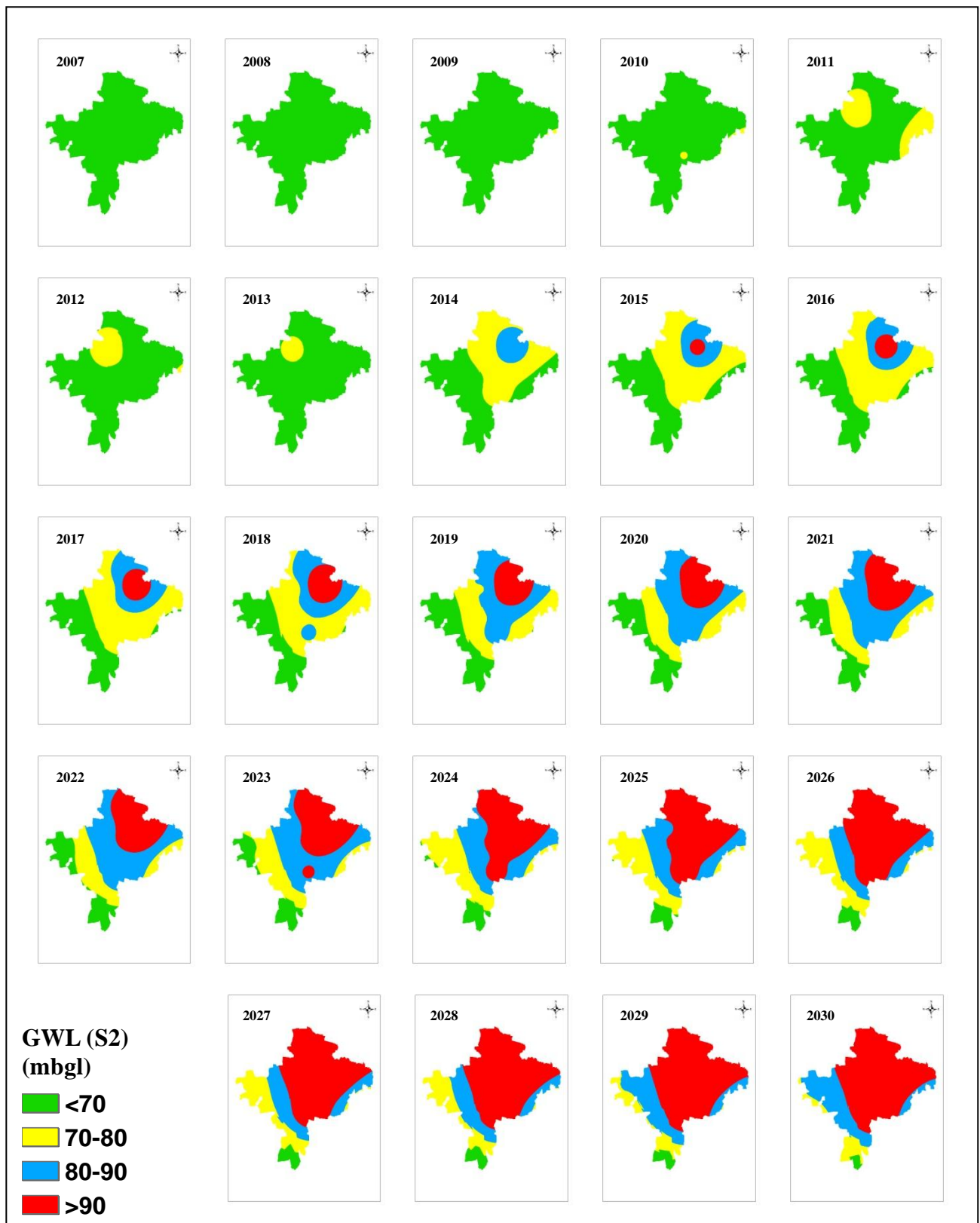


Figure 6.7. Ground water level maps of Chirawa for the scenario S2 from the year 2007 to the year 2030

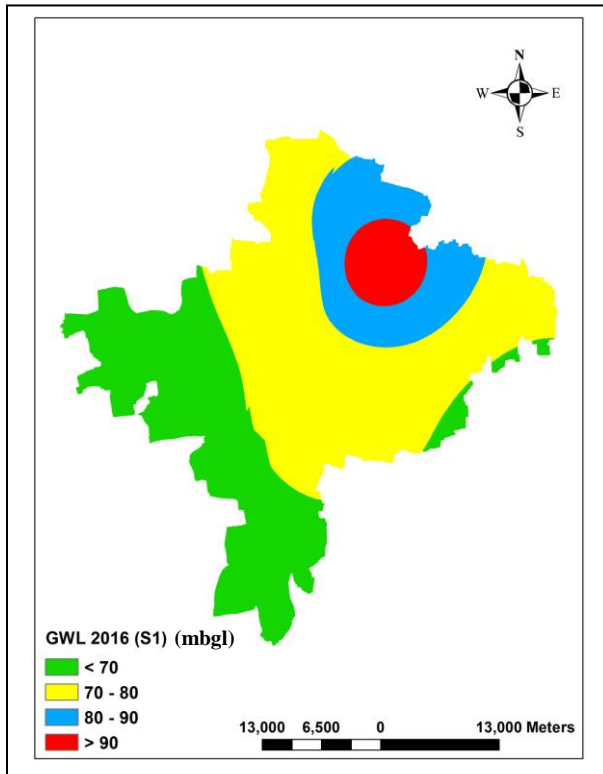


Figure 6.8. GWL for S1 in the year 2016

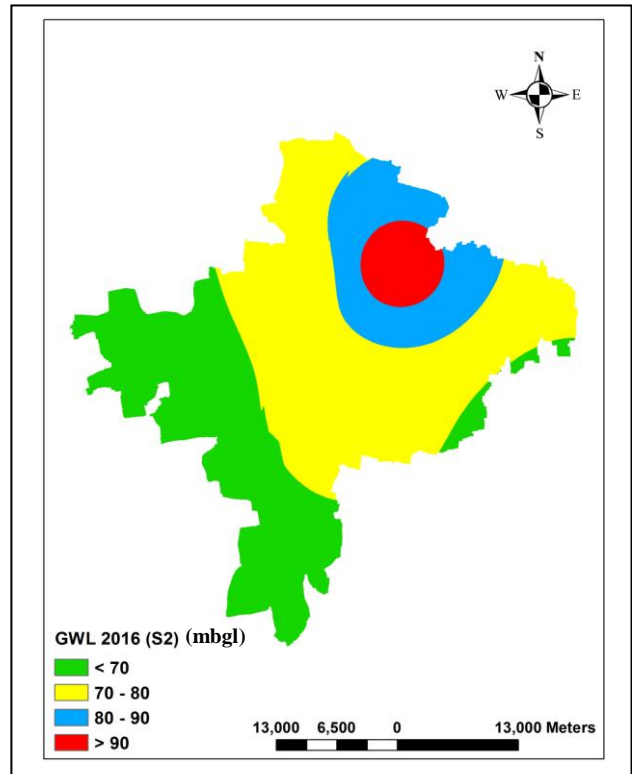


Figure 6.9. GWL for S2 in the year 2016

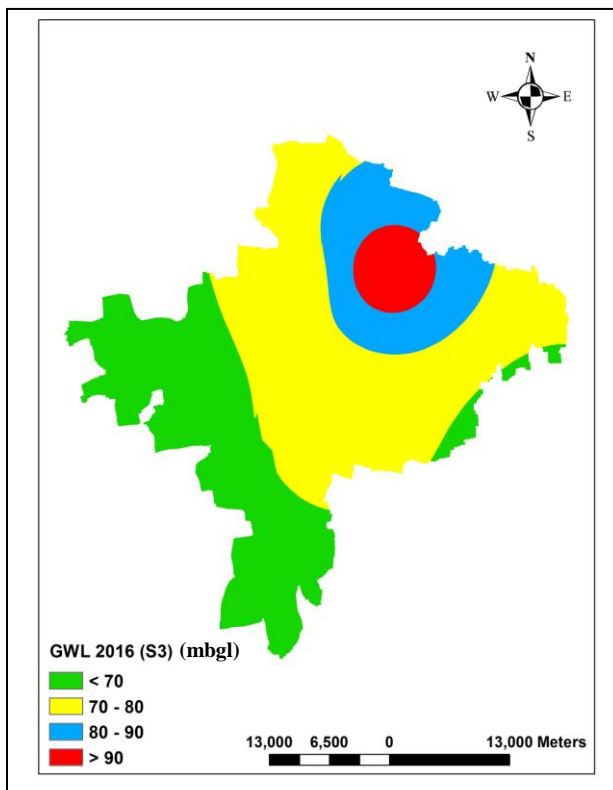


Figure 6.10. GWL for S3 in the year 2016

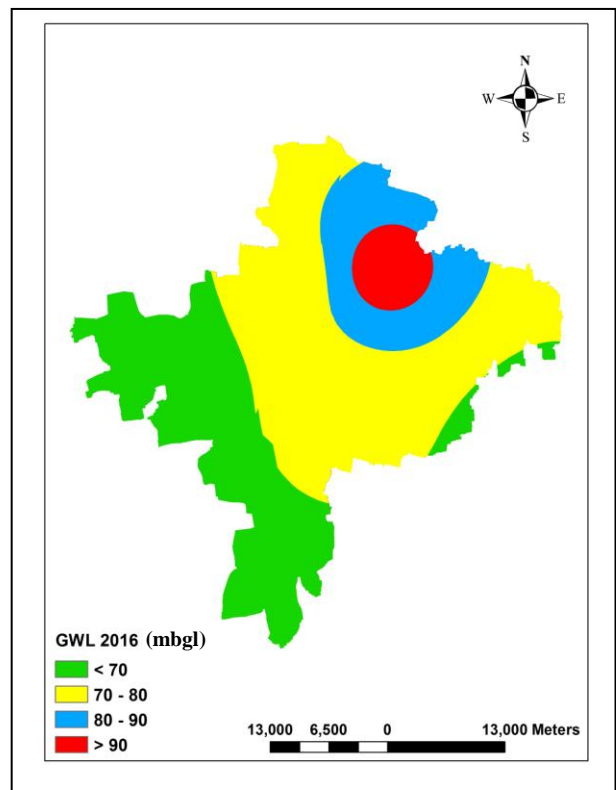


Figure 6.11. GWL in the year 2016



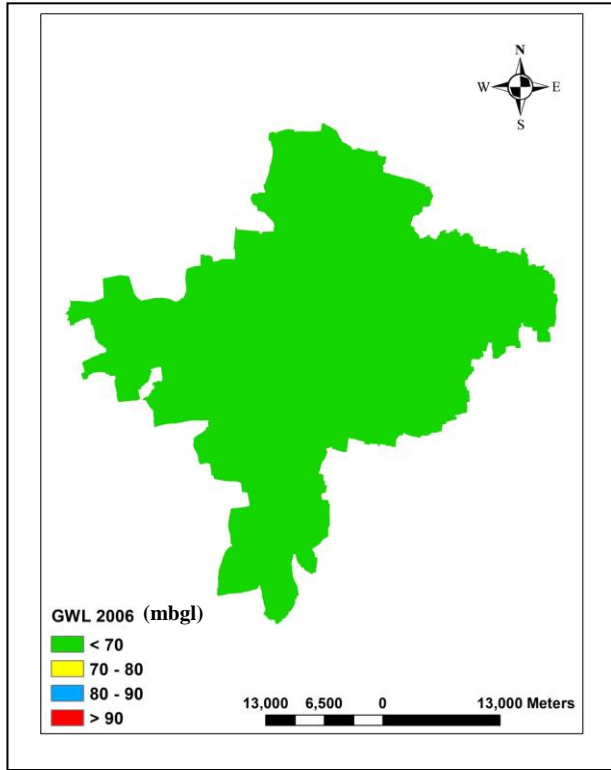


Figure 6.12. GWL in the year 2006

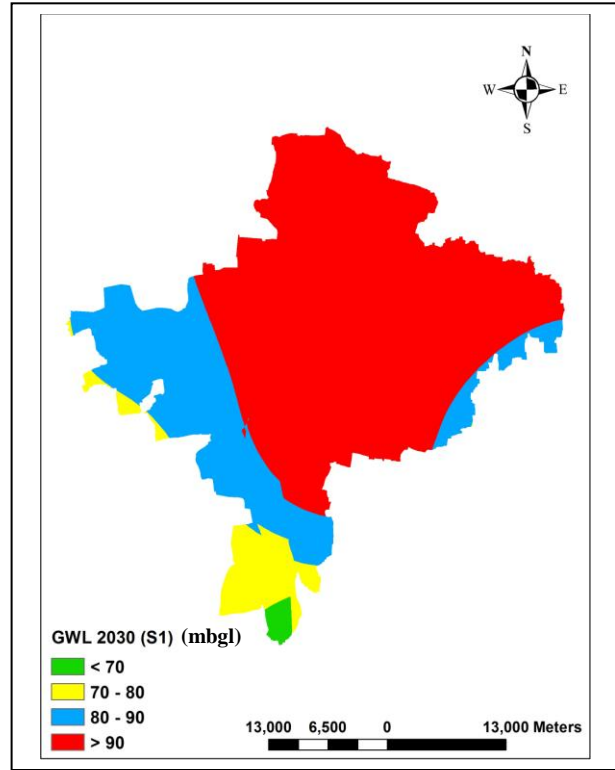


Figure 6.13. GWL for S1 in the year 2030

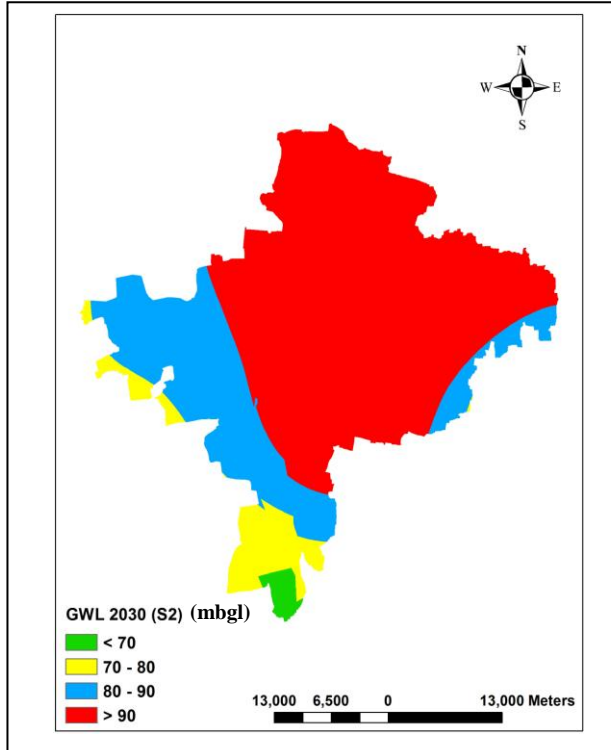


Figure 6.14. GWL for S2 in the year 2030

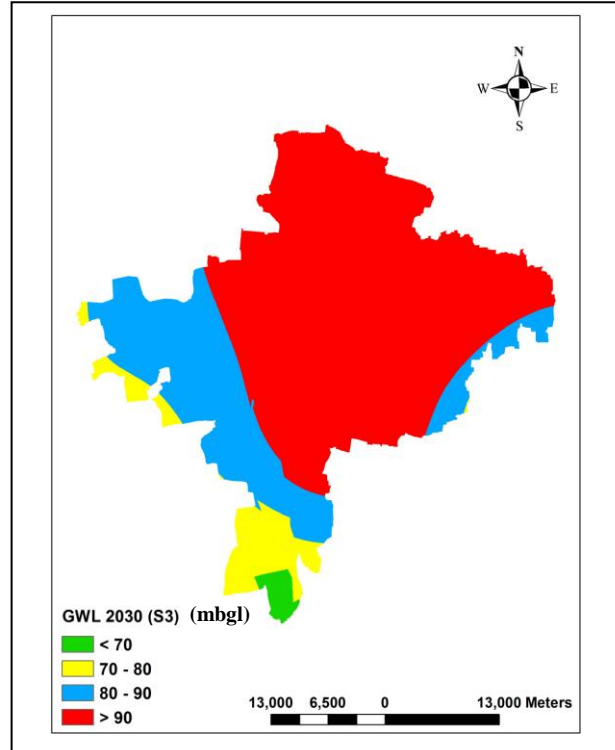


Figure 6.15. GWL for S3 in the year 2030

Table 6.5. Ground water level (mbgl) statistics of Chirawa block for the scenario S1/S2/S3

Year	Mean GWL ( $\mu$ )	Standard Deviation ( $\sigma$ )	Confidence Interval (95%) ( $\mu - 2\sigma, \mu + 2\sigma$ )
2006	53.74	5.95	(41.84, 65.64)
2007	56.51	4.73	(47.05, 65.97)
2008	58.12	5.07	(47.98, 68.26)
2009	60.08	5.56	(48.96, 71.2)
2010	59.38	5.28	(48.82, 69.94)
2011	64.8	6.8	(51.2, 78.4)
2012	65.57	5.56	(54.45, 76.69)
2013	63.04	4.58	(53.88, 72.2)
2014	68.89	9	(50.89, 86.89)
2015	70.78	9.45	(51.88, 89.68)
2016	72.67	9.9	(52.87, 92.47)
2017	74.57	10.38	(53.81, 95.33)
2018	76.47	10.85	(54.77, 98.17)
2019	78.37	11.33	(55.71, 101.03)
2020	80.27	11.81	(56.65, 103.89)
2021	82.17	12.3	(57.57, 106.77)
2022	84.06	12.8	(58.46, 109.66)
2023	85.96	13.29	(59.38, 112.54)
2024	87.86	13.79	(60.28, 115.44)
2025	89.76	14.29	(61.18, 118.34)
2026	91.66	14.79	(62.08, 121.24)
2027	93.56	15.3	(62.96, 124.16)
2028	95.47	15.81	(63.85, 127.09)
2029	97.37	16.32	(64.73, 130.01)
2030	99.27	16.83	(65.61, 132.93)

Table 6.6. Percent error of prediction of ground water level (mbgl) in Chirawa for scenarios S1 to S3

Mean GWL (2016)	S1	S2	S3
Predicted	72.78	72.67	72.64
Observed	72.66	72.66	72.66
% Error	0.16	0.013	0.027

### 6.3.2 Inference of the study

The application of GIS model developed in the study applied over Chirawa block reflects decline in ground water level and it is stretching outwards from the north east region as the center. Step functions applied for drought and surplus scenarios reflect that ground water draft is playing the biggest role for continuous decline whereas with such a ground water draft statistics there is no significant effect of rainfall and evaporation over the site. It seems that, in order to alleviate the ground water level, ground water draft should be practiced in an efficient manner. Alternative measures should be adopted to reduce the draft. Meanwhile, rainfall will make some significant changes to the ground water level.

The GIS model developed in the study is different from the lumped state variable model developed in Chapter 5 in terms of its application areal extent. It can incorporate the distributed characteristics of terrain and climate data over a region with large area.

### 6.4 Summary of the Chapter

Summary of the chapter includes the following points:

- Development of a state variable GIS model determining the future ground water level map with respect to the forecasted maps of influencing parameters (rainfall, evaporation and ground water draft maps). Distributed characteristics of the region are defined by various maps developed for initial ground water level, curve number to evaluate rainfall dependent runoff, reach distance, hydraulic conductivity, and digital elevation (to evaluate ground water flow).

- Determining the ground water level map for the year 2030 for the three scenarios (drought, business as usual, and surplus). First the interpolated maps for rainfall, evaporation, and ground water draft have been generated for the first seven historical years (from the year 2007 to the year 2013), second the future maps have been forecasted for them applying Equation (4.12) from pixel to pixel of their interpolated historical maps. Forecasts of ground water draft maps are fixed as per Equation (4.12) for the three scenarios considered. Rainfall and evaporation maps are also forecasted as per Equation (4.12) for the business as usual scenario. For the drought scenario rainfall and evaporation maps are stepped to lowest of rainfall values and highest of evaporation values respectively in their historical maps for the future years. Conversely, for surplus scenario rainfall and evaporation maps are stepped to highest of rainfall values and lowest of evaporation values respectively in their historical maps for the future years.
- Simulation of the state variable GIS model over the region of Chirawa, Rajasthan (India) for the three scenarios initiating over the ground water level map of the year 2006 generates resultant ground water level maps for the year 2030 with the declining state falling under vulnerable condition as shown from Figure 6.13 to Figure 6.15. It indicates again that ground water draft has the most significant effect on ground water level whereas rainfall and evaporation are not significant by more than 1%.

# **CHAPTER 7: CONCLUSIONS AND FUTURE SCOPE**

## **7.1 Chapter overview**

This chapter finally provides a statement of the work presenting the consolidated findings. Section 7.2 and 7.3 present the list of derived models and their effects respectively. Section 7.4 derives the conclusions of the study while section 7.5 and 7.6 present the limitations and future scope respectively.

## **7.2 The derived models**

During the thesis work three different type of models have been derived:

- a) Model to predict the future values of different chronological variables with respect to their few of the observed initial values specified in Chapter 4.
- b) A state variable hydrological model to determine the states of various water storage elements with respect to their initial states and inputs predicted as per model specified in Chapter 5.
- c) A state variable GIS model to determine the state of ground water resources as per the model specified in Chapter 6.

## **7.3 Discussions**

There are certain advantages of the methods and models developed during thesis work which are mentioned as per the following sections.

### **7.3.1 Effect of the recurrence relation method in prediction**

The recurrence relation technique has helped to derive a generalized equation for prediction with respect to certain initial values or conditions. It has taken moving average method of extrapolation from a set of steps to a single step. It made the moving average forecasting method simpler and easier to apply with lesser memory utilization to store previous step calculations.

### **7.3.2 Effect of the state variable modeling for hydrological scenarios**

The state variable model developed will act as an integrated system to determine the states of various water storage resources for scenarios corresponding to various combinations of the

observed/predicted input variables. These input variables are the broad perspective for the factors affecting storage and removal of the water flux within the hydrological system. Various combinations of different predicted input variables will provide a broad range of possibilities to be analyzed for identifying the extreme case scenarios. It is assumed that if the extreme cases can be handled efficiently other intermediate cases will be under control.

### **7.3.3 Effect of the GIS modeling for scenario development**

GIS modeling of the state variable hydrological system determining the state of ground water resources in future will provide its future maps. Inputs for the climate and socioeconomic variables is supplied in the form of maps instead of using some weather generator module as in other GIS based hydrological models. GIS based system developed will provide a distributed processing environment to the state variable model defined in section 7.3.2.

## **7.4 Conclusions on research findings**

The conclusion on the research is divided into its theoretical and practical counterparts.

### **7.4.1 Theoretical conclusions**

The key theoretical conclusion of the study establishes that:

- a) Certain complex methods applied in the field of prediction and scenario development can be generalized and made simpler to apply.
- b) The complexity can be reduced and can be initiated with a lesser volume of historical data.
- c) The steps in moving average method require to store results for the previous step to be applied in succeeding step which requires memory. Hence the generalized method being solved in one step only will provide a way for efficient memory utilization.
- d) State variable approach provides a way to integrate different social, technical, environmental, economic, political, and values aspects altogether as inputs to a system determining the state of its various components affected by them (inputs) besides response of the system. There might be the situations when the state of system components become undesirable which cannot be observed from the response of the system.

- e) It can provide a dynamism presenting state of different stocks within a system at every time step.
- f) Integration of the hydrological models like rainfall runoff, potential evapotranspiration, stream flow, and pond storage models can develop high level models breaking a water balance system into various processes occurring within a watershed. Such high level models will be lumped models and applicable over a small region with similar characteristics of terrain and climate for the whole region. They can be applied over a large distributed characteristics region breaking it into chunks of smaller regions with their significant terrain and climatic statistics and executing the models for every chunk.
- g) GIS implementation will provide a distributed two/three dimensional observations with respect to the interpolated maps of various input variables of a hydrological system. It is highly suitable for larger regions with distributed terrain and climatic statistics. It can perform simulations over a large area in one step presenting results at every location (pixel) on the region.
- h) GIS based hydrological tools like SWAT (Soil and Water Assessment Tool) perform the water balance calculations with respect to hydrological response units (HRUs) with different areas defined as per the slope, soil, and land use characteristics of the region, while pixel based approach opted in our study can take the analysis to any level of uniform spatial resolution. The major difference is SWAT generates results for each HRU in the text form while in the present study results are generated in the form of maps.

#### **7.4.2 Practical conclusions**

- a) Application of the generalized equations over the region of nine villages in Chirawa block reflects reasonable predictions for the input variables like rainfall, evaporation, crop water requirement, and population with an error close to 6%, 7.5%, 7%, and 1% respectively in business as usual (BAU) scenario. Rainfall and evaporation being highly uncertain have the higher proportion of error as compared to the population which is certain due to its rising graph. Crop water requirement is also uncertain in the study area of nine villages due to fluctuating land use for various crops.

- b) State variable model simulated over the village Ardawta reflects predictions for the ground water level of the observation well site located in Khudana (nearest to village Ardawta) are very close to its actual level. The error of 0.64% for the business as usual (BAU) scenario between predicted and actual value of ground water level for the year 2016 presents that the model developed can generate reasonable scenarios of ground water level and other storage elements of a hydrological system.
- c) Predictions obtained by application of state variable GIS model to determine ground water level in Chirawa block also reflects a good match to the actual level for the year 2016 with an error of 0.013% for the business as usual (BAU) scenario. As per our data set and study region ground water draft has 99% of effect on the ground water resources whereas combined effect of rainfall and evaporation is only about 1%.

### **7.5 Limitations of the study**

- a) Prediction method developed using generalized equations is applicable for discrete time data at regular intervals such that the variables to be predicted must have high probability to occur in the time interval.
- b) Accuracy of the predictions is required to be checked for the generalized equation of various degrees (i.e., for  $N=2, 3, 4, 5, \dots$ ) with respect to the availability of historical data and the equation deriving highest accuracy can be taken ahead for further predictions.
- c) Future predictions for the long range will move towards either rising or declining trend which could not be promising for the climatic data (data with uncertainty), hence it is suitable for short range predictions of rainfall and evaporation.
- d) State variable model developed is a lumped model and to apply it over a region with distributed characteristics it is required to be simulated multiple times.
- e) Slope characteristics of the region are assumed to be defined by Curve Number to evaluate surface runoff.
- f) Model has been simulated for annual time series inputs over the ground water level data only (as per the data available for validation).
- g) GIS model developed also assumes that runoff due to slope can be evaluated by a Curve Number layer generated over a region as per the data for soil and land use.



## 7.6 Future scope of the study

The study can be taken further by:

- a) Generalizing other techniques of prediction like ANN, Fuzzy logic, GAMLSS, Markov model, and Genetic programming.
- b) Development of a generic model to determine the states of all water storage resources with respect to various other climatic variables besides precipitation and temperature (like, wind speed, solar radiations, humidity, etc.) and other parameters (like landuse changes, livestock population, urbanization, etc.) simulating their uncertain behavior to develop scenarios.
- c) Incorporation of slope characteristics besides soil type and land use to determine runoff as per runoff coefficients defined for Rational formula ( $Q = C.I.A$ , where Q, C, I, and A are peak runoff, coefficient of runoff, intensity of rainfall, and area of catchment respectively), etc.
- d) Incorporating state dependent outputs for different sectors, e.g. allocation of the water resources to various demanding sites, e.g., derivation of hydro power, production of crops, etc.
- e) Implementation of the optimization techniques like genetic algorithm, fuzzy logic, etc. to provide better management of the water resources.

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## APPENDICES

### Appendix A: Flowchart and MATLAB codes for predicting input variables through recurrence relation technique

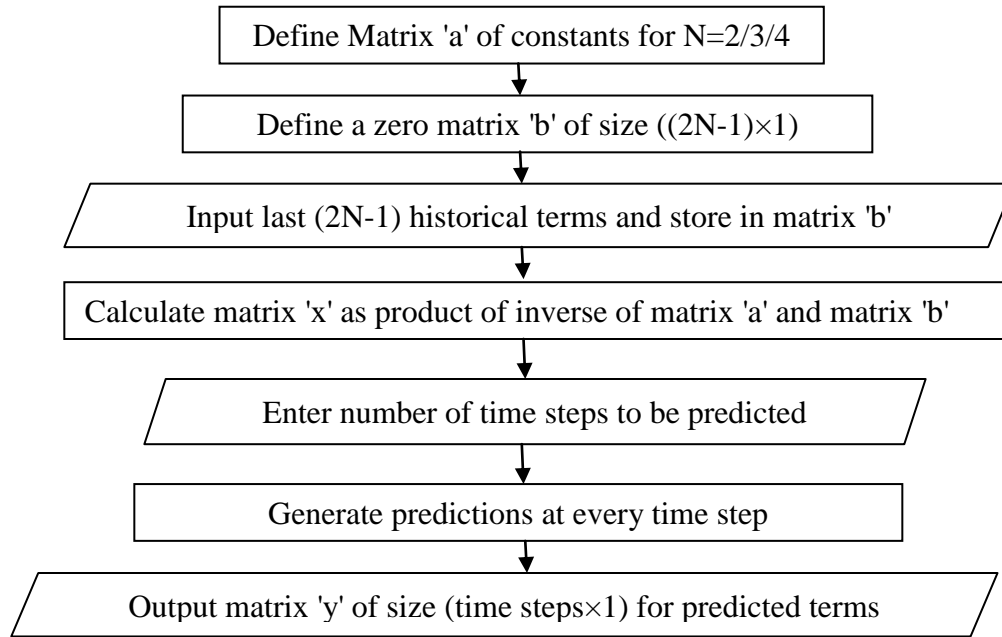


Figure A.1. Flowchart for predicting input variables through generalized recursive relation

For N = 2

```
a = [0 1 1
1 1 -0.75
2 1 0.5625]; %matrix defining the constants%
b = zeros(3,1); %matrix for initial conditions%
disp('enter matrix b:');
for i=1:3
    b(i,1)=input(num2str(i)); %input initial conditions%
end
x = inv(a)*b;
t=input('time step limit:'); %input time step up to prediction is desired%
for n = 1:t
    y(n,1) = (x(1,1)*n+x(2,1))*1^n+x(3,1)*(-0.75)^n;
end
y %output matrix with predicted values up to time step entered%
```

For N = 3

```
a = [0 1 1 1 0
1 1 -0.3955 -0.4134 0.6253
2 1 0.1564 -0.2201 -0.517
3 1 -0.0619 0.4143 0.0762
4 1 0.0245 -0.2189 0.2275]; %matrix defining the constants%
b = zeros(5,1); %matrix for initial conditions%
disp('enter matrix b:');
for i=1:5
    b(i,1)=input(num2str(i)); %input initial conditions%
end
x = inv(a)*b;
t=input('time step limit:'); %input time step up to prediction is desired%

for n = 1:t
    y(n,1) = (x(1,1)*n+x(2,1))*1^n+x(3,1)*(-
0.3955)^n+(0.7496)^n*(x(4,1)*cos(2.1550*n)+x(5,1)*sin(2.1550*n));
end
y %output matrix with predicted values up to time step entered%
```

For N = 4

```
a = [0 1 1 1 0 1 0
1 1 -0.7436 -0.0593 0.7712 -0.2877 0.3891
2 1 0.5529 -0.5913 -0.0914 -0.0686 -0.2239
3 1 -0.4112 0.1056 -0.4506 0.1068 0.0377
4 1 0.3057 0.3412 0.1081 -0.0454 0.0307
5 1 -0.2274 -0.1036 0.2568 0.0011 -0.0265
6 1 0.1691 -0.1919 -0.0951 0.01 0.0081]; %matrix defining the
constants%
b = zeros(7,1);
disp('enter matrix b:'); %matrix for initial conditions%
for i=1:7
    b(i,1)=input(num2str(i)); %input initial conditions%
end
x = inv(a)*b;
t=input('time step limit:'); %input time step up to prediction is desired%
for n = 1:t
    y(n,1) =(x(1,1)*n+x(2,1))*1^n+x(3,1)*(-
0.7436)^n+(0.7735)^n*(x(4,1)*cos(1.6475*n)+x(5,1)*sin(1.6475*n))+(0.4839)^n*(
x(6,1)*cos(2.2075*n)+x(7,1)*sin(2.2075*n));
end
y %output matrix with predicted values up to time step entered%
```

**Appendix B: Flowchart and MATLAB code for the state variable model for generating hydrological scenarios**

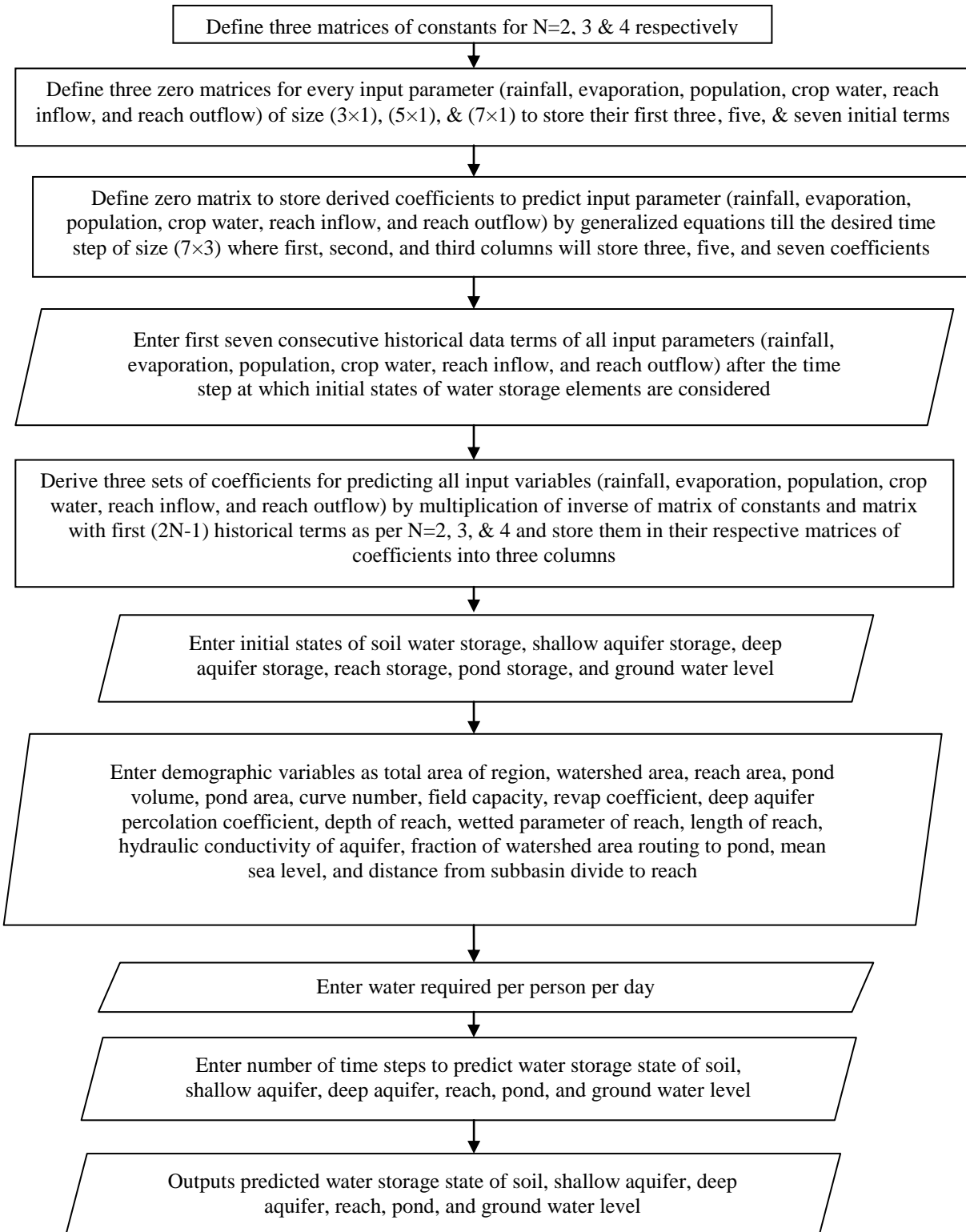


Figure B.1. Flowchart of the state variable model generating hydrological scenarios

```

n2 = [0 1 1
1 1 -0.75
2 1 0.5625]; %matrix defining constants for three initial conditions%
n3 = [0 1 1 1 0
1 1 -0.3955 -0.4134 0.6253
2 1 0.1564 -0.2201 -0.517
3 1 -0.0619 0.4143 0.0762
4 1 0.0245 -0.2189 0.2275]; %matrix defining constants for five initial
conditions%
n4 = [0 1 1 1 0 1 0
1 1 -0.7436 -0.0593 0.7712 -0.2877 0.3891
2 1 0.5529 -0.5913 -0.0914 -0.0686 -0.2239
3 1 -0.4112 0.1056 -0.4506 0.1068 0.0377
4 1 0.3057 0.3412 0.1081 -0.0454 0.0307
5 1 -0.2274 -0.1036 0.2568 0.0011 -0.0265
6 1 0.1691 -0.1919 -0.0951 0.01 0.0081]; %matrix defining constants
for seven initial conditions%

r2 = zeros(3,1); %matrices for three, five, and seven initial conditions of
rainfall in mm%
r3 = zeros(5,1);
r4 = zeros(7,1);

e2 = zeros(3,1); %matrices for three, five, and seven initial conditions of
evaporation in m%
e3 = zeros(5,1);
e4 = zeros(7,1);

p2 = zeros(3,1); %matrices for three, five, and seven initial conditions of
population%
p3 = zeros(5,1);
p4 = zeros(7,1);

c2 = zeros(3,1); %matrices for three, five, and seven initial conditions of
crop water required in Kiloliters%
c3 = zeros(5,1);
c4 = zeros(7,1);

in2 = zeros(3,1); %matrices for three, five, and seven initial conditions of
river inflow in meter cube%
in3 = zeros(5,1);
in4 = zeros(7,1);

o2 = zeros(3,1); %matrices for three, five, and seven initial conditions of
river outflow in meter cube%
o3 = zeros(5,1);
o4 = zeros(7,1);

mcr = zeros(7,3); %matrices to store three, five, and seven coefficients
derived for all input variables%
mce = zeros(7,3);
mcp = zeros(7,3);
mcc = zeros(7,3);
mcin = zeros(7,3);
mco = zeros(7,3);

```

```

disp('For the historical input variables you do not want to include or do not
have data put all the values as 0');

disp('enter seven consecutive data of rainfall in mm:');
for i=1:7
    r(i,1)=input(num2str(i));
end
for i=1:3
    r2(i,1)=r(i,1);
end
for i=1:5
    r3(i,1)=r(i,1);
end
for i=1:7
    r4(i,1)=r(i,1);
end

disp('enter seven consecutive data of evaporation in meters:');
for i=1:7
    e(i,1)=input(num2str(i));
end
for i=1:3
    e2(i,1)=e(i,1);
end
for i=1:5
    e3(i,1)=e(i,1);
end
for i=1:7
    e4(i,1)=e(i,1);
end

disp('enter seven consecutive data of population:');
for i=1:7
    p(i,1)=input(num2str(i));
end
for i=1:3
    p2(i,1)=p(i,1);
end
for i=1:5
    p3(i,1)=p(i,1);
end
for i=1:7
    p4(i,1)=p(i,1);
end

disp('enter seven consecutive data of crop water in Kiloliters:');
for i=1:7
    c(i,1)=input(num2str(i));
end
for i=1:3
    c2(i,1)=c(i,1);
end
for i=1:5
    c3(i,1)=c(i,1);
end
for i=1:7

```



```

        c4(i,1)=c(i,1);
end

disp('enter seven consecutive data of reach inflow in meter cube:');
for i=1:7
    in(i,1)=input(num2str(i));
end
for i=1:3
    in2(i,1)=in(i,1);
end
for i=1:5
    in3(i,1)=in(i,1);
end
for i=1:7
    in4(i,1)=in(i,1);
end

disp('enter seven consecutive data of reach outflow in meter cube:');
for i=1:7
    o(i,1)=input(num2str(i));
end
for i=1:3
    o2(i,1)=o(i,1);
end
for i=1:5
    o3(i,1)=o(i,1);
end
for i=1:7
    o4(i,1)=o(i,1);
end

r2x = inv(n2)*r2; %deriving coefficients for rainfall%
for i=1:3
    mcr(i,1)=r2x(i,1);
end
r3x = inv(n3)*r3;
for i=1:5
    mcr(i,2)=r3x(i,1);
end
r4x = inv(n4)*r4;
for i=1:7
    mcr(i,3)=r4x(i,1);
end

e2x = inv(n2)*e2; %deriving coefficients for evaporation%
for i=1:3
    mce(i,1)=e2x(i,1);
end
e3x = inv(n3)*e3;
for i=1:5
    mce(i,2)=e3x(i,1);
end
e4x = inv(n4)*e4;
for i=1:7
    mce(i,3)=e4x(i,1);
end

```

```

p2x = inv(n2)*p2; %deriving coefficients for population%
for i=1:3
    mcp(i,1)=p2x(i,1);
end
p3x = inv(n3)*p3;
for i=1:5
    mcp(i,2)=p3x(i,1);
end
p4x = inv(n4)*p4;
for i=1:7
    mcp(i,3)=p4x(i,1);
end

c2x = inv(n2)*c2; %deriving coefficients for crop water required%
for i=1:3
    mcc(i,1)=c2x(i,1);
end
c3x = inv(n3)*c3;
for i=1:5
    mcc(i,2)=c3x(i,1);
end
c4x = inv(n4)*c4;
for i=1:7
    mcc(i,3)=c4x(i,1);
end

in2x = inv(n2)*in2; %deriving coefficients for river inflow%
for i=1:3
    mcin(i,1)=in2x(i,1);
end
in3x = inv(n3)*in3;
for i=1:5
    mcin(i,2)=in3x(i,1);
end
in4x = inv(n4)*in4;
for i=1:7
    mcin(i,3)=in4x(i,1);
end

o2x = inv(n2)*o2; %deriving coefficients for river outflow%
for i=1:3
    mco(i,1)=o2x(i,1);
end
o3x = inv(n3)*o3;
for i=1:5
    mco(i,2)=o3x(i,1);
end
o4x = inv(n4)*o4;
for i=1:7
    mco(i,3)=o4x(i,1);
end

%initial states of hydrological elements%
SWi=input('Enter initial soil water in meter cube:');
SAi=input('Enter initial shallow aquifer volume in meter cube:');
DAi=input('Enter initial deep aquifer volume in meter cube:');

```

```

WLi = input('Enter initial Ground Water level in meters:');
RSi=input('Enter initial reach storage volume in meter cube:');
PSi=input('Enter initial pond storage volume in meter cube:');

%Demographic variables
A=input('Enter Total Area in meters square:');
WA=input('Enter Watershed/Catchment Area in meters square:');
RA=input('Enter Reach Area in meters square:');
VP=input('Enter volume of pond in meters cube:');
PA=input('Enter Pond Area in meters square:');
CN=input('Enter Curve Number for land use:');
FC=input('Enter Field Capacity of soil:');
Brevap=input('Enter revap coefficient:');
Bdeep=input('Enter deep aquifer percolation coefficient:');
dreach=input('Enter depth of reach in meters:');
Pch=input('Enter wetted parameter of reach in meters:');
Lch=input('Enter length of reach in Kilometers:');
K=input('Enter hydraulic conductivity of the aquifer in meters/year');
FrWA=input('Enter fraction of watershed area routing to pond:');
MSL=input('Enter Mean Sea Level of the region in meters:');
L=input('Enter distance from sub basin divide to reach in meters');

%Other variables
WP =input('Enter water required per person per day in liters:');

t=input('Enter the number of time steps to predict water statistics');
SWtotal = zeros(t+1,729);SAVtotal = zeros(t+1,729);DAVtotal =
zeros(t+1,729);WLiotal = zeros(t+1,729); RStotal = zeros(t+1,729);PStotal =
zeros(t+1,729);i=1; %matrices to store soil water storage, shallow aquifer
storage, deep aquifer storage, ground water level, reach storage, and pond
storage for 729 combinations of input variables up to the time step t desired
for prediction%
a =0;b=0;c=0;d=0;e=0;f=0;
while i<=729
    for a=0:2
        for b=0:
            for c=0:2
                for d=0:2
                    for e=0:2
                        for f=0:2
                            sim('m2'); %m2 is the simulink model developed to execute%
                            x1 = SW.Data;
                            x2 = SAV.Data;
                            x3 = DAV.Data;
                            x4 = WL.Data;
                            x5 = RS.Data;
                            x6 = PS.Data;
                            for m=1:t+1
                                SWtotal(m,i)= x1(m,1);
                                SAVtotal(m,i)= x2(m,1);
                                DAVtotal(m,i)= x3(m,1);
                                WLiotal(m,i)= x4(m,1);
                                RStotal(m,i)= x5(m,1);
                                PStotal(m,i)= x6(m,1);
                            end
                        end
                    end
                end
            end
        end
    end
    i=i+1;
end

```



## Appendix C: 81 (3<sup>4</sup>) ground water level scenarios generated by the state variable hydrological model

Year/Scenario	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
2007	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29
2008	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02
2009	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15
2010	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26
2011	61.63	61.46	61.46	61.63	61.46	61.46	61.63	61.46	61.46	61.46	61.46	61.46	61.46	61.44	61.44	61.61	61.44	61.44	61.61	61.44	61.44	61.61	61.44	61.44
2012	63.04	62.56	62.56	63.04	62.56	62.56	63.04	62.56	62.56	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53
2013	64.65	63.79	63.65	64.65	63.79	63.65	64.65	63.79	63.65	64.59	63.73	63.60	64.59	63.73	63.60	64.59	63.73	63.60	64.63	63.77	63.64	64.63	63.77	63.64
2014	66.34	65.00	64.80	66.34	65.00	64.80	66.34	65.00	64.80	66.25	64.91	64.71	66.25	64.91	64.71	66.25	64.91	64.71	66.33	64.99	64.79	66.33	64.99	64.79
2015	68.21	66.22	65.97	68.21	66.22	65.97	68.21	66.22	65.97	68.08	66.09	65.84	68.08	66.09	65.84	68.08	66.09	65.84	68.20	66.21	65.96	68.20	66.21	65.96
2016	70.18	67.48	67.09	70.18	67.48	67.09	70.18	67.48	67.09	70.01	67.31	66.92	70.00	67.31	66.92	70.01	67.31	66.92	70.18	67.49	67.10	70.18	67.48	67.10
2017	72.30	68.76	68.23	72.30	68.76	68.23	72.30	68.76	68.23	72.08	68.54	68.01	72.08	68.54	68.01	72.08	68.54	68.01	72.33	68.79	68.26	72.33	68.79	68.25
2018	74.55	70.06	69.39	74.55	70.06	69.39	74.55	70.06	69.39	74.27	69.78	69.11	74.27	69.78	69.11	74.27	69.78	69.11	74.59	70.10	69.43	74.59	70.10	69.43
2019	76.94	71.39	70.55	76.94	71.39	70.55	76.94	71.39	70.55	76.59	71.04	70.21	76.59	71.04	70.21	76.59	71.04	70.21	77.00	71.45	70.62	77.00	71.45	70.62
2020	79.45	72.73	71.71	79.45	72.73	71.71	79.45	72.73	71.71	79.04	72.32	71.29	79.04	72.32	71.29	79.04	72.32	71.29	79.54	72.83	71.80	79.54	72.83	71.80
2021	82.11	74.10	72.87	82.11	74.10	72.87	82.11	74.10	72.87	81.62	73.61	72.38	81.61	73.61	72.38	81.62	73.61	72.38	82.23	74.23	73.00	82.23	74.23	73.00
2022	84.89	75.49	74.04	84.89	75.49	74.04	84.89	75.49	74.04	84.32	74.92	73.47	84.32	74.92	73.47	84.32	74.92	73.47	85.05	75.66	74.21	85.05	75.66	74.21
2023	87.81	76.91	75.22	87.81	76.91	75.22	87.81	76.91	75.22	87.15	76.25	74.56	87.15	76.25	74.56	87.15	76.25	74.56	88.01	77.11	75.42	88.01	77.11	75.42
2024	90.86	78.35	76.39	90.86	78.34	76.39	90.86	78.35	76.39	90.10	77.59	75.64	90.10	77.59	75.63	90.10	77.59	75.64	91.11	78.59	76.64	91.11	78.59	76.64
2025	94.05	79.81	77.58	94.05	79.81	77.58	94.05	79.81	77.58	93.19	78.95	76.72	93.19	78.95	76.72	93.19	78.95	76.72	94.35	80.10	77.87	94.34	80.10	77.87
2026	97.37	81.29	78.77	97.37	81.29	78.77	97.37	81.29	78.77	96.40	80.32	77.80	96.40	80.32	77.80	96.40	80.32	77.80	97.72	81.64	79.11	97.72	81.64	79.11
2027	100.83	82.80	79.96	100.83	82.80	79.96	100.83	82.80	79.96	99.74	81.71	78.88	99.74	81.71	78.88	99.74	81.71	78.88	101.23	83.20	80.36	101.23	83.20	80.36
2028	104.41	84.33	81.16	104.41	84.33	81.16	104.42	84.33	81.16	103.21	83.12	79.95	103.21	83.12	79.95	103.21	83.12	79.95	104.87	84.79	81.62	104.87	84.79	81.62
2029	108.14	85.88	82.36	108.14	85.88	82.36	108.14	85.88	82.36	106.80	84.55	81.03	106.80	84.55	81.03	106.80	84.55	81.03	108.66	86.40	82.89	108.66	86.40	82.88
2030	111.99	87.46	83.57	111.99	87.46	83.57	111.99	87.46	83.57	110.52	85.99	82.10	110.52	85.99	82.10	110.52	85.99	82.10	112.58	88.05	84.16	112.58	88.05	84.16

Year/Scenario	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
2007	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29
2008	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02
2009	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15
2010	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26
2011	61.61	61.44	61.44	61.62	61.44	61.44	61.62	61.44	61.44	61.44	61.44	61.44	61.44	61.44	61.44	61.60	61.43	61.43	61.60	61.43	61.43	61.60	61.43	61.43
2012	63.00	62.53	62.53	63.04	62.56	62.56	63.04	62.56	62.56	63.04	62.56	62.56	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53
2013	64.63	63.77	63.64	64.64	63.78	63.65	64.64	63.78	63.65	64.64	63.78	63.65	64.58	63.72	63.59	64.58	63.72	63.59	64.58	63.72	63.59	64.62	63.76	63.63
2014	66.33	64.99	64.79	66.34	64.99	64.80	66.34	64.99	64.80	66.34	64.99	64.80	66.25	64.90	64.71	66.25	64.90	64.71	66.25	64.90	64.71	66.33	64.98	64.79
2015	68.20	66.21	65.96	68.21	66.22	65.97	68.21	66.22	65.97	68.08	66.09	65.84	68.08	66.09	65.84	68.08	66.09	65.84	68.20	66.21	65.96	68.20	66.21	65.96
2016	70.18	67.49	67.10	70.18	67.49	67.10	70.18	67.49	67.10	70.01	67.32	66.93	70.01	67.32	66.93	70.01	67.32	66.93	70.18	67.49	67.10	70.18	67.48	67.10
2017	72.33	68.79	68.26	72.32	68.78	68.24	72.32	68.78	68.24	72.09	68.55	68.02	72.09	68.55	68.02	72.09	68.55	68.02	72.09	68.55	68.02	72.34	68.80	68.27
2018	74.59	70.10	69.44	74.57	70.08	69.42	74.57	70.08	69.42	74.29	69.80	69.14	74.29	69.80	69.14	74.29	69.80	69.14	74.30	69.80	69.14	74.62	70.13	69.46
2019	77.00	71.45	70.62	76.98	71.43	70.60	76.98	71.43	70.59	76.98	71.43	70.60	76.63	71.08	70.25	76.63	71.08	70.25	76.63	71.08	70.25	77.04	71.49	70.66
2020	79.55	72.83	71.80	79.51	72.79	71.77	79.51	72.79	71.77	79.51	72.79	71.77	79.10	72.38	71.35	79.10	72.38	71.35	79.10	72.38	71.35	79.61	72.89	71.86
2021	82.23	74.23	73.00	82.19	74.19	72.96	82.19	74.19	72.96	82.19	74.19	72.96	81.70	73.70	72.47	81.70	73.70	72.47	81.70	73.70	72.47	82.32	74.31	73.09
2022	85.05	75.66	74.21	85.01	75.61	74.16	85.01	75.61	74.16	84.43	75.04	73.59	84.43	75.04	73.59	84.43	75.04	73.59	84.43	75.04	73.59	85.17	75.78	74.32
2023	88.01	77.11	75.42	87.97	77.07	75.38	87.97	77.07	75.38	87.97	77.07	75.38	87.31	76.41	74.72	87.31	76.40	74.71	87.31	76.41	74.72	88.17	77.27	75.58
2024	91.11	78.59	76.64	91.08	78.56	76.61	91.08	78.56	76.61	91.08	78.56	76.61	90.32	77.80	75.85	90.32	77.80	75.85	90.32	77.80	75.85	91.32	78.81	76.86
2025	94.35	80.10	77.87	94.34	80.09	77.86	94.33	80.09	77.86	94.34	80.09	77.86	93.47	79.23	77.00	93.47	79.23	77.00	93.47	79.23	77.00	94.63	80.39	78.16
2026	97.72	81.64	79.11	97.75	81.67	79.15	97.75	81.67	79.15	97.75	81.67	79.15	96.78	80.70	78.18	96.78	80.70	78.18	96.78	80.70	78.18	98.10	82.02	79.49
2027	101.23	83.20	80.36	101.35	83.32	80.48	101.34	83.32	80.48	101.35	83.32	80.48	100.26	82.23	79.40	100.26	82.23	79.39	100.26	82.23	79.40	101.75	83.72	80.88
2028	104.87	84.79	81.62	105.14	85.05	81.88	105.14	85.05	81.88	105.14	85.05	81.88	103.93	83.85	80.68	103.93	83.84	80.67	103.93	83.85	80.68	105.60	85.51	82.34
2029	108.66	86.41	82.89	109.24	86.98	83.46	109.23	86.98	83.46	109.24	86.													

Year/Scenario	49	50	51	W(52)	53	54	55	56	57	58	59	60	61	62	63	64	65	66	U(67)	68	B(69)	70	71	72
2007	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29
2008	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02
2009	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15
2010	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26
2011	61.60	61.43	61.43	61.60	61.43	61.43	61.62	61.44	61.44	61.62	61.44	61.44	61.62	61.44	61.44	61.60	61.43	61.43	61.60	61.43	61.43	61.60	61.43	61.43
2012	63.00	62.53	62.53	63.00	62.53	62.53	63.04	62.56	62.56	63.04	62.56	62.56	63.04	62.56	62.56	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53
2013	64.62	63.76	63.63	64.62	63.76	63.63	64.64	63.78	63.64	64.64	63.78	63.64	64.64	63.78	63.64	64.58	63.72	63.59	64.58	63.72	63.59	64.58	63.72	63.59
2014	66.33	64.98	64.79	66.33	64.98	64.79	66.33	64.98	64.79	66.33	64.98	64.79	66.33	64.98	64.79	66.24	64.89	64.70	66.24	64.89	64.70	66.24	64.89	64.70
2015	68.20	66.21	65.96	68.20	66.21	65.96	68.19	66.20	65.95	68.19	66.20	65.95	68.19	66.20	65.95	68.06	66.07	65.82	68.06	66.07	65.82	68.06	66.07	65.82
2016	70.19	67.49	67.10	70.19	67.49	67.10	70.16	67.46	67.07	70.16	67.46	67.07	70.16	67.46	67.07	70.16	67.46	67.07	70.16	67.46	67.07	70.16	67.46	67.07
2017	72.34	68.80	68.27	72.34	68.80	68.27	72.27	68.73	68.20	72.27	68.73	68.20	72.27	68.73	68.20	72.05	68.51	67.98	72.05	68.51	67.98	72.05	68.51	67.98
2018	74.62	70.13	69.46	74.62	70.13	69.46	74.51	70.02	69.36	74.51	70.02	69.36	74.51	70.02	69.36	74.23	69.74	69.08	74.23	69.74	69.08	74.23	69.74	69.08
2019	77.04	71.49	70.66	77.04	71.49	70.66	76.90	71.35	70.51	76.90	71.35	70.51	76.90	71.35	70.52	76.55	71.00	70.17	76.55	71.00	70.17	76.55	71.00	70.17
2020	79.61	72.89	71.86	79.61	72.89	71.86	79.41	72.69	71.66	79.40	72.69	71.66	79.41	72.69	71.66	78.99	72.27	71.25	78.99	72.27	71.25	78.99	72.27	71.25
2021	82.32	74.31	73.08	82.32	74.32	73.09	82.05	74.05	72.82	82.05	74.04	72.82	82.05	74.05	72.82	81.56	73.56	72.33	81.56	73.55	72.32	81.56	73.56	72.33
2022	85.17	75.78	74.32	85.17	75.78	74.33	84.83	75.43	73.98	84.83	75.43	73.98	84.83	75.43	73.98	84.25	74.86	73.41	84.25	74.86	73.41	84.25	74.86	73.41
2023	88.17	77.27	75.58	88.17	77.27	75.58	87.74	76.84	75.15	87.74	76.84	75.15	87.74	76.84	75.15	87.08	76.17	74.48	87.08	76.17	74.48	87.08	76.17	74.49
2024	91.32	78.81	76.86	91.33	78.81	76.86	90.78	78.26	76.31	90.78	78.26	76.31	90.78	78.27	76.31	90.02	77.51	75.55	90.02	77.50	75.55	90.02	77.51	75.56
2025	94.63	80.39	78.16	94.63	80.39	78.16	93.96	79.72	77.49	93.96	79.71	77.48	93.96	79.72	77.49	93.10	78.85	76.62	93.10	78.85	76.62	93.10	78.85	76.63
2026	98.10	82.02	79.49	98.10	82.02	79.50	97.27	81.19	78.66	97.27	81.19	78.66	97.27	81.19	78.66	96.30	80.22	77.69	96.30	80.22	77.69	96.30	80.22	77.69
2027	101.74	83.72	80.88	101.75	83.72	80.88	100.71	82.68	79.84	100.71	82.68	79.84	100.71	82.68	79.85	99.62	81.60	78.76	99.62	81.59	78.76	99.62	81.60	78.76
2028	105.60	85.51	82.34	105.60	85.51	82.34	104.28	84.20	81.03	104.28	84.20	81.03	104.28	84.20	81.03	103.08	82.99	79.82	103.07	82.99	79.82	103.08	82.99	79.82
2029	109.76	87.50	83.98	109.76	87.50	83.99	107.99	85.74	82.22	107.99	85.73	82.22	107.99	85.74	82.22	106.65	84.40	80.88	106.65	84.40	80.88	106.66	84.40	80.88
2030	114.85	90.31	86.43	114.85	90.32	86.43	111.83	87.30	83.41	111.83	87.29	83.41	111.83	87.30	83.41	110.36	85.83	81.94	110.36	85.82	81.94	110.36	85.83	81.94

W(52): Worst case scenario; U(67): Business as usual scenario; B(69): Best case scenario

Year/Scenario	73	74	75	76	77	78	79	80	81
2007	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29	57.29
2008	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02	58.02
2009	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15	59.15
2010	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26	60.26
2011	61.60	61.43	61.43	61.60	61.43	61.43	61.60	61.43	61.43
2012	63.00	62.53	62.53	63.00	62.53	62.53	63.00	62.53	62.53
2013	64.62	63.76	63.63	64.62	63.76	63.63	64.62	63.76	63.63
2014	66.32	64.97	64.78	66.32	64.97	64.78	66.32	64.97	64.78
2015	68.18	66.19	65.94	68.18	66.19	65.94	68.18	66.19	65.94
2016	70.16	67.47	67.08	70.16	67.47	67.08	70.16	67.47	67.08
2017	72.30	68.76	68.23	72.30	68.76	68.23	72.30	68.76	68.23
2018	74.56	70.07	69.40	74.56	70.07	69.40	74.56	70.07	69.40
2019	76.96	71.41	70.58	76.96	71.41	70.58	76.96	71.41	70.58
2020	79.50	72.78	71.76	79.50	72.78	71.76	79.50	72.78	71.76
2021	82.18	74.17	72.94	82.18	74.17	72.94	82.18	74.17	72.94
2022	84.99	75.60	74.14	84.99	75.59	74.14	84.99	75.60	74.14
2023	87.94	77.04	75.35	87.94	77.04	75.35	87.94	77.04	75.35
2024	91.03	78.51	76.56	91.03	78.51	76.56	91.03	78.51	76.56
2025	94.25	80.01	77.78	94.25	80.01	77.78	94.25	80.01	77.78
2026	97.61	81.53	79.01	97.61	81.53	79.01	97.61	81.53	79.01
2027	101.11	83.08	80.24	101.11	83.08	80.24	101.11	83.08	80.25
2028	104.74	84.66	81.49	104.74	84.66	81.49	104.74	84.66	81.49
2029	108.51	86.26	82.74	108.51	86.26	82.74	108.51	86.26	82.74
2030	112.42	87.88	84.00	112.42	87.88	84.00	112.42	87.89	84.00

## Appendix D: Python codes and flowcharts for the generation of hydrological scenarios in ArcGIS

### D.1. Flowchart and Python code for deriving future ground water level in GIS

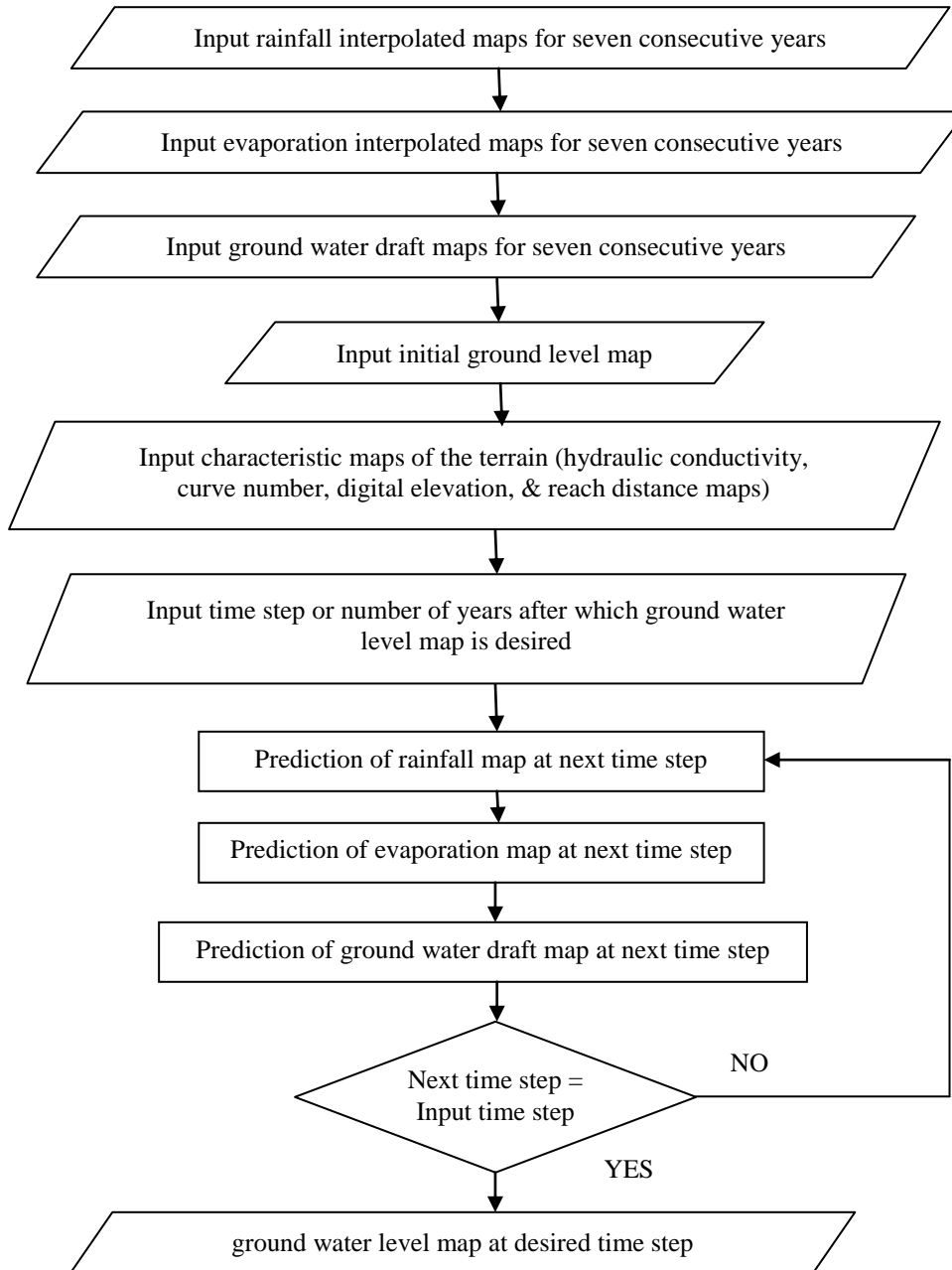


Figure D.1. Flowchart for deriving future ground water level in GIS

```

import arcpy
import numpy
import math

class Toolbox(object):
    def __init__(self):
        """Define the toolbox (the name of the toolbox is the name of the
        .pyt file)."""
        self.label = "Future Water Level"
        self.alias = "Forecast"

        # List of tool classes associated with this toolbox
        self.tools = [FuturewaterLevel]

class FuturewaterLevel(object):
    def __init__(self):
        """Define the tool (tool name is the name of the class)."""
        self.label = "Future Water Level"
        self.description = ""
        self.canRunInBackground = True

    def getParameterInfo(self):
        #First rainfall parameter
        in_rasterr1 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 1",
            name = "in_rasterr1",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Second rainfall parameter
        in_rasterr2 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 2",
            name = "in_rasterr2",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Third rainfall parameter
        in_rasterr3 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 3",
            name = "in_rasterr3",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Fourth rainfall parameter
        in_rasterr4 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 4",
            name = "in_rasterr4",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Fifth rainfall parameter
        in_rasterr5 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 5",
            name = "in_rasterr5",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Sixth rainfall parameter
        in_rasterr6 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 6",
            name = "in_rasterr6",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Seventh rainfall parameter
        in_rasterr7 = arcpy.Parameter(
            displayName = "Input Rainfall Raster 7",
            name = "in_rasterr7",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #First evaporation parameter
        in_rastere1 = arcpy.Parameter(

```



```

        displayName = "Input Evaporation Raster 1",
        name = "in_rastere1",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Second evaporation parameter
in_rastere2 = arcpy.Parameter(
    displayName = "Input Evaporation Raster 2",
    name = "in_rastere2",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Third evaporation parameter
in_rastere3 = arcpy.Parameter(
    displayName = "Input Evaporation Raster 3",
    name = "in_rastere3",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Fourth evaporation parameter
in_rastere4 = arcpy.Parameter(
    displayName = "Input Evaporation Raster 4",
    name = "in_rastere4",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Fifth evaporation parameter
in_rastere5 = arcpy.Parameter(
    displayName = "Input Evaporation Raster 5",
    name = "in_rastere5",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Sixth evaporation parameter
in_rastere6 = arcpy.Parameter(
    displayName = "Input Evaporation Raster 6",
    name = "in_rastere6",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Seventh evaporation parameter
in_rastere7 = arcpy.Parameter(
    displayName = "Input Evaporation Raster 7",
    name = "in_rastere7",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#First ground water draft parameter
in_rasterd1 = arcpy.Parameter(
    displayName = "Input draft Raster 1",
    name = "in_rasterd1",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Second ground water draft parameter
in_rasterd2 = arcpy.Parameter(
    displayName = "Input draft Raster 2",
    name = "in_rasterd2",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Third ground water draft parameter
in_rasterd3 = arcpy.Parameter(
    displayName = "Input draft Raster 3",
    name = "in_rasterd3",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Fourth ground water draft parameter
in_rasterd4 = arcpy.Parameter(
    displayName = "Input draft Raster 4",

```

```

        name = "in_rasterd4",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Fifth ground water draft parameter
in_rasterd5 = arcpy.Parameter(
    displayName = "Input draft Raster 5",
    name = "in_rasterd5",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Sixth ground water draft parameter
in_rasterd6 = arcpy.Parameter(
    displayName = "Input draft Raster 6",
    name = "in_rasterd6",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Seventh ground water draft parameter
in_rasterd7 = arcpy.Parameter(
    displayName = "Input draft Raster 7",
    name = "in_rasterd7",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Aquifer hydraulic conductivity parameter
in_rasteraq = arcpy.Parameter(
    displayName = "Input aquifer raster",
    name = "in_rasteraq",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Curve Number parameter
in_rastercn = arcpy.Parameter(
    displayName = "Input Curve Number Raster",
    name = "in_rastercn",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Reach distance parameter
in_rasterdist = arcpy.Parameter(
    displayName = "Input Reach distance Raster",
    name = "in_rasterdist",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Ground water level parameter
in_rastergw1 = arcpy.Parameter(
    displayName = "Input Ground water level Raster",
    name = "in_rastergw1",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Digital Elevation parameter
in_rasterdem = arcpy.Parameter(
    displayName = "Input Source DEM Raster",
    name = "in_rasterdem",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Input")

#Time step to forecast parameter
in_timestep = arcpy.Parameter(
    displayName = "Input Time Step",
    name = "in_timestep",
    datatype = "long",
    parameterType = "Required",
    direction = "Input")

#Output ground water level at the desired time step
out_raster = arcpy.Parameter(
    displayName = "Output Raster",
    name = "out_raster",

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```

        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Output")

#Define a list of parameters to be referred further
params = [in_rasterr1, in_rasterr2, in_rasterr3, in_rasterr4, in_rasterr5,
in_rasterr6, in_rasterr7, in_rastere1, in_rastere2, in_rastere3, in_rastere4,
in_rastere5, in_rastere6, in_rastere7, in_rasterd1, in_rasterd2, in_rasterd3,
in_rasterd4, in_rasterd5, in_rasterd6, in_rasterd7, in_rasteraq, in_rastercn,
in_rasterdist, in_rastergw1, in_rasterdem, in_timestep, out_raster]
return params

def isLicensed(self):
    """Set whether tool is licensed to execute."""
    return True

def updateParameters(self, parameters):
    """Modify the values and properties of parameters before internal
    validation is performed. This method is called whenever a parameter
    has been changed."""
    return

def updateMessages(self, parameters):
    """Modify the messages created by internal validation for each tool
    parameter. This method is called after internal validation."""
    return

def execute(self, parameters, messages):

#Input the rainfall interpolated maps for seven consecutive historical years
    in_rasterr1=parameters[0].ValueAsText
    in_rasterr2=parameters[1].ValueAsText
    in_rasterr3=parameters[2].ValueAsText
    in_rasterr4=parameters[3].ValueAsText
    in_rasterr5=parameters[4].ValueAsText
    in_rasterr6=parameters[5].ValueAsText
    in_rasterr7=parameters[6].ValueAsText

#Input the evaporation interpolated maps for seven consecutive historical years
    in_rastere1=parameters[7].ValueAsText
    in_rastere2=parameters[8].ValueAsText
    in_rastere3=parameters[9].ValueAsText
    in_rastere4=parameters[10].ValueAsText
    in_rastere5=parameters[11].ValueAsText
    in_rastere6=parameters[12].ValueAsText
    in_rastere7=parameters[13].ValueAsText

#Input the ground water draft interpolated maps for seven consecutive historical years
    in_rasterd1=parameters[14].ValueAsText
    in_rasterd2=parameters[15].ValueAsText
    in_rasterd3=parameters[16].ValueAsText
    in_rasterd4=parameters[17].ValueAsText
    in_rasterd5=parameters[18].ValueAsText
    in_rasterd6=parameters[19].ValueAsText
    in_rasterd7=parameters[20].ValueAsText

#Input the maps for aquifer conductivity, curve number, reach distance, initial ground water
level, and digital elevation for the region under study
    in_rasteraq=parameters[21].ValueAsText
    in_rastercn=parameters[22].ValueAsText
    in_rasterdist=parameters[23].ValueAsText
    in_rastergw1=parameters[24].ValueAsText
    in_rasterdem=parameters[25].ValueAsText

#Input the time step after initial time step to forecast the ground water level map
    in_timestep=int(parameters[26].ValueAsText)
    T = in_timestep

#Output raster of ground water level at the time step desired
    out_raster = parameters[27].ValueAsText

#Assigning raster maps of rainfall to the variables to be converted into two dimensional arrays
    inRasr1 = arcpy.Raster(in_rasterr1)
    inRasr2 = arcpy.Raster(in_rasterr2)
    inRasr3 = arcpy.Raster(in_rasterr3)
    inRasr4 = arcpy.Raster(in_rasterr4)
    inRasr5 = arcpy.Raster(in_rasterr5)
    inRasr6 = arcpy.Raster(in_rasterr6)
    inRasr7 = arcpy.Raster(in_rasterr7)

```

```

#Assigning raster maps of evaporation to the variables to be converted into two dimensional
arrays
inRase1 = arcpy.Raster(in_rastere1)
inRase2 = arcpy.Raster(in_rastere2)
inRase3 = arcpy.Raster(in_rastere3)
inRase4 = arcpy.Raster(in_rastere4)
inRase5 = arcpy.Raster(in_rastere5)
inRase6 = arcpy.Raster(in_rastere6)
inRase7 = arcpy.Raster(in_rastere7)

#Assigning raster maps of ground water draft to the variables to be converted into two
dimensional arrays
inRasd1 = arcpy.Raster(in_rasterd1)
inRasd2 = arcpy.Raster(in_rasterd2)
inRasd3 = arcpy.Raster(in_rasterd3)
inRasd4 = arcpy.Raster(in_rasterd4)
inRasd5 = arcpy.Raster(in_rasterd5)
inRasd6 = arcpy.Raster(in_rasterd6)
inRasd7 = arcpy.Raster(in_rasterd7)

#Assigning raster maps of aquifer conductivity, curve number, reach distance, initial ground water
level, and digital elevation to the variables to be converted into their respective two
dimensional arrays
inRasaq = arcpy.Raster(in_rasteraq)
inRascn = arcpy.Raster(in_rastercn)
inRasdist = arcpy.Raster(in_rasterdist)
inRasgw1 = arcpy.Raster(in_rastergw1)
inRasdem = arcpy.Raster(in_rasterdem)

#Defining the spatial reference of the execution system to generate output within the defined
extent
dsc = arcpy.Describe(inRase1)
sr = dsc.SpatialReference
ext = dsc.Extent
ll = arcpy.Point(ext.XMin,ext.YMin)
cellSize = inRase1.meanCellWidth

#Conversion of input rainfall maps into two dimensional arrays
arr1 = arcpy.RasterToNumPyArray(inRasr1,nodata_to_value=0)
arr2 = arcpy.RasterToNumPyArray(inRasr2,nodata_to_value=0)
arr3 = arcpy.RasterToNumPyArray(inRasr3,nodata_to_value=0)
arr4 = arcpy.RasterToNumPyArray(inRasr4,nodata_to_value=0)
arr5 = arcpy.RasterToNumPyArray(inRasr5,nodata_to_value=0)
arr6 = arcpy.RasterToNumPyArray(inRasr6,nodata_to_value=0)
arr7 = arcpy.RasterToNumPyArray(inRasr7,nodata_to_value=0)

#Conversion of input evaporation maps into two dimensional arrays
arre1 = arcpy.RasterToNumPyArray(inRase1,nodata_to_value=0)
arre2 = arcpy.RasterToNumPyArray(inRase2,nodata_to_value=0)
arre3 = arcpy.RasterToNumPyArray(inRase3,nodata_to_value=0)
arre4 = arcpy.RasterToNumPyArray(inRase4,nodata_to_value=0)
arre5 = arcpy.RasterToNumPyArray(inRase5,nodata_to_value=0)
arre6 = arcpy.RasterToNumPyArray(inRase6,nodata_to_value=0)
arre7 = arcpy.RasterToNumPyArray(inRase7,nodata_to_value=0)

#Conversion of input ground water draft maps into two dimensional arrays
arrd1 = arcpy.RasterToNumPyArray(inRasd1,nodata_to_value=0)
arrd2 = arcpy.RasterToNumPyArray(inRasd2,nodata_to_value=0)
arrd3 = arcpy.RasterToNumPyArray(inRasd3,nodata_to_value=0)
arrd4 = arcpy.RasterToNumPyArray(inRasd4,nodata_to_value=0)
arrd5 = arcpy.RasterToNumPyArray(inRasd5,nodata_to_value=0)
arrd6 = arcpy.RasterToNumPyArray(inRasd6,nodata_to_value=0)
arrd7 = arcpy.RasterToNumPyArray(inRasd7,nodata_to_value=0)

#Conversion of input raster maps of aquifer conductivity, curve number, reach distance, initial
ground water level, and digital elevation into their respective two dimensional arrays
arraq = arcpy.RasterToNumPyArray(inRasaq,nodata_to_value=0)
arrcn = arcpy.RasterToNumPyArray(inRascn,nodata_to_value=0)
arrdist = arcpy.RasterToNumPyArray(inRasdist,nodata_to_value=0)
arrgw1 = arcpy.RasterToNumPyArray(inRasgw1,nodata_to_value=0)
arrdem = arcpy.RasterToNumPyArray(inRasdem,nodata_to_value=0)

#Matrix defining constants for seven initial conditions
a = numpy.matrix([[0.0,1.0,1.0,1.0,0.0,1.0,0.0],[1.0,1.0,-0.7436,-0.0593,0.7712,-
0.2877,0.3891],[2.0,1.0,0.5529,-0.5913,-0.0914,-0.0686,-0.2239],[3.0,1.0,-
0.4112,0.1056,-0.4506,0.1068,0.0377],[4.0,1.0,0.3057,0.3412,0.1081,-
0.0454,0.0307],[5.0,1.0,-0.2274,-0.1036,0.2568,0.0011,-0.0265],[6.0,1.0,0.1691,-
0.1919,-0.0951,0.01,0.0081]])

#Calculate inverse of Matrix a
ainv = numpy.linalg.inv(a)

```

```

#Matrices to store seven initial conditions of rainfall, evaporation and groundwater draft one
pixel at a time
xr = numpy.zeros((7,1))
xe = numpy.zeros((7,1))
xd = numpy.zeros((7,1))

#Count the number of bands, rows, and columns to be executed
l = arcpy.GetRasterProperties_management(in_rasterd1,"BANDCOUNT")
m = arcpy.GetRasterProperties_management(in_rasterd1,"ROWCOUNT")
n = arcpy.GetRasterProperties_management(in_rasterd1,"COLUMNCOUNT")

b = int(l.getOutput(0))
r = int(m.getOutput(0))
c = int(n.getOutput(0))

#Execute the loop number of times equal to the desired time step
for t in range (1,T+1):

#Define empty matrices to store the forecasted values of rainfall, evaporation, ground water
draft at a time step t
arrtr = numpy.zeros((r,c))
arrte = numpy.zeros((r,c))
arrtd = numpy.zeros((r,c))

#Define empty matrices to store the forecasted rainfall dependent surface runoff and forecasted
ground water level dependent ground water flow at a time step t
surro = numpy.zeros((r,c))
gwflow = numpy.zeros((r,c))

#Forecast the rainfall at every pixel for the time step t
for j in range (0,r-1):
    for k in range (0,c-1):
        xr[0][0]=arrr1[j][k]
        xr[1][0]=arrr2[j][k]
        xr[2][0]=arrr3[j][k]
        xr[3][0]=arrr4[j][k]
        xr[4][0]=arrr5[j][k]
        xr[5][0]=arrr6[j][k]
        xr[6][0]=arrr7[j][k]
        yr = ainv*xr
        arrtr[j][k]=(yr[0][0]*t+yr[1][0])*1**t+yr[2][0]*(-
0.7436)**t+(0.7735)**t*(yr[3][0]*math.cos(1.6475*t)+yr[4][0]*math.sin(1.6475*t))+
(0.4839)**t*(yr[5][0]*math.cos(2.2075*t)+yr[6][0]*math.sin(2.2075*t))

#Forecast the evaporation at every pixel for the time step t
xe[0][0]=arre1[j][k]
xe[1][0]=arre2[j][k]
xe[2][0]=arre3[j][k]
xe[3][0]=arre4[j][k]
xe[4][0]=arre5[j][k]
xe[5][0]=arre6[j][k]
xe[6][0]=arre7[j][k]
ye = ainv*xe
arrte[j][k]=(ye[0][0]*t+ye[1][0])*1**t+ye[2][0]*(-
0.7436)**t+(0.7735)**t*(ye[3][0]*math.cos(1.6475*t)+ye[4][0]*math.sin(1.6475*t))+
(0.4839)**t*(ye[5][0]*math.cos(2.2075*t)+ye[6][0]*math.sin(2.2075*t))

#Forecast the ground water draft at every pixel for the time step t
xd[0][0]=arrd1[j][k]
xd[1][0]=arrd2[j][k]
xd[2][0]=arrd3[j][k]
xd[3][0]=arrd4[j][k]
xd[4][0]=arrd5[j][k]
xd[5][0]=arrd6[j][k]
xd[6][0]=arrd7[j][k]
yd = ainv*xd
arrtd[j][k]=(yd[0][0]*t+yd[1][0])*1**t+yd[2][0]*(-
0.7436)**t+(0.7735)**t*(yd[3][0]*math.cos(1.6475*t)+yd[4][0]*math.sin(1.6475*t))+
(0.4839)**t*(yd[5][0]*math.cos(2.2075*t)+yd[6][0]*math.sin(2.2075*t))

#Calculate surface runoff and ground water flow at every pixel for the time step t
s = 25.4*((1000.0/arrcn[j][k])-10)
surro[j][k]= ((arrtr[j][k]-0.2*s)**2)/(arrtr[j][k]+0.8*s)
if arrdist[j][k]==0:
    gwflow[j][k] = 0
else:
    gwflow[j][k] =
((arraq[j][k]*8000)/(arrdist[j][k]**2))*(arrdem[j][k]-arrgw1[j][k])

#Calculate the ground water level at every pixel for the time step t

```

```

        surro[j][k]-gwflow[j][k])/(1000)*848)-arrtd[j][k])/848)
arrgw1[j][k] = arrgw1[j][k]-((((arrtr[j][k]-arrte[j][k]-
#Close the loop
#Convert ground water level array to raster and get the ground water level map at time step t
outras = arcpy.NumPyArrayToRaster(arrgw1,11,cellSize,value_to_nodata=0)
arcpy.DefineProjection_management(outras,sr)
outras.save(out_raster)

return

```

## D.2. Flowchart and Python code for deriving water level decline per year in GIS

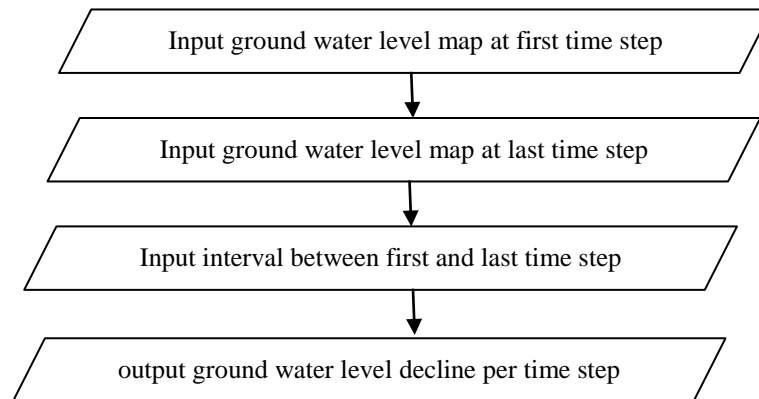


Figure D.2. Flowchart for deriving ground water level decline per year in GIS

```

import arcpy
import numpy
import math

class Toolbox(object):
    def __init__(self):
        """Define the toolbox (the name of the toolbox is the name of the
        .pyt file)."""
        self.label = "Water Level Gradient"
        self.alias = "Grad"

        # List of tool classes associated with this toolbox
        self.tools = [WLGradient]

class WLGradient(object):
    def __init__(self):
        """Define the tool (tool name is the name of the class)."""
        self.label = "water level Gradient"
        self.description = ""
        self.canRunInBackground = True

    def getParameterInfo(self):
        #First gw1 parameter
        in_rasterg1 = arcpy.Parameter(
            displayName = "Input First Ground water level Raster",
            name = "in_rasterg1",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Second gw1 parameter
        in_rasterg2 = arcpy.Parameter(
            displayName = "Input Second Ground water level Raster",
            name = "in_rasterg2",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

        #Time interval parameter

```

```

in_timeint = arcpy.Parameter(
    displayName = "Input Time Interval",
    name = "in_timeint",
    datatype = "long",
    parameterType = "Required",
    direction = "Input")

#Output ground water decline per time step
out_raster = arcpy.Parameter(
    displayName = "Output Raster",
    name = "out_raster",
    datatype = "Raster Layer",
    parameterType = "Required",
    direction = "Output")

#Define a list of parameters to be referred further
params = [in_rasterg1, in_rasterg2, in_timeint, out_raster]
return params

def isLicensed(self):
    """Set whether tool is licensed to execute."""
    return True

def updateParameters(self, parameters):
    """Modify the values and properties of parameters before internal
    validation is performed. This method is called whenever a parameter
    has been changed."""
    return

def updateMessages(self, parameters):
    """Modify the messages created by internal validation for each tool
    parameter. This method is called after internal validation."""
    return

def execute(self, parameters, messages):

#Input the initial and final observed ground water level interpolated maps
    in_rasterg1=parameters[0].ValueAsText
    in_rasterg2=parameters[1].ValueAsText

#Input the time interval between initial and final observed ground water level interpolated maps
    in_timeint=int(parameters[2].ValueAsText)
    T=in_timeint
    out_raster = parameters[3].ValueAsText

#Assigning raster maps of initial and final observed ground water level to the variables to be
converted into two dimensional arrays
    inRasg1 = arcpy.Raster(in_rasterg1)
    inRasg2 = arcpy.Raster(in_rasterg2)

#Defining the spatial reference of the execution system to generate output within the defined
extent
    dsc = arcpy.Describe(inRasg1)
    sr = dsc.SpatialReference
    ext = dsc.Extent
    ll = arcpy.Point(ext.XMin,ext.YMin)
    cellSize = inRasg1.meanCellWidth

#Conversion of input ground water level maps into two dimensional arrays
    arrg1 = arcpy.RasterToNumPyArray(inRasg1,nodata_to_value=0)
    arrg2 = arcpy.RasterToNumPyArray(inRasg2,nodata_to_value=0)

#Count the number of bands, rows, and columns to be executed
    l = arcpy.GetRasterProperties_management(in_rasterg1,"BANDCOUNT")
    m = arcpy.GetRasterProperties_management(in_rasterg1,"ROWCOUNT")
    n = arcpy.GetRasterProperties_management(in_rasterg1,"COLUMNCOUNT")

    b = int(l.getOutput(0))
    r = int(m.getOutput(0))
    c = int(n.getOutput(0))

#Define empty matrices to store the calculated value of ground water fall per unit time
    gw1grad =numpy.zeros((r,c))

#Calculate ground water level decline per unit time at every pixel
    for j in range (0,r-1):
        for k in range (0,c-1):
            gw1grad[j][k] = (arrg2[j][k]-arrg1[j][k])/T

#Convert ground water level gradient array to raster and get the ground water gradient map
    outras = arcpy.NumPyArrayToRaster(gw1grad,ll,cellSize,value_to_nodata=0)

```

```

arcpy.DefineProjection_management(out_raster, sr)
out_raster.save(out_raster)

return

```

### D.3. Flowchart and Python code for deriving annual ground water draft in GIS

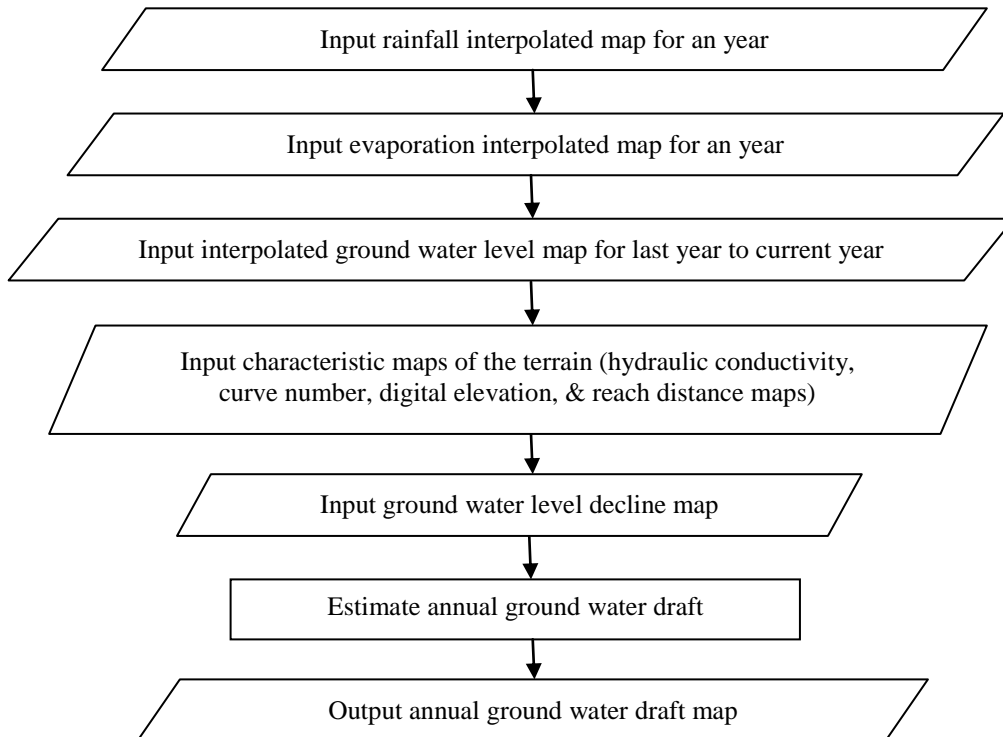


Figure D.3. Flowchart for deriving annual ground water draft in GIS

```

import arcpy
import numpy
import math

class Toolbox(object):
    def __init__(self):
        """Define the toolbox (the name of the toolbox is the name of the
        .pyt file)."""
        self.label = "Annual Draft"
        self.alias = "Draft"

        # List of tool classes associated with this toolbox
        self.tools = [AnnualDraft]

class AnnualDraft(object):
    def __init__(self):
        """Define the tool (tool name is the name of the class)."""
        self.label = "Annual Draft"
        self.description = ""
        self.canRunInBackground = True

    def getParameterInfo(self):
        #rainfall parameter
        in_rasterr = arcpy.Parameter(
            displayName = "Input Rainfall Raster",
            name = "in_rasterr",
            datatype = "Raster Layer",
            parameterType = "Required",
            direction = "Input")

```



```

#evaporation parameter
    in_rastere = arcpy.Parameter(
        displayName = "Input Evaporation Raster",
        name = "in_rastere",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Aquifer Transmissivity parameter
    in_rasteraq = arcpy.Parameter(
        displayName = "Input aquifer raster",
        name = "in_rasteraq",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Curve Number parameter
    in_rastercn = arcpy.Parameter(
        displayName = "Input Curve Number Raster",
        name = "in_rastercn",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Groundflow distance parameter
    in_rasterdist = arcpy.Parameter(
        displayName = "Input Reach distance Raster",
        name = "in_rasterdist",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Initial Groundwater level parameter
    in_rastergw1l = arcpy.Parameter(
        displayName = "Input initial Ground water level Raster",
        name = "in_rastergw1l",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Groundwater level decline parameter
    in_rastergw1ldecpy = arcpy.Parameter(
        displayName = "Input Ground water level decline Raster",
        name = "in_rastergw1ldecpy",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Source DEM parameter
    in_rasterdem = arcpy.Parameter(
        displayName = "Input Source DEM Raster",
        name = "in_rasterdem",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Input")

#Output annual ground water draft
    out_raster = arcpy.Parameter(
        displayName = "Output Raster",
        name = "out_raster",
        datatype = "Raster Layer",
        parameterType = "Required",
        direction = "Output")

#Define a list of parameters to be referred further
    params = [in_rasterr, in_rastere, in_rasteraq, in_rastercn, in_rasterdist,
              in_rastergw1l, in_rastergw1ldecpy, in_rasterdem, out_raster]
    return params

def isLicensed(self):
    """Set whether tool is licensed to execute."""
    return True

def updateParameters(self, parameters):
    """Modify the values and properties of parameters before internal
    validation is performed. This method is called whenever a parameter
    has been changed."""
    return

def updateMessages(self, parameters):

```

```

        """Modify the messages created by internal validation for each tool
        parameter. This method is called after internal validation."""
        return

    def execute(self, parameters, messages):

#Input the rainfall, evaporation, aquifer transmissivity, curve number, reach distance, ground
water level at last time step, ground water gradient, and digital elevation maps
        in_rasterr=parameters[0].ValueAsText
        in_rastere=parameters[1].ValueAsText
        in_rasteraq=parameters[2].ValueAsText
        in_rastercn=parameters[3].ValueAsText
        in_rasterdist=parameters[4].ValueAsText
        in_rastergw1=parameters[5].ValueAsText
        in_rastergw1decpy=parameters[6].ValueAsText
        in_rasterdem=parameters[7].ValueAsText

#Output raster of ground water draft at the current time step
        out_raster = parameters[8].ValueAsText

#Assigning raster maps of rainfall, evaporation, aquifer transmissivity, curve number, reach
distance, ground water level at last time step, ground water gradient, and digital elevation maps
to their respective variables to be converted into two dimensional arrays
        inRasr = arcpy.Raster(in_rasterr)
        inRase = arcpy.Raster(in_rastere)
        inRasaq = arcpy.Raster(in_rasteraq)
        inRascn = arcpy.Raster(in_rastercn)
        inRasdist = arcpy.Raster(in_rasterdist)
        inRasgw1 = arcpy.Raster(in_rastergw1)
        inRasgw1decpy = arcpy.Raster(in_rastergw1decpy)
        inRasdem = arcpy.Raster(in_rasterdem)

#Defining the spatial reference of the execution system to generate output within the defined
extent
        dsc = arcpy.Describe(inRase)
        sr = dsc.SpatialReference
        ext = dsc.Extent
        ll = arcpy.Point(ext.XMin,ext.YMin)
        cellSize = inRase.meanCellWidth

#Conversion of input raster maps of rainfall, evaporation, aquifer transmissivity, curve number,
reach distance, ground water level at last time step, ground water gradient, and digital
elevation maps to their respective two dimensional arrays
        arrr = arcpy.RasterToNumPyArray(inRasr,nodata_to_value=0)
        arre = arcpy.RasterToNumPyArray(inRase,nodata_to_value=0)
        arraq = arcpy.RasterToNumPyArray(inRasaq,nodata_to_value=0)
        arrcn = arcpy.RasterToNumPyArray(inRascn,nodata_to_value=0)
        arrdist = arcpy.RasterToNumPyArray(inRasdist,nodata_to_value=0)
        arrgw1 = arcpy.RasterToNumPyArray(inRasgw1,nodata_to_value=0)
        arrgw1decpy = arcpy.RasterToNumPyArray(inRasgw1decpy,nodata_to_value=0)
        arrdem = arcpy.RasterToNumPyArray(inRasdem,nodata_to_value=0)

#Count the number of bands, rows, and columns to be executed
        l = arcpy.GetRasterProperties_management(in_rasterr,"BANDCOUNT")
        m = arcpy.GetRasterProperties_management(in_rasterr,"ROWCOUNT")
        n = arcpy.GetRasterProperties_management(in_rasterr,"COLUMNCOUNT")

        b = int(l.getOutput(0))
        r = int(m.getOutput(0))
        c = int(n.getOutput(0))

#Define empty matrices to store the rainfall dependent surface runoff, ground water level
dependent ground water flow, and final ground water draft at current time step
        surro = numpy.zeros((r,c))
        gwflow = numpy.zeros((r,c))
        draft =numpy.zeros((r,c))

#Calculate ground water draft for the current time step at every pixel
        for j in range (0,r-1):
            for k in range (0,c-1):
                s = 25.4*((1000.0/arrcn[j][k])-10)
                surro[j][k]= ((arrr[j][k]-0.2*s)**2)/(arrr[j][k]+0.8*s)
                if arrdist[j][k]==0:
                    gwflow[j][k] = 0
                else:
                    gwflow[j][k] =
                    ((arraq[j][k]*8000)/(arrdist[j][k]**2))*(arrdem[j][k]-arrgw1[j][k])
                    draft[j][k] = arrgw1decpy[j][k]*848+((arrr[j][k]-arre[j][k]-
                    surro[j][k]-gwflow[j][k])/1000)*848
#Convert ground water level draft array to raster and get the ground water draft map
        outras = arcpy.NumPyArrayToRaster(draft,ll,cellSize,value_to_nodata=0)

```

```
arcpy.DefineProjection_management(outras,sr)
outras.save(out_raster)
return
```

## LIST OF PUBLICATIONS

- 1 Kumar, G. and Gupta, R., 2017. Time Series Prediction for Water Resource Management in Semi Arid Zone. International Journal of Control Theory and Applications (SCOPUS Indexed, Listed in UGC), 10(6), pp. 39-45
- 2 Gupta, R. and Kumar, G., 2018. Scenario Planning for Water Resource Management in Semi Arid Zone. Physics and Chemistry of the Earth (SCIE indexed, IF: 1.923), 105, pp. 290-299.
- 3 Kumar, G. and Gupta, R., 2018. Sustainable Development: Evaluating Optimal Technique for Spatial Data Forecast. Multidisciplinary Digital Publishing Institute Proceedings, 2(22), 1371, pp. 1-4.

## CONFERENCES

- 1 A Comparative Study on Time Series Extrapolation of Spatial Data, Gaurav Kumar & Rajiv Gupta, National Remote Sensing Centre (NRSC) - User Interaction Meet, 2017, Hyderabad International Convention Centre, Hyderabad, Telangana, India, January 24-25, 2017, Organised by: National Remote Sensing Centre, Hyderabad in association with Geospatial World Forum, 2017
- 2 Time Series Prediction for Water Resource Management in Semi Arid Zone, Gaurav Kumar & Rajiv Gupta, 2nd International Conference on Sustainable Computing Techniques in Engineering, Science and Management, Jain Engineering College, Belgaum, Karnataka, India, January 27-28, 2017, Organised by: Jain College of Engineering, Belagavi (Near Goa), India in association with SN Education Society, India and Universal Research Group on Computers and Electronics Engineering (URGCEE), Atlanta, USA.
- 3 Sustainable Development: Evaluating optimal technique for spatial data forecast, Gaurav Kumar & Rajiv Gupta, Economy, Sustainable Development, and Energy Conference, Queen Margaret University, Edinburgh, Scotland, U.K. June 25-27, 2018.

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## BRIEF BIOGRAPHY OF SUPERVISOR

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