

SYNOPSIS OF RESEARCH WORK

**FORECASTING OF WATER TABLE FLUCTUATIONS FOR
PRIYADARSHINI WATERSHED USING ARTIFICIAL NEURAL NETWORK**

SUBMITTED BY

Mr. PRAKASH BASAVANNI HITTANAGI

B.Tech (Agricultural Engineering)



SUBMITTED TO

DEPARTMENT OF SOIL AND WATER CONSERVATION ENGINEERING,

COLLEGE OF AGRICULTURAL ENGINEERING AND TECHNOLOGY,

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(INDIA)

**FORECASTING OF WATER TABLE FLUCTUATIONS FOR
PRIYADARSHINI WATERSHED USING ARTIFICIAL NEURAL
NETWORK**

A Thesis submitted to

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VIDYAPEETH DAPOLI - 415 712
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**In the partial fulfillment of the requirements for
the degree**

of

**MASTER OF TECHNOLOGY
(AGRICULTURAL ENGINEERING)**

in

**SOIL AND WATER CONSERVATION
ENGINEERING**

by

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CERTIFICATE-I

This is to certify that the thesis entitled "**Forecasting of Water Table Fluctuations for Priyadarshini Watershed Using Artificial Neural Network**" submitted to Faculty of Agricultural Engineering, Dr. Balasaheb Sawant Konkan Krishi Vidyapeeth, Dapoli, Dist.- Ratnagiri, (Maharashtra State) in the partial fulfilment of the requirements for the award of the degree of **Master of Technology (Agricultural Engineering)** in **Soil and Water Conservation Engineering**, embodies the results of bonafide research work carried out by **Mr. Prakash Basavanni Hittanagi (ENDPM 2017/134)** under my guidance and supervision. No part of the thesis has been submitted for any other degree, diploma or publication in any other form.

The assistance and help received during the course of this investigation and source of the literature have been duly acknowledged.

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LIST OF ABBREVIATIONS AND SYMBOLS

ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference Systems and
Bgl	Below ground level
BPANN	Back Propagation Artificial Neural Network
BCM	Billion cubic meter
CC	Correlation coefficient
CGWB	Central Ground Water Board
CAET	College of Agriculture Engineering and Technology
CG	Conjugate Gradient Algorithm
Dept.	Department
E	Coefficient of efficiency
Engg.	Engineering
e.g.	Example
et al.	etalibi and others
etc.	etecetera and so forth
FNN	Feed forward Neural Network
Fig.	Figure
GWL	Groundwater level
i.e.	that is
Km	Kilometer
km ²	Kilometer square
LM	Levenberg-Marquardt Algorithm
MAE	Mean absolute error
MCM	Million cubic meter
M	Meter
M.Tech	Master of Technology
Mm	Mili meter
RBF	Radial Basis Function
RMSE	Root mean square error
R	Regression coefficient
°	Degree
°C	Degree Celsius
%	Percentage

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7. **Title of Thesis** : Forecasting Of Water Table Fluctuations for Priyadarshini Watershed Using Artificial Neural Network
8. **Objectives** : 1. To Compare different algorithms used.
2. To carry out sensitivity analysis of developed models.

ABSTRACT

“FORECASTING OF WATER TABLE FLUCTUATIONS FOR PRIYADARSHINI WATERSHED USING ARTIFICIAL NEURAL NETWORK”

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Groundwater is an important natural resource essential for sustenance of life. Over 98% of the freshwater on the Earth lies below its surface. It is located below the soil surface and largely contained in interstices of bedrocks, sands, gravels, and other interspaces through which precipitation infiltrates and percolates into the underground aquifers due to gravity. The total amount of water in the world is 1.4 billion km³. 97.5% of these waters are in the oceans and the seas and 2.5% is in fresh water. Sweet waters; 0.3% is in lakes and rivers, 30.8% in ground water, soil necropsy and marsh, 68.9% in the form of ice and permanent snow. Groundwater is one of the major sources of supply for domestic, industrial and agricultural purposes.

The weekly Rainfall data, Temperature data, Solar data, Water level data and Permeability data of 9 years were used. Artificial Neural Network is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, The network is composed of a large number of highly interconnected processing elements called as neuron.

They typically consist of hundreds of simple processing units which are wired together in a complex communication network. Each unit or node is a simplified model of real neuron which sends off a new signal or fires if it receives a sufficiently strong input signal from the other nodes to which it is connected, learning in this system involves the adjustment between neurons through synaptic connection. In this study feed-forward neural networks architecture has been used in predicting weekly water table depths. In this study, sensitivity analysis has

been done to measure relative importance of each input variable for precisely predicting groundwater table fluctuations.

Sensitivity analysis is done by removing one input parameter at a time from the model and testing its performance by comparing with original model. Considering training, validation and testing period and all the statistics, it is difficult to say which algorithm is better among the two selected for study. Because there was a lot of variation in all the statistics among the two selected algorithms for training, validation and testing period. But considering the testing period of all the nine wells it was found that LM algorithm was better than CG for wells i.e., well 1 (2-9-1), well 2 (2-9-1), well 3 (1-8-1), well 4 (1-6-1), well 5 (2-9-1), well 6 (1-9-1), well 8 (2-9-1) while CG algorithm was better than LM for wells i.e., well 7 (2-5-1) and well 9 (3-5-1) So these algorithms for particular well were selected for sensitivity analysis. As the results found were based on trial and error methods Levenberg- Marquardt (LM) algorithm provides better results than Conjugate Gradient algorithm.

Levenberg- Marquardt (LM) best results for ANN network architecture of model for well 1 (2-9-1), well 2 (2-9-1), well 3 (1-8-1), well 4 (1-6-1), well 5 (2-9-1), well 6 (1-9-1), well 7 (3-5-1), well 8 (2-9-1), well 9 (2-9-1). The predicted water level trend followed the observed trend closely, showing the accuracy of the network. In present study, results were found and based on sensitivity analysis models selected and their statistics for all the nine wells. It was observed that selected algorithms predicted the water table depths in a better way in terms of its performance statistics.

The values of R for LM and CG were found to be 0.836 and 0.743, respectively. The observed values of RMSE for LM and CG were found to be 0.100 and 0.101, respectively. Similarly, the value of E for LM and CG were found to be -376.40 and -20.88, respectively. The above result concludes Levenberg-Marquardt predicts the water table depth better than Conjugate Gradient.

(Keywords : ANN, Sensitivity analysis, Levenberg-Marquardt, Conjugate Gradient)

I. INTRODUCTION.

1.1 General

Groundwater is an important natural resource essential for sustenance of life. Over 98% of the freshwater on the Earth lies below its surface. It is located below the soil surface and largely contained in interstices of bedrocks, sands, gravels, and other interspaces through which precipitation infiltrates and percolates into the underground aquifers due to gravity. (Wagh *et.al* 2014). The total amount of water in the world is 1.4 billion km³. 97.5% of these waters are in the oceans and the seas and 2.5% is in fresh water. Sweet waters; 0.3% is in lakes and rivers, 30.8% in ground water, soil necropsy and marsh, 68.9% in the form of ice and permanent snow. It is understood that the amount of available fresh water that humans can easily use because of the fact that 90% of the fresh water resources are so small and in the underground. (Ünes *et.al* 2017).

The water resource potential or annual water availability of the country in terms of natural runoff (flow) in rivers is about 1,869 Billion Cubic Meter (BCM)/year. However, the usable water resources of the country have been estimated as 1,123 BCM/year. This is due to constraints of topography and uneven distribution of the resource in various river basins, which makes it difficult to extract the entire available 1,869 BCM/year.

Out of the 1,123 BCM/year, the share of surface water and ground water is 690 BCM/year and 433 BCM/year, respectively. Setting aside 35 BCM for natural discharge, the net annual ground water availability for the entire country is 398 BCM.

The overall contribution of rainfall to the country's annual ground water resource is 68% and the share of other resources, such as canal seepage, return flow from irrigation, recharge from tanks, ponds and water conservation structures taken together is 32%. Due to the increasing population in the country, the national per capita annual availability of water has reduced from 1,816 cubic metre in 2001 to 1,544 cubic metre in 2011.2 This is a reduction of 15%. (Suhag, 2016). Maharashtra, the third largest state in India has a total geographical area of 3, 07,762 sq km and lies between latitudes of 15°45' and 22° 00' N and longitudes of 73° 00' and 80° 59' E in the west-central part of India abutting on the Arabian Sea. Maharashtra is one of the most well endowed States in the country in respect of rainfall, but it may soon become a State

where large parts of it face perennial water shortage an overwhelming population of rural Maharashtra and to some extent urban population is dependent on groundwater for drinking purposes. The availability of groundwater is extremely uneven, both in space, time and depth. The uneven distribution of groundwater in the State can be mainly attributed to highly heterogeneous lithology and variability and regional variation of rainfall. Large areas of Maharashtra are occupied by hard rocks and because of variations in their basic characteristics, physiography and variability in the rainfall, there are limitations on the availability of groundwater. The total rechargeable groundwater resource in the State is computed as 35732.2MCM and the Net ground water availability is 33806.46MCM. Out of these, 0.17 MCM is withdrawn for different uses viz irrigation, domestic and industry etc, 190.332 MCM is earmarked for domestic and industrial requirement and the remaining is available for future irrigation. The pre-monsoon decadal water level trend, shows a rising trend, up to 0.1 m/year recorded in 37 % of the wells and covering about 1,16,010 sq km of the State during the past decade 2007-2016. Whereas, rising trend of > 0.1 m/year is observed only in 1103 sq km area of the State. The declining trend of pre-monsoon water level was observed in 62 % of the wells covering 1, 89,986 sq km. Declining trend upto 0.1 m/year is observed in about 1,88,651 sq km while only 1334 sq km area is showing declining trend of more than 0.1 m/year.(Anonymous, 2017)

Dapoli is a Taluka of Ratmagiri, lies in costal strip with Net Annual Ground Water Availability 3769.62 ha-mand Existing Gross Ground Water Draft for Irrigation 587.46 ha-m. The groundwater level till January 2017 was 2.70 mbgl which is -.088 less than November 2016. In the last 10 years (2007-2017) January , groundwater level is decreased to -60 m bgl. .(Anonymous, 2017)

1.2 Artificial Neural Network

The basic concept of an artificial neural network (ANN) is derived from an analogy with the biological nervous system of the human brain and how the latter processes information through its millions of neurons interconnected to each other by synapses.

Borrowing this analogy, an ANN is a massively parallel system composed of many processing elements (neurons), where the synapses are actually variable weights, specifying the connections between individual neurons and which are adjusted. The ANN technique is applied as a new approach and an attractive tool to study and predict groundwater levels without applying physically based hydrologic parameters. The

approach may improve the understanding of complex groundwater system and is able to show the effects of hydrologic, meteorological and anthropical impacts on the groundwater conditions. (Sirhan and Koch 2013).

1.3 Justification

Groundwater is one of the major sources of supply for domestic, industrial and agricultural purposes. To gain insight in the processes including the groundwater system, one needs knowledge about the essential variables and how they fluctuates over time. Forecasting the ground water level fluctuations is an important requirement for planning conjunctive use in any basin.

1.4 Objectives

This study was undertaken with the objective of development of artificial neural network models for forecasting groundwater levels of the study area. The specific objectives of the study are:

- i. To compare different algorithms used.
- ii. To carry out sensitivity analysis of developed models

II. REVIEW OF LITERATURE

2.1. ANN to predict the Water Table Level

Bustami *et al.*, 2006 The predicted values of precipitation were then used to forecast water level of the same gauging station and yielded accuracy value of 85.3%, compared to only 71.1% accuracy of water level prediction with no estimation made to its missing precipitation data. These results showed that ANN is an effective tool in forecasting both missing precipitation and water level data, which are utmost essential to hydrologists around the globe. sequestration potential than the natural forest because of ongoing scientific management practices, uniform age and stand structure.

Sreekanth, *et al.*, 2009 studied the performance of the artificial neural network (ANN) model, i.e. standard feed-forward neural network trained with Levenberg-Marquardt algorithm, was examined for forecasting groundwater level at Maheshwaram watershed, Hyderabad, India. The model efficiency and accuracy were measured based on the root mean square error (RMSE) and regression coefficient (R

²). The model provided the best fit and the predicted trend followed the observed data closely (RMSE = 4.50 and $R^2 = 0.93$). Thus, for precise and accurate groundwater level forecasting, ANN appears to be a promising tool.

Sirhan and Koch 2013 The initial ANN model for predicting groundwater levels is set up using monthly groundwater time series data recorded between 2000 and 2010 at 70 wells across the Gaza Strip and employing seven independent predictor variables, namely, initial groundwater level, abstraction rate, recharge from rainfall, hydraulic conductivity, distance of the pumping wells from the coastal shoreline, depth to the well screen and well density. The best architecture of this initial ANN model found by trial and error turns out to be a 3-layer perceptron network (MLP), i.e. is an ANN with one hidden layer between input and output layer.

Sujatha and Kumar, 2015 As its groundwater levels showed a rapid decline in the last decade due to the overexploitation for the domestic, agricultural and industrial needs, accurate prediction is very essential to plan better conservation of groundwater resources. Results showed that Feed forward neural network trained with training algorithm Levenberg-Marquardt issuitable for accurate prediction of groundwater levels

2.2. Sensitivity Analysis of Developed Models

Gevrey *et al.*, 2003 Convinced by the predictive quality of artificial neural network (ANN) models. The data tested in the study concerns the prediction of the density of brown trout spawning redds using habitat characteristics. The PaD method was found to be the most useful as it gave the most complete results, followed by the Profile method that gave the contribution profile of the input variables. The Perturb method allowed a good classification of the input parameters as well as the Weights method that has been simplified but these two methods lack stability. Next came the two improved stepwise methods (a and b) that both gave exactly the same result but the contributions were not sufficiently expressed. Finally, the classical stepwise methods gave the poorest results.

III. MATERIALS AND METHODS

3.1. Study area

The research work will be carried out at the Priyadarshini watershed, College of Agricultural Engineering and Technology, Dr. Balasaheb Sawant Konkan Krishi Vidyapeeth, Dapoli, Dist- Ratnagiri (M.S.). The Priyadarshini Watershed is located at 17.1° N latitude, 73.26° E longitudes and 250 m above mean sea level. The region comes under heavy rainfall with average annual rainfall of 3500 mm. Priyadarshini watershed has 38.72 ha area. The ambient temperature of the region varies from 7.5 °C to 38.5 °C and relative humidity varies from 55 percent to 99 percent in different seasons. The climate of the region is hot and humid. The region has hilly topography with lateritic soils.

3.2. Software required for study

Neuro Solutions

The world we live is becoming even more reliant on the use of electronic gadget and computers to control the behavior of real world resources. neural networks are important for their ability to adapt. neural nets represent entirely different models from those related to the other symbolic systems.

3.3. Data Description

The weekly data of 9 years (2005-2014) were collected for Rainfall, Temperature, Solar, from Department of Agronomy, COA, Dapoli and Well depth and Permeability data of Priyadarshini Watershed was collected from department of Soil and Water Conservation Engineering, CAET, Dapoli.

3.4. Artificial neural network

ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, The network is composed of a large number of highly interconnected processing elements called as neuron. They typically consist of hundreds of simple processing units which are wired together in a complex communication network. Each unit or node is a simplified model of real neuron which sends off a new signal or fires if it receives a sufficiently strong Input signal from the other nodes to which it is connected. Learning in this system involves the adjustment between neurons through synaptic connection. (Maind and wankar 2014) In this study feed-forward neural networks architecture will be used in predicting monthly water table depths.

3.5. ANN Architecture

In this study, will be use four parameters as input, rainfall data, permeability data, solar data and temperature.

Input Nodes – neurons interfaces to the real world to receive its inputs as “Input Layer”. The layer of input neurons receive the data either from input files or directly from electronic sensors in real-time applications they just pass on the information to hidden nodes. (Maind and wankar 2014)

Hidden Nodes -hidden layer receives the signals from all of the neurons in a layer above it, typically an input layer. After a neuron performs its function it passes its output to all of the neurons in the layer below it (Maind and Wankar, 2014). To calculate number of hidden layers to be use we use $(2n+1)$. Where n = no. of nodes.

Output Nodes – neurons provide the real world with the network's outputs. Output nodes are collectively referred to as “Output Layer” and are responsible for computations and transferring information from the network to outside world. In this study, The groundwater level will be estimated. (Maind and Wankar, 2014)

3.6. Feed-forward neural network (FNN)

Feed-forward neural networks have been applied successfully in many different problems since advent of error back propagation learning algorithm. This network architecture and the corresponding learning algorithm can be viewed as a generalization of popular least-mean-square (LMS) algorithm. In feed-forward networks, data flow through network in one direction from input layer to output layer through hidden layer(s). Each output value is based solely on current set of inputs. In most networks, nodes of one layer are fully connected to the nodes in the next layer; however, this is not a requirement of feed-forward networks. A multilayer perception network consists of an input layer, one or more hidden layers of computation nodes, and an output layer. Input signal propagates through the network in a forward direction, layer by layer. Key disadvantages are that it train slowly, and require lots of training data.

3.7. Building of Neural Networks

For developing ANN model generally data sets are required for the training, validation and testing of the ANN networks. In this study, observed rainfall data, infiltration data, Water level, permeability data, Temperature data, and Solar data will be used to train and validate an artificial neural-network. Levenberg–Marquardt (LM), Conjugate Gradient Algorithm (CG) used as the learning algorithm. The Neural Network will be optimized using Neuro Solutions . In the training stage, to define the output accurately, the number of nodes will be increased step-by-step in the hidden layer. The software normalizes the given data. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function will be used in hidden and output layer. After the successful training of the network, the network will be tested with the test data. Using the results produced by the network, statistical methods will be used to make comparisons.

3.8. Transfer Function

The output activation function for binary classification problems (i.e. outputs values that range (0,1) is the logistic sigmoid. The logistic sigmoid has the following form:

$$f(x) = \frac{1}{1+e^{-x}} \quad \dots 3.1$$

and outputs values that range (0,1). The logistic sigmoid is motivated somewhat by biological neurons and can be interpreted as the probability of an artificial neuron “firing” given its inputs.

3.9. Learning Algorithm

Supervised Learning

In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is called the "training set." During the training of a network the same set of data is processed many times as the connection weights are ever refined. The current commercial network development packages provide tools to monitor how well an artificial neural network is converging on the ability to predict the right answer. These

tools allow the training process to go on for days, stopping only when the system reaches some statistically desired point, or accuracy. When finally the system has been correctly trained, and no further learning is needed, the weights can, if desired, be "frozen."(Maind and wankar 2014)

3.10. Training with different algorithms

Determining the best values of all the weights is called training the ANN. In a supervised learning mode, actual output of a neural network is compared to predicted output. Weights, which are usually randomly set to begin with, are then adjusted so that next result will produce less variation between predicted and actual output. Training consists of presenting input and output data to network and allowing to run for certain epochs. These data are training data. For each input provided to the network, the corresponding predicted output set is given as well as processed through 5000 epochs. It is considered complete when the artificial neural network reaches a desired performance level. At this level the network has achieved the desired statistical accuracy as it produces required outputs for a given sequence of inputs. When further learning is found to be unnecessary, resulting weights are typically fixed for the application. Once a supervised network performs well on the training data, it is important to see what it can do with a new set of data. If a system does not give desired output for this test set, then training period should continue. testing is important to ensure that network has learned the basic patterns involved in a application and has not memorized all the data. Two different algorithms are being used in this study in order to identify the one which trains a given network more efficiently.

3.10.1 Conjugate Gradient Algorithm (CG)

This is the direction in which the performance function is decreasing most rapidly. It turns out that, although the function decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence

$$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}} \quad \dots 3.2$$

3.10.2 Levenberg-Marquardt (LM)

Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When performance

function has form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as

$$H = J^T J \quad \dots 3.3$$

and gradient can be computed as

$$g = J^T e \quad \dots 3.4$$

where ,J is Jacobian matrix that contains first derivatives of network errors with respect to weights and biases, and **e** is a vector of network errors. Jacobian matrix can be computed through a standard back propagation technique that is much less complex than computing the Hessian matrix.

Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad \dots 3.5$$

When scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase performance function. In this way, performance function will always be reduced at each iteration of the algorithm.

3.11. Neuro Solution Predictions.

The software used for the study purpose is Neuro solution 5.0 version. The prediction of desired output in Neuro solution is done by following steps :-

3.11.1. Selection and Assigning of Data

The first step after the initiation of application is to selection of Feed forward network methods, many methods are listed in a small Neural Builder tool box. For this study purpose Generalized Feed forward network is opted after the selection of network method next option sign icon is clicked, which shows a new Neural Builder with a Browsing and feeding input data for training set. Clicking on browse option will allow user to feed the input files. The input file should be in .csv format. After the files are fed the desired data should be selected and marked as desired by selecting the options from below the input data. Click or select next option for further process

3.11.2. Building of Architecture

The next Neural Builder box is Cross Validation and Testing sets presents the options for selecting percentages for cross validation exemplars and testing exemplars, these exemplars are fewer selected data which represents the whole data. These are selected Randomly from datasets. For this study purpose 15 % is selected for Cross validation and testing respectively. After selection of exemplars next icon is clicked which proceeds to next neural builder option box which is Generalized Feed Forward Neural Builder Box. This gives the information about our input, output files and exemplars selected for training. It also gives us option to select number of hidden layers to be selected. Hidden layers are selected by the requirement of the datasets. For this study purpose, one hidden layer is selected. The next option is selected which shows us Layers Neural Builder option box. The first option box is for Hidden layer, Processing elements option is used to select number of nodes for training, number of nodes is selected according to the requirement. The number of nodes varies with different type of data and with number of input files. The next option is Transfer which helps to select transfer functions, for this study purpose SigmoidAxon function is selected as it is widely and mostly used for ground water level prediction. Next option is Learning Rule, which lists many algorithms, for this study purpose Levenberg-Marquardt and Conjugate Gradient are compared. The next options shows next output layer builder which is not to be disturbed and move on to next builder box

3.11.3 Supervised Learning Control and Probe Configuration

After moving to next neural builder box Supervised learning control options appear, these controls the termination and time duration of testing sets by setting epochs. The larger the epochs the more time is needed for sets to train and large epochs usually give

more accurate data than small epochs. Sometimes datasets are trained to desired values before reaching to its set epochs so epochs freeze to a certain value, we can manually command the dataset to train even epochs stopped. After termination set to minimum next icon is selected.

In Probe configuration the readings are and analysis of trained data is selected. These selected options have various analysis methods and readings. Bar graphs and charts can also be analyzed. The General option is ticked and Build option is pressed. The general options gives the RMSE, R, MAE and E value of the trained dataset. Clicking Build option will open applications build wizard which shows network structure and all the selected analysis tools which will give result as the network start training.

3.11.4 Testing Wizard and Output

After Building network, the network is trained by clicking green colour triangular play option on the left hand side of tool box. The trained datasets give the selected general values from probe configuration. After termination of training by completing 5000 epochs Testing wizard is clicked and a new pop up options will open. Select Production in Dataset to test option from Testing Wizard-Step 1 and browse the same well input file which was selected initially for comparison. If the input data is normalized the output will be in same form. This application Normalizes data. Click next and output will be generated. copy the predicted data for further process.

3.12. Performance evaluation criteria

Four different criteria will be used in order to evaluate effectiveness of each network and its ability to make precise predictions. These are Nash-Sutcliffe Coefficient (CE), Root Mean Square Error (RMSE), Mean absolute error (MAE) and Correlation Coefficient (CC) and given by following equations

3.12.1. Root mean square error (RMSE)

The Root Mean Square Error (**RMSE**) (also called the root mean square deviation, RMSD) is a frequently used measure of the difference between values predicted by a model and values actually observed from environment that is being modeled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power.

The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{mod,i})^2}{n}} \quad \dots 3.6$$

where ,

X_{obs} is observed values and

X_{mod} is modeled values at time/place i

n is number of values

3.12.2. Nash-Sutcliffe coefficient (E)

The Nash-Sutcliffe model efficiency coefficient (E) is commonly used to assess the predictive power of hydrological discharge models. However, it can also be used to quantitatively describe the accuracy of model outputs for other things than discharge (such as nutrient loadings, temperature, concentrations etc.). (Nash and Sutcliffe, 1970) It is defined as:

$$E = 1 - \frac{\sum_{i=1}^n (X_{obs,i} - X_{mod})^2}{\sum_{i=1}^n (X_{obs,i} - \overline{X_{obs}})^2} \quad \dots 3.7$$

where ,

X_{obs} is observed values and

X_{mod} is modeled values at time/place i

Nash-Sutcliffe efficiencies can range from $-\infty$ to 1. An efficiency of 1 ($E = 1$) corresponds to a perfect match between model and observations. An efficiency of 0 indicates that model predictions are as accurate as mean of observed data, whereas an efficiency less than zero ($-\infty < E < 0$) occurs when the observed mean is a better predictor than the model. Essentially, closer the model efficiency is to 1.

3.12.3. Pearson correlation coefficient (R)

Correlation often measured as a correlation coefficient indicates the strength and direction of a linear relationship between two variables (for example model output

and observed values). A number of different coefficients are used for different situations. The best known is Pearson product-moment correlation coefficient (also called Pearson correlation coefficient or the sample correlation coefficient), which is obtained by dividing the covariance of the two variables by product of their standard deviations. If a series n observations and n model values, then Pearson product-moment correlation coefficient can be used to estimate correlation between model and observations.

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}} \quad \dots 3.8$$

where ,

x is observed values and

$\bar{x}$ is mean value for x

y is modeled values at time/place i

$\bar{y}$ is mean value for y

The correlation is +1 in case of a perfect increasing linear relationship, and -1 in case of a decreasing linear relationship, and values in between indicates the degree of linear relationship between for example model and observations. A correlation coefficient of 0 means there is no linear relationship between the variables. Square of the Pearson correlation coefficient (R), known as coefficient of determination, describes how much of the variance between two variables is described by the linear fit.

33.12.4 Mean Absolute Error (MAE)

Measures average magnitude of errors in a set of predictions, without considering their direction. It's average over the test sample of absolute differences between prediction and actual observation where all individual differences have equal weight.

$$MAE = \frac{1}{n} \sum_{j=1}^n |y_j - \hat{y}_j| \quad \dots 3.9$$

where,

Y_j is observed values and

$\hat{Y}_j$ is modeled values at time/place i .

n is number of values

3.13. Sensitivity analysis

Sensitivity analysis is a method for extracting cause and effect relationship between inputs and outputs of network (Hung *et al.*, 2008). In ANN modeling effects of each network inputs on the network output should be observed. This shows which input channels are the most significant, which helps to decide to the insignificant parameters and removing them. Will reduce size of the datasets and network. This reduces complexity and training time.

In this study, sensitivity analysis will be done to measure relative importance of each input variable for precisely predicting groundwater table fluctuations. It is done by removing one input parameter at a time from the model and testing its performance by comparing with original model.

This method is the classical stepwise method that consists of adding or rejecting step by step one input variable and noting the effect on the output result. Based on the changes in MAE, the input variables can be ranked according to their importance in several different ways depending on different arguments. For instance the largest changes in MAE due to input deletions can allow these inputs to be classified by order of significance. In another approach the largest decrease in MAE can identify the most important variables based on sensitivity analysis. (Gevrey *et.al.*, 2003).

IV. RESULTS

India is fast moving towards a crises of ground water over use and the availability of surface water is greater than ground water. However, owing to the decentralized availability of ground water, it is easily accessible and forms the largest share of India's agriculture and drinking water supply. As a result of over use, groundwater table is

decreasing day by day. So, for casting and predicting water table depth tends to manage groundwater level depth for sustaining groundwater. The result of the study taken for the objective of development of ANN models for forecasting water table. This chapter presents results along with discussions under the following headings

4.1 Comparison of Algorithms.

4.2 Sensitivity Analysis.

4.1. Comparison of Algorithms

The Nash-Sutcliffe coefficient(E), root mean square error, (RMSE), mean absolute error (MAE), and Pearson coefficient (R) given by equations 3.6 to 3.9 were used to assess the models response to that of observed value for different algorithms for developed ANN models during training, validation and testing period and presented in table 4.1. It is observed that the maximum LM value of R for training and validation are 0.908 and 0.903 shown in well 2 (2-9-1) and testing is 0.949, shown in well 8(2-9-1) whereas minimum value for training is 0.684 shown in well 1 (4-4-1) for validation and testing are 0.159 and 0.773 well 9(3-5-1) as presented in the table 4.1

The maximum observed R value for CG training, validation and testing are 0.76 shown in well 3(4-5-1), 0.85 shown in well 9(3-5-1) and 0.891 shown in well 7(2-5-1) whereas the minimum value for training and testing are 0.671 and 0.458 shown in well 1(4-4-1) for validation the minimum R value is 0.638 well 2 (4-7-1)

It is observed that the Pearson coefficient (R) indicates the strength and direction of linear relationship between two variable the correlation is +1 in case of perfect increasing linear relationship and -1 in case of decreasing linear relationship a correlation coefficient of 0 means there is no linear relationship between the variables minimum value is (0.159) during validation period of well 9(2-9-1) for the LM algorithm and was maximum value is (0.949) during testing period of well 8 (2-9-1) for the LM algorithms. The variation of root mean square error (RMSE) statistics, a measure of residual variance which illustrates the architecture between the computed and observed water table depths, was minimum (0.050) during training period of well 2 (2-9-1) for LM algorithm and was maximum (0.303) during validation period of well 1(2-9-1) for the LM algorithm. The mean absolute error (MAE) was found to be minimum (0.005) during validation period of well 8(2-8-1) for CG algorithm and was

maximum (0.216) during validation period of well 6 (4-4-1) for LM algorithm. The Nash-Sutcliffe coefficient (E) was found to be varying from -506.05 (during validation period of well 1(2-9-1) for LM algorithm) to 0.896 (during testing period of well 1(2-9-1) for LM algorithms). Fig.4.1 to 4.27 shows observed and predicted weekly water table depths of all the nine wells for different algorithms during training, validation and testing period. It was observed that the predicted water table depths followed the observed water table pattern.

Considering training, validation and testing period and all the statistics it is difficult to say which algorithm is better among the two selected for study. Because there was a lot of variation in all the statistics among the two selected algorithms for training, validation and testing period. But considering the testing period of all the nine wells it was found that LM algorithm was better than CG for wells i.e., well 1 (2-9-1), well 2(2-9-1), well 3 (1-8-1), well 4 (1-6-1), well 5 (2-9-1), well 6 (1-9-1), well 8(2-9-1) while CG algorithm was better than LM for wells i.e., well 7 (2-5-1) and well 9(3-5-1) So these algorithms for particular well were selected for sensitivity analysis

Table 4.1. Statistics of LM and CG algorithms for developed ANN models

Well no	Model steps	R		RMSE		E		MAE	
		LM	CG	LM	CG	LM	CG	LM	CG
1	Training	0.684	0.671	0.146	0.084	-66.98	-6.450	0.011	0.007
	Validation	0.369	0.664	0.303	0.084	-506.05	-12.450	0.060	0.006

	Testing	0.905	0.458	0.058	0.188	0.896	-201.44	0.011	0.014
2	Training	0.908	0.713	0.050	0.081	-5.660	-13.610	0.004	0.006
	Validation	0.903	0.638	0.123	0.081	-45.007	-2.722	0.024	0.006
	Testing	0.943	0.695	0.067	0.084	-24.252	-1.827	0.012	0.006
3	Training	0.855	0.766	0.071	0.101	-7.542	-17.912	0.006	0.009
	Validation	0.901	0.773	0.117	0.108	-1.598	-11.151	0.023	0.008
	Testing	0.901	0.757	0.101	0.066	-4.390	-1.55	0.019	0.005
4	Training	0.764	0.680	0.0991	0.113	-0.332	-3.752	0.009	0.008
	Validation	0.868	0.749	0.263	0.152	-37.447	-4.230	0.052	0.011
	Testing	0.893	0.800	0.133	0.122	0.361	-1.615	0.025	0.009
5	Training	0.829	0.704	0.099	0.104	-14.548	-7.452	0.009	0.009
	Validation	0.805	0.708	0.177	0.083	-7.663	-67.926	0.0355	0.006
	Testing	0.865	0.776	0.118	0.098	-571.59	-0.154	0.022	0.007
6	Training	0.854	0.681	0.080	0.133	-60.563	-29.970	0.007	0.012
	Validation	0.889	0.722	0.108	0.167	0.194	-1.990	0.216	0.012
	Testing	0.944	0.857	0.107	0.183	-3.157	-1.043	0.020	0.014
7	Training	0.715	0.693	0.149	0.169	-51.661	-61.645	0.013	0.015
	Validation	0.638	0.826	0.202	0.123	-45.523	-0.154	0.040	0.009
	Testing	0.880	0.891	0.220	0.084	-8.186	0.655	0.042	0.006
8	Training	0.884	0.756	0.067	0.096	-166.52	-7.742	0.006	0.008
	Validation	0.870	0.775	0.132	0.066	-21.706	0.169	0.026	0.005
	Testing	0.949	0.535	0.087	0.079	-0.368	0.354	0.016	0.006
9	Training	0.738	0.763	0.086	0.089	-61.015	-14.5	0.007	0.008
	Validation	0.159	0.855	0.141	0.132	-1.176	0.821	0.028	0.026
	Testing	0.773	0.864	0.090	0.049	-3.211	0.830	0.017	0.003

As the results found were based on trial and error methods Levenberg-Marquardt (LM) algorithm provides better results than Conjugate Gradient algorithm as shown in the Fig.4.28. Levenberg-Marquardt (LM) best results for ANN network architecture of model for well 1(2-9-1), well 2(2-9-1), well 3(1-8-1), well 4(1-6-1), well 5(2-9-1), well 6(1-9-1), well 7(3-5-1), well 8(2-9-1), well 9(2-9-1).

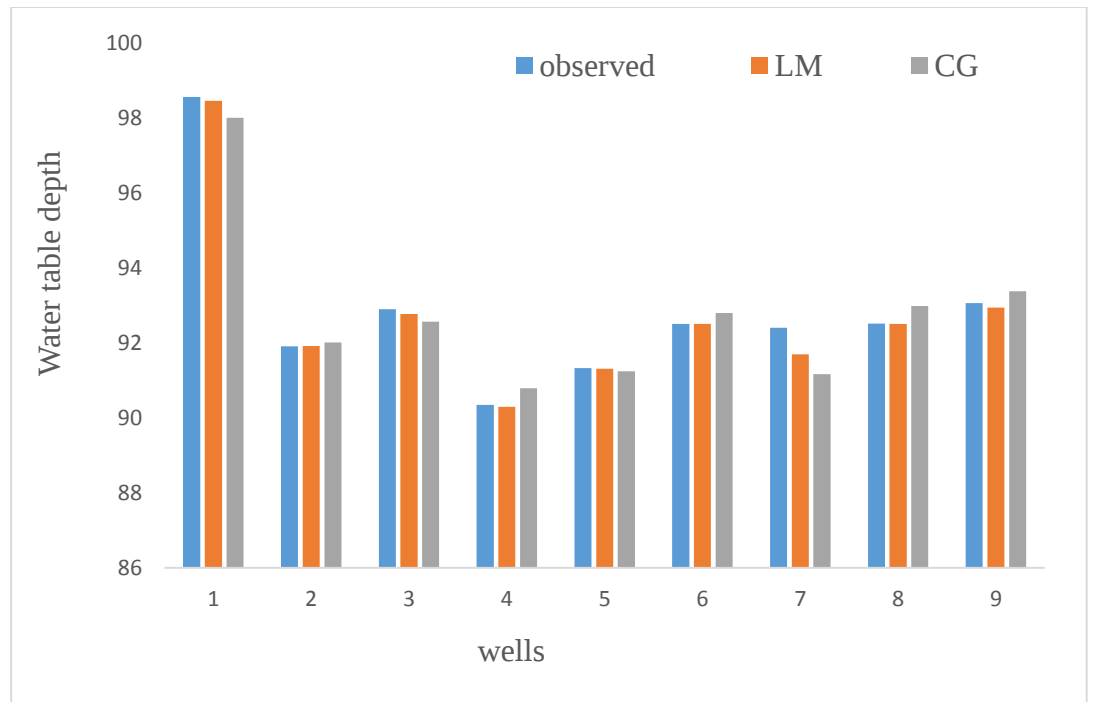


Fig.4.28: Observed and predicted weekly water table depth of average value of LM and CG algorithm

Table 4.2 to 4.3 shows the sensitivity analysis for all the nine wells for LM and CG algorithms along with selected network architectures. The observed data for LM showed maximum R value 0.9717 for well 2(2-9-1) with rainfall and permeability as input parameters and minimum R value 0.717 for well 1(2-9-1) with rainfall and permeability as input parameters and the average R value from all the well predicted from Levenberg-Marquardt is 0.834.

Similarly the observed data for CG showed the maximum R value 0.802 well 9 (3-5-1) with rainfall, permeability and temperature as input parameters and minimum R value 0.702 well 1(4-4-1) with all the 4 input parameters such as rainfall, permeability, solar, soil temperature and the average R value from all the wells predicted from Conjugate Gradient is 0.743. From Table 4.4 and 4.5, LM was found to be better model compared to CG for R value.

The observed maximum value of RMSE for LM is 0.235 shown in well 1 (2-9-1) with input parameters as rainfall and permeability and minimum value is 0.046 well 2(2-9-1) with input parameters as rainfall and permeability.

Similarly for E and MAE the maximum value are 0.921 shown for well 8 (2-9-1) with input parameters rainfall and permeability and 0.018 shown for well 1 (2-9-1) with input parameters rainfall and permeability, respectively. Minimum value for E and

MAE are -3203 shown in well 1(2-9-1) with input parameters as rain fall and permeability and 0.003 shown in well 2(2-9-1) with input parameters as rainfall and permeability, respectively.

The observed maximum value of RMSE for CG is 0.130 shown in well 6 (4-4-1) with all the input parameters and minimum value is 0.078 well 8(2-8-1) with input parameters as rainfall and permeability.

Table 4.2: Sensitivity analysis for LM algorithm

Wells	Parameter used	ANN structure	R	RMSE	E	MSE
1	Rainfall and Permeability	2-9-1	0.717	0.235758	-3203	0.01029
2	Rainfall and Permeability	2-9-1	0.917	0.046594	-1.986	0.003563
3	Permeability	1-8-1	0.861	0.069284	-19.577	0.005298
4	Permeability	1-6-1	0.800	0.119728	-123.707	0.009156
5	Permeability and Solar	2-9-1	0.842	0.082861	1.306	0.006337
6	Permeability	1-9-1	0.886	0.069331	-26.470	0.005308
7	Permeability, Temperature and Solar	3-5-1	0.792	0.13298	-15.630	0.010169
8	Rainfall and permeability	2-9-1	0.901	0.066517	0.921	0.005087
9	Rainfall and permeability	2-9-1	0.810	0.084246	0.529	0.006442

Table 4.3: Sensitivity analysis for CG algorithm

Wells	Parameter used	ANN structure	R	RMSE	E	MSE
1	Rainfall, Permeability, Solar and Temperature	4-4-1	0.702	0.091	-127.438	0.00856
2	Rainfall, permeability, Solar and Temperature	4-7-1	0.707	0.081	-2.151	0.00625

3	Rainfall, Permeability, Solar and Temperature	4-5-1	0.771	0.087	-15.384	0.006
4	Rainfall, Permeability, Solar and Temperature	4-9-1	0.715	0.120	-20.747	0.009
5	Rainfall, Permeability, solar and Temperature	4-6-1	0.722	0.099	-18.890	0.007
6	Rainfall, Permeability, Solar and Temperature	4-4-1	0.736	0.130	-4.660	0.010
7	Rainfall and Temperature	2-5-1	0.780	0.129	0.726	0.009
8	Rainfall and Permeability	2-8-1	0.757	0.078	0.316	0.005
9	Rainfall and Permeability and Tempeature	3-5-1	0.802	0.096	0.289	0.007

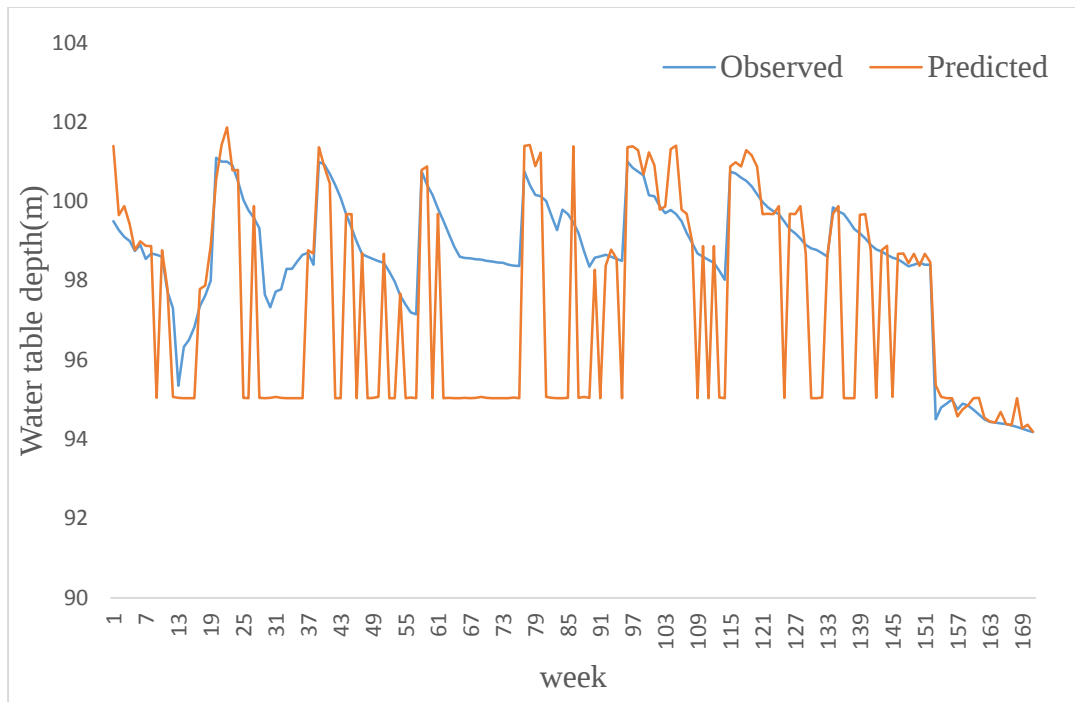


Fig.4.29: Observed and predicted weekly water table depth of well 1 for sensitivity analysis for LM algorithm

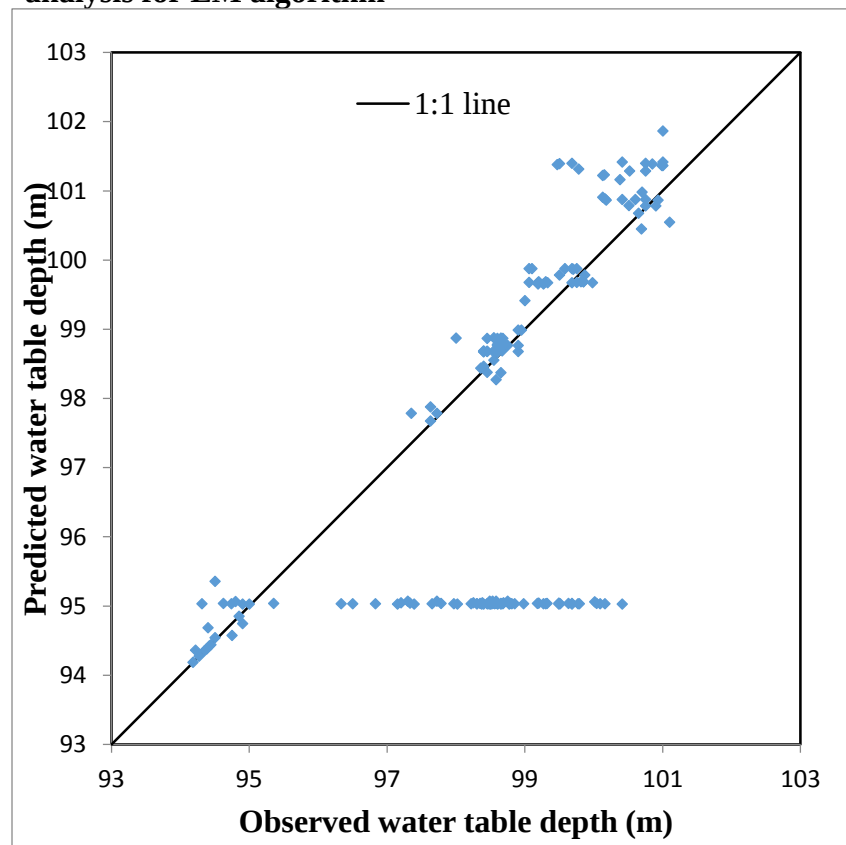


Fig.4.30: Scatter plot for observed and predicted water table depth of well 1 for LM algorithms

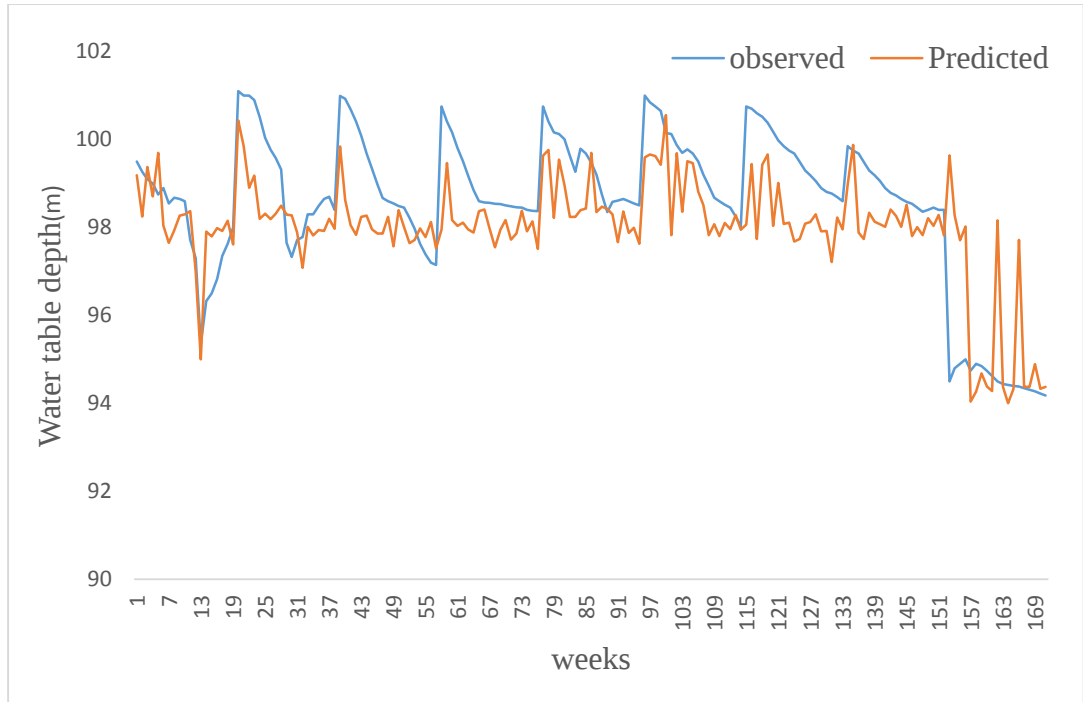


Fig.4.31: Observed and predicted weekly water table depth of well 1 for sensitivity analysis for CG algorithm

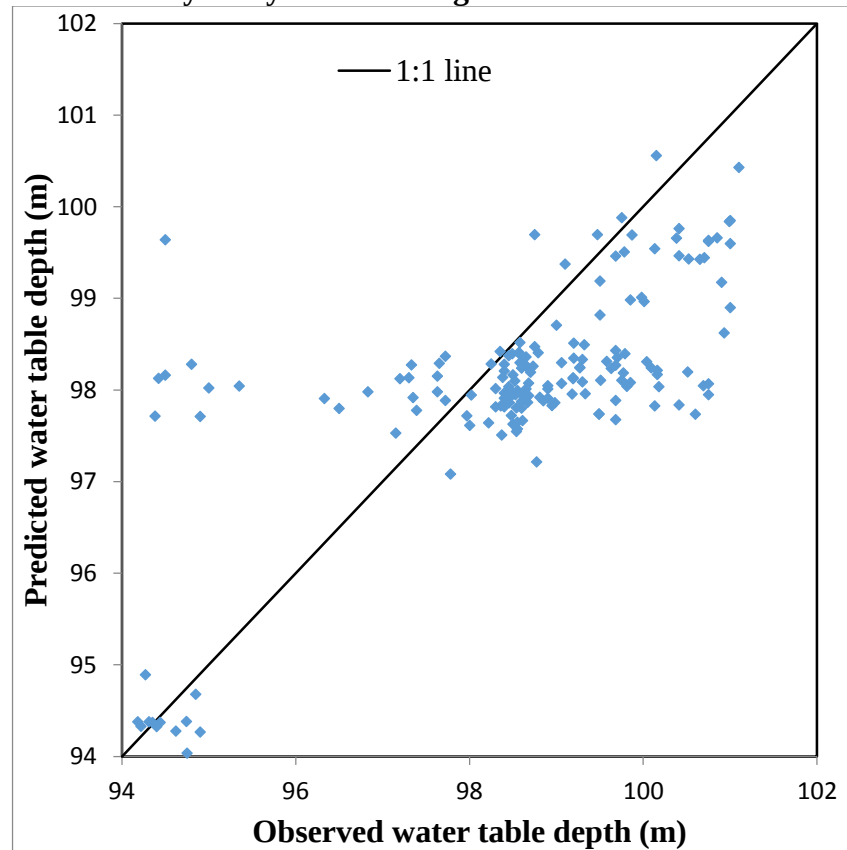


Fig.4.32: Scatter plot for observed and predicted water table depth of well 1 for CG algorithm

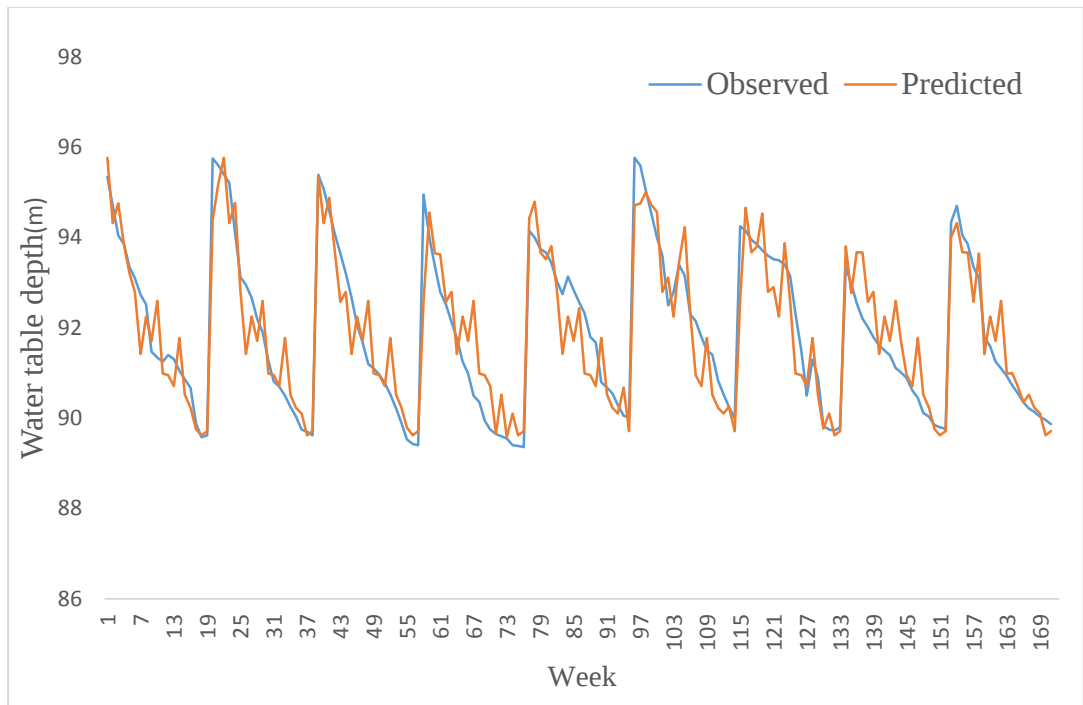


Fig.4.33: Observed and predicted weekly water table depth of well 2 for sensitivity analysis for LM algorithm

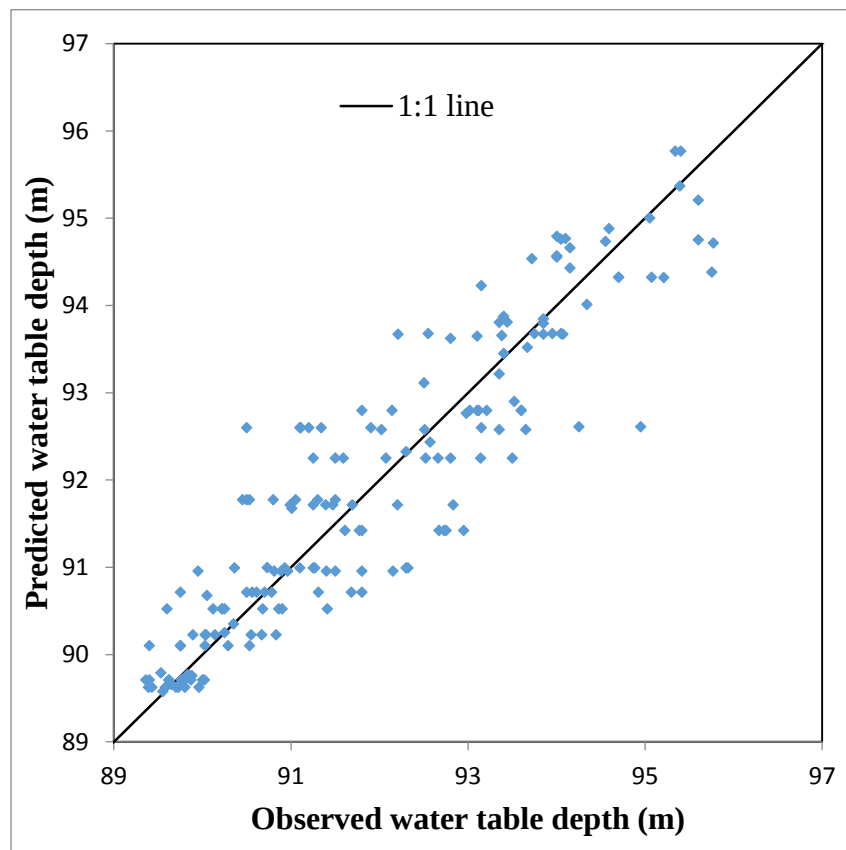


Fig.4.34: Scatter plot for observed and predicted water table depth of well 2 for LM algorithm

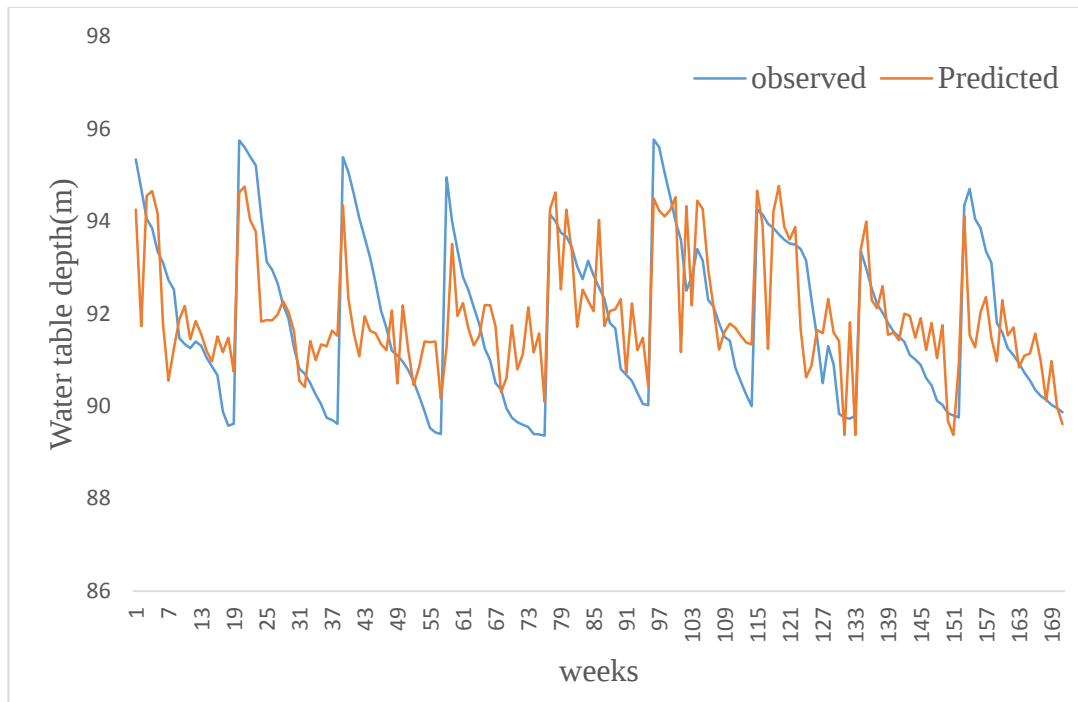


Fig.4.35: Observed and predicted weekly water table depth of well 2 for sensitivity analysis for CG algorithm

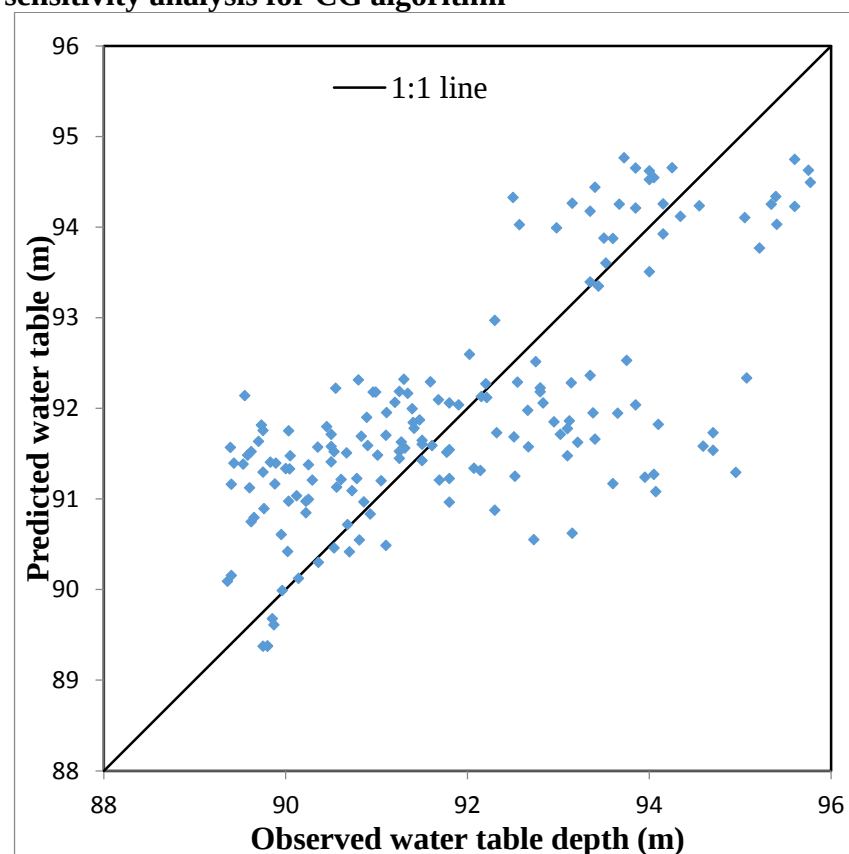


Fig.4.36: Scatter plot for observed and predicted water table depth of well 2 for CG algorithm

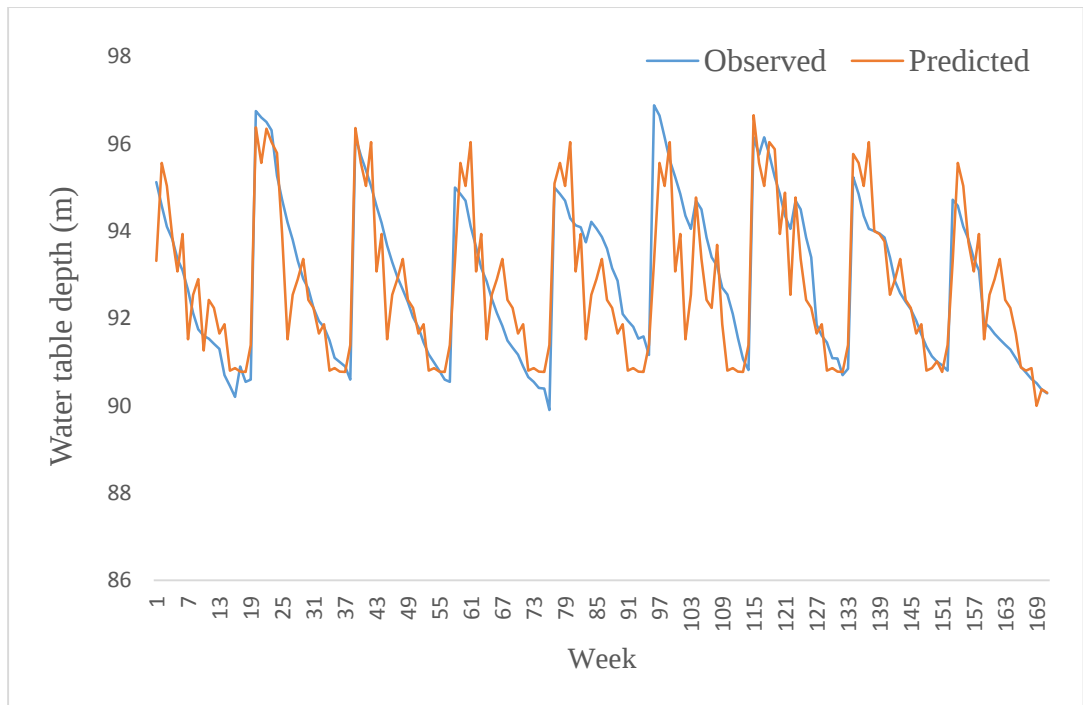


Fig.4.37: Observed and predicted weekly water table depth of well 3 for sensitivity analysis for LM algorithm

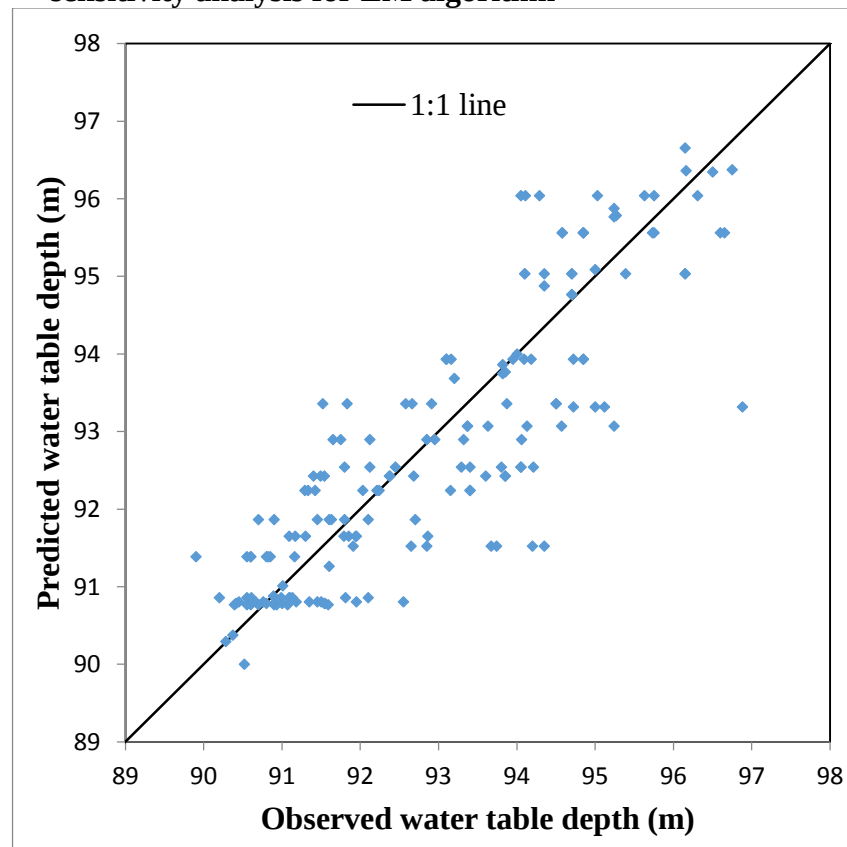


Fig.4.38: Scatter plot for observed and predicted water table depth of well 3 for LM algorithm

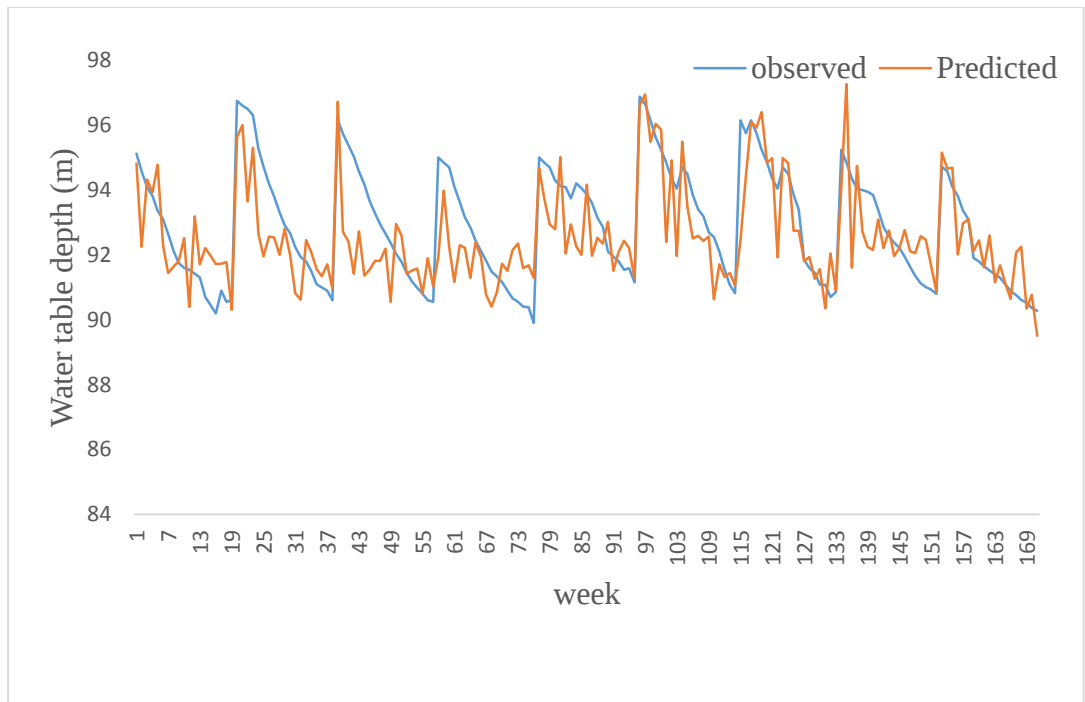


Fig.4.39 Observed and predicted weekly water table depth of well 3 for sensitivity analysis for CG algorithm

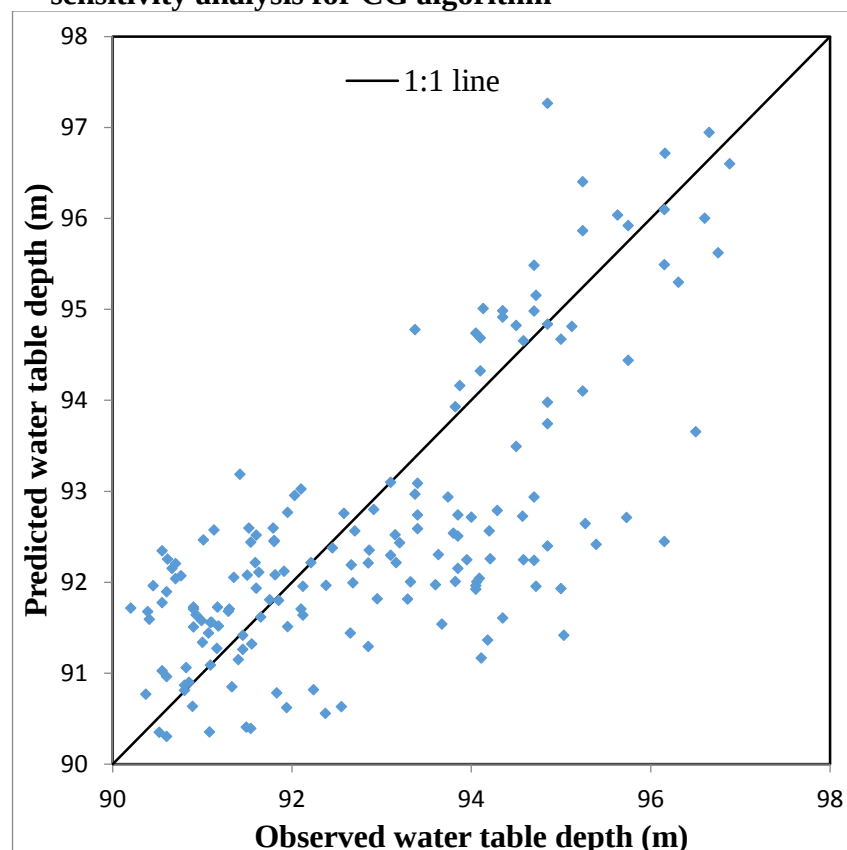


Fig.4.40: Scatter plot for observed and predicted water table depth of well 3 for CG algorithm

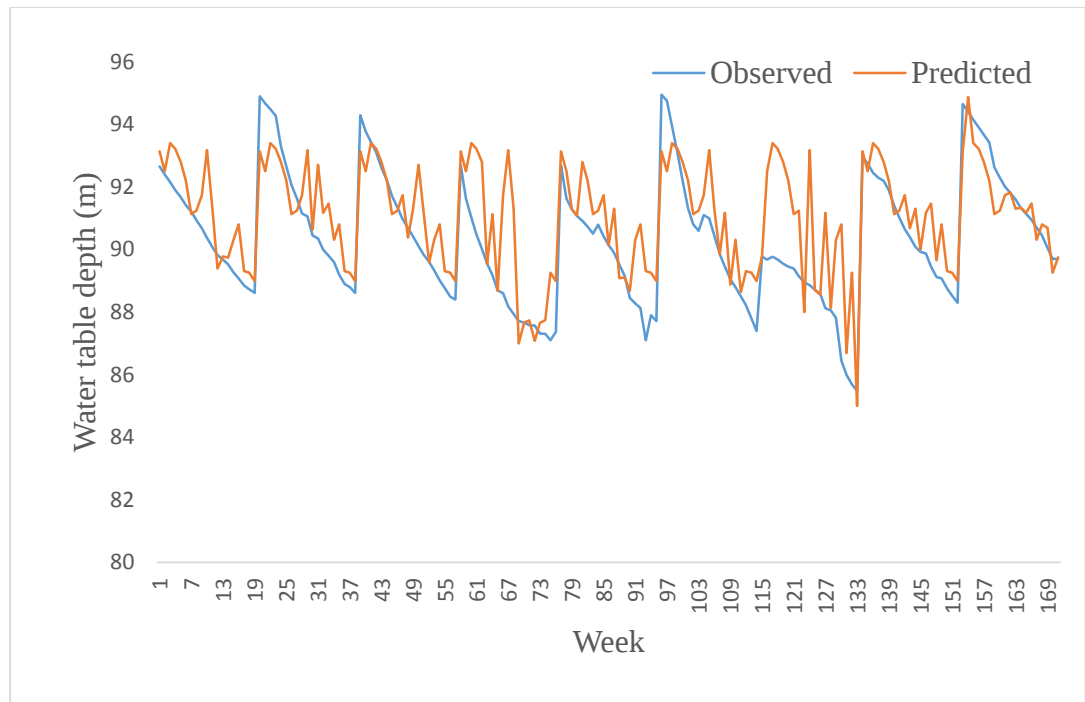


Fig.4.41: Observed and predicted weekly water table depth of well 4 for sensitivity analysis for LM algorithm

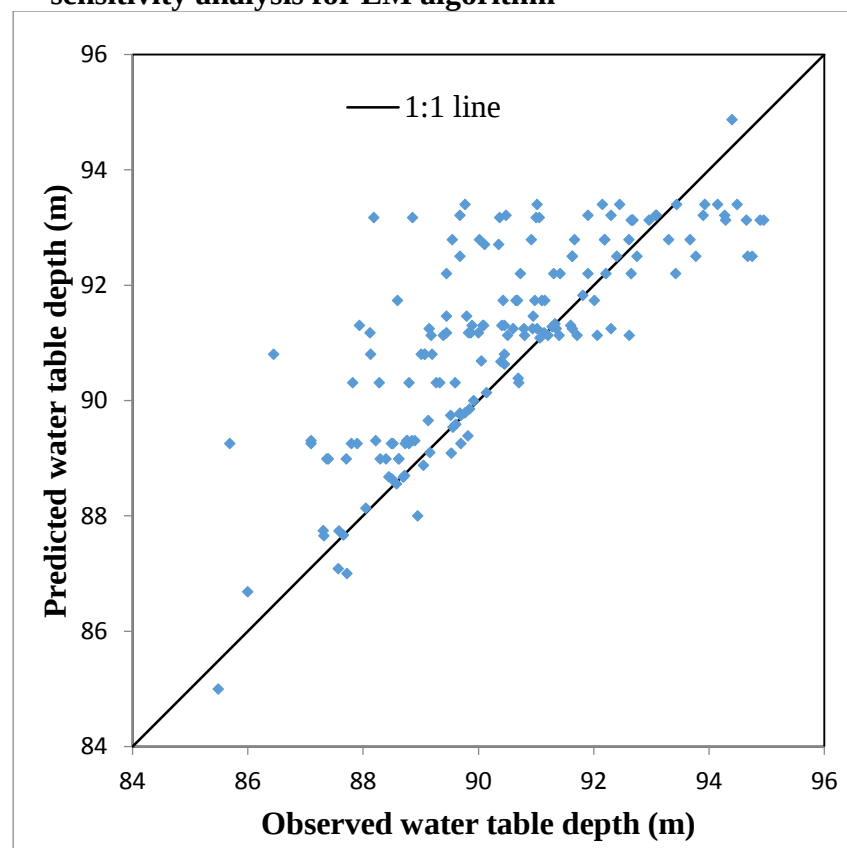


Fig.4.42: Scatter plot for observed and predicted water table depth of well 4 for LM algorithm

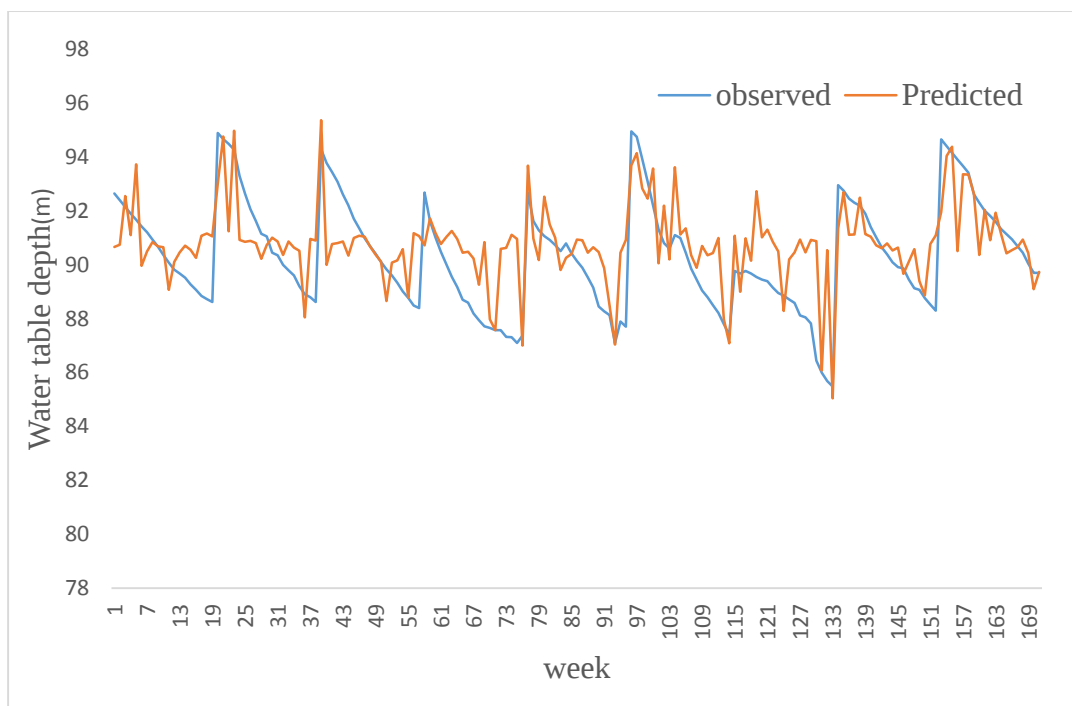


Fig.4.43: Observed and predicted weekly water table depth of well 4 for sensitivity analysis for CG algorithm

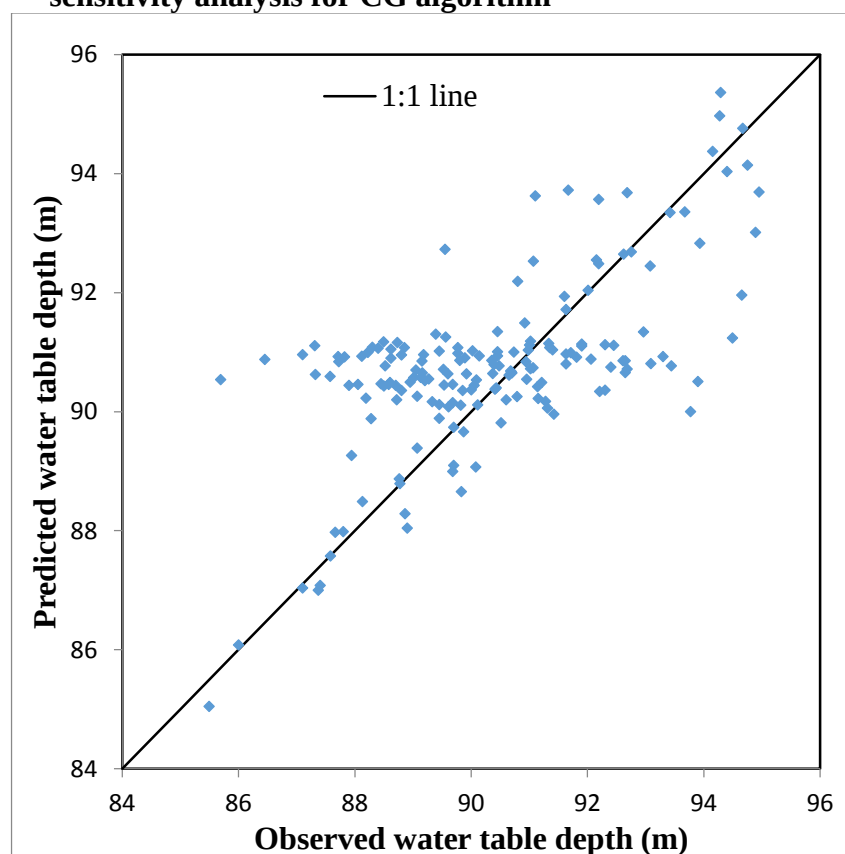


Fig.4.43: Scatter plot for observed and predicted water table depth of well 4 for CG algorithm

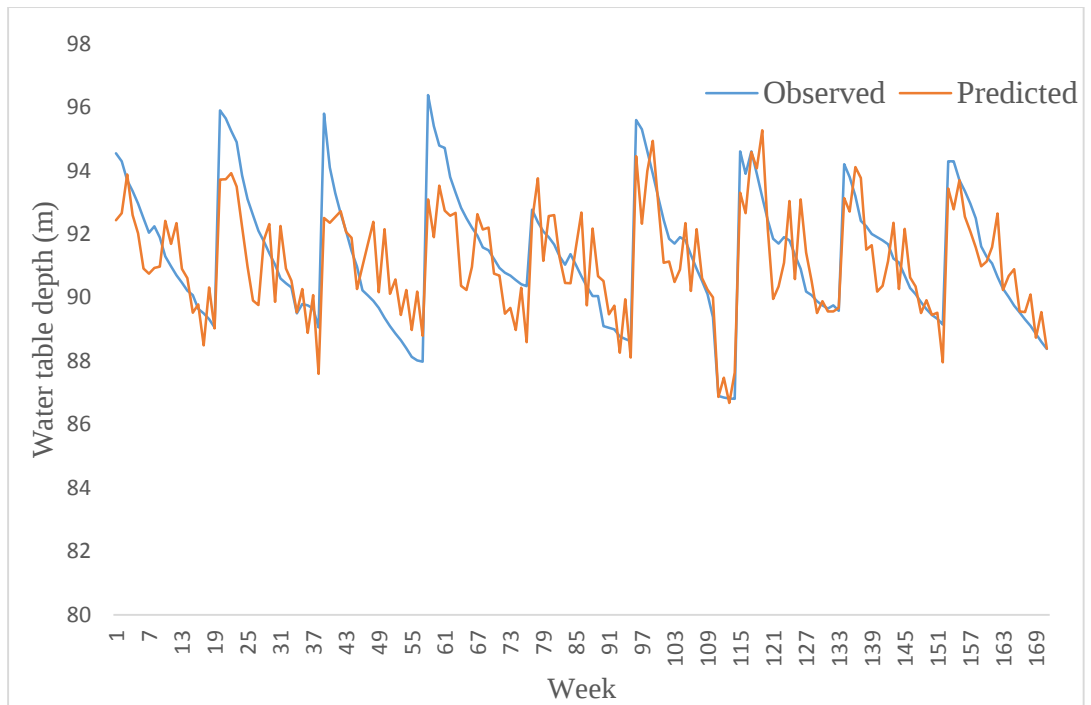


Fig.4.44: Observed and predicted weekly water table depth of well 5 for sensitivity analysis for LM algorithm

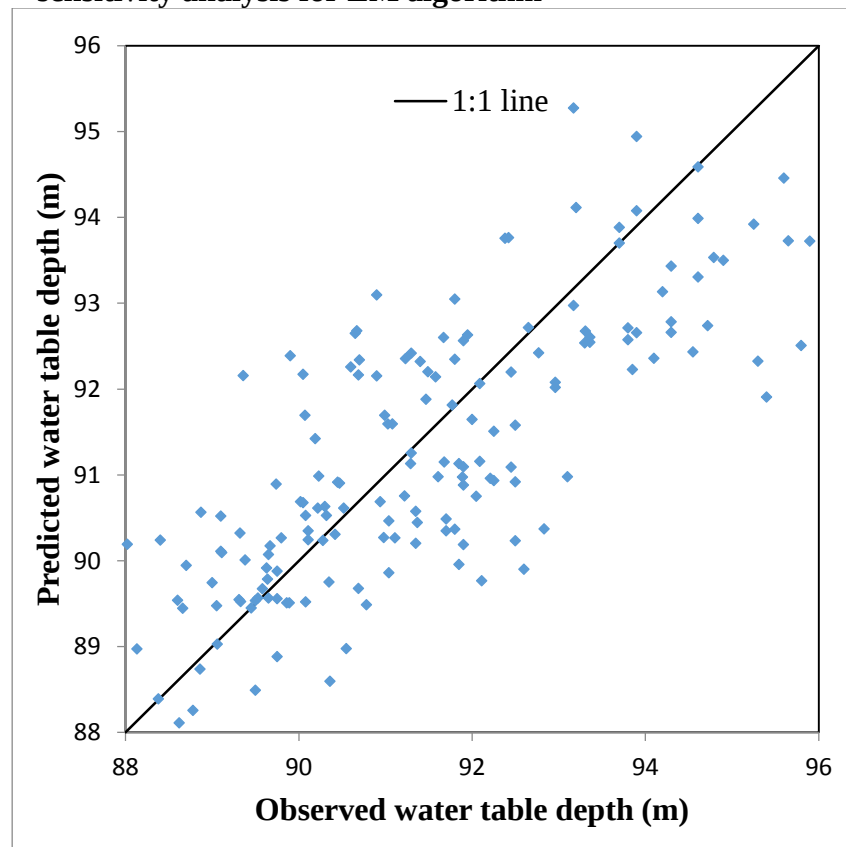


Fig.4.45: Scatter plot for observed and predicted water table depth of well 5 for LM algorithm

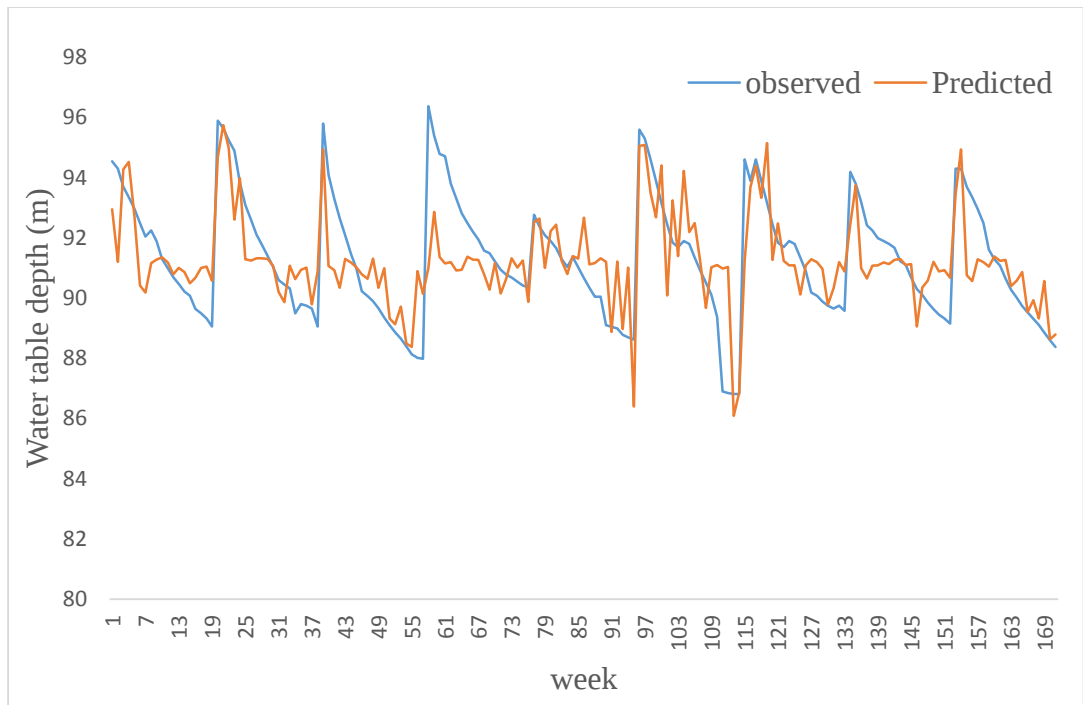


Fig.4.46: Observed and predicted weekly water table depth of well 5 for sensitivity analysis for CG algorithm

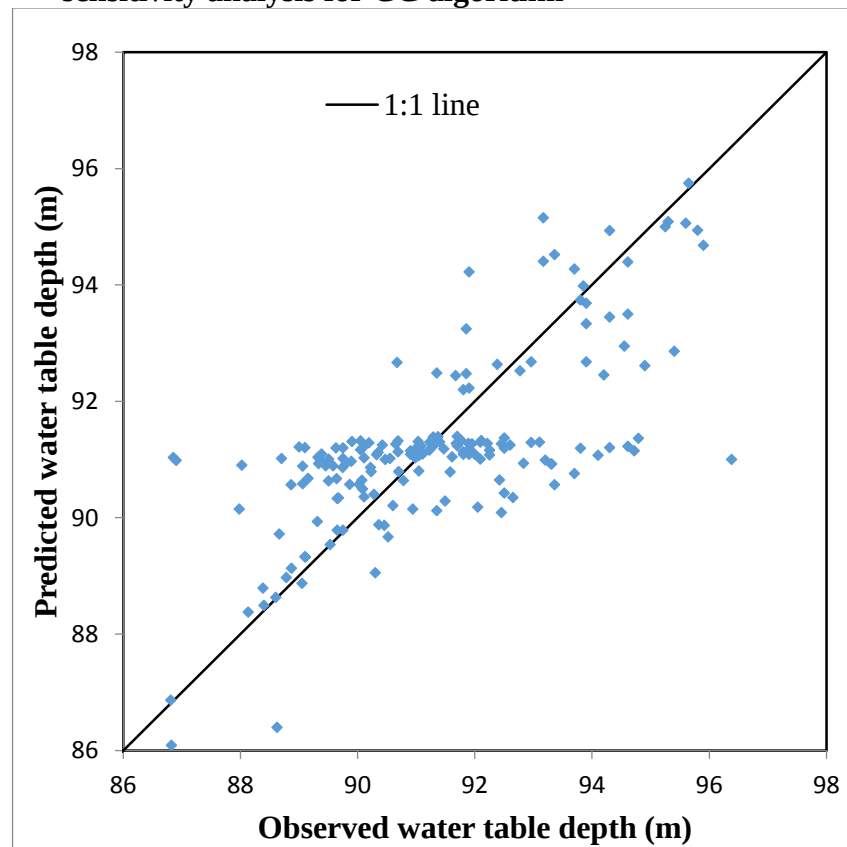


Fig.4.47: Scatter plot for observed and predicted water table depth of well 5 for CG algorithm

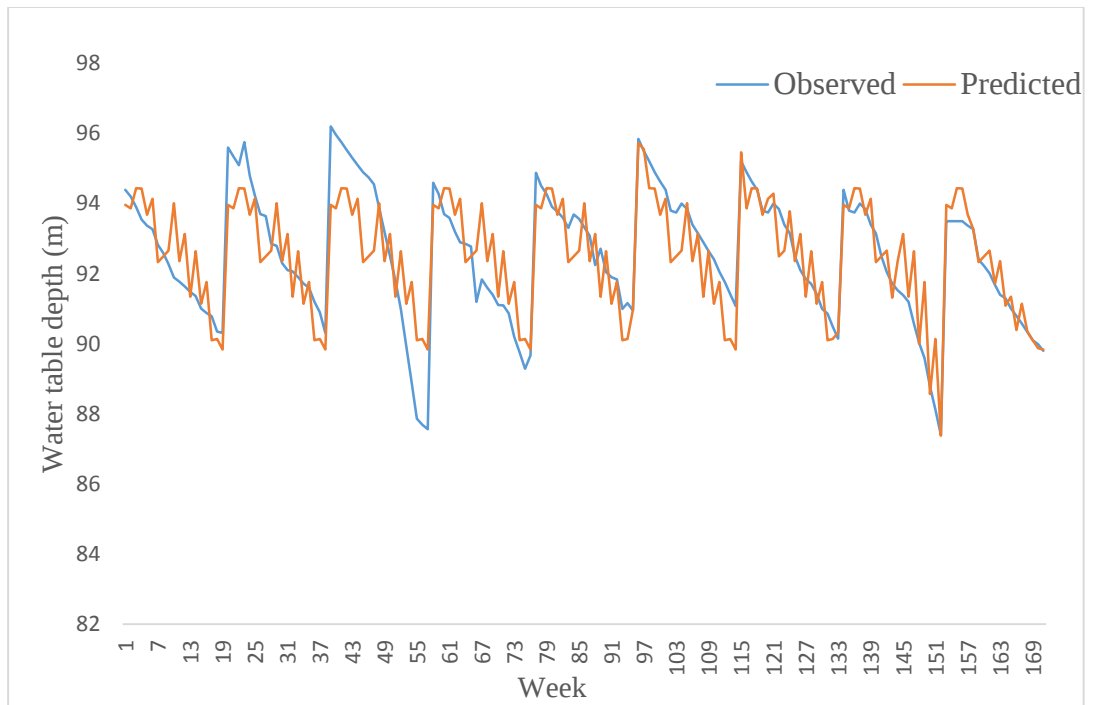


Fig.4.48: Observed and predicted weekly water table depth of well 6 for sensitivity analysis for LM algorithm

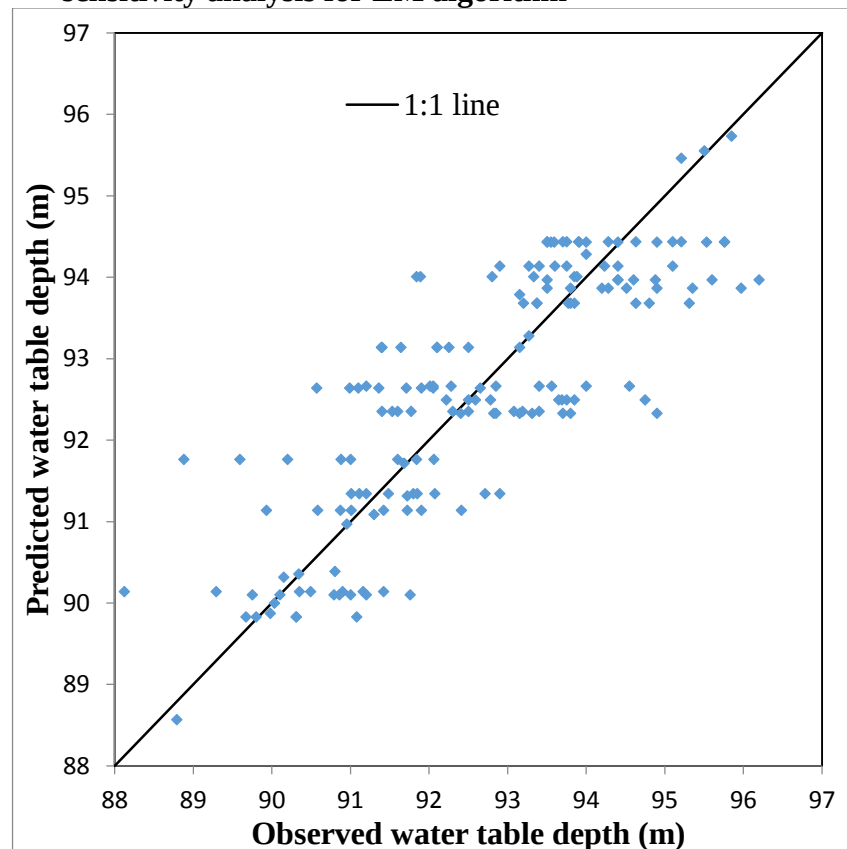


Fig.4.49: Scatter plot for observed and predicted water table depth of well 6 for LM algorithm

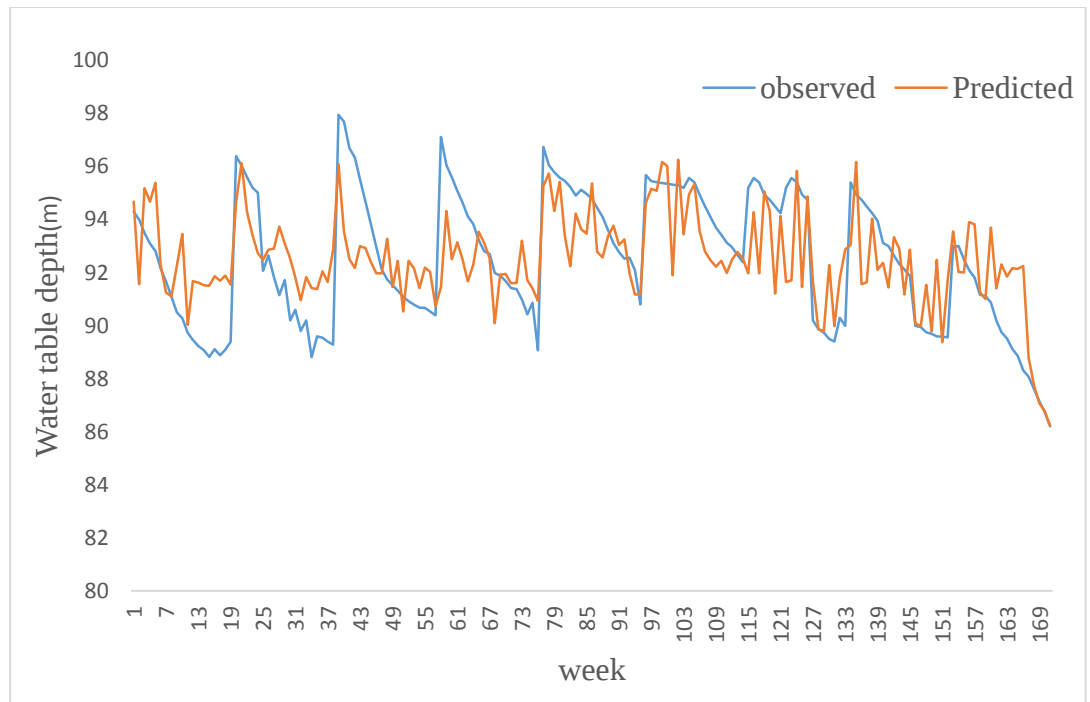


Fig.4.50: Observed and predicted weekly water table depth of well 6 for sensitivity analysis for CG algorithm

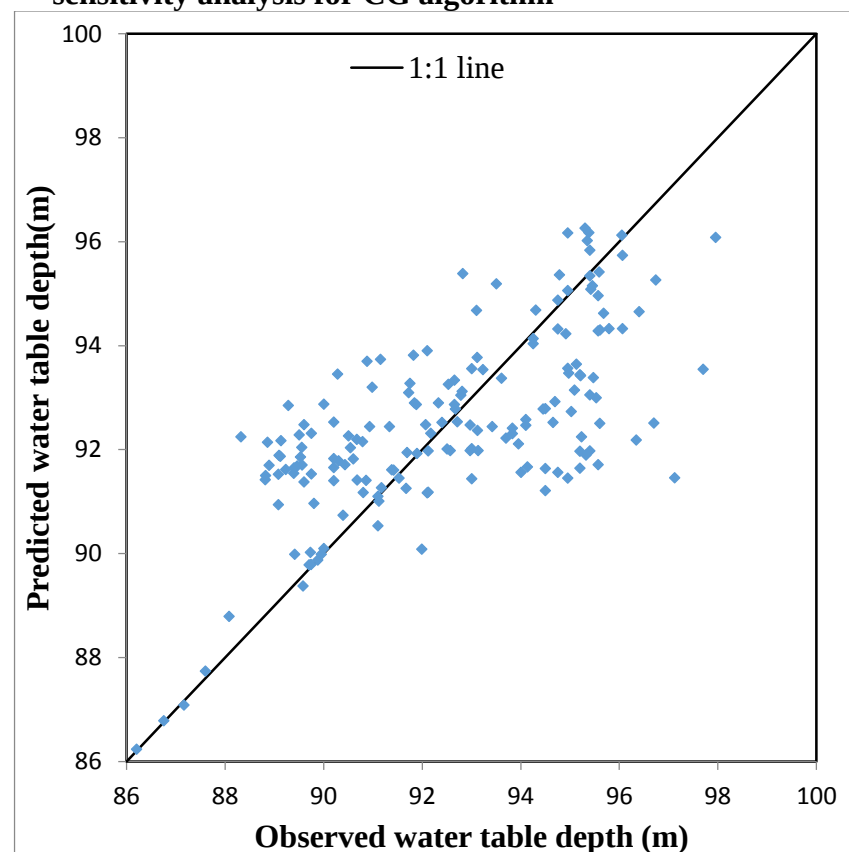


Fig.4.51: Scatter plot for observed and predicted water table depth of well 6 for CG algorithm

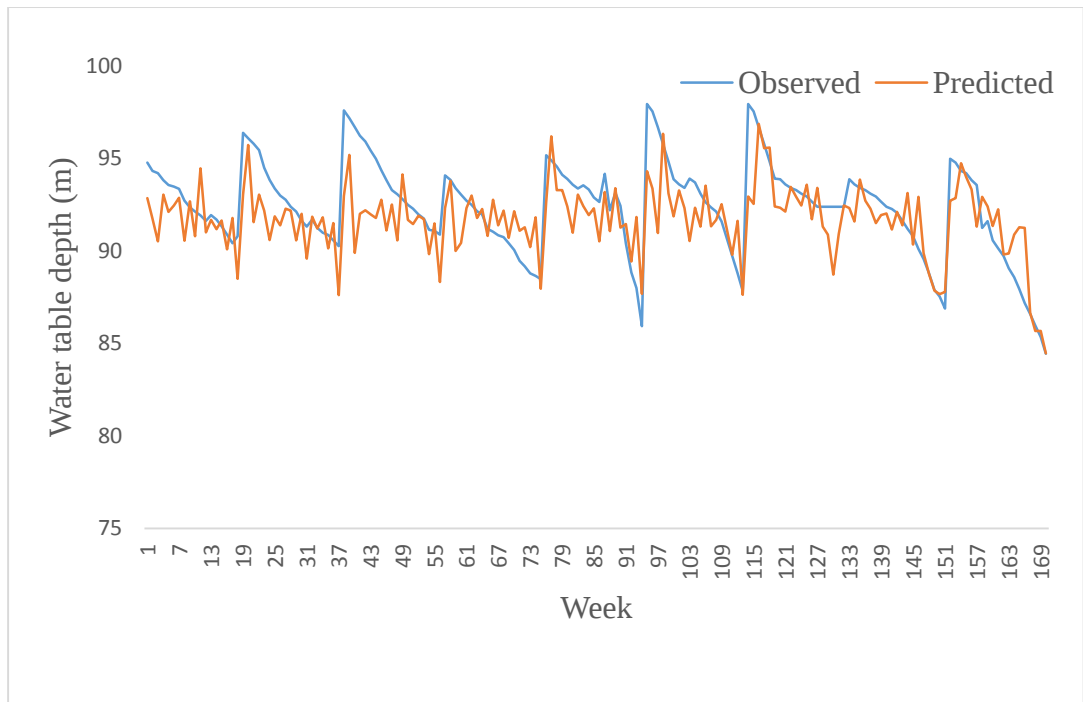


Fig.4.52: Observed and predicted weekly water table depth of well 7 for sensitivity analysis for LM algorithm

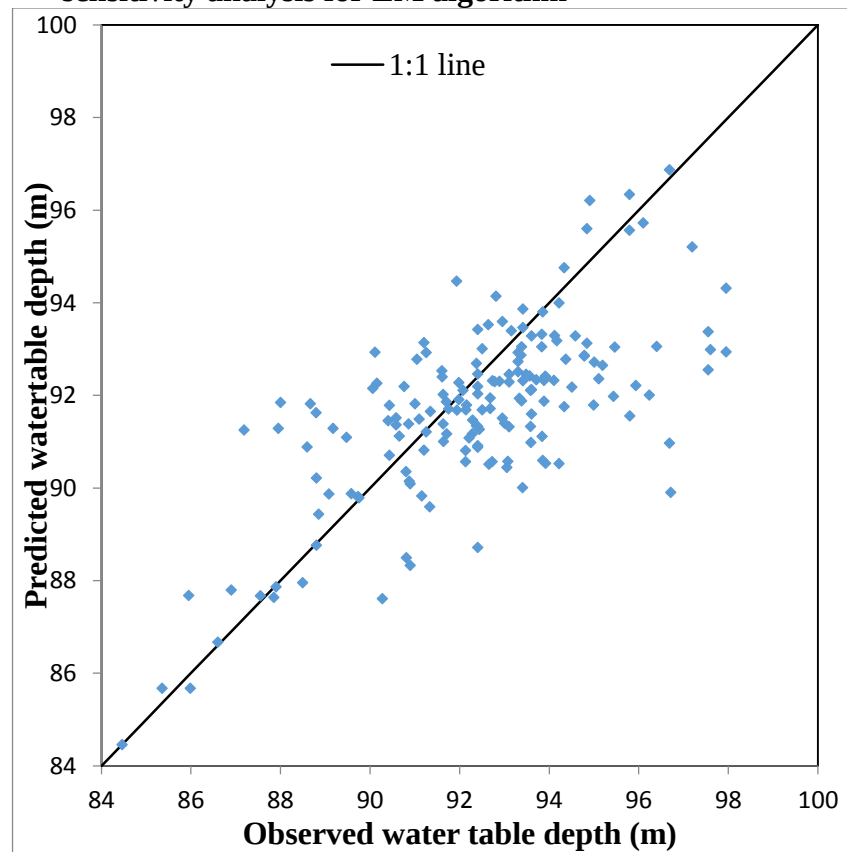


Fig.4.53: Scatter plot for observed and predicted water table depth of well 7 for LM algorithm

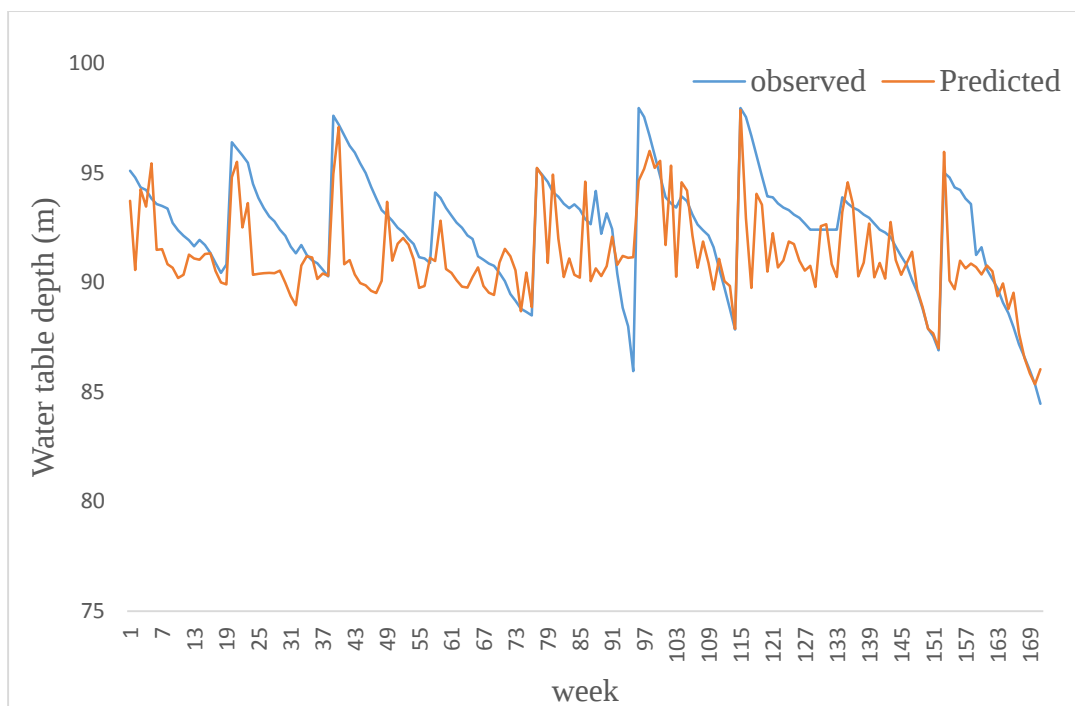


Fig.4.54: Observed and predicted weekly water table depth of well 7 for sensitivity analysis for CG algorithm

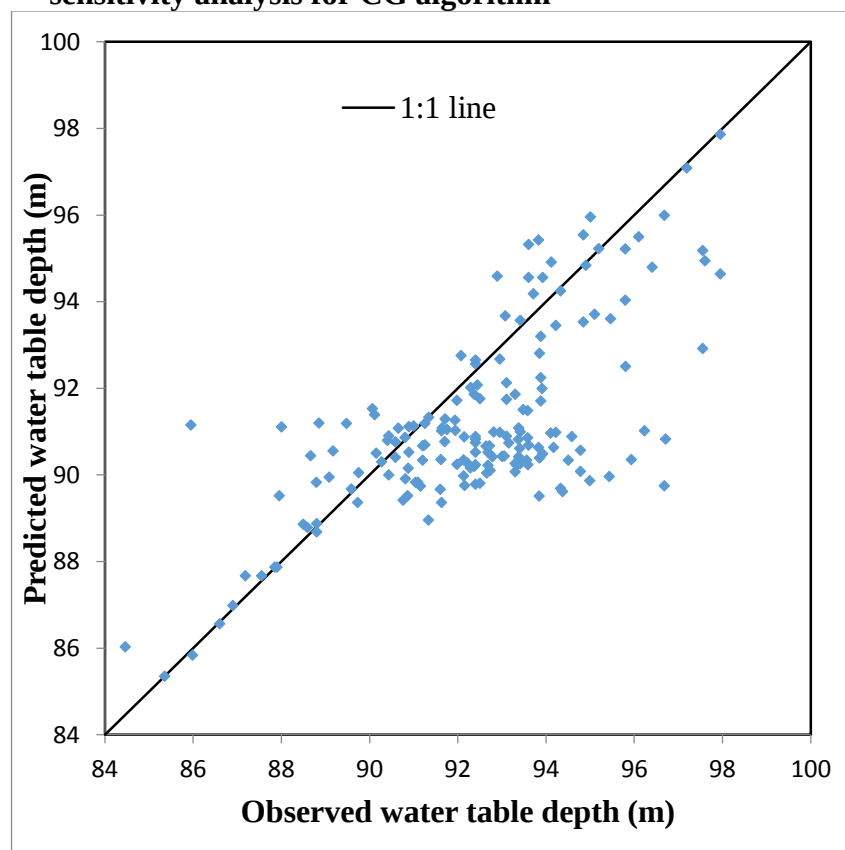


Fig.4.55: Scatter plot for observed and predicted water table depth of well 7 for CG algorithm

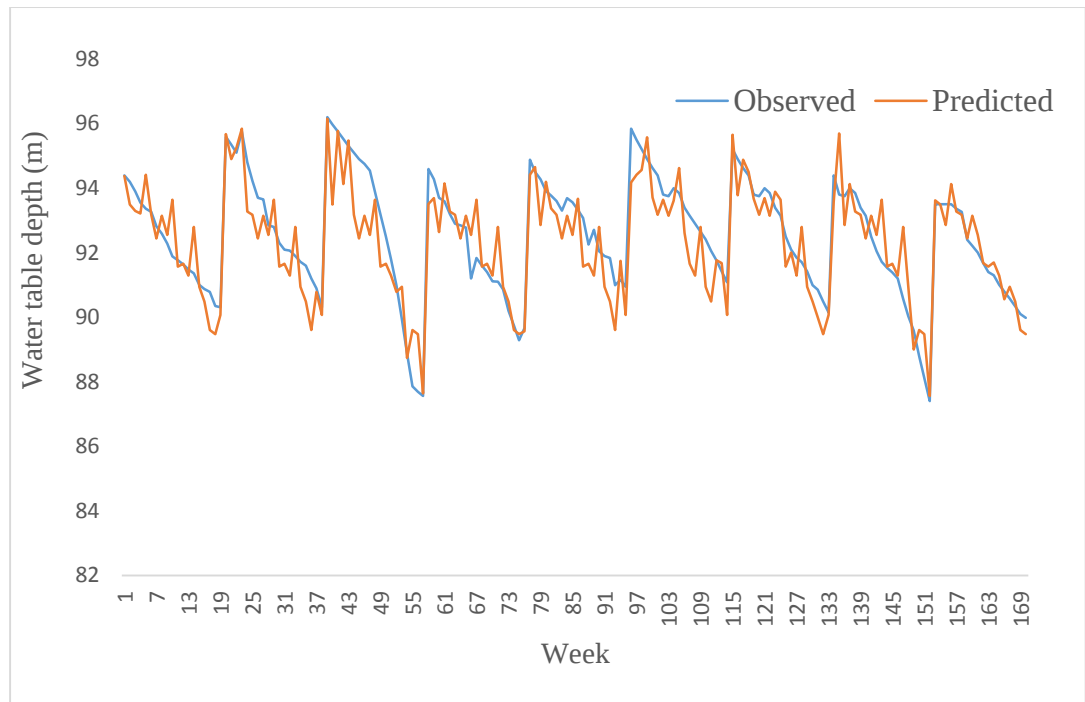


Fig.4.56: Observed and predicted weekly water table depth of well 8 for sensitivity analysis for LM algorithm

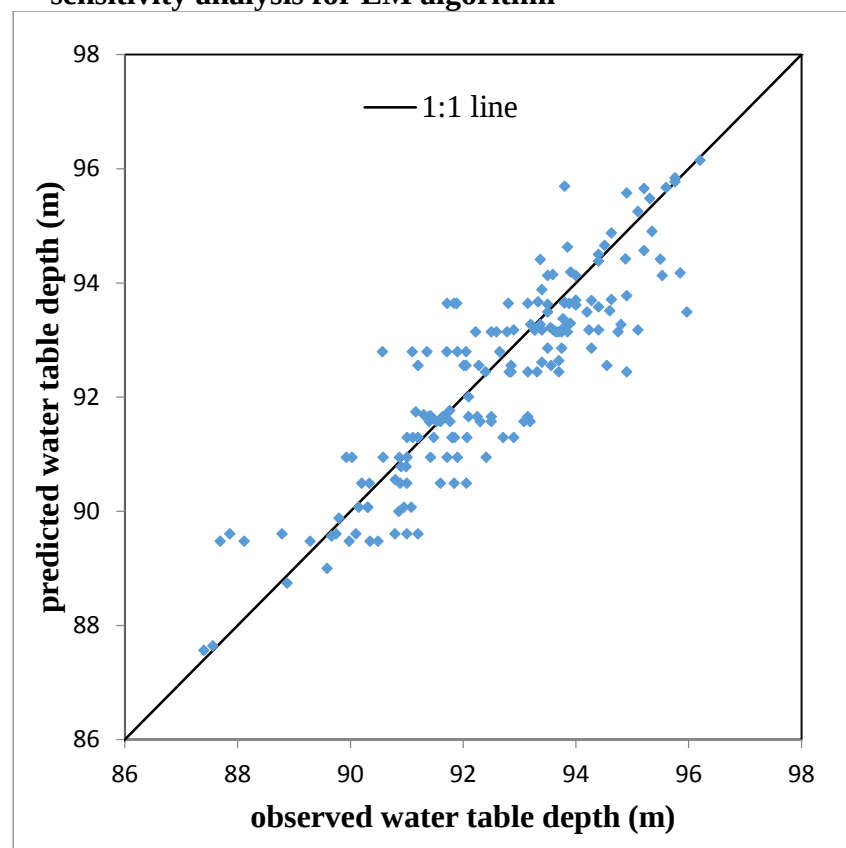


Fig.4.57: Scatter plot for observed and predicted water table depth of well 8 for LM algorithm

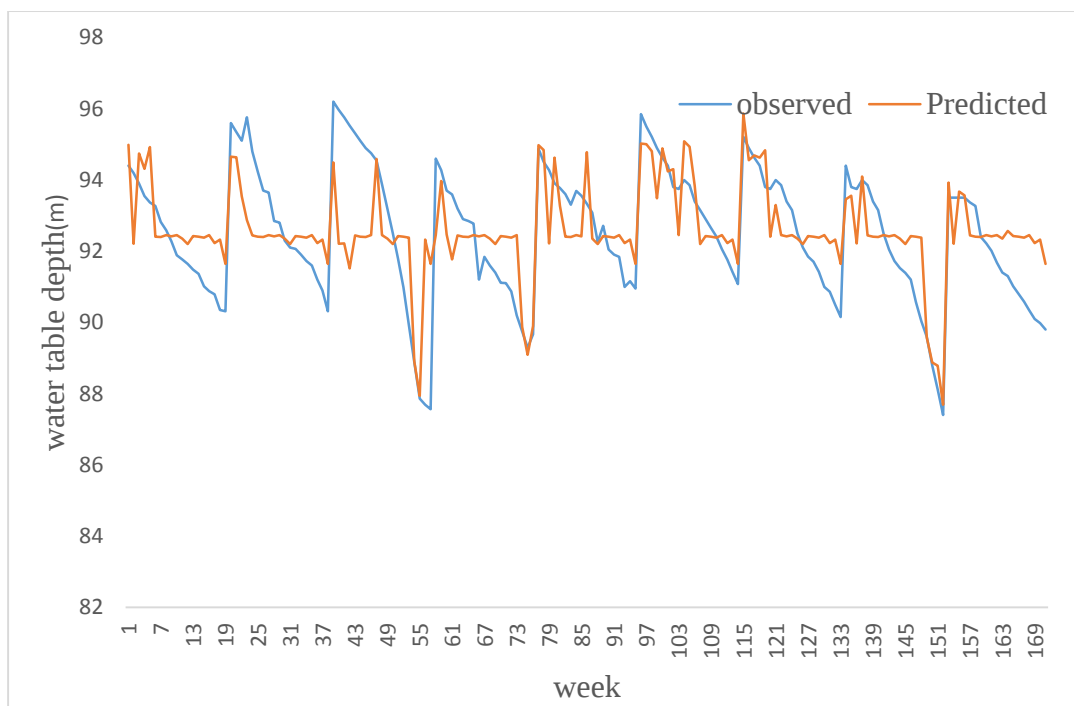


Fig.4.58: Observed and predicted weekly water table depth of well 8 for sensitivity analysis for CG algorithm

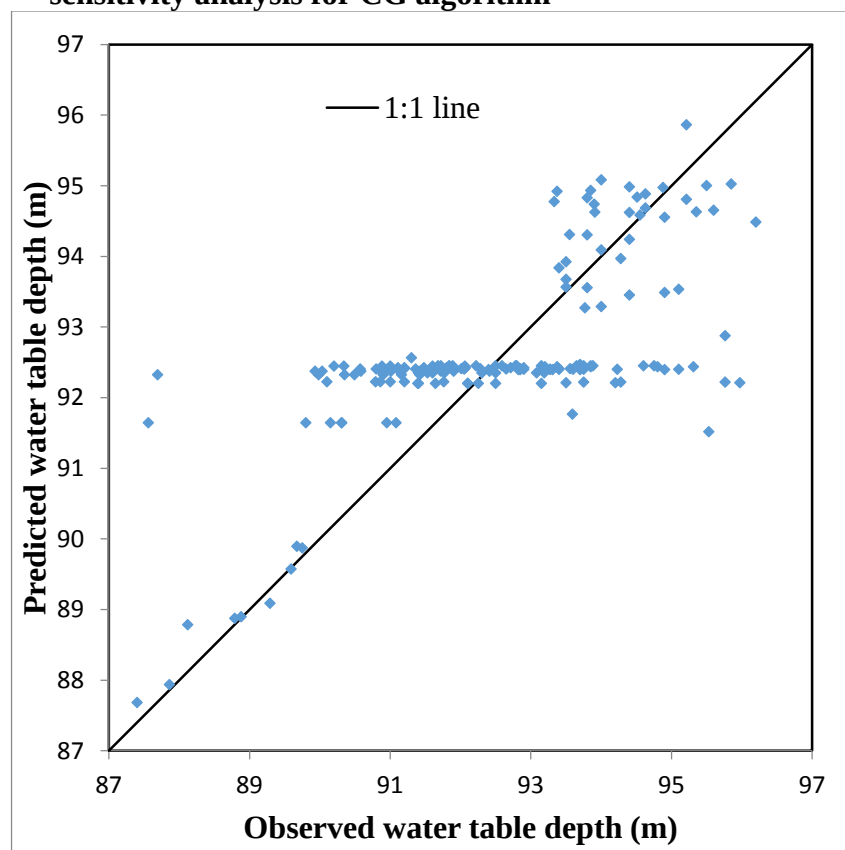


Fig.4.59: Scatter plot for observed and predicted water table depth of well 8 for CG algorithm

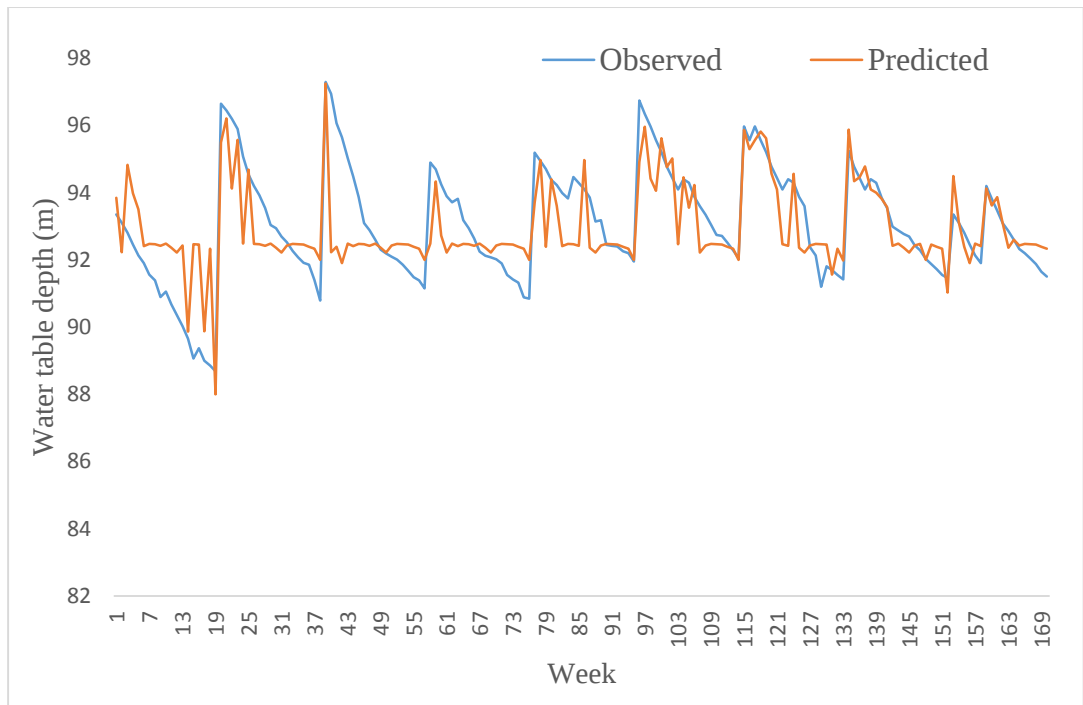


Fig.4.60: Observed and predicted weekly water table depth of well 9 for sensitivity analysis for LM algorithm

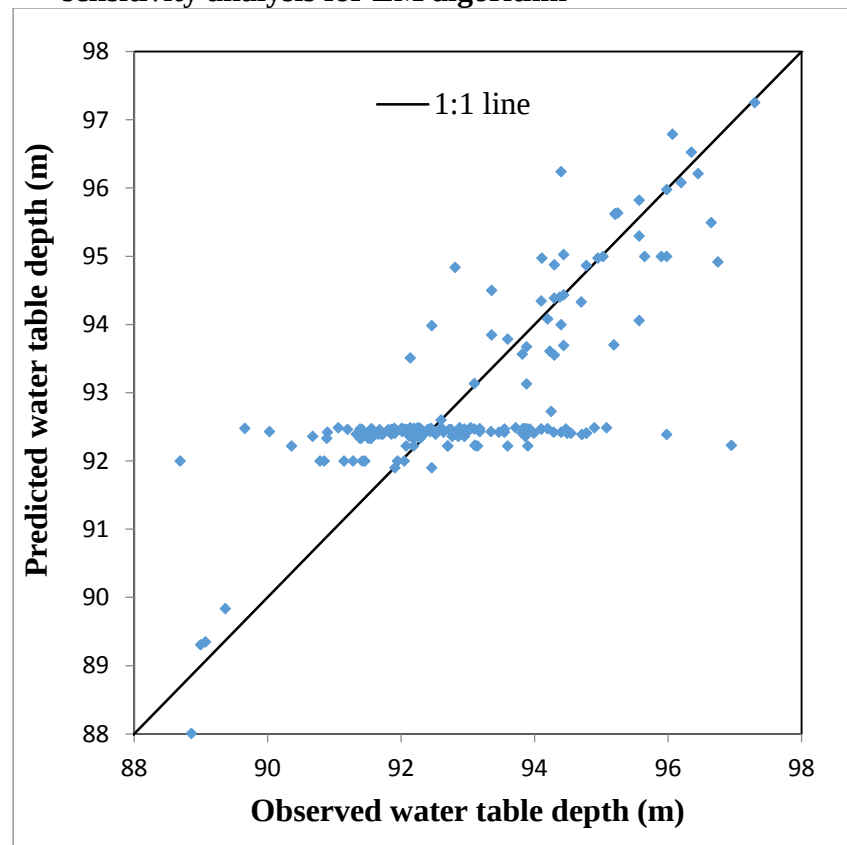


Fig.4.61: Scatter plot for observed and predicted water table depth of well 9 for LM algorithm

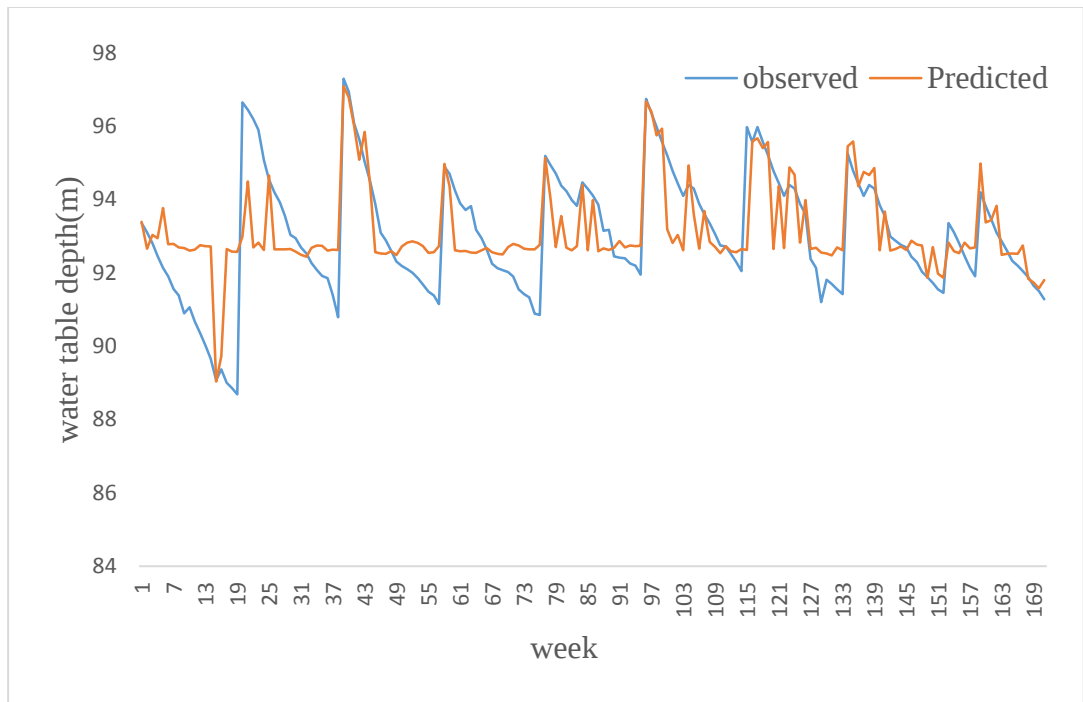


Fig.4.62: Observed and predicted weekly water table depth of well 9 for sensitivity analysis for CG algorithm

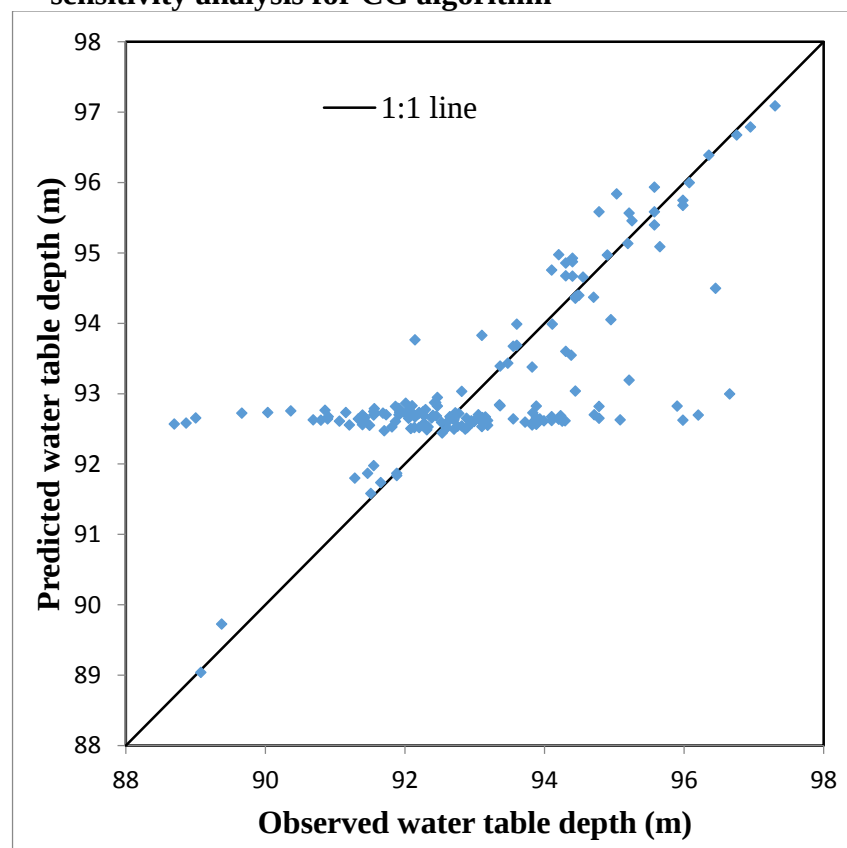


Fig.4.63: Scatter plot for observed and predicted water table depth of well 9 for CG algorithm

Considering sensitivity analysis for all the nine wells of LM and CG, the better graph pattern is shown in LM compared to that of CG. Because the predicted data almost overlapping the observed data.

The scatter plots shows the correlation of predicted data to the water depth of observed well. Shown in scatter plots Fig 4.30 to 4.63, the scatter plots concludes that Fig 4.30 of well 1 have moderately correlation to observed data with r greater than 0.717 but lesser than 0.8 (Sahoo *et al.*, 2017) and for well 7, R is 0.792 which is also moderately correlated, shown in Fig 4.53. All other well have strongly correlated with observed value with maximum value for well 2, R is 0.917 for Levenberg-Marquardt algorithm, shown in Fig 4.34.

Similarly, for Conjugate Gradient for well 9, r is 0.802, which is strongly correlated to the observed value, shown in Fig 4.63, rest of 8 wells are moderately correlated as the value of r is less than 0.8.

Table 4.4 to 4.5 shows the sensitivity analysis for all the nine well selected algorithms along with selected network architectures during sensitivity analysis. The step wise method for LM well 2 (2-9-1) were represented rank 1 and for well 1(2-9-1) were represented rank 9. The ranks were selected based upon MAE value of each well. Similarly for CG well 8 (2-8-1) were represented rank 1 and for well 6 (4-4-1) represent rank 9.

Table 4.4: Sensitivity analysis by stepwise method for LM algorithm

Wells	ANN Structure	R	MAE	Rank
1	2-9-1	0.717	0.010	9
2	2-9-1	0.917	0.003	1
3	1-8-1	0.861	0.005	3
4	1-6-1	0.800	0.009	7
5	2-9-1	0.842	0.006	5
6	1-9-1	0.886	0.005	4
7	3-5-1	0.792	0.010	8
8	2-9-1	0.901	0.005	2
9	2-9-1	0.810	0.006	6

Table 4.5: Sensitivity analysis by stepwise method for CG algorithm

Wells	ANN Structure	R	MAE	Rank
1	4-4-1	0.702	0.009	6
2	4-7-1	0.707	0.006	3
3	4-5-1	0.771	0.006	2
4	4-9-1	0.715	0.009	8
5	4-6-1	0.722	0.007	5
6	4-4-1	0.736	0.010	9
7	2-5-1	0.780	0.009	7
8	2-8-1	0.757	0.005	1
9	3-5-1	0.802	0.007	4

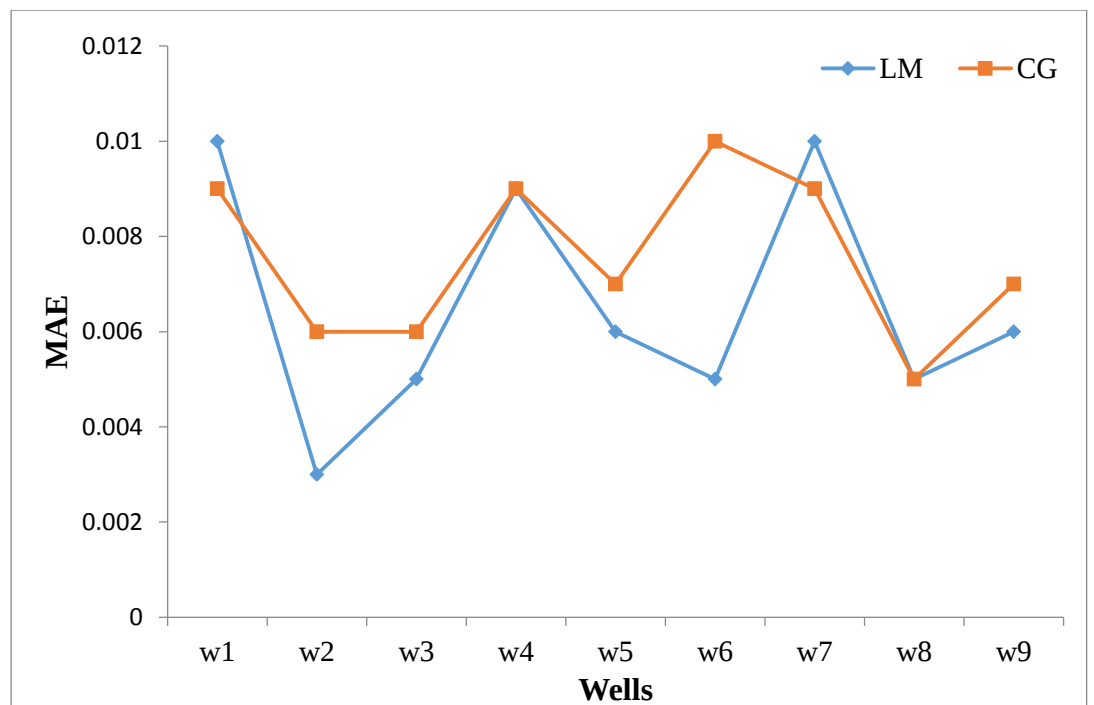


Fig.4.46 Comparison of sensitivity analysis of MAE between LM and CG

V. CONCLUSIONS

- The two algorithms i.e. Levenberg–Marquardt Algorithm (LM) and Conjugate Gradient Algorithm (CG), gave good predictions of water table depths in the study area.
- Results of sensitivity analysis showed that permeability is the most important variable for determining observed values. Levenberg-Marquardt (LM) was found to be best for well 1 (2-9-1), well 2 (2-9-1), well 3 (1-8-1), well 4 (1-6-1), well 5 (2-9-1), well 6 (1-9-1) and well 8 (2-9-1) while CG algorithm was better than LM for well 7 (2-5-1) and well 9 (3-5-1) .
- ANN models during sensitivity analysis showed that selected algorithms have predicted the water table depths in a better way in terms of its statistical performance.
- The sensitivity analysis in the study was useful for confirming and even slightly refining the conceptual framework of the system, as well as providing insights for improving ANN prediction performance.
- Sensitivity analysis showed that permeability parameter effects the output most. Three wells have permeability as only one input, which gives better results.
- The average R value for three well is 0.846.

VI. BIBLIOGRAPHY

- Al-Aboodi A. H., Kifah .M., Khudhair Ali. S. and Al-Aidani.. 2016. Prediction of Groundwater Level in Safwan-Zubair Area Using Artificial Neural Networks. *Basrah. Journal for Engineering Sciences*, vol. 16, (1):42-50.
- Anonymous, 2000. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. *Journal of Hydrologic Engineering*. Vol 5(2):115-123.
- Anonymous, 2017. Government of India Ministry of Water Resource River Development And Ganga Rejuvenation CGWB, Ground Water Year Book of Maharashtra and Union Territory of Dadar And Nagar Haveli.
- Asadi. Haniyeh., K. Shahedi., B. Jarihani. and R. C. Sidle., 2019. Rainfall-Runoff Modelling Using Hydrological Connectivity Index and Artificial Neural Network Approach. *Water*, Vol. 212(11); doi:10.3390/w11020212.
- Bustami, R, N. Bessaih, C. Bong, S. Suhaili. 2006. Artificial Neural Network for Precipitation and Water Level Predictions of Bed up River. *IAENG International Journal of Computer Science*, 34:2, IJCS_34_2_10 .
- Chang. Chia-Ling. and Chung-Sheng Liao. 2012. Parameter Sensitivity Analysis of Artificial Neural Network for Predicting Water turbidity. *International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering*, Vol 6(10):657-660.
- Chitsazan. M, Gholamreza. R. and A. Neyamadpour. 2015. Forecasting Groundwater Level by Artificial Neural Networks as an Alternative Approach To Groundwater Modeling. *Journal Geological Society of India*. Vol.85. Pp.98-106.
- Coppola E; Rana A; Poulton M; Szidarovszky F; Uhl V. 2005. A neural network model for predicting water table elevations. *Ground Water*, Vol. 43(2). pp.: 231-241.
- Coppola. Emery., Ferenc. Szidarovszky., Mary. Poulton. and Emmanuel. Charles. 2017. Artificial Neural Network Approach for Predicting Transient Water Levels in a

Multilayered Groundwater System under Variable State, Pumping, and Climate Conditions.vol.8(6):348-360.

Coulibaly. Paulin., Francois. Anctil., Ramon. Aravena. and Bernard Bobde. 2001. Artificial neural network modeling of water table depth fluctuations, *Journal of Water Research Resource* .vol. 37(4), Pp: 885-896. DOI: 10.1504/IJHST.2016.07934456.

Feng, S., S. Kang, Z. Huo, S. Chen and X. Mao. 2008. Neural networks to simulate regional ground water levels affected by human activities. *Ground Water*, 46(1):80–90.

Gangwar. Sneh 2013. Status, Quality and Management of Groundwater in India. *International Journal of Information and Computation Technology*. Vol:3,(7) ,pp. 717-722.

Gebdang. B., R., Ke Zhang., Hongjun Bao. and Xirong Ma. 2018. Application and Sensitivity Analysis of Artificial Neural Network for Prediction of Chemical Oxygen Demand *Water Resour Manage* vol. 32:273–283.DOI 10.1007/s11269-017-1809-0.

Gevrey. Murie., Ioannis. Dimopoulos. and Sovan. Lek. 2003. Review and comparison of methods to study the contribution of variables in artificial neural network models. *Ecological Modelling* 160: 249-264.

Ghadampour. Zahra. and Gholamreza. Rakhsh and Sehroo. 2010. Using Artificial Neural Network to Forecast Groundwater Depth in Union County Well. *International Journal of Civil and Environmental Engineering*, Vol:4,(2):52-55.

Hao. Jianbin. and Banqiao. Wang. 2014. Parameter Sensitivity Analysis on Deformation of Composite Soil-Nailed Wall Using Artificial Neural Networks and Orthogonal Experiment. *Mathematical Problems in Engineering*, Vol;1, pp 1-8 .doi: 10.1155/2014/502362.

- Haykin Simon. 2012. Neural Networks and Learning Machines. *Journal of Geoscience Research*, vol:3(2).
- Hung, N. Q., M. S. Babel, S. Weesakul, and N. K. Tripathi. 2008. An artificial neural network model for rainfall forecasting in Bangkok, Thailand. *Hydrology and Earth System Sciences Discussion*, 5:183-218.
- Husn. N. E. A., S. H. Bari., Md. M. H. Shourov., M. Tauhid and U. Rahman. 2016. Ground water level prediction using artificial neural network. *International Journal of Hydrology Science and Technology*, 6(4):371-381.
- Inan T. and G. Tayfur. 2012. A prediction model for the level of well water.. *Scientific Research and Essays*, Vol. 7(50), pp. 4242 - 4252.
- Lia. Q. and Y. P. Chen., 2010, Personalized text snippet extraction using statistical language models Pattern Recognition. *Pattern Recognition*. 43: 378 -386.
- Lohani. A. K and Krishan. G. 2015. Application of artificial neural network for Groundwater Level Simulation in Amitsar and gurudaspur districts of Punjab, India, *Journal of Earth Science and Climatic Change*. vol. 6:274:1-7. doi 10.4172/2157-7617.1000274.
- Maind. S. B. and Wankar P. 2014. Research Paper on Basic of Artificial Neural Network. *International Journal on Recent and Innovation Trends in Computing and Communication*. vol: 2(1) pp: 96-100.
- Mekanik. F., M. A. Imteaza., S. Gato-Trinidad., A. Elmahdi., 2013. Multiple regression and Artificial Neural Network for long-term rainfall forecasting using large scale climate modes *Journal of Hydrology* .503:11-21.
- Mohanty, S., M. K. Jha, A. Kumar, R. C. Srivastava and B. K. James. 2007. Groundwater level forecasting in Kathajodi River basin using artificial neural network. Third International Groundwater Conference (IGC-2007), held at TNAU, Coimbatore, India, TS-5-12.

- Nair. S .S. and Sindhu. G., 2016, Groundwater level forecasting using Artificial Neural Network. *International Journal of Scientific and Research Publications*, Vol: 6,(1):234-238.
- Nash J. E. And J. V. Sutcliffe., 1970. River Flow Forecasting Through Conceptual Models Part I- A Discussion Of Principles. *Journal Of Hydrology*, Vol.10: 282-290.
- Nayak. P., C., Y. R. Satyaji Rao. and K. P. Sudheer. 2006. Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach. *Journal of Water Resources Management*, 20: 77–90.
- Piaseck. Adam., Jakub. Jurasz. and Rajmund. Skowron. 2017. Forecasting Surface Water Level Fluctuations of Lake Serwy (Northeastern Poland) by Artificial Neural Networks And Multiple Linear Regression., Vol: 25(04): 379–388
<https://doi.org/10.3846/16486897.2017.1303498>.
- Piasecki. Adam., Jakub. Jurasz., Rajmund Skowron. 2015. Application of Artificial Neural Networks (ANN) in Lake Drwęckie water level modelling. *Limnol. Reva.*, Vol: 15(1), 21-29.DOI 10.2478/limre-2015-0003.
- Putra. E. A. P., A. Nugrahanti. and S. Kasmungin., 2018, Sensitivity analysis in using of artificial neural network models to determine infill well locations in a mature oil field. *Earth And Environmental Science*, Vol: 212:1-12.
- Rede. H. N. 2012. A Study of Fluctuations in the Level of Underground Water in Jalna district Maharashtra state, India *Geoscience Research*, Vol: 3 (2), pp.-109-111.
- Saha. Dipankar., Shashank Shekhar., Shakir Ali., S. S. Vittala. And N. J .Raju. 2016 Recent Hydrogeological Research in India. *Proc Indian Natn Sci Acad vol: 82(3)*: 787- 803. DOI: 10.16943/ptinsa/2016/48485.
- Sahoo. S., T. A. Russo., J. Elliott. and I. Foster. 2017. Water Resources Machine learning algorithms for modeling groundwater level changes in agricultural

regions of the U.S. *Journal of water resource research*. DOI: 10.1002/2016wr019933.

Sharma. B. and K. Venugopalan.,2014, Comparison of Neural Network Training Functions for Hematoma Classification in Brain CT Images. *IOSR Journal of Computer Engineering*. Vol: 16(1).pp: 31-35.

Shojaeefard. Mohammad. Hasan., Mostafa. Akbar., Mojtaba. Tahani. and Foad Farhani. 2013. Sensitivity Analysis of the Artificial Neural Network Outputs in Friction Stir Lap Joining of Aluminium to Brass. *Advances in Materials Science and Engineering*. Vol. 1 Article ID 574914, pp (7) <http://dx.doi.org/10.1155/2013/574914>.

Singh. Amandeep., Sushant. Bhardwaj., Sanjay. Kumar. and Narender Kumar. 2018. A review: Groundwater level forecasting using artificial neural network. *Journal of Pharmacognosy and Phytochemistry*. Vol:7(3): 2433-2436.

Sirhan, H. ,Koch, M. , 2013. Numerical Modeling of three-dimensional coupled Flow and Salinity Transport in the Gaza Coastal Aquifer, South Palestine , In: Proceedings of the “6th International Conference on Water Resources and Environment Research, ICWRER 2013”, Koblenz, Germany, June 3-7, 2013.

Sreekanth. P.D., Geethanjali. N., Sreedevi. P. D., Ahmed. Shakeel., Ravi. Kumar., N. and Kamala. Jayanthi. P. D. 2009, Forecasting groundwater level using artificial neural networks. *Current Science*, vol: 96(7). 933-939.

Suhag. R., 2016. Overview of groundwater in India . Committee Water Resources.1-11.

Sujatha. P. and G.N. P. Kumar., 2005. Prediction of Groundwater Levels Using Different Artificial Neural network Architectures and Algorithms, Proceedings on the international conference on artificial intelligence (ICAI), Unpublished Doctor of Philosophy thesis submitted to Dept of civil engineering, Sri Venkateshwara University, Tirupati.

- Sun. Yabin., Dadiyorto Wendi., Dong Eon Kim. and Shie-Yui Liong. 2016. Application of artificial neural networks in groundwater table forecasting a case study in a Singapore Swamp forest. *Hydrology and Earth System Science.*, 20, 1405–1412, 2. doi:10.5194/hess-20-1405-2016.
- Tsanis. Paulin. Coulibaly., Loannis. K., and Loannis. N. 2008. Improving groundwater level forecasting with a feed forward neural network and linearly regressed projected precipitation. *Journal of Hydro informatics*, Vol:10(4):317-330.
- Ty. T. V., L. V. Phat., H. V. Hiep., 2018. Groundwater Level Prediction Using Artificial Neural Networks: A Case Study in Tra Noc Industrial Zone, Can Tho City. *Journal of Water Resource and Protection*, Vol. 10, 870-883.
- Ünes. Fatih., Mustafa. Demirci., Eyup. Ispir., Yunus. Ziya. Kaya., Mustafa. Mamak. and Bestami. Tasar. 2017. Estimation of Groundwater Level Using Artificial Neural Networks: a case study of Hatay Turkey. (CC BY-NC 4.0) License. *International 10th Conference on Environmental Engineering Vilnius Gediminas Technical University, Lithuania*, 1-6.
- Wagh. V. M., R.S. Pawar, D.B. Panaskar and M.L. Aamalawar. 2014. Status of Groundwater Quality. *Asian Journal of Biochemical and Pharmaceutical Research*. Vol. 4(3):59-65.
- Waseem. M., N. Mani., G. Andiego. and M. Usman., 2017. A Review of Criteria of Fit For Hydrological Models. *International Research Journal of Engineering and Technology (IRJET)*. Vol.4 (11):1765-1772.

