Prediction of Water Table Elevation Fluctuation through Fuzzy Logic & Artificial Neural Networks

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Abstract

Soft Computing tools are becoming very popular in solving hydrological problems. These tools have immense strength to deal with such complex problems. Water Table elevation estimation is an important aspect to understand the mechanism of ground water resources. The present study aims at the application of Artificial Neural Networks (ANN) & Fuzzy logic for simulation of water table elevation. This paper also investigates the best model to forecast water table elevation. Ten ANN models are developed in this study. These developed models are trained, tested and validated on the available data of Budaun District. Comparing observed data and the estimated data through developed ANN models and Fuzzy models, it has been observed that the developed Fuzzy models predict better results for four models and for model-5 ANN bore better results.

Keywords: *Soft Computing, Artificial Neural Networks, Fuzzy models, Water table elevation*

1. Introduction

Groundwater is a highly valuable resource.Measurement and analysis of groundwater level is needed for maintaining groundwater availability. Worldwide, groundwater accounts for about one-third of one percent of the earth's water, or about 20 times more than the total of surface waters on continents & islands.The realisation of the concept of natural resources and its conservancy is presently looked upon as one of the main interests of our civilisation. About 97% of the world's water resources are confined in the sea with no practical value for human consumption. Of the remaining 3%, about 75% is bound in ice sheets, glaciers etc. and only 25% is available as surface water and groundwater. The distribution of this 25% consists of 0.3% in lakes and rivers, and remaining 99.7% is available as groundwater [8]. It is thus clear how important groundwater is, for agricultural, domestic, and industrial uses and is acquired by constructing and operating extraction wells, both in present and future scenario.

2. Groundwater Resource

Groundwater is water located beneath the earth's surface in soil pores and in the fractures of rock formation. Groundwater comes from rain, snow, sleet, and hail that soaks into the ground. The water moves down into the ground because of gravity, passing between particles of soil, sand, gravel, or rock until it reaches a depth where the ground is filled, or saturated, with water. The area that is filled with water is called the saturated zone and the top of this zone is called the water table .The water table may be very near to the ground's surface or it may be hundreds of feet below.

The water in lakes, rivers, or oceans is called surface water. Groundwater and surface water sometimes trade places. Groundwater can move through the ground and into a lake or stream. Water in a lake can soak down into the ground and become groundwater. Groundwater is stored in the ground in materials like gravel or sand. It's kind of like the earth is a big sponge holding all that water. Water can also move through rock formations like sandstone or through cracks in rocks. Groundwater may appear at the surface in the form of springs.

Mathematical groundwater models are obtained through solutions of suitably constrained differential equations that describe groundwater behaviour in a system of interest. These equations have been available since the late nineteenth century. The fact, which was more important that the availability of analytical solutions applied only to simplified solutions, which did not simulate the real time flow conditions. There are still many groundwater flow problems for which analytical solutions are difficult. The reason is that these problems are complex, possessing non-linear features that cannot be included in analytical solutions. Sometimes analytical solutions are yet applied to such problems by over simplifying the complex hydro-geological situation. Since the assumptions underlying the solution are approximations, it is obvious that the results will be inaccurate or at times even totally erroneous. Lack of data is especially the problem for physically distributed hydrological models [9].

3. Artificial Neural Network

The development of Artificial Neural Networks began approximately 50 years ago [15], inspired by a desire to understand the human brain and emulate its functioning. Within the last two decades, it has experienced a huge resurgence due to the development of more sophisticated algorithms and the emergence of powerful computation tools. It has been proved that ANN models show better results in river stage-discharge modelling in comparison to traditional models [7]. The human brain always stores the information as a pattern. Any capability of the brain may be viewed as a pattern recognition task. The high efficiency and speed with which the human brain processes the patterns inspired the development of ANN and its application in field of pattern recognition. ANN is a computing model that tries to mimic the human brain and the nervous system in a very primitive way to emulate the capabilities of the human being in a very limited sense. ANNs have been developed as a generalization of mathematical models of human cognition or neural biology. Comparison to a conventional statistical stage-discharge model show the superiority of an approach using ANN [6]. Basic principle of ANN is shown in Figure 1.

Development of ANN is based on the following rules:

1. Information processing occurs at many single elements called nodes, also referred to as units, cells, or neurons.
2. Signals are passed between nodes through connection links.
3. Each connection link has an associated weight that represents its connection strength.
4. Each node typically applies a nonlinear transformation called an activation function to its net input to determine its output signal.

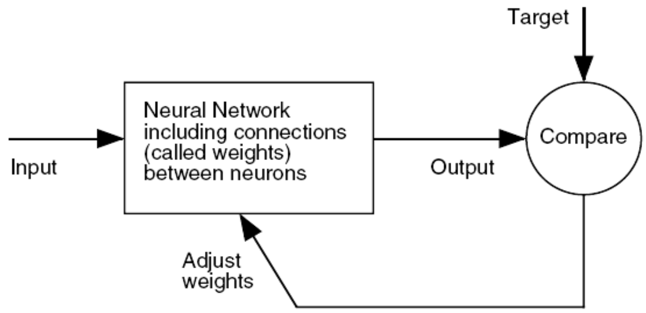

Figure 1. Basic Principle of Artificial Neural Networks

An ANN is network of parallel, distributed information processing system that relates an input vector to an output vector. It consists of a number of information processing elements called neurons or nodes, which are grouped in layers. The input layer processing elements receive the input vector and transmit the values to the next layer of processing elements across connections where this process is continued. This type of network, where data flow one way (forward), is known as a feedforward network. A feedforward ANN has an input layer, an output layer, and one or more hidden layers between the input and output layers. Each of the neurons in a layer is connected to all the neurons of the next layer, and the neurons in one layer are connected only to the neurons of the immediate next layer. The strength of the signal passing from one neuron to the other depends on the weight of the interconnections. It is found that ANNs are robust tools for modeling many of the nonlinear hydrologic processes such as rainfall-runoff, stream flow, ground-water management, water quality simulation, and precipitation [2]. The hidden layers enhance the network's ability to model complex functions. Performance of BPANN (Back Propagation Artificial Neural Network) models is compared with the developed linear transfer function (LTF) model and was found superior. ANNs was found to be very efficient in modeling stage-discharge relationship [10]. However, the integration of these different soft computing technologies to produce a single,hybrid solution, Adaptive neuro-fuzzy inference system(ANFIS)can be applied successfully and provide high level of accuracy and reliability for reservoir water level forecasting in the next three hours [12]. Also among ANN, MFIS, ANFIS, Soft Computing techniques, simulation results reveal that ANFIS is an efficient & promising tool for groundwater level forecasting [13].

4. Fuzzy Methodology

Fundamental aspect of the many hydro-geological studies is the problem of forecasting the water table depth at given points. During the last decade of 19th century, the artificial neural network and thereafter fuzzy logic techniques have become popular in data forecast of time series particularly in the application where the deterministic approach presented serious drawback, due to the noisy or random nature of data. These learning based approaches, which can be considered an alternative to classical methods, exploit the statistical relationships between inputs and outputs, without explicitly considering the physical process relationships, which exists between them. Although fuzzy logic attempts to simulate human "Vagueness" of reasoning, in practice many characteristics of this approach, such as ability to learn and generalize, the ability to cope up with noise, the distributed processing, which maintains robustness can be of great help in many engineering tasks. Moreover, in general, this technique can be included in overall concept of soft computing approach [16]. Faster running fuzzy logic rule-based models can also be used in place of existing, physical model in the modelling of filtration processes [4].Again the problem of groundwater modelling does not require a very precise measurement, and moreover a precise model can be very complicated and uneconomical in terms of development time. Secondly the variables involved in the problem are fuzzy in nature. Therefore, a fuzzy logic can provide better solutions in simple way [14]. Lofti A. Zadeh (1965) who proposed the fuzzy set theory in his seminal paper [18]. Fuzzy sets are distinguished from ordinary sets in terms of partial membership. Fuzzy set theory exhibits immense potential for effective solving of the uncertainty in the problem. Fuzziness means 'vagueness'. Fuzzy set theory is an excellent mathematical tool to handle the uncertainty arising due to vagueness. Understanding human speech and recognising characters are some common instances with fuzzy manifests [16]. Some relevant earlier works related to field are -For estimation of Groundwater recharge based on inputs temperature, rainfall stream flow [1]. Water level forecasting through fuzzy logic and ANN approaches [15]. Adaptive fuzzy modelling verses artificial neural networks. Water level forecasting in the Vembanad Water System using ANN [17]. Groundwater modelling using hybrid of artificial neural network with Genetic algorithm [11].

5. Study Area

Budaun District, the study area is a part of Ganga-Ramganga interbasin and it lies between longitudes of 78^0 15' and 79^0 30' E; and latitudes of 27^0 30' and 28^0 30' N.

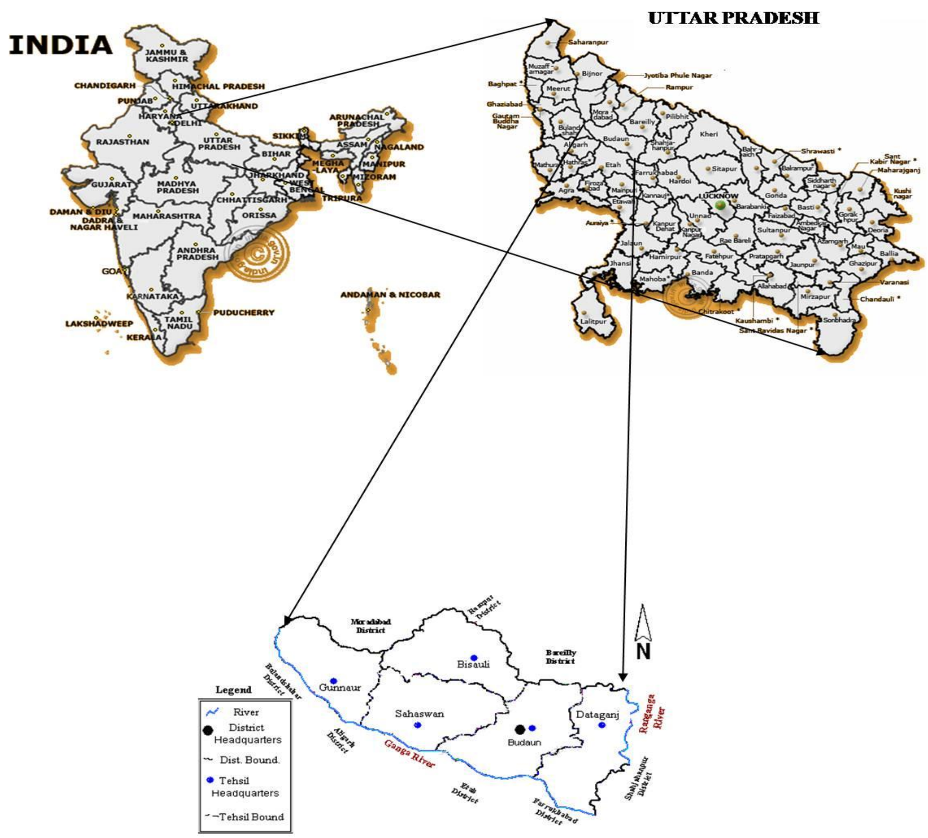

Figure 2. Index map of Baduan District

It is a part of Gangetic alluvial plain of quaternary to recent age with flat /topography and slopes from north-west to south-east. The height above mean sea level varies from 245 m in the extreme east to 298 m in the extreme north. It is plain of Ganga and Ramganga Rivers (Figure 2).

6. Methodology

Matlab 7.0 is used to develop ANN & Fuzzy logic models. The statistical and hydrological evaluation criteria used in the present study are Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE), Correlation Coefficient (R) and Coefficient of Efficiency (CE) or Coefficient of Determination (DC or R^2).

7. Development of Models

7.1 Development of Basic Models

Model 1:

A simple model was developed by taking two parameters ground water recharge and ground water discharge as input and water table elevation as output using the representation.

i.e., W (t) = f{R (t), D (t)}.

Model 2:

In this model our inputs are ground water recharge, ground water discharge for the current year and water table elevation for the previous year's post monsoon season and the output is water table elevation for the current year.

i.e., W (t) =f{R (t),D (t),W (t-1)}.

Model 3:

In this model our inputs are ground water recharge, ground water discharge for the current year and ground water recharge for the previous year's post monsoon season and the output is water table elevation for the current year.

i.e., W (t) =f{R (t), D (t), R (t-1)}.

Model 4:

In this model our inputs are ground water recharge, ground water discharge for the current year and ground water recharge for the previous year's post monsoon season and ground water discharge for the previous year's post monsoon season & the output is water table elevation for the current year.

i.e., W (t) =f{R (t), D (t), R (t-1), D (t-1)}.

Model 5:

In this model our inputs are ground water recharge, ground water discharge for the current year and ground water recharge for the previous year's post monsoon season and ground water discharge for the previous year's post monsoon season, water table elevation for the previous years post monsoon season & the output is water table elevation for the current year.

i.e., W(t)=f{R(t),D(t),R(t-1),D(t-1) ,W(t-1)}.

7.2 ANN Water table Elevation Fluctuation Models

All five basic models are developed for one hidden layer & two hidden layers. For two hidden layers models, number of neurons is varied by hit & trial. Thus best model was selected for two hidden layers for a particular model on the basis of correlation coefficient(R). We arrived at ten models, five for one hidden layer & five for two hidden layers (Table 1).

Table 1. Development of Various ANN Water Table Elevation Models

Model	No. of hidden layers	Output	Input Variables
ANN – 1	One	Wt	Rt, Dt
ANN – 2	One	Wt	Rt, Dt, Wt-1
ANN – 3	One	Wt	Rt, Dt, Rt-1
ANN – 4	One	Wt	Rt, Dt, Rt-1, Dt-1
ANN – 5	One	Wt	Rt, Dt, Rt-1, Dt-1, Wt-1
ANN – 1	Two	Wt	Rt, Dt
ANN – 2	Two	Wt	Rt, Dt, Wt-1
ANN – 3	Two	Wt	Rt, Dt, Rt-1
ANN – 4	Two	Wt	Rt, Dt, Rt-1, Dt-1
ANN – 5	Two	Wt	Rt, Dt, Rt-1, Dt-1, Wt-1

Table 2. Water table Elevation Fluctuation ANN Models

S. No.	Best Model	Hidden Layer	R^2	R	MAD	RMSE
1	**ANN – 1**	**One**	**0.915**	**0.957**	**0.5846**	**0.7285**
2	ANN – 2	One	0.913	0.9593	0.5916	0.759
3	ANN – 3	One	0.889	0.9429	0.63631	0.8444
4	ANN – 4	One	0.848	0.9022	1.3856	1.5768
5	ANN – 5	One	0.913	0.9495	0.6	0.81162
6	ANN –1	Two	0.949	0.9525	0.4653	0.62217
7	**ANN – 2**	**Two**	**0.955**	**0.9767**	**0.2927**	**0.531218**
8	ANN – 3	Two	0.87	0.89	0.3126	0.9128
9	ANN – 4	Two	0.917	0.9715	0.636944	0.79808
10	ANN – 5	Two	0.828	0.9345	0.848	1.10058

Table 2 gives the tabulation of performance of the different models with one hidden layer and two hidden layers. The performance indicators in throughout the study are Correlation Coefficient(R), Coefficient of Efficiency (R^2), Mean Absolute Deviation (MAD) & Root Mean Square Error (RMSE).

7.3 Development of Fuzzy Models

In rule based fuzzy systems, relationships among variables are represented by means of fuzzy if-then rules *e.g.*, “if antecedent proposition then consequent proposition”. In this paper five fuzzy models are developed using inputs as recharge and discharge with specified time lag and level of water table as output.

8. Results and Discussion

8.1 Comparative Analysis of ANN Models and Fuzzy Models for Water Table Elevation Fluctuation.

MODEL 1:

a) ANN Model 1- (hidden layer two)

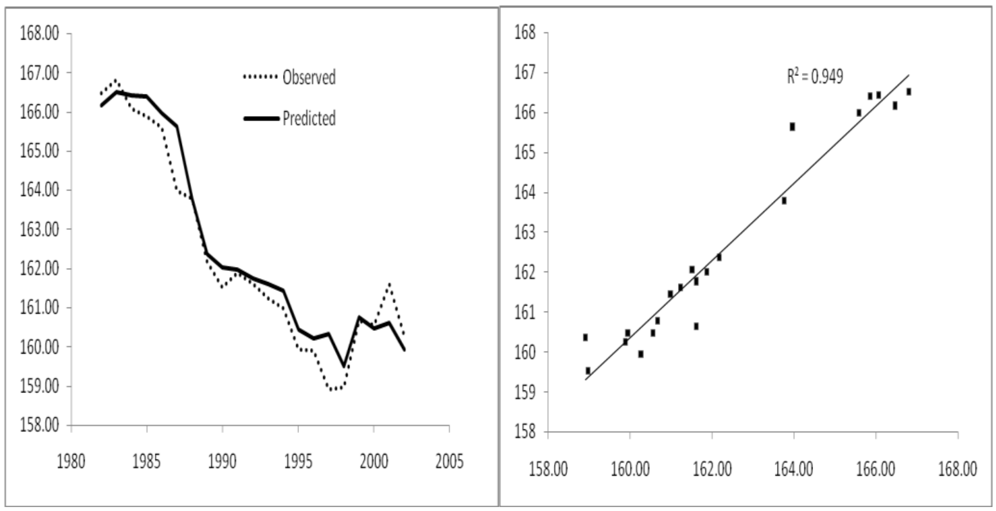

Figure 3(a) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for ANN1

b) Fuzzy Model 1:

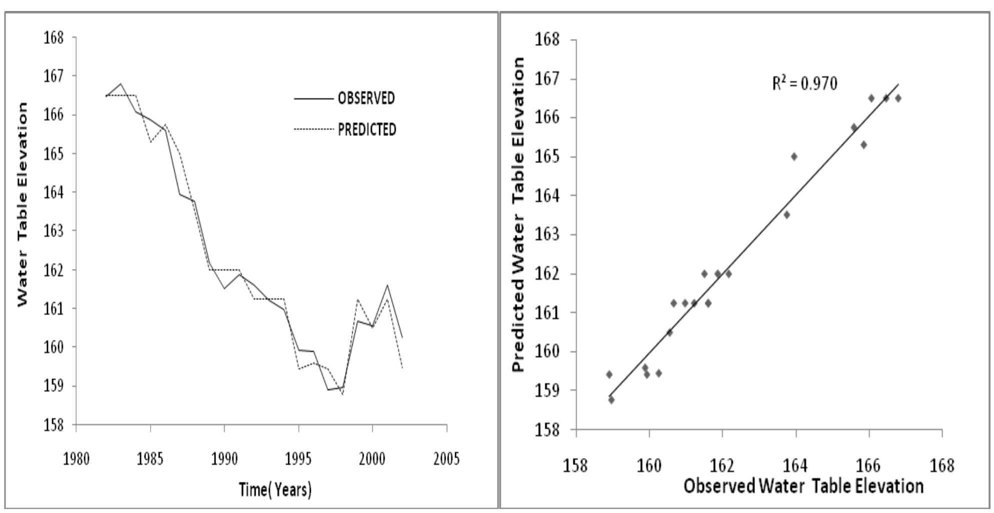

Figure 3(b) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for Fuzzy Model 1

MODEL 2:

a) ANN Model 2- (hidden layer two)

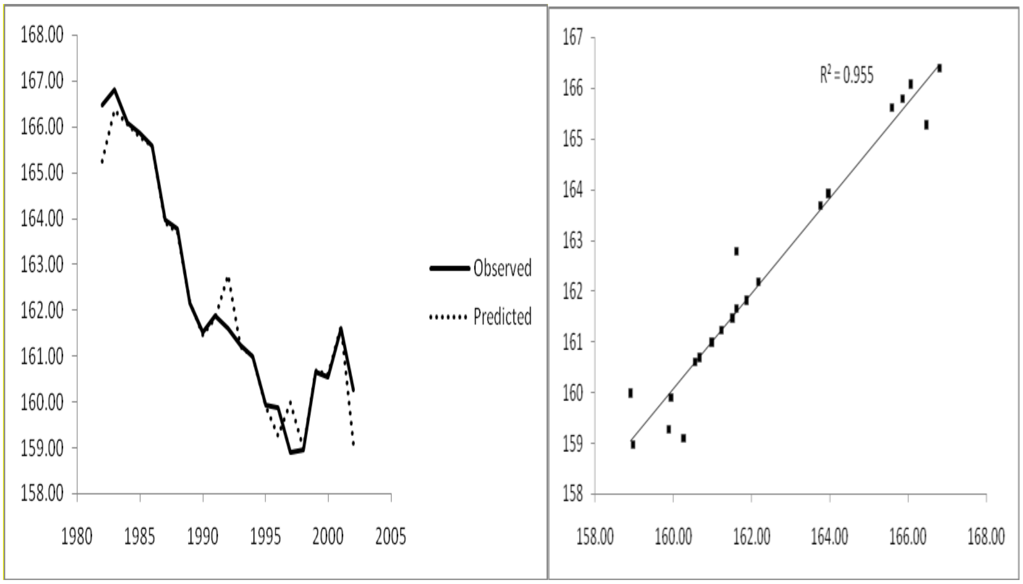

Figure 4(a) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for ANN2

b) Fuzzy Model 2

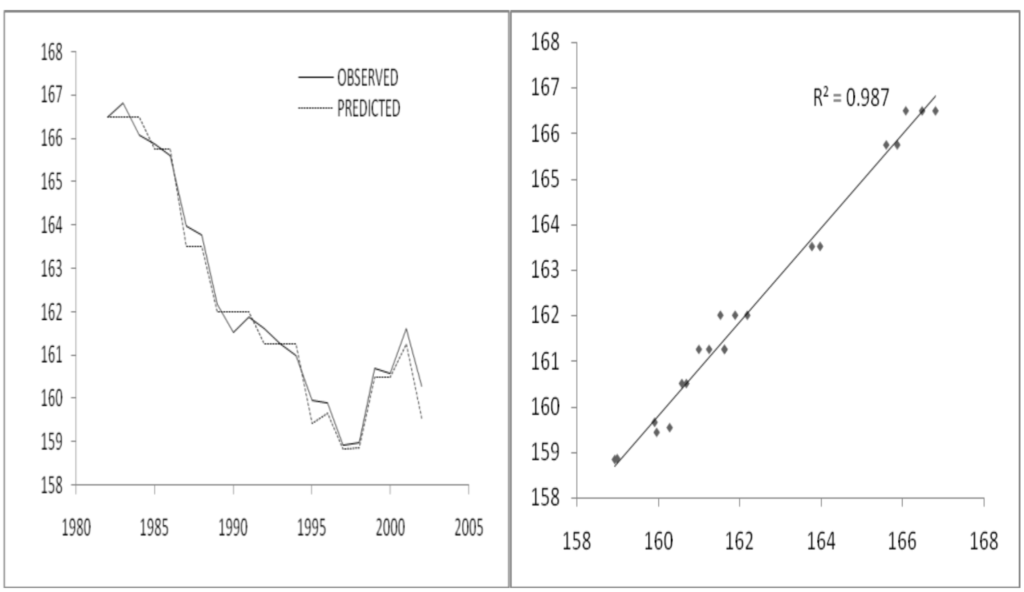

Figure 4(b) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for Fuzzy Model 2

MODEL 3:

a) ANN Model 3- (hidden layer one)

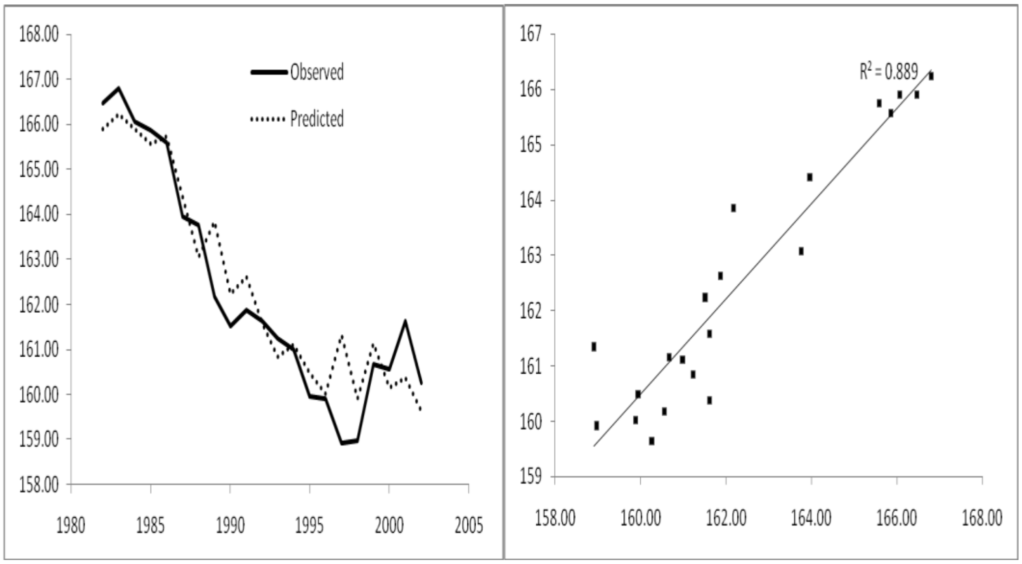

Figure 5(a) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for ANN3

b) Fuzzy Model 3

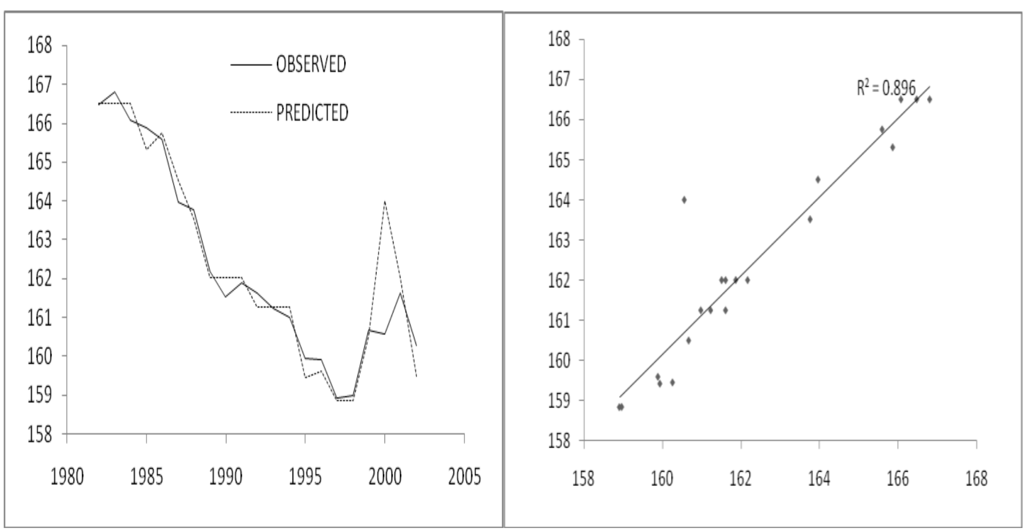

Figure 5(b) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for Fuzzy Model 3

MODEL 4:

a) ANN Model 4- (hidden layer one)

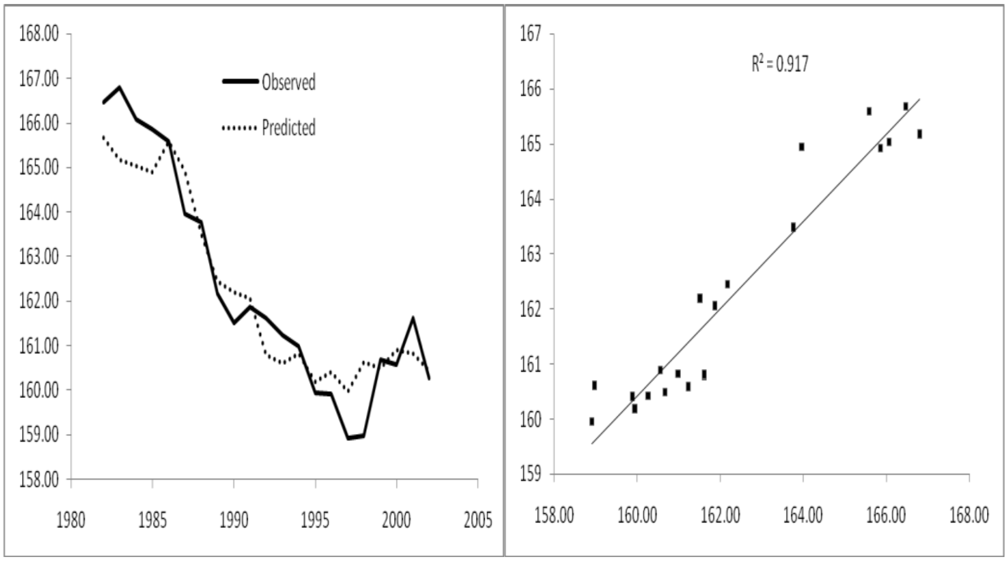

Figure 6(a) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for ANN4

b) Fuzzy Model 4

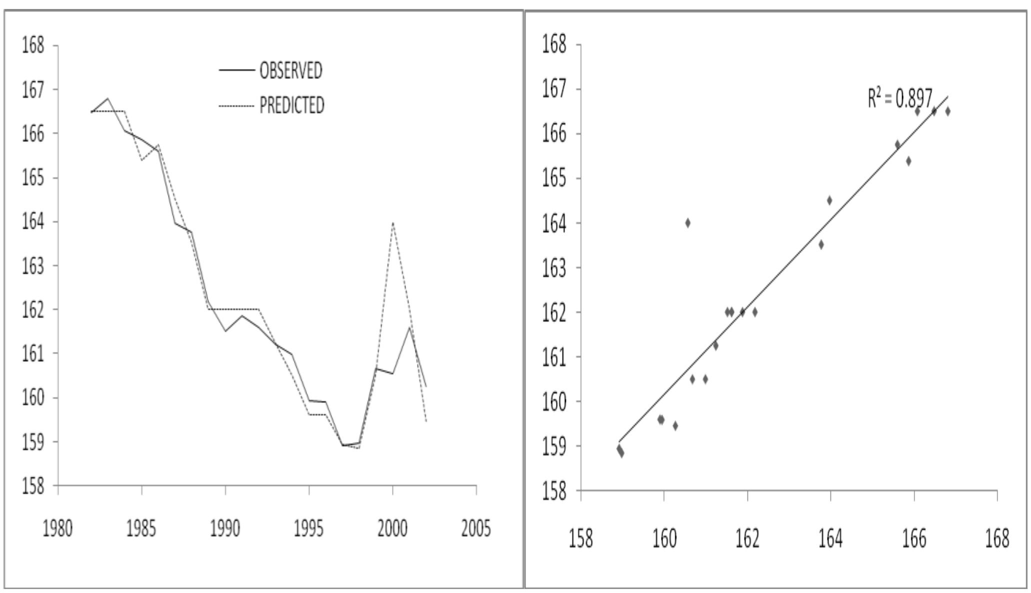

Figure 6(b) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for Fuzzy Model 4

MODEL 5:

a) ANN Model 5- (hidden layer one)

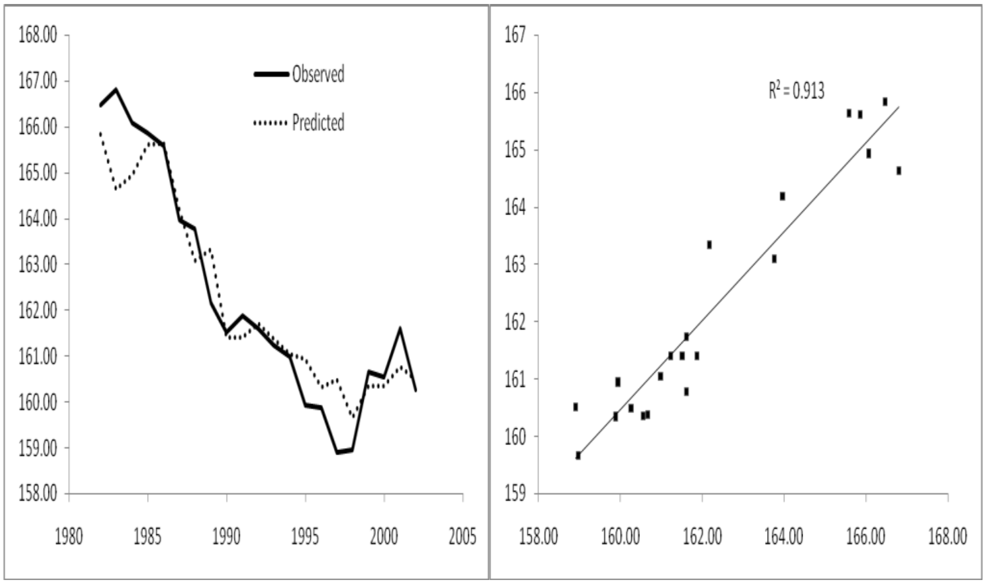

Figure 7(a) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for ANN 5

b) Fuzzy Model

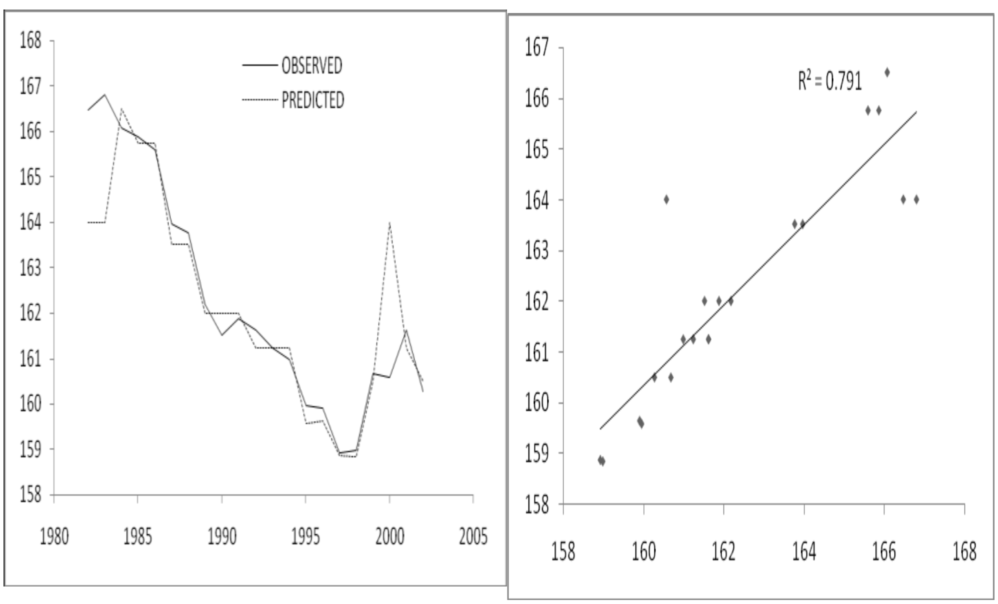

Figure 7(b) Comparative Plots of Observed and Predicted Water Table Elevation Fluctuation and their Corresponding Scatter Plots for Fuzzy Model 5

Table 3. Best Five ANN Models are Compared to Fuzzy Models and MAD, R2, R and RMSE is Stated for each Model

S .No.	Model	Hidden Layer	MAD	R	R^2	RMSE
1.	ANN-1	2	2	0.974351	0.949	0.622178
2.	ANN-2	2	0.292719	0.977273	0.955	0.531218
3.	ANN-3	1	0.63631	0.943034	0.889	0.844415
4.	ANN-4	1	1.385652	0.921227	0.848	1.576821
5.	ANN-5	1	0.60	0.955659	0.913	0.811623
6.	FUZZY-1	N.A	0.36	0.985183	0.970	0.437822
7.	FUZZY-2	N.A	0.2605476	0.993646	0.987	0.317821
8.	FUZZY-3	N.A	0.453329	0.946941	0.896	0.830402
9.	FUZZY-4	N.A	0.45	0.947367	0.897	0.829164
10.	FUZZY-5	N.A	0.62279	0.889737	0.791	1.137557

In this study five basic models were developed (discussed in 7.1). Then these five models are trained and tested for one hidden layers and two hidden layers Artificial Neural Networks. On the basis of performance evaluation criteria ANN -2 model performed better results in both cases (one hidden layer and two hidden layers). Figures 3 to 7 gives the comparative plots of the observed and estimated water table elevation fluctuation and their corresponding scatter plots for ANN and Fuzzy Models. It can be observed from table 3 that R^2 is varying from 0.848 to 0.955 for ANN models and from 0.791 to 0.987 for Fuzzy models. Fuzzy model results were found better than ANN for the first 4 models & for the last model ANN results were found better than Fuzzy.

9. Summary and Conclusions

1. Soft computing techniques like ANN and Fuzzy are reliable and more accurate than conventional methods.

2. On the basis of performance evaluation of models, ANN-2 with two hidden layers gave best results among ten developed ANN models.
3. Fuzzy- 2 gave best results among all ANN and Fuzzy Models.
4. This paper also demonstrate that ANN technique give good results for more number of inputs while for less number of inputs fuzzy technique gives better result.

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