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Full Length Research Paper

Application of Artificial Neural Networks for Predicting Groundwater Levels in Hard Rock Basins

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The objectives of this study were to determine the factors that influence and control the water table fluctuation in a specific geomorphologic situation, to develop a forecasting model and examine its potential in predicting water table depth using limited data. Prediction of region specific water table fluctuation would certainly guide the way towards conceiving, designing and taking scientific measures to ensure sustainable groundwater management. Analysis of change in groundwater table depth, groundwater flow directions within the watershed showed that the influencing factors of rainfall, groundwater draft from near by structures and the resulting fluctuation in groundwater table depth were well correlated in a specific geological situation. Models for prediction of water table depth were developed based on artificial neural networks (ANNs). The study employed multilayer feed forward neural network with backpropagation learning method to develop the model. The neural networks with different numbers of hidden layer neurons were developed using 4 years (2005 - 2008) monthly rainfall, potential evapotranspiration (PET), and water table depth from nearby, influencing wells data as input and one month ahead water table depth as output. The best model was selected based on the root mean square error (RMSE) of prediction using independent test data set. The results of the study clearly showed that ANN can be used to predict water table depth in a hard rock aquifer with reasonably good accuracy even in case of limited data situation.

Key words: Water table fluctuation, rainfall, groundwater draft, ANN.

INTRODUCTION

Groundwater level is an indicator of groundwater availability, groundwater flow, and the physical characteristics of an aquifer or groundwater system. In the State of Orissa (India), more than 85% of geographical area falls under consolidation formations with low groundwater development status. Average groundwater development of the State has been assessed to be 18.31%, which is far below the national average groundwater development. The state as a whole has a huge balance of groundwater resources with a wide scope for its development (Pati, 2009). But, due to presence of hard rock areas and many associated problems with complex hydrological system, it has not been exploited to the desirable levels.

In last 10 years, out of total monitoring wells, 55% showed depletion in water table depth during pre-monsoon dry season. This leads to the associated problem of lowering tubewell depth and drying of open dug wells in these areas. Few areas with associated problems of lowering tubewell depth and drying of open dug wells has become the major issue. This also indicat-ed the decreasing trend of groundwater table depth over a period of time. The possible reason could be increase in groundwater draft due to population growth, low

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Abbreviations: PET, Potential evapotranspiration; **ANN,** Artificial neural network; **GDM,** Gradient Descent with momentum; **RMSE,** Root mean square error; **R^2,** Coefficient of determination; **GIS,** Geographical Information system; **WTF,** Water table fluctuation; **W,** Weight, the strength of connection between neurons; **N,** number of iteration; **x,** Input value; **η,** Learning rate; **ϕ,** Output; ***I*,** Sum of the weighted inputs; ***q*,** Neuron index of the output layer; $_q$, Error signal; ***μ*,** momentum coefficient; **w (N+1),** Change of weight during *N* to *N*+1 learning cycles; **x_{norm},** normalized value; **x_0,** Original input value; **x_{max},** Maximum of input values; **x_{min},** Minimum of input values; **$WTD_t(t)$,** Water table depth in target well at time t; **$WTD_i(t)$,** Water table depth in i^{th} (i =1…n) well nearby to target well.

groundwater recharge etc. As the demand increases, it may not be feasible to check the draft of groundwater resources but there is a chance to increase the recharge rate to the aquifer by suitable means. It is necessary to quantify the present rate of groundwater recharge, monitor the change in water table depth and then predict the future trend of water table depth before any inter-vention. Keeping this in view, study was carried out in Munijhara watershed of Nayagarh block, Orissa. Present groundwater development in Nayagarh block is only 15.52% (GEC, 1997).

Management of water resources requires input from hydrological studies. This is mainly in the form of estima-tion or forecasting of the magnitude of a hydrological parameter. Many approaches have evolved over the last few decades to make hydrological forecasts which include conceptual and statistical methods. The concep-tual or physically-based models try to explain the underlying processes. But these models require a large quantity of good quality data, sophisticated programs for calibration and a detailed understanding of the underlying physical process. A reliable water supply planning policy, specifically during the dry season, necessitates accurate-ly acceptable predictions of water table depth fluctuations. The prediction of groundwater levels in a well, based on continuous monitoring of selected nearby wells is of immense importance in the management of groundwater resources (Coulibaly et al., 2001). The current trend seems to model the data rather than the physical process. The main advantage of this approach over traditional methods is that it does not require the complex nature of the underlying process under conside-ration to be explicitly described in mathematical form. This makes ANNs an attractive tool for modeling water table fluctuations.

A comprehensive review of the applications of ANNs to hydrology can be found in the ASCE Task Committee report (ASCE, 2000a, b). Literature showed that feasibility of using artificial neural networks (ANNs) was studied to estimate groundwater level in piezometers in unconfined chalky aquifer of North France (Lallahem et al., 2005), to estimate aquifer parameter values (Balkhair, 2002), to forecast the groundwater level using rainfall, temperature, and stream discharge as inputs (Daliakopoulos et al., 2005), and to evaluate the groundwater level in fractured media (Lallahem et al., 2004). Affandi et al. (2007) compared the capability of an ANN with five different backpropagation (BP) algorithms for estimating groundwater level fluctuation. Seven different types of network architectures and training algorithms were investigated and compared in terms of model prediction efficiency and accuracy. Result showed that accurate predictions were achieved with a standard feed forward neural network trained with the Lavenberg-Marquardt (Daliakopoulos et al., 2005).

It is worth mentioning that sufficient lengths of water table depth measurements are usually unavailable in developing countries (Coulibaly et al., 2001). Such coun-tries typically have very few observable wells and lack long-period time-series data due to budget limitations and government policy (Affandia et al., 2007). This necessi-tates developing models that are capable of forecasting ground water table depth using limited data. In many other areas, efforts were made to develop neural network based forecasting models with limited data (Aminian et al., 2005; Sudheer et al., 2003; Wang et al., 2008). Keeping it in view, an attempt was made to determine the factors that influence and control the water table fluctuation in a specific geologic situation develop ANN based model and test its potential in predicting ground water table depth with limited climatic and nearby wells data.

MATERIALS AND METHODS

Study area

The study was carried out in Munijhara micro watershed, which lies between 20° 05'and 20° 09'N latitude and 85° 05' to 85° 09'E longitude (Figure 1). The area is located in Nayagarh block of Nayagarh district of Orissa (India), which occupies the central part of Eastern Orissa and is underlain by hard rocks, includes Khondalite-Charnockite suit of rocks and granites rocks. Altitude of the region varies from 80 - 100 m above mean sea level (MSL). Total area of the watershed is 45 km^2 out of which only 2.69 km^2 (6%) area is under forest cover and rest is cultivated, pasture and residential areas. The main drain in the watershed is Munijhara with drainage density of 0.35 km/km^2 and is of third order. Boundaries of watershed make the area a typical geo-hydrological unit with single outlet. Goundwater flow in the watershed coincides with the topographic map of the area. Subsurface lithology (12 – 15 m depth) is dominated by granite and hard rock aquifer (CGWB, 2004) . From the field survey, it was observed that groundwater is being abstracted from 166 numbers of tube wells and 450 numbers of open wells for domestic and agricultural purposes. There is also presence of few water storage structures of village ponds and big structures in each village but it often get dried during summer season.

Climatic condition

Climatically this region is sub humid and receives average annual rainfall of 1449 mm, 80% of which occurs in the monsoon season (June- September). The mean minimum and maximum temperature of this region are 13°C in January and 44°C in May respectively and mean relative humidity is 90%. Except monsoon periods, ground-water is the only source of available resources both for domestic and crop demand throughout the year.

Artificial neural networks

Artificial neural network (ANN) is an information processing para-digm inspired by biological nervous systems, such as our brain. It consists of large number of highly interconnected processing elements, called neurons, working together (Tsoukalas and Uhrig, 1997). An ANN consists of input, hidden and output layers and each layer includes an array of processing elements. A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights, and the activation function (Fausett, 1994).

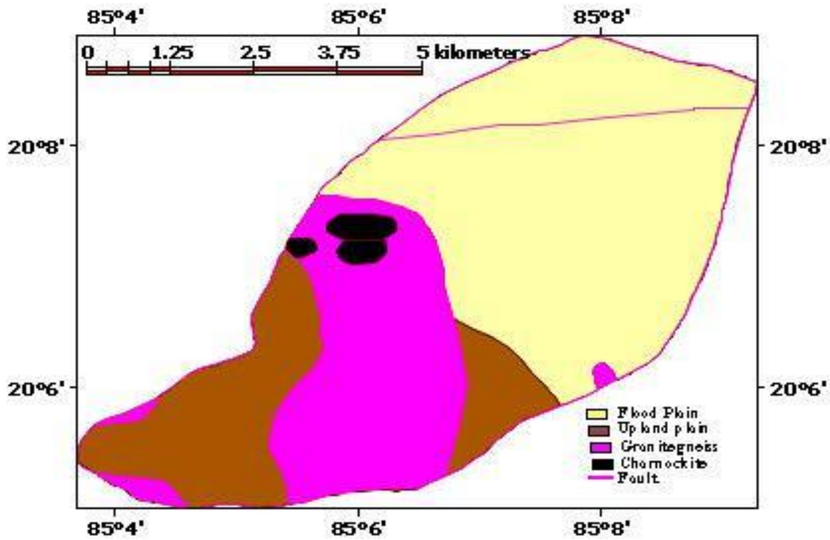

Figure 1. Geology and geomorphological map of Munijhara watershed.

Feed forward neural network

The most popular ANN architecture in hydrologic modelling is the feed forward neural network trained with a back propagation algorithm (ASCE 2000a, b). Feed forward neural networks are among the most common neural networks in use (Mehrotra et al., 1997). Feed forward neural networks have been applied successfully for solving different problems since the advent of the error back propagation learning algorithm. This network architecture and the corresponding learning algorithm can be viewed as a generalization of the popular least-mean-square (LMS) algorithm (Haykin, 1999). A feed forward neural network consists of an input layer, one or more hidden layers of computation nodes, and an output layer. Figure 3 shows a typical feed forward network with input layer consisting of seven neurons, one hidden layer consisting of eight neurons, and output layer consisting of one output neuron. The input signal propagates through the network in a forward direction, layer by layer. Their main advantage is that they are easy to handle, and can approximate any input/output map, as established by Hornik et al. (1989) . Back propagation learning algorithm used gradient descent with momentum term to calculate derivatives of performance cost function with respect to the weight and bias variables of the network. Each variable is adjusted according to the gradient descent with momentum. This is probably the simplest and most common way to train a network (Haykin, 1999). For each step of the optimization, if performance decreases the learning rate is increased.

Training of a feed forward neural network involves two phases. The calculation of the output is carried out, layer by layer in the forward direction. The output of one layer is the input to the next layer. In the reverse pass, the weights of the output neuron layer are adjusted first since the target value of each output neuron is available to guide the adjustment of the associated weights. The weights in the output and hidden layer neurons can be calculated using equations (1) and (2), respectively (Tsoukalas and Uhrig 1996):

$$w(N+1) = w(N) - \eta.\delta.\phi \qquad (1)$$

$$w(N+1) = w(N) + \eta.x.\sum_{q=1}^{r} \delta_q \qquad (2)$$

Where, w=weight; N=number of iteration; x=input value; η=learning rate; ϕ=output; and δ is defined as $2.\varepsilon_q.\partial\phi/\partial I$, I being the sum of the weighted inputs, q=neuron index of the output layer, and q=error signal. This training method is known as the standard back propagation training method. Since, it uses a form of gradient descent, it is assumed that the error surface slope is always negative and hence, constantly adjusting weights toward minimum. It is very easy for the training process to get trapped in a local minimum. The problem of the local minima can be avoided by adding a momentum term to the weight change, to permit larger learning rates. The change of weight is then computed as follows:

$$\Delta w(N+1) = -\eta.\delta.\theta + \mu.\Delta w(N) \qquad (3)$$

Where, µ=momentum coefficient and w (N+1) =change of weight during N to N+1 learning cycles. Therefore, the new value of weight becomes equal to the previous value of the weight plus the weight change, which includes the momentum term. This training method is known as back-propagation with momentum which uses gradient descent with momentum (GDM) algorithm. The feed forward network with a back propagation-based gradient descent learning rule has been shown to be a good choice for solving problems with non-linear relationship (Haykin, 1999; Shamseldin, 1997; Hsu et al., 1995; Bose and Liang, 1996). Therefore, in this study, we used feed forward neural network with back propagation learning algorithm to approximate the relation between input parameters (water table depth in target and nearby influencing well, rainfall and PET) in question, and the resulting output parameter (one month ahead water table depth in target well).

Data sets

Monthly rainfall data during 1993-2007 was collected from different departments of Nayagarh and analyzed to determine the rainfall distribution. Monthly monitoring of fluctuation in water table depth during 2005 - 2008 was carried out in 64 numbers of spatially distributed dug wells in Munijhara watershed of Nayagarh block of Orissa. Out of total selected dug wells, 55, 25 and 20% of dug wells were located in flood plain, granite gneiss and upland plain, respectively. Contour map representing the pre and post monsoon water table fluctuation for the entire watershed was prepared by krigging method. Analysis of change in groundwater table depth, groundwater flow directions within the watershed was carried out. For the purpose of model development, monthly PET data were also collected for period of 2005-2008. Rainfall and PET were directly taken as input variables as these are well known factors that influence the water table depth. However, the nearby wells that have direct influence on the water table depth of target well were determined through a linear cross correlation. In this way, the nearby wells having higher correlation coefficient (> 0.80) with the water table depth in target wells were selected as input variables for the models. A total of 4 years monthly data (January, 2005 - December, 2008) related to above mentioned variables were used for model development.

Normalization of data

Normalization is a transformation performed on input data to distribute the data evenly and scale it into an acceptable range for the network (mostly in the range of 1 - 1 or 0 - 1). Because the neurons of the middle layer were assigned a sigmoidal activation function that speed-up ANN leaning if input data is in range of 1 - 1 or 0 - 1. Keeping this in view, the normalization was carried out so that the all input data fall in the range of 0 - 1. The following equation was used:

$$x_{norm} = 0.1 + 0.8 \frac{x_o - x_{min}}{x_{max} - x_{min}} \quad (4)$$

where, x_{norm}=normalized value; x_0=original observed value; x_{max}=maximum value; and x_{min}= minimum value.

Model evaluation criteria

Two different criteria viz: Root Mean Square Error (RMSE) and coefficient of determination (R^2) were used in order to evaluate the effectiveness of each network and its ability to make precise predictions.

The Root Mean Square Error (RMSE) was calculated by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (X_i - X_i')^2}{N}} \quad (5)$$

Where X_i is the observed data, X_i' is the calculated data and N is the number of observations. The RMSE can give a quantitative indication of the model error in terms of a dimensioned quantity. An RMSE equal to zero indicates a perfect match between the observed and predicted values.

The R^2 was calculated by:

$$R^2 = 1 - \frac{(X_i - X_i')^2}{X_i^2 - \frac{(X_i')^2}{N}} \quad (6)$$

In R^2 efficiency criterion, the best fit between observed and calculated values would have R^2=1.

Network training, validation and testing

Before applying the ANN to the data, the input and output data were normalized to fall in the range of 0 - 1. The normalized data set was divided into three subsets for the purpose of training, validation and testing. Out of total 4 years monthly data, 50 and 25% were used for model training and validation, respectively and 25% were used for model test. The training data set was used to train a neural net by minimizing the error of this data set during training. The validation data set was used to determine the per-formance of a neural network during training. The test set was used for checking the overall performance of a trained and validated network. A total of 9 networks, 3 each for upland plain, flood plain and granite formation were developed and trained using SNNS 4.2 software. For ANN architectures, the numbers of nodes in the input layer were fixed at seven, six and five in case of the models for upland plain, flood plain, and granite zones, respectively with one node in output layer. The numbers of nodes in the hidden layer of different models were varied from 6 - 10. The activation function used was log-sigmoid. Back propagation algorithm using gradient descent with momentum term was used to train the neural network. Figure 2 shows a typical architecture of the ANN (7 - 8 - 1) model for ground water depth forecasting in upland plain geological formation. To obtain the best ANN architecture, several possibilities were considered in this study. Training and validation data sets were shuffled before training and validation to ensure the random-ness during ANNs training and validation. The networks were trained and performances were measured in terms of error rate on training and validation data set simultaneously. Each ANN architecture was trained for different learning rates and momentum values, and error rate on training and validation data set were monitored using error graph module of the software. The training was stopped as soon as validation error rate started stabilizing or increasing because it may lead to network memorization or over training. In this way, by means of trial and error, optimum network parameters viz; learning rate and momentum values were deter-mined for all three networks for each geological formations of the watershed. After training was over, the weights were saved and the trained network was run on test data to evaluate the performance of these networks.

RESULTS AND DISCUSSION

Rainfall distribution

Rainfall analysis (1993 - 2007) showed that mean annual and monsoon rainfall of Nayagarh was 1350 and 1131.02 mm respectively. The standard deviation for annual and monsoon (June - October) rainfall were 291.7 and 251.17 with coefficient of variation of 20.87 and 22.2%, respec-tively (Table 1). Kharif, summer and rabi season contributes 83, 11 and 4% to mean annual rainfall of the area. High demand of water in rainfed area without irrigation facilities usually met through groundwater. But, status of groundwater development for study area show-ed that there is an urgent need to recharge groundwater through conservation structures. For construction of water conservation structures, there is need to predict the monsoon rainfall of any area.

Water table fluctuation

The WTF method requires a very good knowledge of

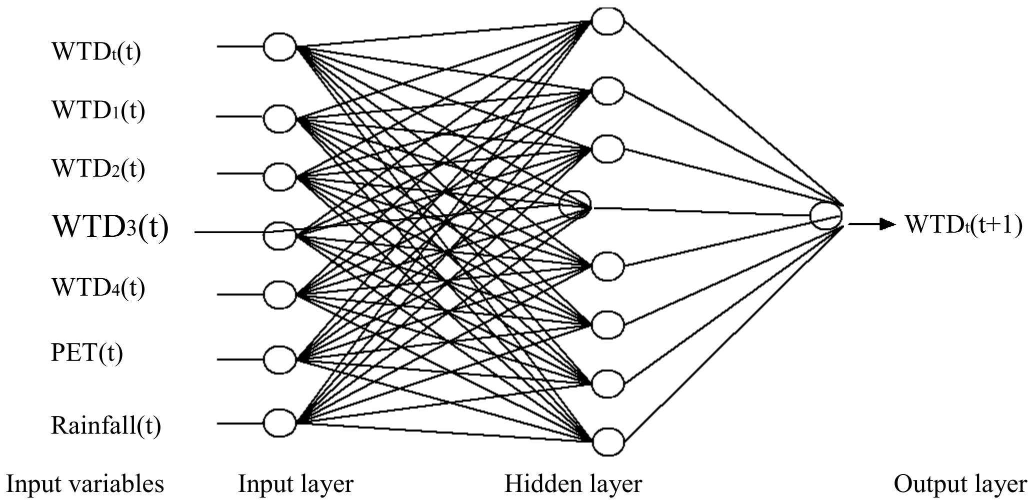

Figure 2. A typical architecture of the ANN (7 - 8 - 1) model for ground water depth forecasting in upland plain geological formation.

Table 1. Rainfall analysis of Nayagarh (1993 - 2007).

Statistical parameters	Annual rainfall (mm)	Monsoon rainfall (mm)
Mean	1350.13	1131.02
Standard Deviation	291.73	251.17
Coefficient of variance (%)	21.60	22.00
Sample variance	85108.94	63084.94
Kurtosis	-0.52	0.25
Skewness	0.14	0.80
Range	821.9 - 1824.1	753.6 - 1657.4
Confidence Level (95.0%)	161.56	139.09

piezometric level throughout the entire basin. This could be achieved owing to a very dense observation network (64 wells in 40 km^2 area) provided mainly defunct wells used for domestic purposes only where the rate of withdrawal of water is comparatively less. Sophocleous (1991) pointed out that the WTF method could be misleading if the water level fluctuations are confused with those resulting from pumping, barometric, or other causes. Care was taken to avoid any interference from pumping wells to the monitoring wells. Monthly moni-toring and analysis of fluctuation in water table depth during 2005 - 2008 of was carried out and contour map was prepared for pre and post monsoon season. It was observed that the groundwater depth in pre monsoon season was almost similar, however, there was change in water table depth in post monsoon season only. Mean water table depth during June-2008 and November- 2008 was 81.9 and 84 m, respectively, which was the maximum difference in water table depth (2.11 m) in last 3 year, that is, 2006 - 2008. The reason can be attributed to more number of total rainy days (85) and maximum amount of rainfall (1187.9 mm) received during monsoon 2008.

Relationship of water table fluctuation in different geological formations

Geological and geomorphological area of watershed was extracted using GIS tools from the district resource map of Nayagarh developed by Geological Survey of India, Bhubaneswar, Orissa (Figure 1). Geomorphologically, the watershed was classified as flood plain (23 km^2) and upland plain (17 km^2). Out of total monitoring wells located in the watershed, 55% wells are in flood plain area and rest 25 and 20% are in granite gneiss and up-land plains, respectively. Trend of water table fluctuation in different geologic formations and all the possible influencing factors like rainfall, Potential evapotranspi-ration (PET) and effect of nearby monitoring wells in the specific geomorphologic conditions that may affect the change in water table depths were analyzed. The correla-tion coefficient between rainfall, PET and water table fluctuation among the monitoring wells located in the flood plain zone was worked out to be 0.88 - 0.98. But, in case of upland plain areas dominated by hard rocks and granite zones, negative correlation between water table fluctuation and rainfall was observed.

Table 2. Performance indices of ANN models with different architectures[a] .

Geological Formations	ANN architecture	RMSE(m)	R^2
	ANN(7-8-1)	0.83	0.96
Upland Plain	ANN(7-9-1)	0.89	0.98
	ANN(7-10-1)	0.89	0.95
	ANN(6-7-1)	0.63	0.87
Flood Plain	ANN(6-8-1)	0.67	0.84
	ANN(6-9-1)	0.66	0.82
	ANN(5-6-1)	1.33	0.59
Granite	ANN(5-7-1)	1.82	0.38
	ANN(5-8-1)	1.81	0.36

[a]Based on one year's test data.

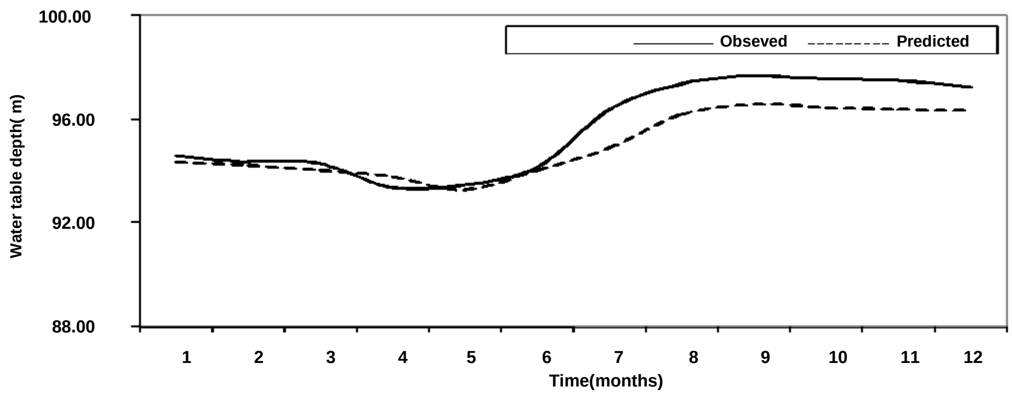

Figure 3. Comparison of observed groundwater depths with predicted results using ANN (7 - 8 - 1) model for the monitoring well of upland plain geological formation for the period January 2008 - December 2008.

Performance of ANN models

To evaluate the performance of trained ANN models for all the three geological formations, we run the trained and validated networks using independent test dataset. Two statistical indices of performance were computed for the test result: the root mean square error and the coefficient of determination (R^2). Table 2 shows the performance indices of ANN models with different architectures and for different locations using the testing data set. The models giving lowest RMSE value on test data were selected as the best models. In case of upland plain, the model ANN (7-8-1) gave the lowest RMSE value 0.83, hence it is selected as the best model. Similarly, in case of flood plain, the model ANN (6 - 7 - 1) gave the lowest RMSE value 0.63 and in granite zone the model ANN (5 - 6 - 1) gave lowest RMSE value 1.33. These models were selected as the best models. It is evident from the table that high correlation between observed and predicted result (correlation coefficient in the range of 0.84 - 0.98) were obtained for the flood plain and upland plain forma-tion using different ANN models but for granite formation, correlation is somewhat lower. To provide a visual interpretation and appreciation of the results, Figures 3 - 5 showed the variations of observed water table depth and those estimated by ANN (7 - 8 - 1) for upland plain formation, ANN (6 - 7- 1) for flood plain formation and ANN(5-6-7) for granite formation areas of watershed, respectively. These figures show good agreement betw-een observed and predicted value of water table depth in monitoring wells located in upland and flood plain areas. While values in the later part of these graphs are slightly underestimated by ANN, earlier values are better model-ed by it which represent the water scarce period in this agro climatic region and therefore this type of better prediction accuracy is very much desirable to manage ground water resources more effectively. Among all the models, the prediction accuracy in flood plain and upland plain areas were comparatively better than that of granite zone. The result shows that the RMSE values of all the models for granite formation were quite high, thereby making prediction accuracy relatively low in comparison to flood plain and upland plain. It may be due to less influence of nearby monitoring wells on water table fluctuation in monitoring well in this formation. The RMSE values obtained in this study using limited data were well

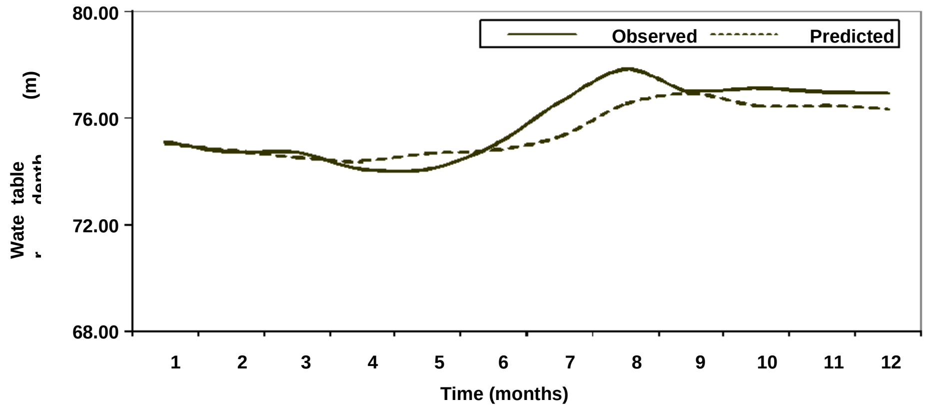

Figure 4. Comparison of observed groundwater depths with predicted results using ANN (6-7-1) model for the monitoring well of flood plain geological formation for the period January 2008 - December 2008.

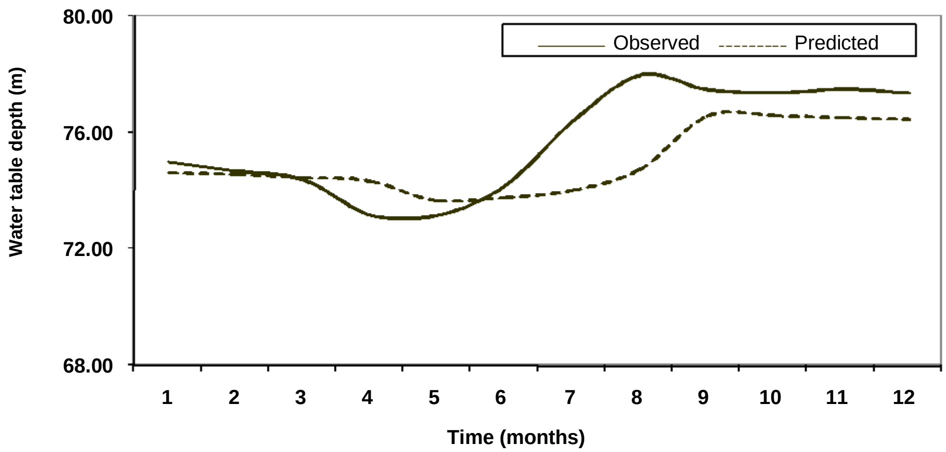

Figure 5. Comparison of observed groundwater depths with predicted results using ANN (5-6-1) model for the monitoring well of granite geological formation for the period January 2008 - December 2008.

compared with some of the similar previous studies that used larger data set (Coulibaly et al., 2001; Daliakopoulos et al., 2005; Krishna et al., 2008). The results from this study suggest that ANN can provide a reliable method to forecast water table depth with good accuracy even with limited data.

Conclusions

In this study, the factors that influence and control water table fluctuation in a specific geologic situation were determined and used to develop ANN models for forecasting ground water table depth one month ahead for different geological formations. The results clearly showed that ANN can be used to predict water table depth in a hard rock aquifer with reasonably good accuracy even in case of limited data situation. The result of this is in good agreement with previous related studies done with larger length of data. Therefore, it can be concluded that an ANN is an effective tool for forecasting ground water table depth for the purposes of groundwater management, even though only limited data samples were available. In this study, the models were calibrated with limited input data set monitored during study period only, the performance of the model can further be improved with sufficient data sets. It would be interesting to find out how would other architectures and training algorithms of ANN perform in poor data situation. Using other soft computing methods to forecast water table depth can also be an enlightening study to pursue.

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