Water Resour Manage (2015) 29:5521–5532
DOI 10.1007/s11269-015-1132-6

Using Artificial Neural Network Approach for Simultaneous Forecasting of Weekly Groundwater Levels at Multiple Sites

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Received: 8 November 2014 / Accepted: 7 September 2015 /
Published online: 3 October 2015

Abstract Reliable forecast of groundwater level is necessary for its sustainable use and for planning land and water management strategies. This paper deals with an application of artificial neural network (ANN) approach to the weekly forecasting of groundwater levels in multiple wells located over a river basin. Gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm was employed to predict groundwater levels 1 week ahead at 18 sites over the study area. Based on the domain knowledge and pertinent statistical analysis, appropriate set of inputs for the ANN model was selected. This consisted of weekly rainfall, pan evaporation, river stage, water level in the surface drain, pumping rates of 18 sites and groundwater levels of 18 sites in the previous week, which led to 40 input nodes and 18 output nodes. During training of the ANN model, the optimum number of hidden neurons was found to be 40 and the model performance was found satisfactory (RMSE= 0.2397 m, r=0.9861, and NSE=0.9722). During testing of the model, the values of statistical indicators RMSE, r and NSE were 0.4118 m, 0.9715 and 0.9288, respectively. Using the same inputs, the developed ANN model was further used for forecasting groundwater levels 2, 3 and 4 weeks ahead in 18 tubewells. The model performance was better while forecasting groundwater levels at shorter lead times (up to 2 weeks) than that for larger lead times.

Keywords Groundwater-level forecasting · Neural network modeling · Backpropagation GDX algorithm · Alluvial aquifer system

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1 Introduction

Groundwater simulation models have emerged as an important tool among water resources researchers and planners to optimize groundwater exploitation and to protect this vital resource. Physically based numerical models are being used during past several years for simulation and analysis of groundwater systems and thereby taking corrective measures for the efficient utilization of water resources. These models serve as a tool for depicting hydrological variables and understanding physical processes taking place in the aquifer system. With the proliferation of use of computers, they are being widely used by engineers, environmentalists and hydrogeologists to problems ranging from aquifer safe yield analysis to groundwater quality and remediation issues. However, these modeling techniques are very data intensive, laborious and expensive. Therefore, the use of physical based models is highly restricted in developing countries due to lack of adequate and good quality data. In such cases, when the data is not sufficient and getting accurate predictions is more important than conceiving the actual physics of the system, empirical models serve an attractive alternative as they can provide useful results using relatively less data and time. Artificial Neural Network (ANN) techniques are one of such models, which are treated as universal approximators and have the ability to identify a relationship from a given pattern (ASCE 2000a). Unlike physically based numerical models, ANNs do not require explicit characterization and quantification of physical properties, nor accurate representation of the governing physical laws (Coppola et al. 2005). The ability to learn and generalize from sufficient data pairs makes it possible for ANNs to solve large-scale complex problems (ASCE 2000a; Haykin 1999) including water management problems.

The ANN technique has been used in various branches of hydrology which includes rainfall-runoff modeling, precipitation forecasting, modeling of streamflows, evapotranspiration, water quality and groundwater management (Gobindraju and Ramachandra Rao 2000; ASCE 2000a; b). Particularly, in groundwater hydrology, the neural network technique has been used for aquifer parameter estimation (Aziz and Wong 1992; Morshed and Kaluarachchi 1998; Balkhair 2002; Shigdi and Garcia 2003; Garcia and Shigdi 2006; Samani et al. 2007; Karahan and Ayvaz 2008; Viveros and Parra 2014), groundwater quality prediction (Hong and Rosen 2001; Milot et al. 2002; Kuo et al. 2004; Banerjee et al. 2011; Chang et al. 2013), and groundwater level prediction (Coulibaly et al. 2001; Coppola et al. 2003, 2005; Daliakopoulos et al. 2005; Nayak et al. 2006; Uddameri 2007; Krishna et al. 2008; Ghose et al. 2010; Mohanty et al. 2010; Yoon et al. 2011; Taormina et al. 2012; Sahoo and Jha 2013; He et al. 2014; Emamgholizadeh et al. 2014). In most of the past studies on ANN modeling of groundwater level, ANN models were developed for simulating groundwater level in a single well or in a few wells only. However, this paper focuses on the application of ANN approach for the weekly forecasting of groundwater levels in a group of wells in an alluvial aquifer system.

2 Study Area

The study area is located in the Mahanadi Delta of Odisha, India (Fig. 1) and is surrounded by the Kathajodi River and its branch Surua. It is located between 85° 54' 21" and 86° 00' 41" E longitude and 20 ° 21' 48" to 20 ° 26' 00" N latitude. The

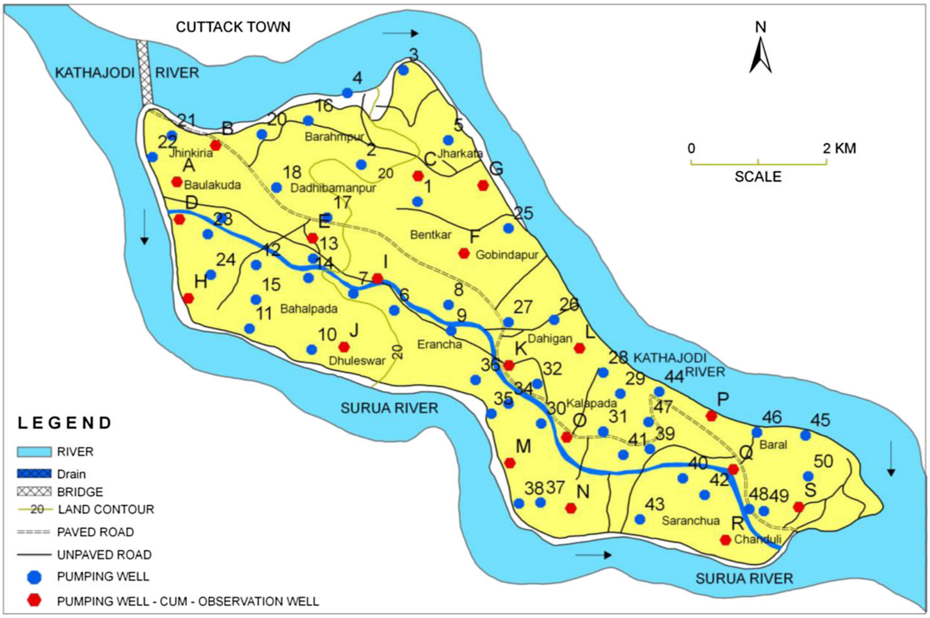

Fig. 1 Location of observation and pumping wells in the study area

altitude of the area varies from 18 to 23 m MSL. The total area of the river island is 35 km^2 and agriculture is the major occupation of the inhabitants. Total cultivated area in the region is 2445 ha of which 1365 ha (55.83 %) is irrigated land. Total low lands in the region are 408 ha, medium lands are 1081 ha and high lands are 956 ha. All the low lands, medium lands and 618 ha of total high lands are used for paddy cultivation in the monsoon season (June to October). In the post-monsoon season, majority of the low lands are used for paddy cultivation and a substantial portion of the medium lands and high lands are under vegetable cultivation. Owing to the lack of irrigation infrastructure for surface water, all the irrigated lands are irrigated by groundwater. There are about 100 government tubewells in the study area, which are the major source of groundwater withdrawal for irrigation. These have been constructed and managed by the Orissa Lift Irrigation Corporation, Cuttack; but now they have been handed over to the water users' associations (WUAs). Of the hundred tubewells in the study area, presently 69 tubewells are in operation. Besides the government tubewells, there are a few private dug wells, which are mainly used for the drinking purpose. However, some of these dug wells get dry during dry (non-rainy) seasons (March-May), and thereby creating drinking water scarcity in the study area.

Even though the Kathajodi River and Surua River flow on both sides of the study area, there is a water shortage during dry periods. Embankments have been provided on the banks of the rivers to prevent the entry of river water into the inhabited area during flood events. Therefore, entire rainwater of the region is drained through a main drain and discharged through a single outlet into the River (Fig. 1). A sluice gate is provided at the outlet to prevent river water inflow into the study area during flood events. During this time, surface waterlogging problem is often encountered in the downstream portion of the study area.

3 Materials and Methods

3.1 Data Collection and Monitoring

Groundwater level data in the study area was obtained by monitoring groundwater levels at 19 sites (A to S in Fig. 1) on a weekly basis from February 2004 to June 2007. However, the groundwater level data of 18 sites were considered for this study as groundwater level monitoring could not be continued at one site for the entire period. The climatic data were obtained from a meteorological station at Central Rice Research Institute (CRRI), Cuttack, Odisha located at about 2 km from the study area. As the weekly river stage data adjacent to the project site were not available, the river stage data measured at the Naraj gauging station were collected from the Central Water Commission Office, Bhubaneswar, Odisha. As the river stage at Naraj directly influences the river stage around the study area, the use of river stage data of Naraj for neural network modeling is justified.

3.2 Design of Neural Network Model

In this study, the widely used feedforward neural network (FNN) architecture was employed. It is one of the simplest neural networks and has been successfully used for water resources variable modeling and prediction (Maier and Dandy 2000; ASCE 2000a). In a feedforward neural network, the nodes are generally arranged in layers, starting from a first input layer and ending at the final output layer. The nodes in one layer are connected to those in the next, but not to those in the same layer. Thus, the output of a node in a layer is only dependant on the input it receives from previous layers and corresponding weights. Figure 2 illustrates feedforward network having one hidden layer, ‘n’ nodes in the input layer and ‘m’ nodes in the output layer.

The hidden neurons and the output neurons were calculated using the following ANN functions.

$$z_j = f_A\left(\sum_{i=1}^{n} x_i w_{ij} + \tau_j\right) \tag{1}$$

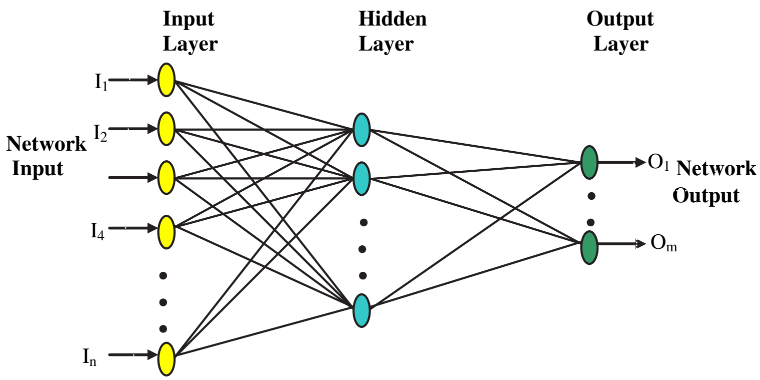

Fig. 2 Configuration of feedforward three-layer ANN for the study area

$$y_k = g_A\left(\sum_{j=1}^{h} z_j\beta_{jk} + \phi_k\right) \tag{2}$$

Where, the ANN model has n input neurons ($x_1, \ldots, x_n$), h hidden neurons ($z_1, \ldots, z_h$), and m output neurons ($y_1, \ldots, y_m$); i, j, and k are the indices representing input, hidden, and output layers, respectively; τ_j is the bias for neuron z_j and ϕ_k is the bias for neuron y_k; w_{ij} is the weight of the connection from neuron x_i to neuron z_j and β_{jk} is the weight of connection from neuron z_j to y_k; g_A and f_A are activation functions.

The neural network model was designed to predict groundwater levels in 18 tubewells (Fig. 1) with 1-week lead time using a set of suitable input parameters. Based on the correlation analysis between groundwater level and the selected input parameters, weekly groundwater level at 1-week lag time, weekly rainfall, weekly river stage, weekly evaporation, weekly water level in the main surface drain and weekly pumping from tubewells were considered as final input parameters. There were altogether 40 input nodes and 18 output nodes in the ANN model of the study area. The 40 input nodes represent groundwater levels with 1-week lag time at the 18 sites, groundwater pumping rates of the 18 tubewells, weekly rainfall, average weekly pan evaporation, average weekly river stage, and average weekly water level at the drain outlet. The 18 output nodes represent groundwater levels at the 18 sites in the next time step (i.e., 1 week ahead). Three ANN algorithms, namely gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Levenberg-Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm were used for predicting groundwater levels in Kathajodi-Surua Inter-basin (Mohanty et al. 2010).

3.3 Model Training and Testing

The structure of the neural network consisted of one hidden layer along with the input and output layer. The optimal number of nodes in the hidden layer was optimized by trial and error based on selected criteria of evaluation. The activation function of the hidden layer and output layer was set as log-sigmoid transfer function as this proved by trial and error to be the best among a set of other options. The log-sigmoid function is defined as follows:

$$f(s) = \frac{1}{1+e^{-s}}, \text{ where } s \text{ is any variable} \tag{3}$$

In this study, supervised type of learning with a batch mode of data feeding was used for ANN modeling. Out of the 174 weeks datasets available, 122 datasets were used for training the ANN model and 52 datasets were used for testing the model. The ANN modeling was performed using MATLAB software.

3.4 Model Evaluation Criteria

Observed groundwater level hydrographs and ANN model simulated groundwater level hydrographs were plotted for visual checking of the model performance. Besides the visual checking, three statistical indicators (goodness-of-fit criteria) were used to evaluate the effectiveness of the developed ANN model, which are correlation coefficient (r), root mean squared error (RMSE) and Nash-Sutcliffe efficiency (NSE). Correlation coefficient determines (r) whether two ranges of the data move together, i.e., whether large values of one dataset are associated with large values of the other dataset, whether small values of one dataset are associated with large values of the other dataset, or whether values in both datasets are unrelated. The root mean squared error (RMSE) indicates the degree of error in modeling. The NSE is a measure of explained variance by the model. For the best-fit between observed and predicted groundwater levels under ideal conditions, the values of r would be 1, RMSE would be 0 and NSE would be 1. These statistical indicators are expressed as follows:

$$r = \frac{\sum_{i=1}^{N} \left(h_{oi} - \overline{h_o}\right)\left(h_{pi} - \overline{h_p}\right)}{\sqrt{\sum_{i=1}^{N} \left(h_{oi} - \overline{h_o}\right)^2 \sum_{i=1}^{N} \left(h_{pi} - \overline{h_p}\right)^2}} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \left(h_{pi} - h_{oi}\right)^2}{N}} \tag{5}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N} \left(h_{oi} - h_{pi}\right)^2}{\sum_{i=1}^{N} \left(h_{oi} - \overline{h_o}\right)^2} \tag{6}$$

Where, h_{oi} is observed groundwater level in the i^{th} week [L], h_{pi} is predicted groundwater level in the i^{th} week, $\overline{h_o}$ is mean of the observed groundwater levels [L], $\overline{h_p}$ is mean of the predicted groundwater levels [L], and N=total number of observed data [dimensionless].

4 Results and Discussion

4.1 Groundwater Level Forecasting in a Group of Wells

With the ANN model having 40 input nodes and 18 output nodes, the Lavenberg-Marquardt and Bayesian regularization models consumed a lot of time for completing a single iteration to be evaluated by the trial and error method. Maier and Dandy (1998) also reported that the Lavenberg-Marquardt algorithm has a great computational and memory requirement and thus it can only be used in small networks. The same is true for the Bayesian regularization algorithm also. In contrast, the GDX algorithm could effectively be evaluated through trial and error procedure due to less memory requirement. Thus, the GDX model was found suitable for forecasting groundwater level in a large group of wells simultaneously in a river basin, and hence was used in the current study. The ANN architecture with lowest RMSE value, highest correlation coefficient and highest Nash-Sutcliffe efficiency was considered to yield optimum number of hidden neurons, and it was found to be 40 by trial and error method. Figure 3 shows the variation of RMSE and NSE with number of nodes in hidden layer during the testing of the model. During the training of the model, the statistical indicators r, RMSE and NSE were 0.9861, 0.2397 m and 0.9722 respectively, whereas the corresponding parameters were 0.9715, 0.4118 m and 0.9288 during testing of the model. The values of the statistical indicators show that the performance of the model is satisfactory during both training and testing period, and it is able to forecast groundwater levels 1 week in advance with a reasonable accuracy.

Figure 4a to c show the comparison of observed and predicted groundwater levels at three sites, i.e., Dadhibamanpur (E) from the upstream side of the basin, Kulakalapada (L) towards the middle of the basin and Kulasarichuan (R) from the downstream side of the basin. These figures indicate that there is a very good matching between observed and predicted groundwater levels at all the sites. Based on the model evaluation criteria (statistical indicators) and the graphical comparison, it can be inferred that the developed ANN model forecasts groundwater levels at multiple sites satisfactorily.

4.2 Forecasting of Groundwater Levels at Higher Lead Times

While a 1 week ahead forecast is good enough for groundwater management in the aquifer, forecasts of higher lead time are required for efficient planning of integrated management of

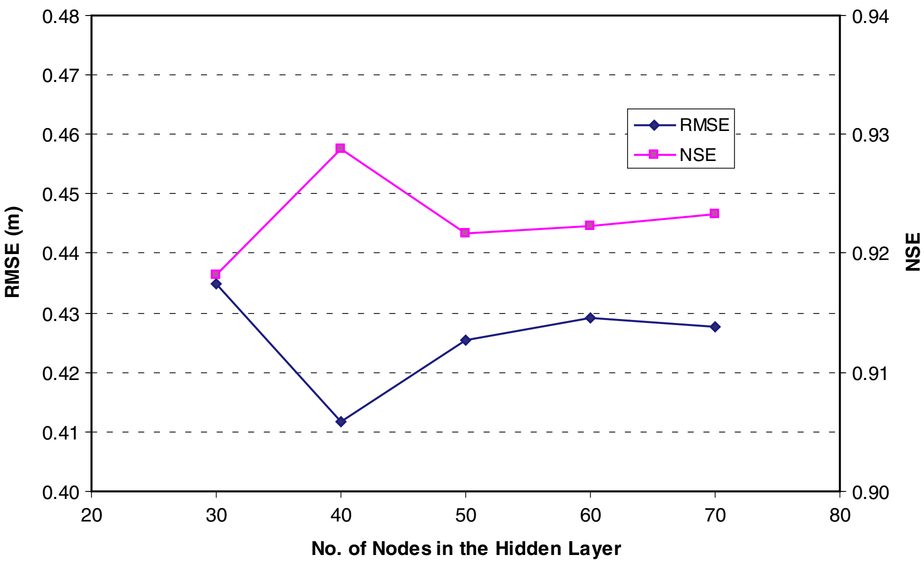

Fig. 3 Variation of RMSE and NSE with the number of nodes in the hidden layer

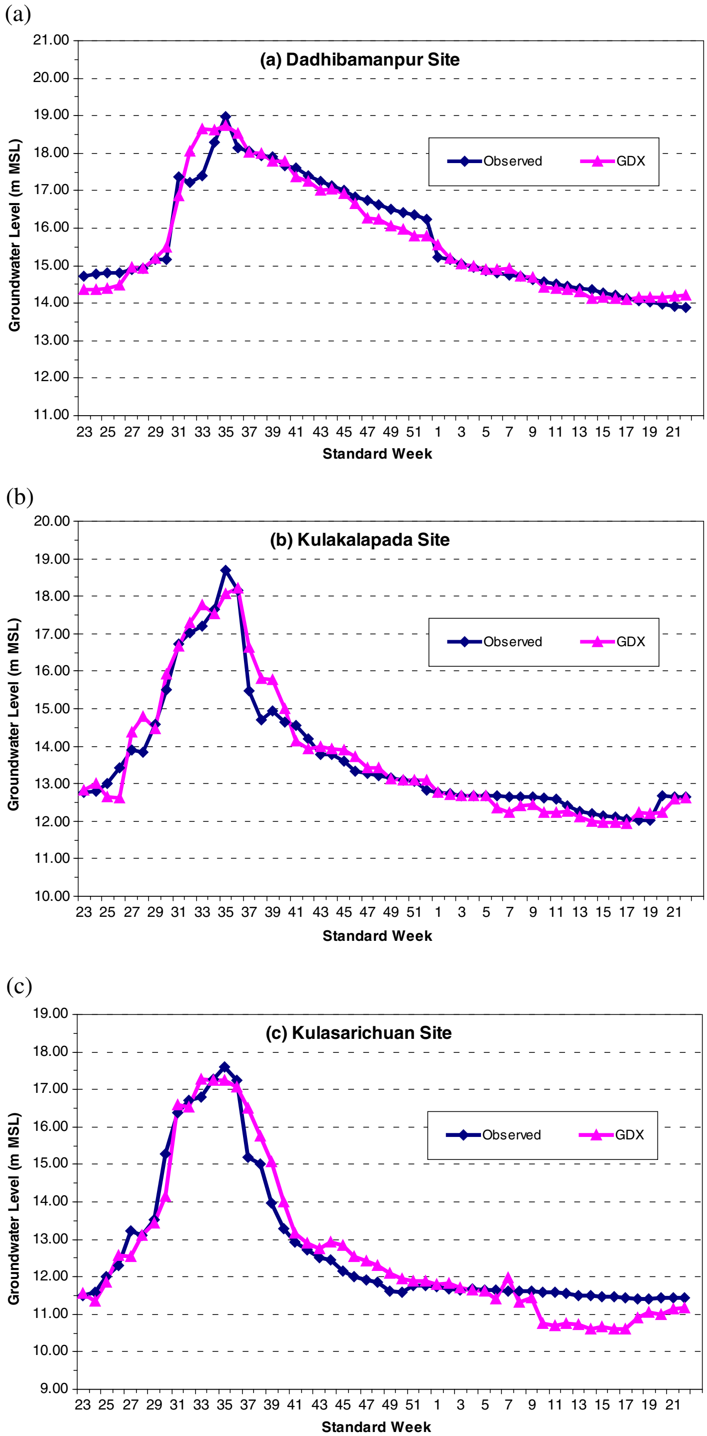

Fig. 4 **a** to **c** Comparison between observed and predicted groundwater levels at Dadhibamanpur, Kulakalapada and Kalusarichuan sites during testing period

surface water and groundwater. Therefore, the ANN model was further used to forecast groundwater levels at 2-, 3- and 4-week in advance in the study area. It may be noted that the inputs used for this analysis were the same as that used for forecasting groundwater levels at 1 week in advance. The performance of this model in terms of r, RMSE and NSE statistics during the training and testing period is shown in Table 1. It is apparent from this table that during the training period, the r value varies from 0.9861 for 1-week lead time forecast to 0.9306 for 4-week lead time forecast, the RMSE value varies from 0.2397 m for 1-week lead time to 0.4831 m for 4-week lead time and the value of NSE varies from 0.9722 for 1-week lead time to 0.8841 for 4-week lead time. During testing period, the r value varies from 0.9715 for 1-week lead time forecast to 0.9270 for 4-week lead time forecast, the RMSE value varies from 0.4118 m for 1-week lead time to 0.6148 m for 4-week lead time and the value of NSE varies from 0.9288 for 1-week lead time to 0.8471 for 4-week lead time. It is evident that even though prediction of groundwater level for higher lead times is reasonably satisfactory, the values of r and NSE are slightly decreased and the RMSE value is slightly increased with an increase in the lead time. It indicates that the model can forecast groundwater levels at lower lead times more accurately. A variation was also observed in the performance of the model in predicting groundwater levels in different wells; this can be attributed to the quality of data available.

The observed and simulated groundwater levels at different lead time forecasts are shown in Fig. 5 (a to c) for three sites, Dadhibamanpur (Site E), Kulakalapada (Site L) and Kulasarichuan (Site R), respectively. These figures also indicate better matching between observed and simulated groundwater levels for the smaller lead times (up to 2 weeks) compared to large lead time. Thus, it can be inferred that the performance of the ANN model generally decreases with an increase in the lead time. However, the groundwater-level prediction for higher lead times (up to 4 weeks) is also reasonably accurate in this study. Thus, it could be inferred that despite the data constraints in this study, the developed ANN models predicted weekly groundwater levels over the river basin reasonably well for 1-, 2-, 3- and 4-week lead times. The neural networks also have the advantage of not requiring explicit characterization and quantification of the physical properties and condition of the aquifer system. Also, the data requirement of ANNs is generally easier to collect and quantify than the physically based models. However, the numerical models can be more appropriate for long-term predictions, whereas the ANN technique may be better for real-time short-horizon predictions at selected locations (Coppola et al. 2005).

Table 1 Goodness-of-fit statistics for different lead time forecasts

Lead time	r		RMSE (m)		NSE	
	Training	Testing	Training	Testing	Training	Testing
1 week	0.9861	0.9715	0.2397	0.4118	0.9722	0.9288
2 weeks	0.9639	0.9407	0.3885	0.5540	0.9260	0.8713
3 weeks	0.9306	0.9336	0.5226	0.5866	0.8652	0.8589
4 weeks	0.9403	0.9270	0.4831	0.6148	0.8841	0.8471

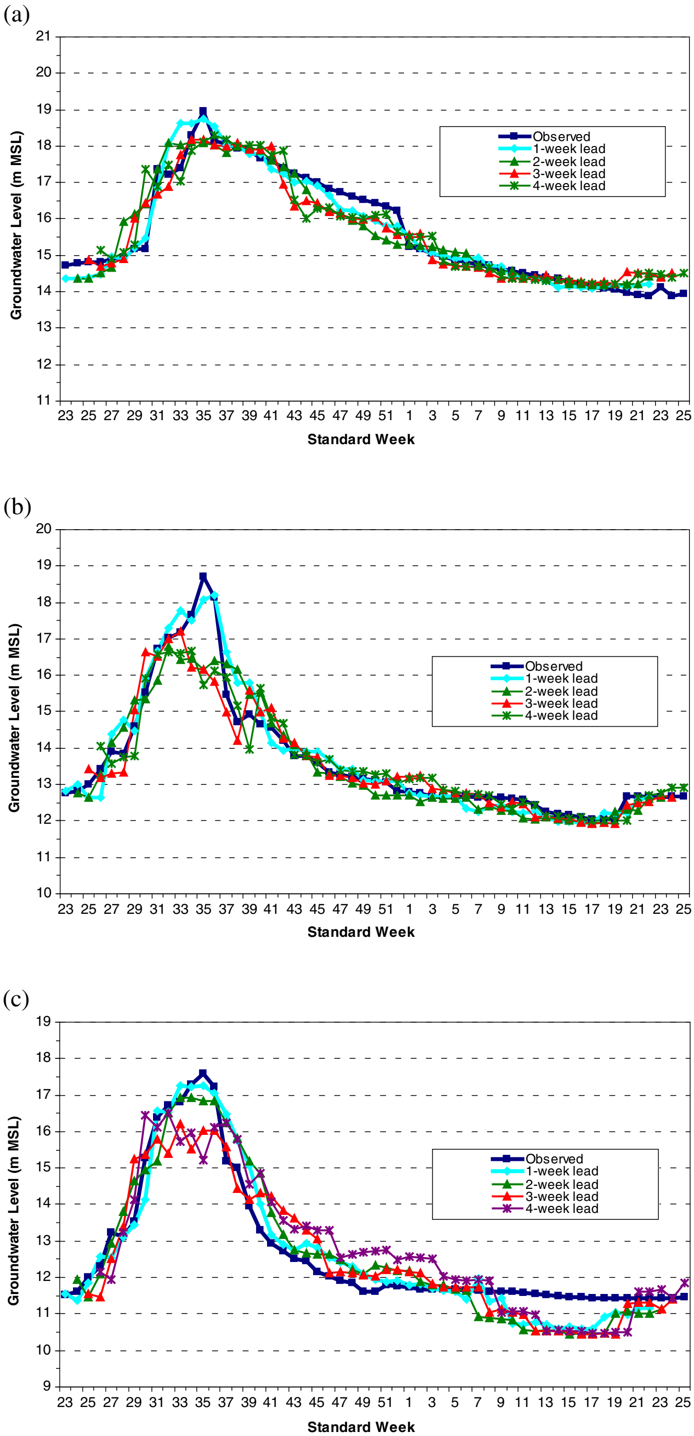

Fig. 5 **a** to **c** Comparison between observed and simulated groundwater levels at Dadhibamanpur, Kulakalapada and Kalusarichuan sites at different lead time forecast

5 Conclusions

This paper demonstrates the effectiveness of artificial neural network (ANN) modeling in forecasting weekly groundwater levels in a group of wells located in an alluvial aquifer system. Owing to less memory requirement, the Gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm was found suitable for simultaneously forecasting groundwater levels in a large group of wells. The developed ANN model was capable of forecasting groundwater levels in the study area 1-week in advance with a reasonable accuracy. This model was further used to forecast groundwater levels at 18 sites for higher lead times, viz., 2- 3- and 4-week lead times. The analysis of the modeling results revealed reasonably good prediction/forecast of groundwater levels for all the three larger lead times, though the accuracy of prediction was found to decrease with increasing lead times.

The developed model can be used to get a reasonable estimate of groundwater level 1 week ahead in the study area, thereby it can help in the proper planning of groundwater utilization. In future, the present work can be extended to develop ANN models to estimate groundwater level at a monthly time step so that groundwater-level prediction can be done at a longer time ahead. In addition, a sensitivity analysis of the ANN model can be conducted to find out most significant number of ANN connections, which in turn can improve the robustness of the developed ANN model.

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