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Artificial Neural Network Modeling for Groundwater Level Forecasting in a River Island of Eastern India

Sheelabhadra Mohanty · Madan K. Jha · Ashwani Kumar · K. P. Sudheer

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Abstract Forecasting of groundwater levels is very useful for planning integrated management of groundwater and surface water resources in a basin. In the present study, artificial neural network models have been developed for groundwater level forecasting in a river island of tropical humid region, eastern India. ANN modeling was carried out to predict groundwater levels 1 week ahead at 18 sites over the study area. The inputs to the ANN models consisted of weekly rainfall, pan evaporation, river stage, water level in the drain, pumping rate and groundwater level in the previous week, which led to 40 input nodes and 18 output nodes. Three different ANN training algorithms, viz., gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Levenberg–Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm were employed and their performance was evaluated. As the neural network became very large with 40 input nodes and 18 output nodes, the LM and BR algorithms took too much time to complete a single iteration. Consequently, the study area was divided into three clusters and the performance evaluation of the three ANN training algorithms was done separately for all the clusters. The performance of all the three ANN training algorithms in predicting groundwater levels over the study area was found to be almost equally good. However, the performance of the BR algorithm was found slightly superior to

S. Mohanty (✉) · A. Kumar
Directorate of Water Management,
Bhubaneswar 751 023, Orissa, India
e-mail: smohanty_wtcer@yahoo.co.in

M. K. Jha
AgFE Department, IIT Kharagpur,
Kharagpur 721 302, West Bengal, India
e-mail: madan@agfe.iitkgp.ernet.in

K. P. Sudheer
Department of Civil Engineering,
IIT Madras, Chennai, Tamil Nadu, India
e-mail: kps.iitm@gmail.com

that of the GDX and LM algorithms. The ANN model trained with BR algorithm was further used for predicting groundwater levels 2, 3 and 4 weeks ahead in the tubewells of one cluster using the same inputs. It was found that though the accuracy of predicted groundwater levels generally decreases with an increase in the lead time, the predicted groundwater levels are reasonable for the larger lead times as well.

Keywords Artificial neural network · Groundwater level prediction · Backpropagation GDX algorithm · Lavenberg-Marquardt algorithm · Bayesian regularization algorithm · River island

1 Introduction

Groundwater is one of the most valuable natural resources and it has become a dependable source of water in all climatic regions of the world (Todd and Mays 2005). In the developing countries, it is emerging as a poverty-alleviation tool owing to the fact that groundwater can be delivered directly to poor communities more cost-effectively, promptly and easily than the surface water (IWMI 2001). Unfortunately, the dwindling of groundwater levels and aquifer depletion due to over-exploitation together with growing pollution of groundwater are threatening the sustainability of water supply and ecosystems. Numerous consequences of unsustainable groundwater use are becoming increasingly apparent worldwide, particularly in developing countries and the major concern is how to maintain a long-term sustainable yield from aquifers (Alley and Leake 2004; Kalf and Woolley 2005; Sophocleous 2005; Todd and Mays 2005). Thus, sustainable management of water resources in general and groundwater resource in particular is of utmost importance for both present and future generations.

Groundwater modeling has emerged as a powerful tool to help water managers optimize groundwater use and to protect this vital resource. Physically based numerical models are being used during past several years for simulation and analysis of groundwater systems. With the proliferation of use of computers, they are being widely used by engineers, hydrogeologists and environmentalists. They have been applied to problems ranging from aquifer safe yield analysis to groundwater remediation and quality issues. These modeling techniques are very data intensive, labour intensive and expensive. Under data-scarce conditions, which are a common scenario in most developing countries, the use of physical based models is highly restricted. Therefore, in such cases, empirical models serve an attractive alternative as they can provide useful results using relatively less data and are less laborious and cost-effective. Artificial Neural Network (ANN) models are one of such models, which are treated as universal approximators and are very much suited to dynamic nonlinear system modeling (ASCE 2000a). Unlike physically based numerical models, ANNs do not require explicit characterization and quantification of physical properties and conditions of the system under investigation. ANNs learn the system's behavior from representative data. 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). An attractive feature of ANNs is their ability to develop a relation between the outputs and inputs of a process without the physics being explicitly provided to them. The advantages of ANN models over physically based models are discussed in French et al. (1992).

The applications of ANN technique in hydrology range from real-time modeling to event-based modeling. It has been used for rainfall-runoff modeling, precipitation forecasting as well as for modeling of streamflows, evapotranspiration, water quality and groundwater (Gobindraju and Ramachandra Rao 2000; ASCE 2000a, b). Compared to surface water hydrology, relatively less number of studies on ANN application in groundwater hydrology has been reported in the literature. 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), groundwater quality prediction (Hong and Rosen 2001; Milot et al. 2002; Kuo et al. 2004), 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; Banerjee et al. 2009).

In most of the past studies on groundwater level prediction by ANN, ANN models have been developed for predicting groundwater level in a single well or a few wells

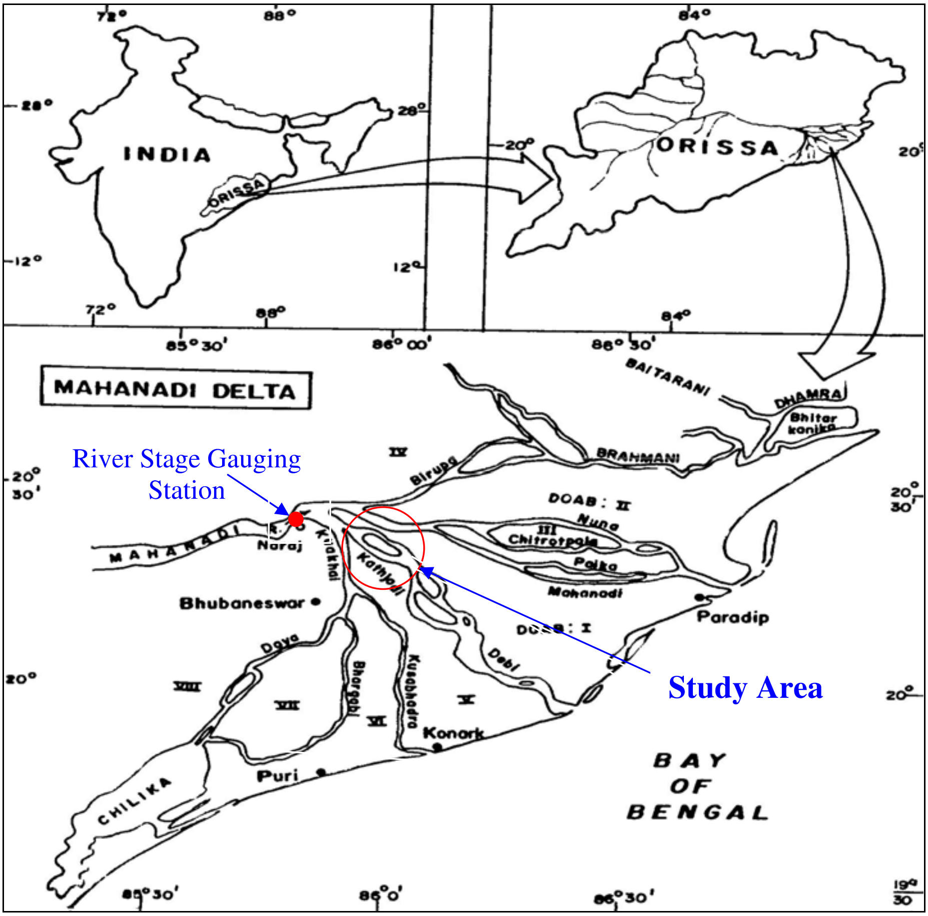

Fig. 1 Location map of the study area

using a set of input parameters. However, in the present study, a methodology is presented to predict groundwater levels simultaneously in a large number of wells over a basin by using an ANN model. Thus, the methodology is of great practical importance. The applicability of the methodology is demonstrated by using three ANN training algorithms namely gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Lavenberg-Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm for predicting groundwater levels in a river island located in the tropical humid region, eastern India. This study is first of its kind in north India in general and eastern India in particular.

2 Study Area

The study area selected for this study is known as Bayalish Mouza which is located in the Kathajodi River basin of Orissa, India (Figs. 1 and 2). It is a typical river island 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 total area of the river island is 35 km^2. The study area has a tropical humid climate with an average annual rainfall of 1,535 mm, of which 80% occurs during June to October months. The normal mean monthly maximum and minimum temperatures of the region are 38.8°C and 15.5°C in May and December, respectively. The mean monthly maximum and minimum evapotranspiration rates are 202.9 and 80.7 mm in May and December, respectively.

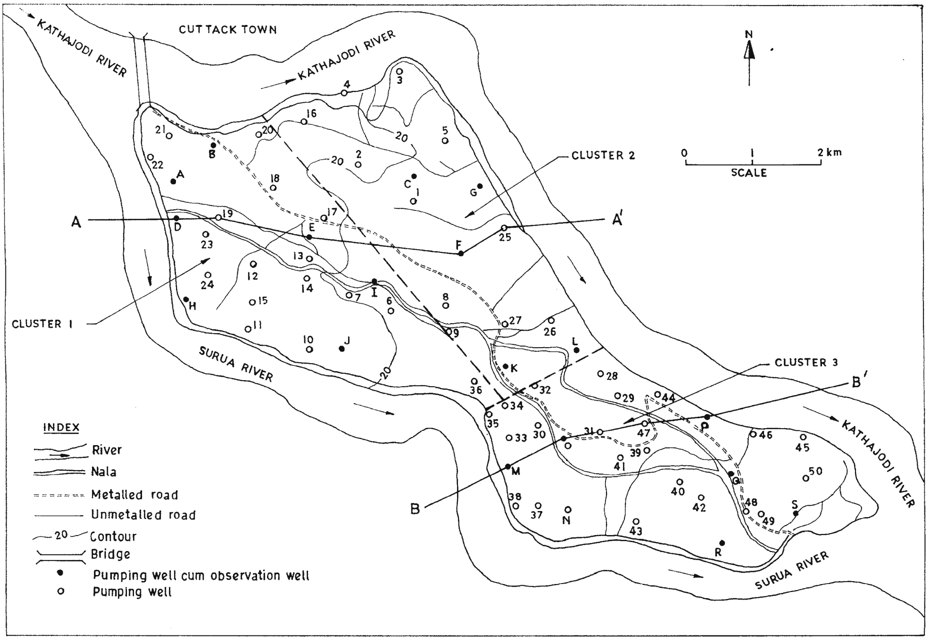

Fig. 2 Location of pumping and observation wells in the study area

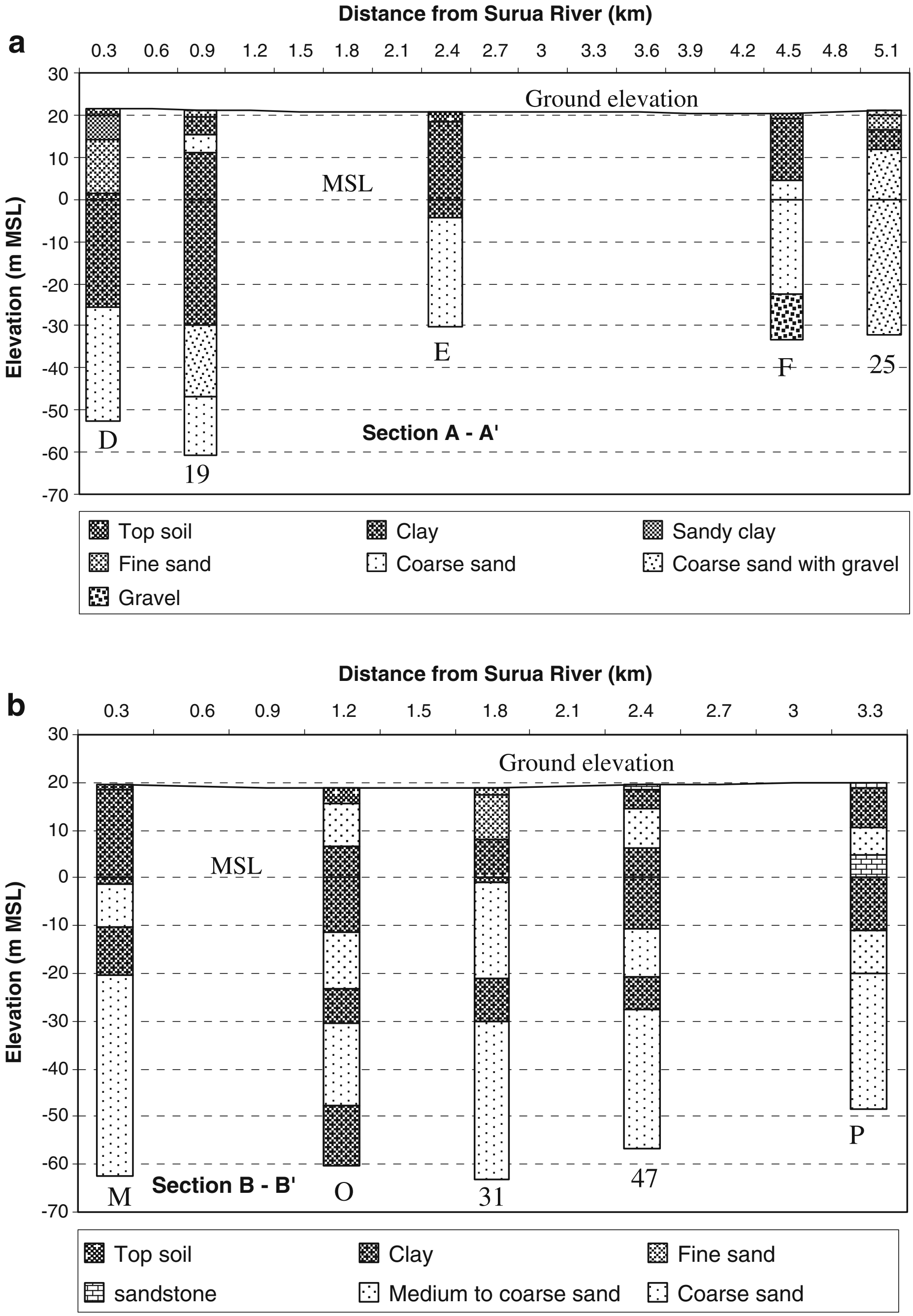

Fig. 3 **a** Lithologic profile of the study area along the section A–A′ (**b**) Lithologic profile of the study area along the section B–B′

Groundwater is the major source of irrigation in the study area. There are 69 government tubewells in the area, which constitute major sources of groundwater withdrawals for irrigation. These tubewells are constructed and managed by the Orissa Lift Irrigation Corporation, Government of Orissa, India. Now, they are gradually being handed over to the local water users' associations. The lithologic data of the study area indicate the existence of a confined aquifer. Figure 3a, b show the lithologic profiles of the study area along cross-sections A–A′ and B–B′, respectively. It is apparent from Fig. 3a that aquifer is present at a deeper depth in the western side and at a shallower depth in the eastern side of the river basin. Figure 3b shows that there is more than one layer of water bearing formation towards the downstream side of the river basin. The water bearing formation (i.e., aquifer) mostly consists of coarse sand, medium to coarse sand and pebbles, with the coarse sand as a dominant formation. The thickness of the aquifer varies from 20 to 55 m over the basin. The top confining layers having a thickness of 15 to 50 m comprise clay or sandy clay with isolated patches of coarse sand or medium sand in between. The groundwater level responds significantly to the rainfall or variation in river stage, indicating a good connection with surface water bodies (Mohanty et al. 2009). Thus, the top confining layer is a semi-confining layer in reality and hence the aquifer is a semi-confined in nature. The aquifer transmissivity varies from a minimum of 528.5 m^2/day at Site B to a maximum of 3,484.8 m^2/day at Site O with an average value of 1,778.86 m^2/day. The storage coefficient of the aquifer ranges from a minimum of 1.43×10^{-4} at Site H to a maximum of 9.9×10^{-4} at Site O with an average value of 4.61×10^{-4} (Mohanty et al. 2009).

There is no water shortage during the monsoon season in the study area, but in the summer season, the farm ponds dry up and the groundwater withdrawal is not sufficient to meet the entire water requirement of the farmers. Thus, the study area suffers from water scarcity during summers and the water scarcity is aggravated during the years having below average rainfall.

3 Methodology

3.1 Data Acquisition and Monitoring

Groundwater level data in the study area was obtained by monitoring the groundwater level at 19 sites (A to S in Fig. 2) on a weekly basis. The monitoring work continued from February 2004 to June 2007. The sites for groundwater level monitoring were selected in such a way that they can represent some north–south and east–west cross-sections across the basin. As groundwater level monitoring could not be at one site (site N) for full period, groundwater level data of 18 sites was considered for this study. The daily rainfall was monitored by installing a rain gauge in the study area, whereas the daily pan evaporation data were obtained from a meteorological station at Central Rice Research Institute, Cuttack located about 2 km from the study area. As the weekly river stage data near the project site was not available, the river stage data measured at Naraj (Fig. 1) where the Kathajodi River originates from the main river Mahanadi, were collected from the Central Water Commission Office, Bhubaneswar and used in this study. As the river stage at Naraj directly influences the river stage around the study area, the river stage data of Naraj were used for ANN modeling.

3.2 Overview of ANN Architectures and Training Algorithms

An ANN is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin 1999). 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). In this study, feedforward neural network architecture has been used and three ANN training algorithms, viz., gradient descent with momentum and adaptive learning rate back-propagation (GDX) algorithm, Levenberg–Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm have been evaluated to identify a suitable algorithm which performs the best in predicting weekly groundwater levels over the study area.

3.2.1 Feedforward Neural Network

Feedforward neural networks have been successfully applied in different problems since the advent of error propagation learning algorithm. This network architecture is the simplest of all neural network architectures. In a feedforward network, the nodes are generally arranged in layers, starting from a first input layer and ending at the final output layer. There can be several hidden layers with each layer having one or more nodes. Figure 4 shows the feedforward network for the current study having one hidden layer with several nodes in input and output layer. Information passes from the input to the output side. 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. The main advantage of feedforward neural networks are that they are easy to handle, and can approximate any input/output map, as established by Hornik et al. (1989).

3.2.2 Training Algorithms

Coulibaly et al. (1999) reported that more than 23 learning rules have been proposed for training an artificial neural network; however, none of them can guarantee the global minimum solution. Therefore, efficient network training is a challenging part

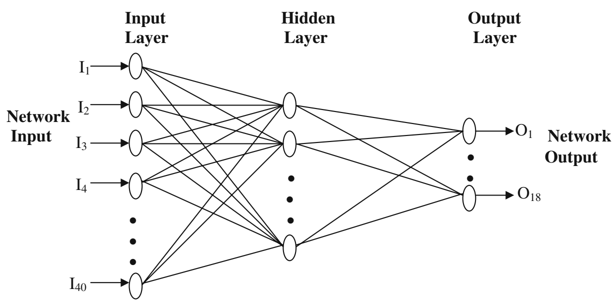

Fig. 4 Configuration of feedforward three-layer ANN for the study area

of network design. A critical examination of the available literature indicates that more than 90% of the experiments make use of feedforward neural network trained by standard backpropagation algorithm (BPA), which is basically a gradient based optimization technique developed by Rumelhart et al. (1986). Standard backpropagation is a gradient descent algorithm in which network weights are moved along the negative of the gradient of the performance function. The term ‘backpropagation’ refers to the manner in which the gradient is computed for nonlinear multilayer networks.

Although backpropagation training has proved to be efficient in lots of applications, it has inherent limitations of gradient based techniques such as slow convergence and the local search nature. Among the various modifications proposed to the backpropagation algorithm, the conventional second-order nonlinear optimization methods such as the conjugate-gradient, the Levenberg–Marquardt and the quasi-Newton algorithms are usually faster than any variant of the BPA (Masters 1995; Hagen et al. 1996). The Levenberg–Marquardt algorithm is designed specifically for minimizing a sum of squared error (Bishop 1995) and to overcome the limitations in the standard BPA.

Building a model with minimum number of input variables and parameters to achieve high predictive accuracy without under or over fitting problems is very much essential. Too many neurons in the hidden layer lead to over fitting, i.e., the training data will be well modeled but the network models the noise in the data as well as the trends. On the other hand, a network with an insufficient number of hidden nodes will have difficulty in learning data. Thus, both too small and too large networks have poor prediction performance. Therefore, the network will not generalize well on the testing data. To overcome this problem, Mackay (1991) proposed the use of Bayesian regularization algorithm which is able to deal with the over fitting issue.

Gradient descent with momentum and adaptive learning rate backpropagation With a standard backpropagation algorithm, the learning rate is held constant throughout the training. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm may oscillate and become unstable. If the learning rate is too small, the algorithm will take too long to converge. In order to overcome the problem, the gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm combines adaptive learning rate with momentum training. An adaptive learning rate attempts to keep the learning step size as large as possible while keeping learning stable. Each variable is adjusted according to the gradient descent with momentum. Acting like a low pass filter, momentum allows the network to ignore small features in the error surface. This training algorithm is one of the simplest and most common ways to train a network.

Levenberg–Marquardt In backpropagation algorithm, the local gradient given by gradient descent does not point directly towards the minimum. Gradient-descent then takes many small steps to reach minimum and thus leads to slow learning. To overcome this, Levenberg–Marquardt algorithm, a second order optimization procedure for multilayer FNN training is used. Levenberg–Marquardt method is a modification of the Newton algorithm for finding an optimal solution to a minimization problem. It is designed to approach second order training speed and accuracy without having to compute the Hessian matrix. It uses an approximate to the Hessian matrix in the following Newton-like weight update (Daliakopoulos et al. 2005).

$$x_{i+1} = x_i - \left[J^T J + \mu I\right]^{-1} J^T e \tag{1}$$

Where, x = weights of the neural network, J = Jacobian matrix of the performance criteria to be minimized, μ = a scalar that controls the learning process, and e = residual error vector. When the scalar μ is zero, this is just Newton's method using the approximate Hessian matrix. When μ is large the equation becomes gradient descent with small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible.

Levenberg–Marquardt algorithm is one of the fastest methods for training feed-forward neural networks. However, due to high memory requirement, it can only be used in small networks (Maier and Dandy 1998). Nevertheless, many researchers have been successfully using it (e.g., Toth et al. 2000; Coulibaly et al. 2000, 2001; Anctil et al. 2004; Daliakopoulos et al. 2005).

Bayesian regularization The Bayesian approach involves the optimization of an objective function that comprises the conventional sum of squared error function as well as an additional term, called 'regularizer'. The motivation for using the regularizer is to penalize the more complex weight functions in favor of simpler functions. The Bayesian approach also enables the optimal weight decay parameters to be adjusted automatically during training (Mackay 1991; Bishop 1995). The salient advantages of Bayesian updating are as follows:

1. It provides a unifying approach for dealing with issues of model complexity and over fitting.
2. The modification in the error function aims to improve the model's generalization capability.
3. The prediction generated by a trained model can be assigned an error bar to indicate its confidence level.

In the Bayesian framework, the uncertainty in the weight space is assigned a probability distribution representing the degree of belief in the different values of the weight vector. This function is initially set to some prior distribution. Once the data has been observed, it can be converted to a posterior distribution through the use of Bayes' theorem. By maximizing the posterior distribution over the weights, the most probable parameter values can be obtained. Bayesian regularization has been effectively used by several researchers (e.g., Porter et al. 2000; Coulibaly et al. 2001; Anctil et al. 2004; Daliakopoulos et al. 2005).

3.3 Design of ANN

One of the most important steps in the model development process is the determination of significant input variables. Generally some degree of a priori knowledge is used to specify the initial set of candidate inputs (e.g., Campolo et al. 1999; Thirumalaiah and Deo 2000). Although a priori identification is widely used in many applications and is necessary to define a candidate set of inputs, it is dependent on an expert's knowledge, and hence, is very subjective and case dependent. When the relationship to be modeled is not well understood, then an analytical technique, such as cross-correlation, is often employed (e.g., Sajikumar and Thandaveswara 1999; Coulibaly et al. 2000; Sudheer et al. 2002). The major disadvantage associated with using cross-correlation is that it is only able to detect linear dependence between two variables. Therefore, cross-correlation is unable to capture any nonlinear dependence that may exist between the inputs and the output, and may possibly result in the omission of important inputs that are related to the output in a nonlinear fashion. Intuitively, the preferred approach for determining appropriate inputs involves a combination of a priori knowledge and analytical approaches (Maier and Dandy 1997).

In the present study, the ANN model was designed to predict groundwater levels in 18 tubewells (Fig. 2) with 1 week lead time using a set of suitable input parameters. The input parameters for the ANN model were decided by considering the parameters which have potential to affect the groundwater level. A cross correlation analysis between the water levels in the tube wells at various lags suggested that Lag 1 correlation is highly significant in the water level time series in all the 18 wells. To examine the effect of rainfall and river stage on groundwater, they were plotted along with the weekly groundwater level. Figure 5 shows the weekly variation of groundwater levels at four sites along with the weekly rainfall, which indicates that groundwater levels are generally higher on high rainfall days. Hence, rainfall is one potential input parameter which influences groundwater of the study area. Similarly, Fig. 6 shows the weekly variation of groundwater levels at the four sites along with the river stage data. As there is a good correlation between the river stage data and the groundwater level data, river stage is another potential input parameter which influences the groundwater of the study area. In a semi-confined aquifer, apart from rainfall, evaporation is another parameter which can influence the recharge to groundwater. Therefore, weekly pan evaporation was also considered as one of the input parameters for the ANN model.

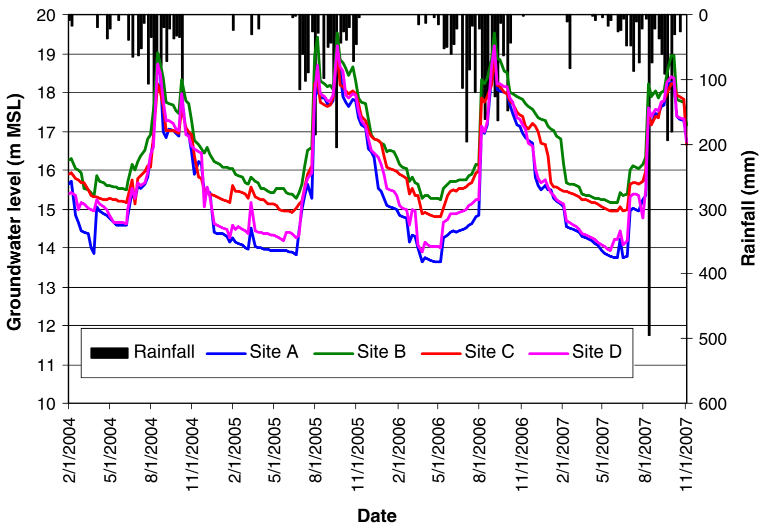

Fig. 5 Weekly groundwater level fluctuations at sites A to D with *bar graphs* of rainfall

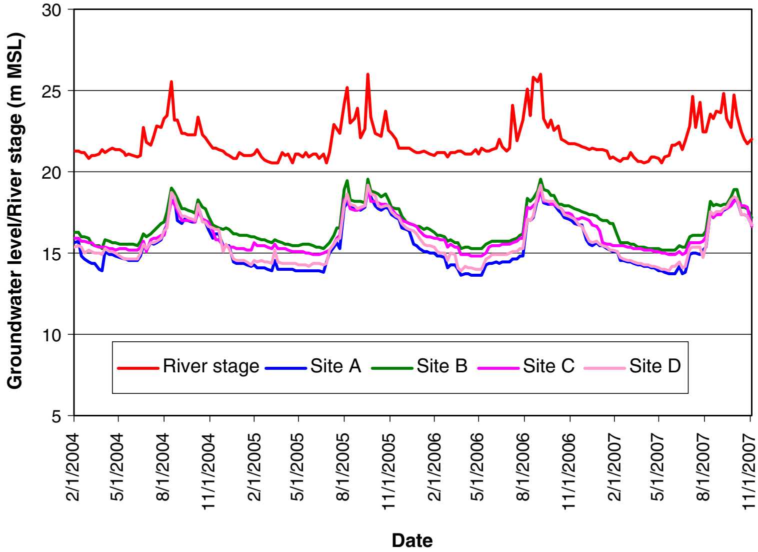

Fig. 6 Well hydrographs at sites A to D with river stage hydrograph at Naraj gauging station

Moreover, in the study area, entire rainwater of the region is drained through a main drain and discharged at a single outlet into the river. A sluice gate is provided at the outlet of the area to prevent ingress of river water during flood events. During these flood events, water level in the main drain rises and waterlogging problem is encountered in the downstream side of the study area. The water level in the main drain has been also considered as an input parameter because it influences the groundwater, especially in the downstream portion of the study area. There are 69 tubewells in the study area. However, by considering weekly pumping of 69 tubewells, 69 input parameters will make the model quite big and difficult to work with. Hence for ANN modeling, it was assumed that the weekly pumping of selected 18 tubewells represents the specific pumping pattern in that locality, which is reasonable for the study area because the 18 tubewells are uniformly distributed over the area and pumping pattern of each of the 18 tubewells almost matches with the nearby tubewells. As the records of history of pumping from the tubewells were not available, the pumping rates of the 18 tubewells were obtained from the farmers and were considered as one of ANN input parameters. Thus, there were altogether 40 input nodes and 18 output nodes in the initial ANN model of the study area. The 40 input nodes represent initial groundwater levels 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).

The structure of the neural network was determined by trial and error. The optimal number of nodes in the hidden layer and the stopping criteria were optimized by trial and error for obtaining accurate output. 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. In this study, supervised type of learning with a batch mode of data feeding was used in ANN modeling. Out of the 174 weeks data sets available, 122 data sets were used for training the ANN model and 52 data sets were used for testing the model. The entire ANN modeling was performed by using MATLAB 6.5 software.

3.4 Evaluation Criteria

Four statistical criteria (or statistical indicators) were used in order to evaluate the effectiveness of three artificial neural network models developed in this study. They are correlation coefficient (R), bias, root mean square error (RMSE) and Nash-Sutcliffe efficiency or model efficiency (E) and are given by the following equations:

$$R = \frac{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)\left(P_i - \bar{P}\right)}{\sqrt{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2 \sum_{i=1}^{n}\left(P_i - \bar{P}\right)^2}} \tag{2}$$

$$Bias = \frac{1}{N}\sum_{i=1}^{n}(O_i - P_i) \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{N}} \tag{4}$$

$$E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2} \tag{5}$$

Where, O_i = observed value for ith data, P_i = predicted value for ith data, $\bar{O}$ = mean of observed value, $\bar{P}$ = mean of predicted value, and n = number of observations. The best fit between observed and predicted values under ideal conditions would yield RMSE = 0, bias = 0, $R^2 = 1$ and E = 1.

4 Results and Discussion

4.1 Performance Evaluation of ANN Training Algorithms

With the ANN model having 40 input nodes and 18 output nodes, the Levenberg–Marquardt and Bayesian regularization models consumed a lot of computer memory and were difficult to be evaluated by the trial and error method. Maier and Dandy (1998) also reported that the Levenberg–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

Table 1 Input and output parameters for the three clusters

Cluster	Input parameters	Output parameters
Cluster 1	Initial groundwater levels at 7 sites (A, B, D, E, H, I and J); average weekly pumping rates of 7 tubewells (A, B, D, E, H, I and J); weekly total rainfall; average weekly river stage; and average weekly pan evaporation	Groundwater levels at 7 sites (A, B, D, E, H, I and J) in the next time step (i.e., 1 week ahead)
	Total 17 input parameters	Total 7 output parameters
Cluster 2	Initial groundwater levels at 5 sites (C, F, G, K and L); average weekly pumping rates of 5 tubewells (C, F, G, K and L); weekly total rainfall; average weekly river stage; and average weekly pan evaporation	Groundwater levels at 5 sites (C, F, G, K and L) in the next time step (i.e., 1 week ahead)
	Total 13 input parameters	Total 5 output parameters
Cluster 3	Initial groundwater levels at 6 sites (M, O, P, Q, R and S); average time weekly pumping rates of 6 tubewells (M, O, P, Q, R and S); weekly total rainfall; average weekly river stage; average weekly pan evaporation; and average weekly water level in the main drain	Groundwater levels at 6 sites (M, O, P, Q, R and S) in the next step (i.e., 1 week ahead)
	Total 16 input parameters	Total 6 output parameters

algorithm could effectively be evaluated through trial and error procedure due to less memory requirement. In order to run the LM and BR models effectively, an effort was made to reduce the size of the network and the entire study area was divided into three clusters as shown in Fig. 2, with three separate ANN models predicting groundwater levels 1 week advance at sites present in the respective cluster. Cluster 1 contains seven sites namely A, B, D, E, H, I and J (Fig. 2). Cluster 2 contains five sites namely C, F, G, K and L and Cluster 3 contains six sites namely M, O, P, Q, R and S. The division of the study area into three clusters and modeling each cluster separately will not have any effect on the final output as the pumping in the tubewells of any cluster has a very minor effect on the water level in tubewells of other clusters.

In each cluster, groundwater levels at the sites in the previous time step, pumping rates of the tubewells, weekly total rainfall, average weekly pan evaporation and average weekly river stage were considered as input parameters. In the third cluster, however, an additional input parameter average weekly water level in the drain was considered as it has potential to affect the groundwater level in this cluster only. Thus, Cluster 1 had 17 input nodes and seven output nodes, Cluster 2 had 13

Table 2 Optimum number of hidden neurons for the three ANN training algorithms

Cluster	GDX	LM	BR
Cluster 1	10	40	10
Cluster 2	30	20	20
Cluster 3	30	20	40

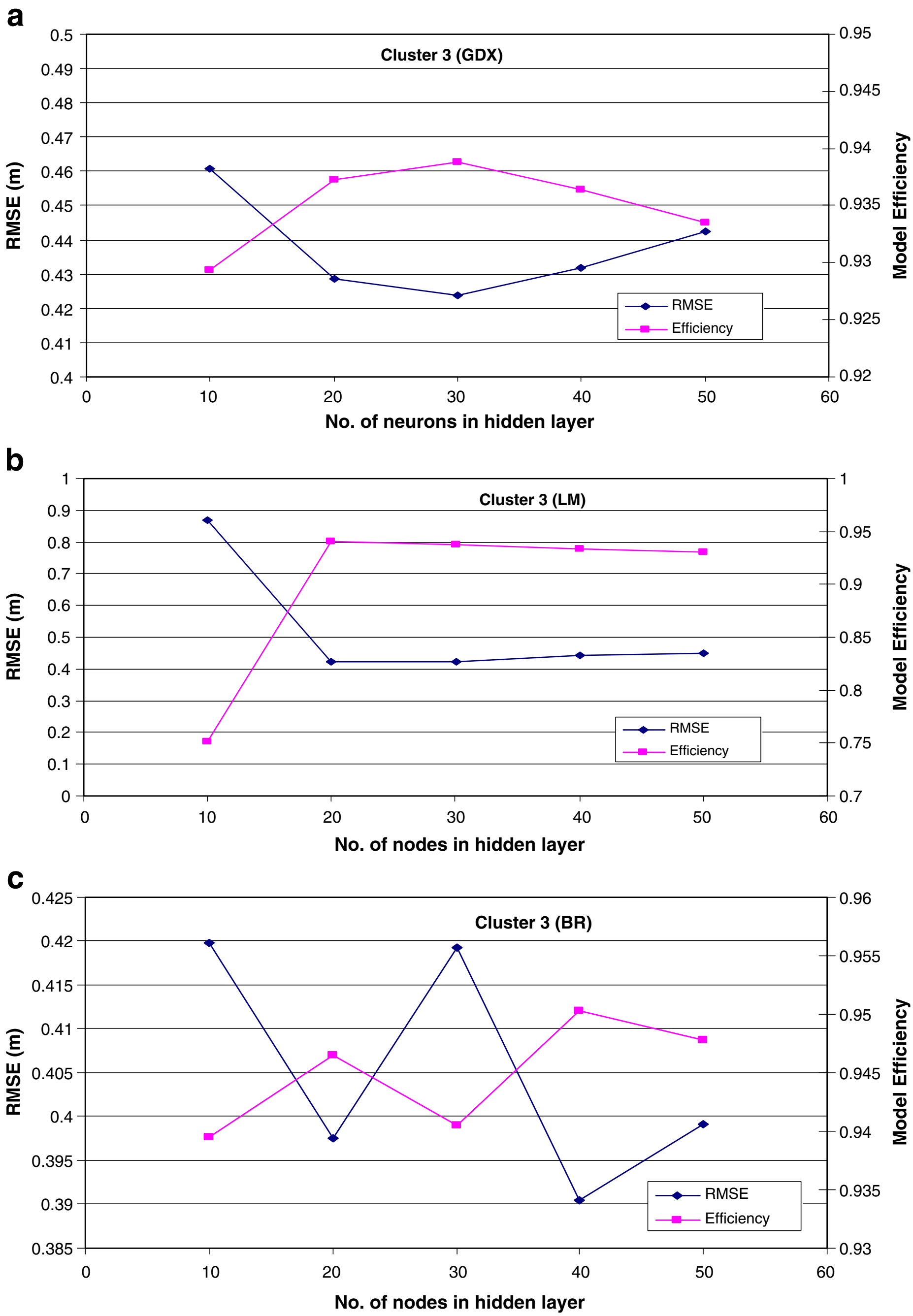

Fig. 7 **a**–**c** Variation of RMSE and model efficiency with the number of nodes in the hidden layer for cluster 3

input nodes and five output nodes and Cluster 3 had 16 input nodes and six output nodes as shown in Table 1. The performance of GDX, LM and BR algorithms in predicting groundwater levels 1 week ahead was evaluated separately for all the three clusters. The optimal number of hidden neurons for each cluster and algorithm was determined by the trial and error method. The ANN architecture with lowest RMSE value, highest correlation coefficient and highest Nash-Sutcliffe coefficient was considered to yield optimum number of hidden neurons. This procedure was repeated for all the three clusters with three different training algorithms. The optimum number of hidden neurons for the three training algorithms and three clusters thus obtained are presented in Table 2. Figure 7a–c show the variation of RMSE and model efficiency (E) with the number of nodes in hidden layer for three different algorithms, respectively for Cluster 3 as an example. The values of statistical indicators for the three training algorithms for the three clusters are shown in Table 3 during training and testing periods. The values of the statistical indicators have been obtained by taking the average of values obtained for the number of sites in each cluster. It can be seen from Table 3 that the performance of all the three training algorithms is good during both training and testing periods; they are able to forecast groundwater levels 1 week in advance with a reasonable accuracy in all the three clusters. For the GDX training algorithm during testing period, the correlation coefficient (R) values range from 0.9678 to 0.9756, bias values from −0.0618 to −0.0159 m, Nash-Sutcliffe efficiency (E) values from 0.9307 to 0.9388, and RMSE values from 0.3722 to 0.4239 m. For the LM training algorithm during testing period, the R values range from 0.9697 to 0.9815, bias values from −0.0806 to −0.0292 m, E values from 0.9318 to 0.9380, and RMSE values from 0.3760 to 0.4244 m, whereas these figures for the BR algorithm are 0.9721 to 0.9793, −0.0613 to 0.0027 m, 0.9366 to 0.9518, and 0.3182 to 0.3905 m respectively.

It is apparent from these performance criteria that all the three ANN training algorithms yield more or less same results, but the Bayesian regularization (BR) algorithm performs slightly better than the remaining two algorithms. It is followed by the Lavenberg-Marquardt (LM) algorithm and the GDX algorithm respectively.

Figure 8a–c show the comparison of predicted groundwater levels (1 week ahead) by different training algorithms with the observed groundwater levels at three

Table 3 Comparison of GDX, LM and BR algorithms

Algorithm	R		Bias (m)		E		RMSE (m)	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Cluster 1 (1-week lead time)								
GDX	0.9739	0.9678	0.0499	−0.0267	0.9460	0.9307	0.3235	0.3785
LM	0.9881	0.9697	0.0058	−0.0600	0.9743	0.9318	0.2178	0.3760
BR	0.9895	0.9721	0.0194	−0.0613	0.9785	0.9366	0.2031	0.3648
Cluster 2 (1-week lead time)								
GDX	0.9766	0.9733	0.0003	−0.0618	0.9536	0.9319	0.2823	0.3722
LM	0.9953	0.9772	−0.0032	−0.0292	0.9905	0.9321	0.1274	0.3782
BR	0.9773	0.9793	−0.0084	−0.0430	0.9546	0.9518	0.2777	0.3182
Cluster 3 (1-week lead time)								
GDX	0.9664	0.9756	−0.0039	−0.0159	0.9336	0.9388	0.4133	0.4239
LM	0.9935	0.9815	−0.0394	−0.0806	0.9856	0.9380	0.1927	0.4244
BR	0.9695	0.9785	−0.0317	0.0027	0.9378	0.9503	0.4008	0.3905

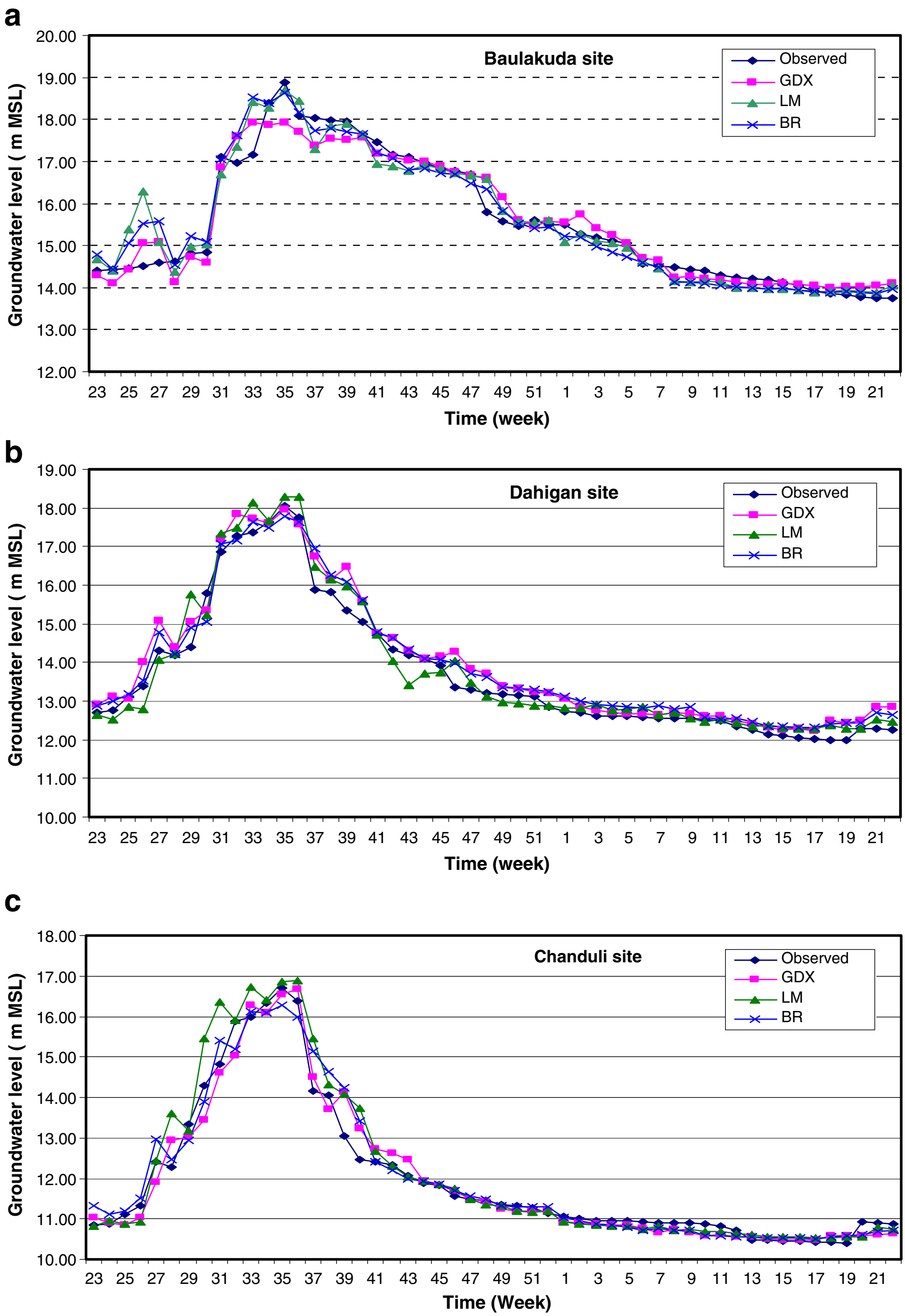

Fig. 8 **a–c** Comparison between the observed groundwater levels and the groundwater levels predicted 1 week ahead by GDX, LM and BR algorithms at Baulakuda, Dahigan and Chanduli sites during testing period

different locations from each cluster, i.e., Baulakuda (A) from the first cluster, Dahigan (K) from the second cluster and Chanduli (S) from the third cluster of the study area. These figures indicate that there is a very good matching between observed and simulated groundwater levels at all the sites. Based on the performance criteria used in this study and the graphical comparison, it can be inferred that all the three algorithms yield more or less same results. However, the performance of the Bayesian regularization algorithm can be considered superior based on the statistical indicators used in this study. On the other hand, the GDX algorithm can effectively be used for large networks with little less accuracy than the Lavenberg-Marquardt algorithm and the Bayesian regularization algorithm respectively. In practice, however, any of these three algorithms could be used for groundwater prediction in the study area.

4.2 Forecasting of Groundwater Levels at Higher Lead Times

As out of the three ANN training algorithms examined in this study, the Bayesian regularization algorithm performed marginally better than the remaining two algorithms, it was further used to forecast groundwater levels at 2-, 3- and 4-week in advance in one cluster (Cluster 1 was selected as an example). It is worth mentioning that the ANN inputs used for this analysis were the same as that used for predicting groundwater levels at 1 week in advance. The performance of these models in terms of R, Bias, E and RMSE statistics along the prediction time horizon during the testing period is shown in Table 4. The values of the statistical indicators have been obtained by taking the average of values obtained for the seven sites. It is apparent from this table that the R value varies from 0.9721 for 1-week lead time forecast to 0.9389 for 4-week lead time forecast, the value of E varies from 0.9366 for 1-week lead time to 0.8647 for 4-week lead time, the value of bias varies from −0.0613 m for 1-week lead time to −0.1286 m for 4-week lead time and the value of RMSE varies from 0.3648 m for 1-week lead time to 0.5456 m for 4-week lead time. It is interesting to note that the performance of the 3-week lead time forecast model is better than the 2-week lead time forecast model. Thus, based on the statistical indicators, it can be inferred that the predicted groundwater levels for the higher lead times (2 to 4 weeks) are reasonable in this study, but the performance of the ANN model generally decreases with an increase in the lead time.

Moreover, the magnitude of residual or prediction errors (i.e., the difference between observed and predicted groundwater levels) for different lead times is illustrated in Fig. 9a–c for three sites, i.e., Baulakuda (A), Dadhibamanpur (E) and Dhuleswar (J), respectively as an example. In these figures, a positive sign indicates

Table 4 Goodness-of-fit statistics for different lead time forecasts

Lead time	R		Bias (m)		E		RMSE (m)	
(week)	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1	0.9895	0.9721	0.0194	−0.0613	0.9785	0.9366	0.2031	0.3648
2	0.9658	0.9469	−0.0008	−0.0837	0.9327	0.8866	0.3615	0.4919
3	0.9617	0.9573	0.0088	−0.0267	0.9245	0.9065	0.3816	0.4480
4	0.9604	0.9389	−0.0657	−0.1286	0.9199	0.8647	0.3951	0.5456

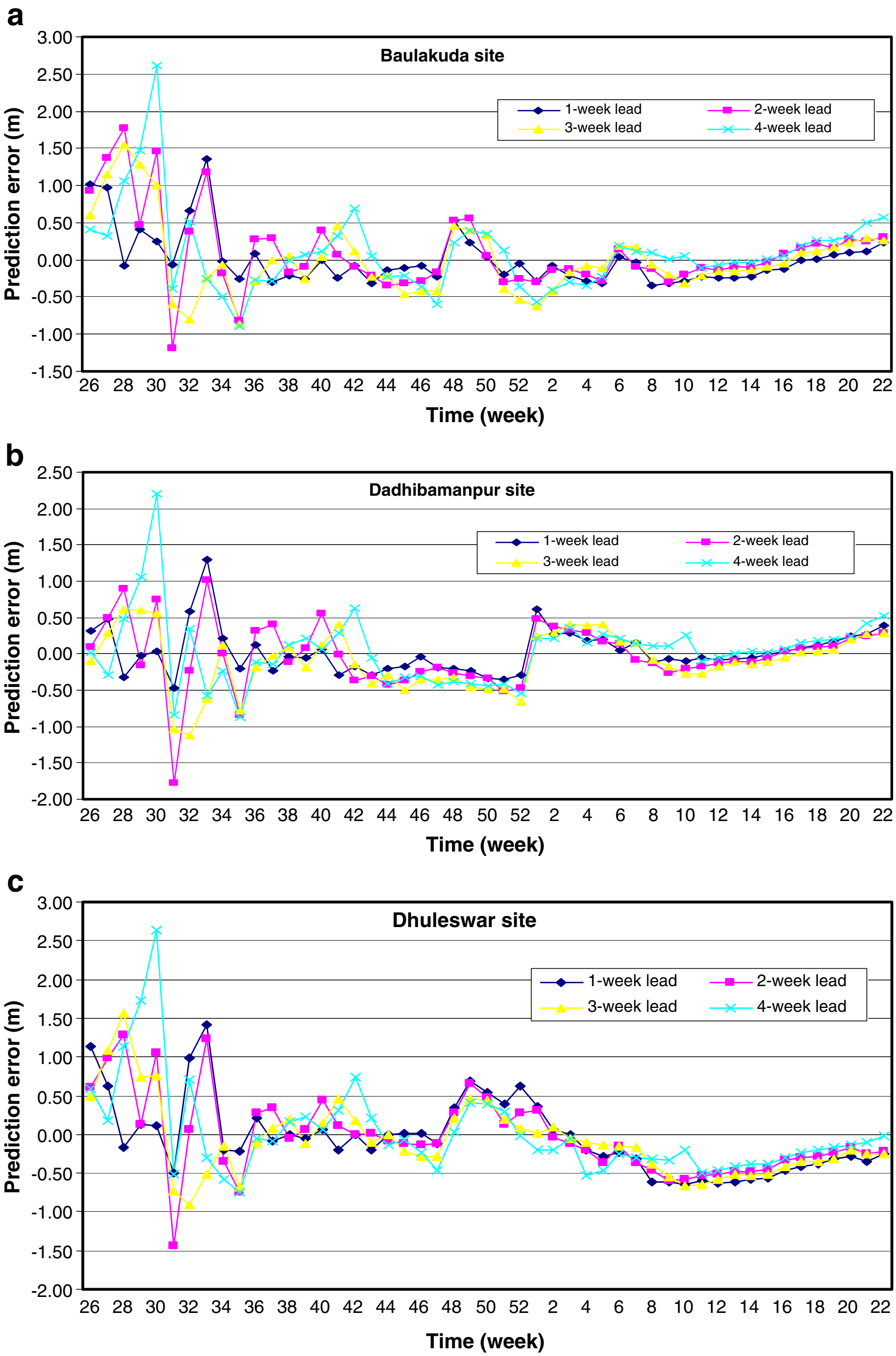

Fig. 9 **a–c** Variation of prediction errors at Baulakuda, Dadhibamanpur and Dhuleswar sites for different lead times

overestimation and negative sign indicates underestimation of groundwater levels by the model. At Baulakuda site, for the 1-week lead time, the residual error ranges from −0.35 to 1.36 m, whereas for the 4 week lead time, the residual error varies from −0.57 to 2.62 m. The corresponding figures for Dadhibamanpur site are −0.47 to +1.29 m for the 1-week lead time and −0.84 to +2.21 m for the 4-week lead time and for Dhuleswar site are −0.51 to +1.42 m for the 1-week lead time and −0.75 to +2.64 m for the 4-week lead time. It is obvious from Fig. 9a–c that there is an increase in the range of error at all the three sites with an increase in the prediction time horizon from 1-week lead time to 4-week lead time. Thus, with an increase in the lead time there is an increase in the prediction/residual error, which confirms the earlier finding based on the performance criteria.

On the whole, it can be inferred that despite the data constraints in this study, the developed ANN models could predict weekly groundwater levels over the river island reasonably well for 1-, 2-, 3- and 4-week lead times. Thus, the ANN technique is more suitable where the knowledge of hydrological/hydrogeological parameters is limited. According to Coppola et al. (2005), while numerical models may be more appropriate for long-term predictions, the ANN technique may be better for real-time short-horizon predictions at selected locations that require a high accuracy.

5 Conclusions

In this paper, three artificial neural network models have been developed for groundwater level forecasting in a river island located in the tropical humid region, eastern India. ANN modeling was carried out using feedforward neural network architecture to predict groundwater levels 1 week ahead at 18 sites over the study area. The inputs of the ANN models were weekly rainfall, pan evaporation, river stage, water level in the drain, pumping rate and groundwater level in the previous week. Thus, there were altogether 40 input nodes and 18 output nodes. The performance of three ANN training algorithms, viz., Gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Levenberg–Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm was evaluated using salient statistical indicators and visual checking. It was observed that the BR and LM algorithms had a very high memory requirement and hence, they were difficult to be evaluated by the trial and error method. As a result, the entire study area was divided into three clusters and ANN modeling was performed separately for each cluster.

The analysis of the ANN modeling results revealed that all the three training algorithms yield more or less same results, and hence any of these three algorithms can be used for predicting groundwater levels over the study area. However, the performance of the Bayesian regularization (BR) algorithm is considered superior based on the statistical indicators used in this study. The ANN model trained with BR algorithm was further used to predict groundwater levels at 7 sites in Cluster 1 with higher lead times (2- 3- and 4-week lead times) using the same inputs. It was found that the groundwater prediction is reasonably good for all the three lead times, but the accuracy of prediction decreases with increasing lead times. Overall, it can be concluded that despite the limited data used in this study, the developed ANN models are capable of predicting weekly groundwater levels over the study area reasonably well even for higher lead times.

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