Research Bulletin No. 77

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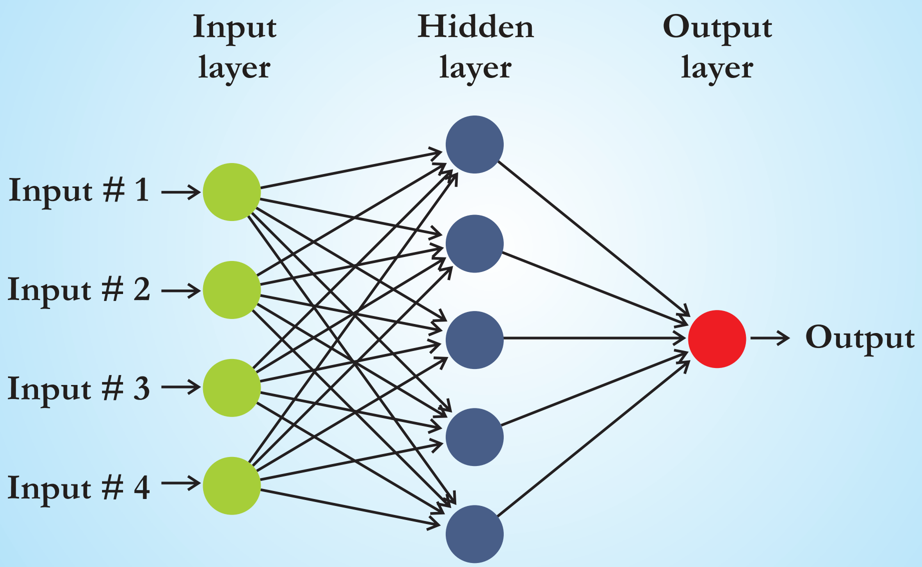

ICAR-Indian Institute of Water Management
(Indian Council of Agricultural Research)
Bhubaneswar, 751023, Odisha

2016

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ICAR

Groundwater Level Forecasting in a Deltaic Aquifer of Eastern India using Artificial Neural Network Approach

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Correct citation :

Mohanty, Sheelabhadra; Jha, Madan K.; Jena, Susanta K.; Kumar Ashwani; Panigrahi, Pravukalyan; James, Bijoy K.; Ambast, Sunil K. 2016. Groundwater Level Forecasting in a Deltaic Aquifer of Eastern India using Artificial Neural Network Approach. Bulletin No.-77. ICAR- Indian Institute of Water Management, Indian Council of Agricultural Research, Chandrasekharpur, Bhubaneswar, India, 30 p.

Published by:

Director,
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Chandrasekharpur, Bhubaneswar, Odisha, 751023, India.
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Printed at :

Space Setter Press & Publicity Pvt. Ltd.
84, Chandaka Industrial Estate
Patia, Bhubaneswar - 751024

Preface

Groundwater is a very important and invaluable natural resource. Its unique qualities that it is generally free from pathogens, easily accessible and free from suspended particles has made it the most important and preferred source of water for agricultural and domestic uses. It is estimated that groundwater provides about 50% of the current global domestic water supply, 40% of the industrial supply, and 20% of water use in irrigated agriculture. 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

However, 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. The groundwater simulation models have emerged as the tool of choice among water resources researchers and planners for addressing questions about the impacts of groundwater development. But the physically based modeling techniques are very data intensive, labour intensive and expensive. In such cases, when sufficient data is not available and getting accurate predictions is more important than conceiving the actual physics of the system, empirical models like artificial neural networks serve an attractive alternative as they can provide useful results using relatively less data and time.

In the current study, artificial neural network models have been developed for groundwater level forecasting in Kathajodi-Surua Inter-basin within Mahanadi Deltaic system of Odisha. Three different training algorithms, i.e. Gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Levenberg- Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm have been used and compared for their efficacy in forecasting groundwater levels. The neural network models have been used to forecast groundwater levels for higher lead times as well. It was found that artificial neural network technique can be successfully used for groundwater level forecasting in deltaic aquifers.

Authors

Contents

1. Introduction

Groundwater is an invaluable natural resource which supports human health, economic development and ecological diversity. It is renewable but finite resource, which is generally characterized by stable temperature and chemical composition. Its unique qualities that it is generally free from pathogens, easily accessible and free from suspended particles has made it the most important and preferred source of water for agricultural and domestic uses. However, overexploitation of groundwater has resulted in adverse effects on the local and regional ecosystems at different parts of the world. A growing number of regions are facing increasing water stresses owing to burgeoning water demands, profligate use, and escalating pollution worldwide (Rodda, 1992; Falkenmark and Lundqvist, 1997). Hence, the key concern is how to maintain a long-term sustainable yield from aquifers (e.g., Hiscock *et al.,* 2002; Alley and Leake, 2004) in the face of impending climate effects and socio-economic changes.

Groundwater simulation models have emerged as an important tool to help water resources researchers and planners to 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 and thereby taking corrective measures for the efficient utilization of water resources. With the proliferation of use of computers, they are being widely used by engineers, hydrogeologists and environmentalists to solve problems ranging from aquifer safe yield analysis to groundwater quality and remediation issues. However, 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) 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 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 Ramchandra 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 Kalurachchi 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; Coppola et al. 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, in this study, the application of ANN approach for the weekly forecasting of groundwater levels in a group of wells in an alluvial aquifer system has been done.

2. Study Area

The study area is a typical river island within Mahanadi deltaic system of eastern India and is surrounded on both sides by the Kathajodi River and its branch Surua (Fig.1). It is locally called as 'Bayalish Mouza' and have an enclosed area of 35 km^2. It is located between 85^0 54' 21" to 86^0 00' 41" E longitude and 20^0 21' 48" to 20^0 26' 00" N latitude. The study area has a tropical humid climate with an average annual rainfall of 1650 mm, of which 80% occurs during June to October months. The normal mean monthly maximum and minimum temperatures of the region are 38.8^{0}C and 15.5^0 C in May and December, respectively. The mean monthly maximum and minimum evapotranspiration rates are 202.9 mm and 80.7 mm in May and December, respectively.

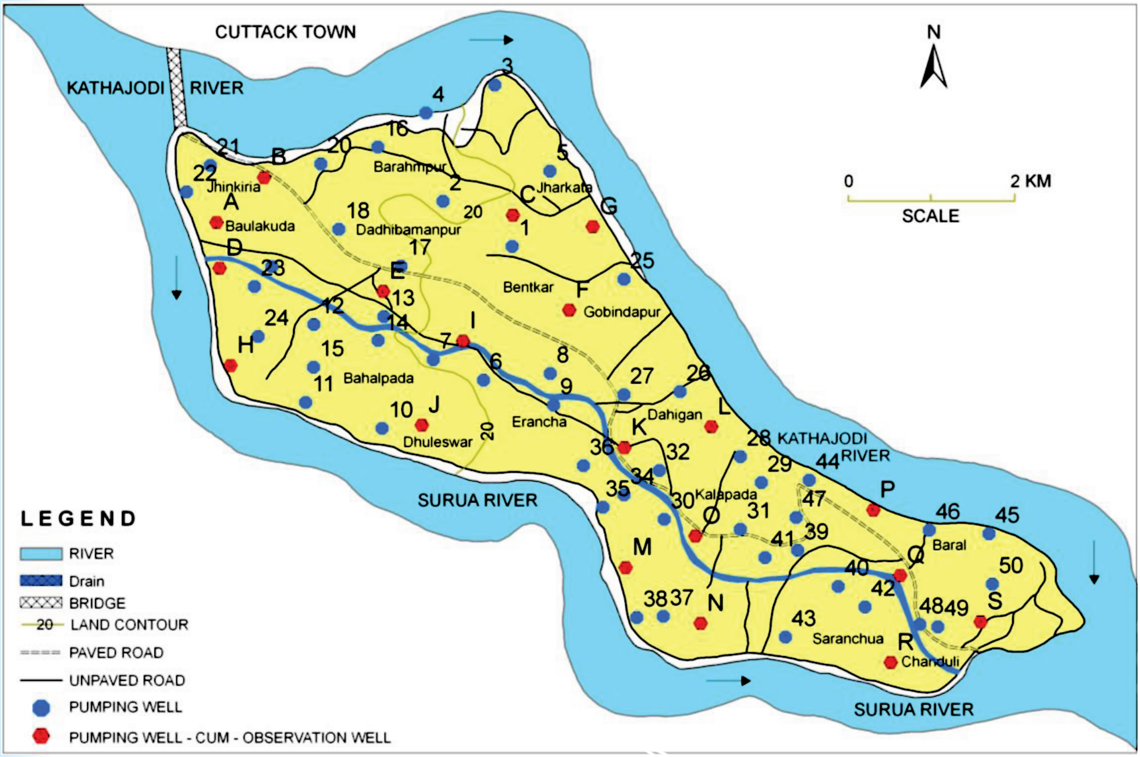

Fig. 1: Location of the study area along with pumping and observation wells

Agriculture is the major occupation of the inhabitants. Total cultivated area in the study area is 2445 ha, of which 1365 ha is irrigated land. The area under low land is 408 ha, medium land 1081 ha and high land is 956 ha. Paddy is the major crop in the monsoon season, whereas crops like vegetables, potato, groundnut, greengram, blackgram and horsegram are grown in the post-monsoon season. Surface irrigation infrastructure is not there in the study area and all the irrigated lands are irrigated by groundwater. At present there are 69 functioning government tubewells in the basin, which are the major sources of groundwater withdrawal. These tubewells were earlier constructed and managed by Orissa Lift Irrigation Corporation (OLIC), Cuttack, Orissa, but now they have been handed over to the water users' associations (WUAs). Although there is no water shortage during the monsoon season, in the summer season, the farm ponds dry up and the groundwater supply is not sufficient to meet the entire water demand for irrigation.

During the monsoon season, a different kind problem, i.e. waterlogging is encountered in the study area. 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 the main drain and discharged at a single outlet into the river. A sluice gate is provided at the outlet of the area to prevent entry of river water during flood events. During this time, surface waterlogging problem is often encountered in the downstream side of the study area.

2.1 Groundwater monitoring

Since no groundwater data were available in the study area, a groundwater monitoring program was initiated in February 2004. For the monitoring of groundwater levels, nineteen tubewells were selected spread over the study area. The locations of the nineteen monitoring wells are shown as red circles (A to S) in Fig. 1. The other tubewells are shown as blue circles (1 to 50). Groundwater levels were monitored in the 19 tubewells on a weekly basis from February 2004 to October 2007. The geographic locations of the tubewells in the study area were found with the help of a global positioning system (GPS).

3. Concept of Artificial Neural Network Modelling

Artificial neural network (ANN) is a massively parallel-distributed information processing system that has certain performance characteristics, which resemble the biological neural network of human brain (Haykin, 1999). In the human brain, 'neuron' is a fundamental unit that receives and combines signals from other neurons through input paths called 'dendrites'. If the combined input signal is stronger than the threshold value, the neuron activates, producing an output signal, which is transferred through the 'axon' to the dendrites of many other neurons (Haykin, 1999). Each signal coming into a neuron along a dendrite passes through a junction called 'synapse'. This junction is filled with neurotransmitter fluid that either accelerates or retards the flow of electrical charges to the cell body called 'soma'. This functioning of a biological neuron forms the basis of ANN modeling.

3.1 Neural network architectures

ANN is characterized by its architecture that represents the pattern of connection between the nodes (input, hidden and output nodes), its method of determining the connection weights and the activation function (Fausett, 1994). The neural network architecture can be classified based on number of layers or based on the direction of information flow and processing. Some of the prominent neural network architectures are: (a) feedforward networks, (b) recurrent networks, (c) radial basis functions and (d) self-organizing feature maps (ASCE, 2000a).

Feedfroward neural network (FNN) 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 this network, the nodes are generally arranged in layers, starting from a first input layer and ending at the final output layer with information passing from the input to output side. There can be several hidden layers with each layer having one or more nodes. Figure 2 shows a typical feedforward network having one hidden layer with several nodes in the input and 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. The main advantage of feedforward neural networks is that they are easy to handle, and can approximate any input/output map (Hornik *et al.,* 1989). In this study, feedforward neural network architecture has been used.

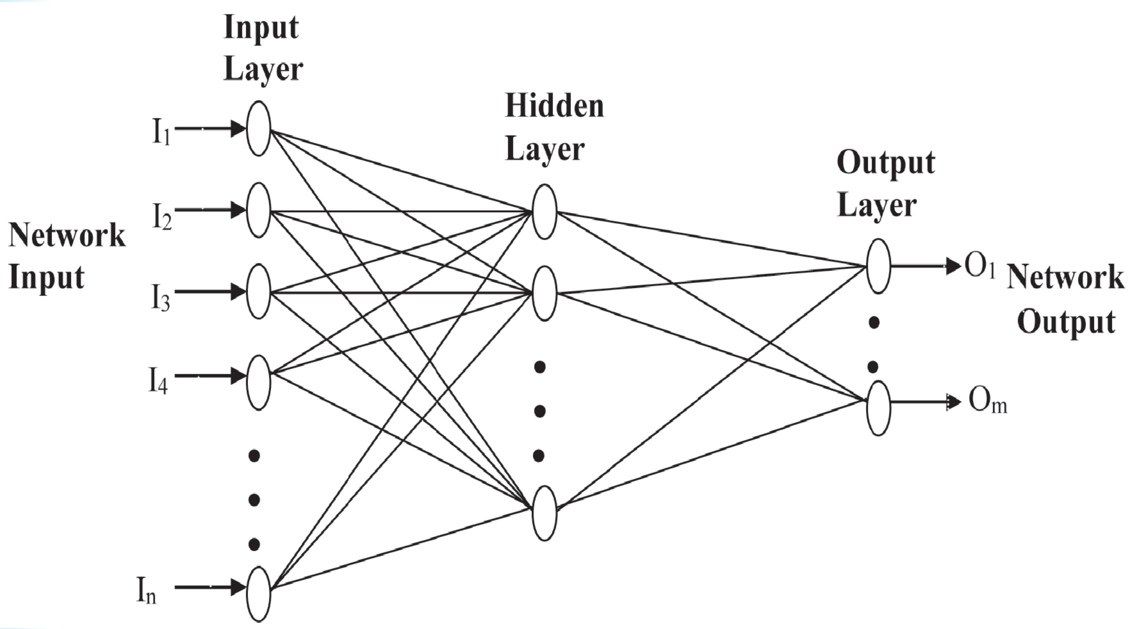

Fig. 2: A Typical Feedforward Three-layer Neural Network (ASCE, 2000a)

In the recurrent neural network architecture, information flows through the nodes in both directions, from input to the output side and vice versa. This is generally achieved by provision of one feedback loop for recycling previous network outputs as current inputs (Haykin, 1999). Lateral connections are sometimes used where nodes within a layer are also connected. Further, a radial basis function network is a three- layer network in which the hidden layer performs a fixed non-linear transformation with no adjustable parameters (Leonard *et al.,* 1992). This layer consists of a number of nodes and a parameter vector called *centre* which can be considered the weight vector of the hidden layer. The self-organizing feature maps are typically used for density estimation or for projecting patterns from high dimensional to low dimensional space. This projection is non-parametric and is obtained by mapping input patterns into the responses of a lattice (ASCE, 2000a).

3.2 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 of neural 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 several 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 a high predictive accuracy without under or over fitting problems is very 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 (Maier and Dandy, 1998). 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, i.e., 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 overfitting issue. A brief description of gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Levenberg-Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm is presented below; these algorithms have been used in this study.

Gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm

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 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 time to converge. In order to overcome this problem, the gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm has been proposed, which combines adaptive learning rate with momentum training (Haykin, 1999). 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 (Haykin, 1999).

Levenberg- Marquardt (LM) algorithm

In the 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 difficulty, the Levenberg-Marquardt algorithm, which is a second-order optimization procedure for multilayer FNN training, is used. The Levenberg-Marquardt algorithm is a modification of the well-known Newton algorithm for finding an optimal solution to a minimization problem (Bishop, 1995). It is designed to approach a 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).

$$x_{i+1} = x_i - \left[J^T J + \mu I\right]^{-1} J^T e \qquad \text{.................. (1)}$$

Where, x = weights of the neural network, J = Jacobian matrix of the performance criteria to be minimized, m = a scalar that controls the learning process, and e = residual error vector. When the scalar m is zero, this is just Newton's method using the approximate Hessian matrix. When m is large, Eqn. (3.19) becomes gradient descent with a small step size. As the Newton's method is faster and more accurate near an error minimum, the goal is to shift towards Newton's method as quickly as possible.

The Levenberg-Marquardt algorithm is one of the fastest methods for training feedforward 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 using it successfully (e.g., Coulibaly *et al.,* 2000; Toth *et al.,* 2000; Coulibaly *et al.,* 2001; Anctil *et al.,* 2004; Daliakopoulos *et al.,* 2005).

Bayesian regularization (BR) algorithm

The Bayesian approach involves the optimization of an objective function that comprises the conventional sum of squared error (SSE) function as well as an additional term called 'regularizer'. The motivation for using the regularizer is to penalize the more complex weight functions in favour 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:

- It provides a unifying approach for dealing with issues of model complexity and overfitting.
- The modification in the error function aims to improve the model's generalization capability.
- 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 have been observed, it can be converted to a posterior distribution through the use of Baye's theorem. By maximizing the posterior distribution over the weights, the most probable parameter values can be obtained. The Bayesian regularization algorithm 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).

4. Development of Neural Network Model for Groundwater Level Forecasting

In the development of ANN models, the steps like selection of adequate model inputs, data division and pre-processing, the choice of suitable network architecture, selection of network internal parameters, termination criteria and model testing need careful addressing (Maier and Dandy, 2000). The present study was taken up to develop neural network models to assess their efficacy in predicting groundwater levels in the study area. In most of the past studies on groundwater level prediction by ANN, models have been developed for predicting groundwater levels in a single well or a few selected wells using a set of input parameters. However, in the present study, an attempt has been made to predict groundwater levels simultaneously in a large number of wells over the basin by using ANN technique.

4.1 Design of ANN models

Determination of appropriate network architecture and training algorithm is one of the most important tasks in the model building process. An optimal architecture may be considered the one yielding the best performance in terms of error minimization, while retaining a simple and compact structure (ASCE, 2000a). The ANN architecture and training algorithms are generally selected based on the past experience in the field of research, or by comparative evaluation of different architectures and/or algorithms. In the present study, widely used feedforward neural network architecture was used. Three ANN models, 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. The ANN models were designed to predict groundwater levels in 18 tubewells (Fig. 1) with one-week lead time using a set of suitable input parameters.

4.2 Selection of input parameters

One of the most important steps in the ANN model development process is the determination of significant input variables. A firm understanding of the hydrological and hydrogeological systems under consideration can lead to a better choice of input variables (ASCE, 2000a). This helps in avoiding omission of key input variables and preventing inclusion of spurious inputs that tend to confuse the training process. Generally, some degree of *a priori* knowledge is used to specify the initial set of candidate inputs (Campolo *et al.,* 1999; Thirumalaiah and Deo, 2000). Although *a priori* identification is widely used in many applications and is necessary to define a possible 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 analytical techniques, such as cross-correlation and auto-correlation are often employed (e.g., Sajikumar and Thandaveswara, 1999; Coulibaly *et al.,* 2000; Sudheer *et al.,* 2002). However, a major disadvantage associated with using cross-correlation is that it is only able to detect linear dependence between two variables. Therefore, cross-correlation is sometimes 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 input parameters for the ANN model were decided by considering the parameters which have potential to affect the groundwater level. The groundwater level at 1-week lag time, weekly rainfall and river stage were considered as input parameters as they definitely affect the groundwater level 1 week ahead. In a semi-confined aquifer, apart from rainfall, evaporation is another hydrologic 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. Moreover, in the study area, entire rainwater of the area 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 entry 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 was also considered as an input parameter because it influences the groundwater, especially in the downstream portion of the study area.

The correlation coefficients between the groundwater levels with the selected input parameters were calculated to analyze their suitability for selection as input parameters. The correlation coefficients of groundwater level with the groundwater level at 1-week lag time, weekly rainfall, river stage, evaporation and water level in the main drain are shown in Table 1. The correlation coefficient (r) of groundwater level with the groundwater level at 1-week lag time varies from a minimum of 0.895 to a maximum of 0.965, whereas that between groundwater level and weekly rainfall varies from a minimum of 0.333 to a maximum of 0.659. The correlation coefficient of groundwater level with river stage varies from a minimum of 0.686 to a maximum of 0.891, whereas the correlation coefficient of groundwater level with weekly evaporation varies from a minimum of 0.311 to a maximum of 0.557. On the other hand, the correlation coefficient of groundwater level with water level in the drain varies from a minimum of 0.582 to a maximum of 0.758. From Table 1, it is evident that groundwater level has best correlation with groundwater-

Table 1: Correlation Coefficients for Groundwater Level versus Different Inputs

Site	Correlation Coefficient (r)				
	Groundwater Level versus Groundwater Level at 1-Week Lag Time	Groundwater Level versus Weekly Rainfall	Groundwater Level versus River Stage	Groundwater Level versus Weekly Evaporation	Groundwater Level versus Water Level in the Drain
Site A	0.952	0.382	0.728	0.469	0.616
Site B	0.948	0.381	0.729	0.523	0.640
Site C	0.952	0.375	0.720	0.476	0.621
Site D	0.950	0.376	0.737	0.456	0.626
Site E	0.954	0.358	0.703	0.540	0.609
Site F	0.949	0.379	0.722	0.507	0.641
Site G	0.915	0.589	0.886	0.311	0.752
Site H	0.959	0.380	0.725	0.506	0.601
Site I	0.951	0.398	0.741	0.515	0.638
Site J	0.965	0.333	0.686	0.557	0.582
Site K	0.939	0.578	0.857	0.346	0.732
Site L	0.920	0.581	0.867	0.362	0.750
Site M	0.955	0.585	0.860	0.362	0.744
Site N	0.895	0.659	0.812	0.400	0.728
Site O	0.921	0.627	0.878	0.311	0.745
Site P	0.935	0.582	0.891	0.370	0.758
Site Q	0.931	0.586	0.887	0.357	0.756
Site R	0.950	0.562	0.844	0.397	0.748
Site S	0.931	0.581	0.879	0.353	0.776

level at 1-week lag time followed by river stage and water-level in the drain, respectively. The correlation coefficient between the groundwater-level and weekly rainfall is less than 0.5 at 9 sites, whereas the same with weekly evaporation is less than 0.5 at 13 sites. In spite of low r values at some sites, all the parameters were considered as inputs for ANN modeling because r reflects only linear correlation, but ANN takes care of non-linear correlation also.

There are 69 tubewells in the study area. However, by considering weekly pumping of 69 tubewells, 69 input parameters made 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 the pumping pattern of each of the 18 tubewells almost matches with the nearby tubewells. Hence, the pumping rates of the 18 tubewells were considered as 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 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., one week ahead).

4.3 Clustering of the study area

The ANN model having 40 input nodes and 18 output nodes was difficult to be trained by the trial and error method while using Levenberg-Marquardt (LM) and Bayesian regularization (BR) algorithms; they consumed a lots of computer memory and proved to be very time consuming. Maier and Dandy (1998) also reported that the Levenberg-Marquardt algorithm has a great computational and memory requirement, and hence it is mostly useful for 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 and computational requirements. In order to run the LM and BR models effectively, an effort was made to reduce the size of the neural network by dividing the study area into three clusters as shown in Fig. 3, and developing three separate ANN models for the three clusters to predict groundwater levels one week advance at the sites present in a particular cluster. Cluster 1 contains 7 sites namely A, B, D, E, H, I and J. Cluster 2 contains 5 sites namely C, F, G, K and L, and Cluster 3 contains 6 sites namely M, O, P, Q, R and S (Fig. 3). The division of the study area into three clusters and modeling groundwater separately in three clusters would not have any effect on the final output as the pumping of the tubewells in a given cluster has a very minor effect on the water level in the 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, weekly pan evaporation and weekly river stage were considered as input parameters. In the third cluster, however, an additional input parameter 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 7 output nodes, Cluster 2 had 13 input nodes and 5 output nodes and Cluster 3 had 16 input nodes and 6 output nodes as shown in Table 2.

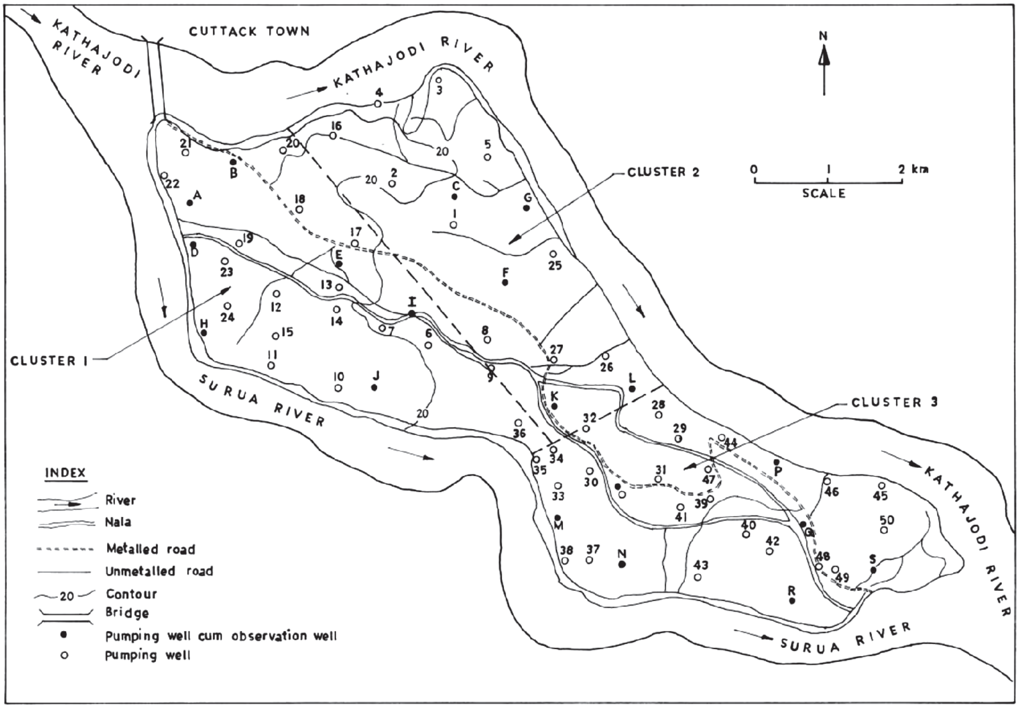

Fig. 3: Division of the Study Area into Three Clusters for ANN Modeling

Table 2: 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 **Total:** 17 input parameters	Groundwater levels at 7 sites (A, B, D, E, H, I and J) in the next time step (i.e., one week ahead) **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 **Total** : 13 input parameters	Groundwater levels at 5 sites (C, F, G, K and L) in the next time step (i.e. one week ahead) **Total**: 5 output parameters
Cluster 3	Initial groundwater levels at 6 sites (M, O, P, Q, R and S); Average 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 **Total:** 16 input parameters	Groundwater levels at 6 sites (M, O, P, Q, R and S) in the next time step (i.e. one week ahead) **Total:** 6 output parameters

4.4 Structure of the model

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 and the number of hidden nodes corresponding to the least root mean squared error (RMSE) and highest Nash-Sutcliffe efficiency (NSE) was selected as optimal number of hidden neuron. 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 for ANN modeling. Out of the 174 weeks datasets available, 122 datasets were used for training the ANN models and 52 datasets were used for testing the models. The ANN modeling was performed by using MATLAB 6.5 software.

The optimum number of hidden neurons for each cluster and the three algorithms determined by the trial and error method are presented in Table 3. The optimum number of hidden neurons varied from 10 to 40, and no uniform pattern of variation of optimum number of hidden neurons was observed with respect to the clusters and the training algorithms. Figs. 4 (a to c) show the variation of RMSE and model efficiency (NSE) with the number of nodes in hidden layer for three different algorithms, respectively for Cluster 1. Similarly Figs. 5 (a to c) and Figs. 6 (a to c) show the variation of RMSE and model efficiency with the number of nodes in hidden layer for three algorithms for Cluster 2 and 3 respectively. The RMSE values are lowest and the model efficiency values are highest in all the figures with respect to the optimum number of hidden neurons presented in Table 3. Here also no uniform pattern of variation of RMSE and model efficiency was observed across different clusters and training algorithms.

Table 3: 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

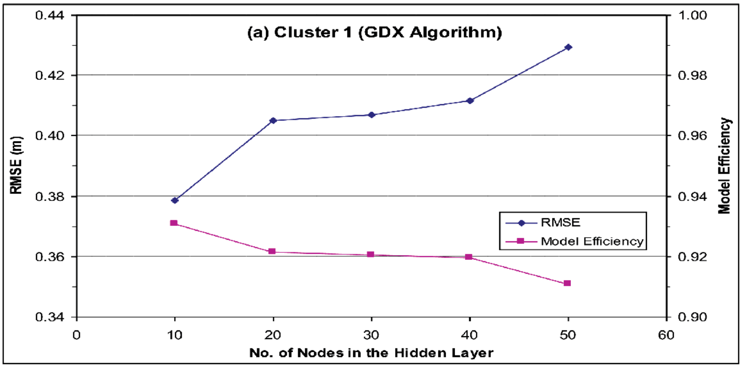

Fig. 4 (a): Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the GDX Algorithm in Cluster 1

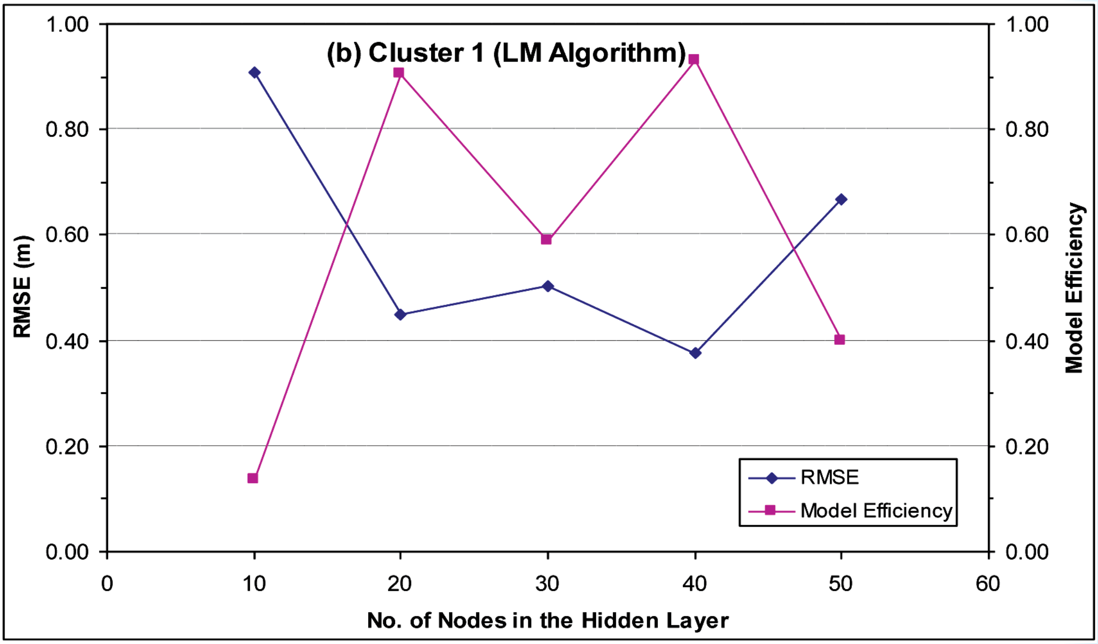

Fig. 4 (b): Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the LM Algorithm in Cluster 1

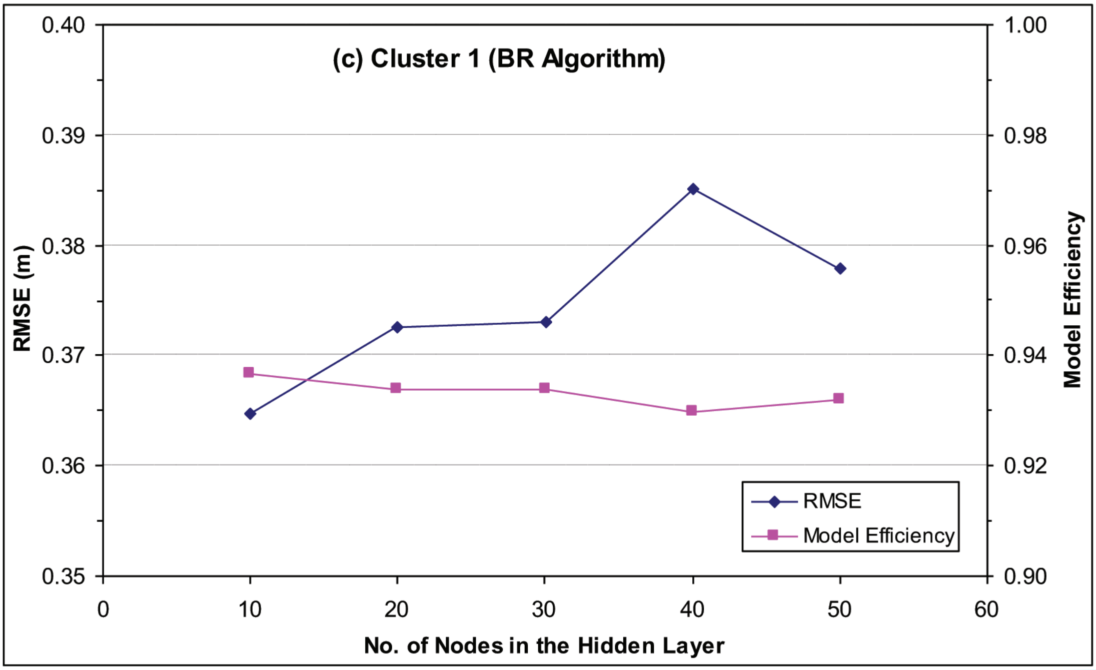

Fig. 4 (c) : Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the BR Algorithm in Cluster 1

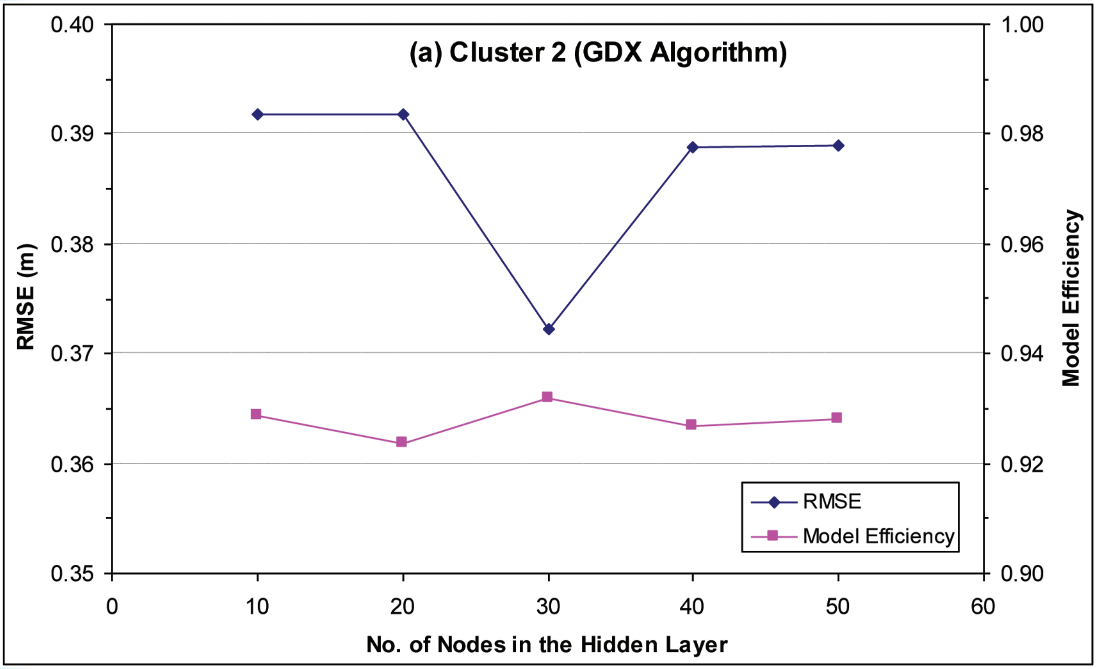

Fig. 5 (a): Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the GDX Algorithm in Cluster 2

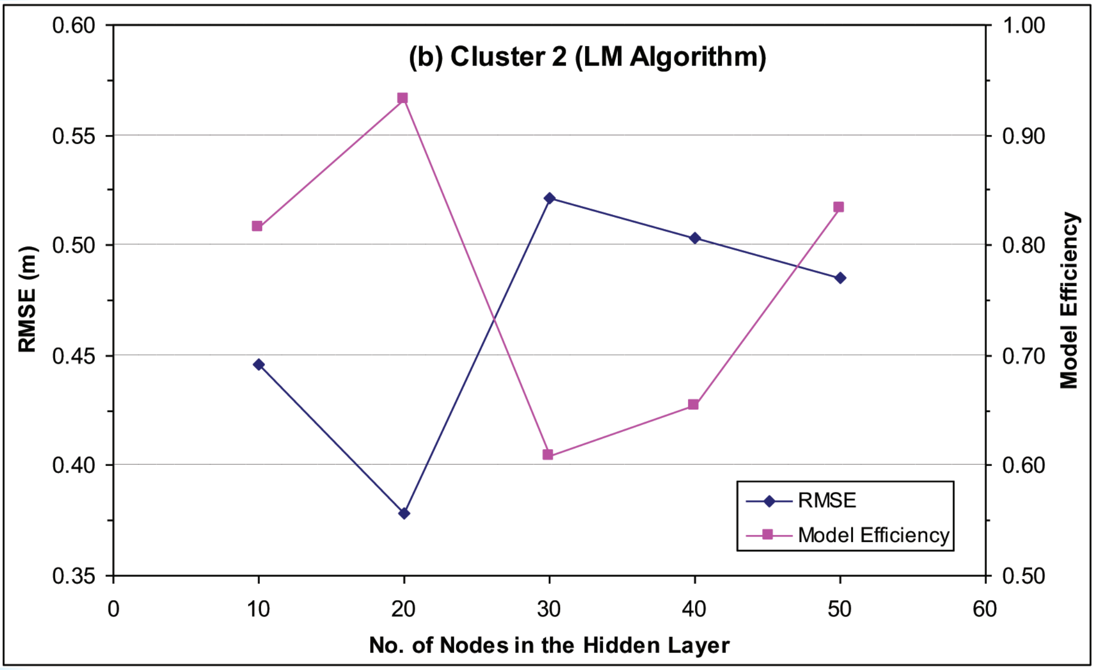

Fig. 5 (b): Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the LM Algorithm in Cluster 2

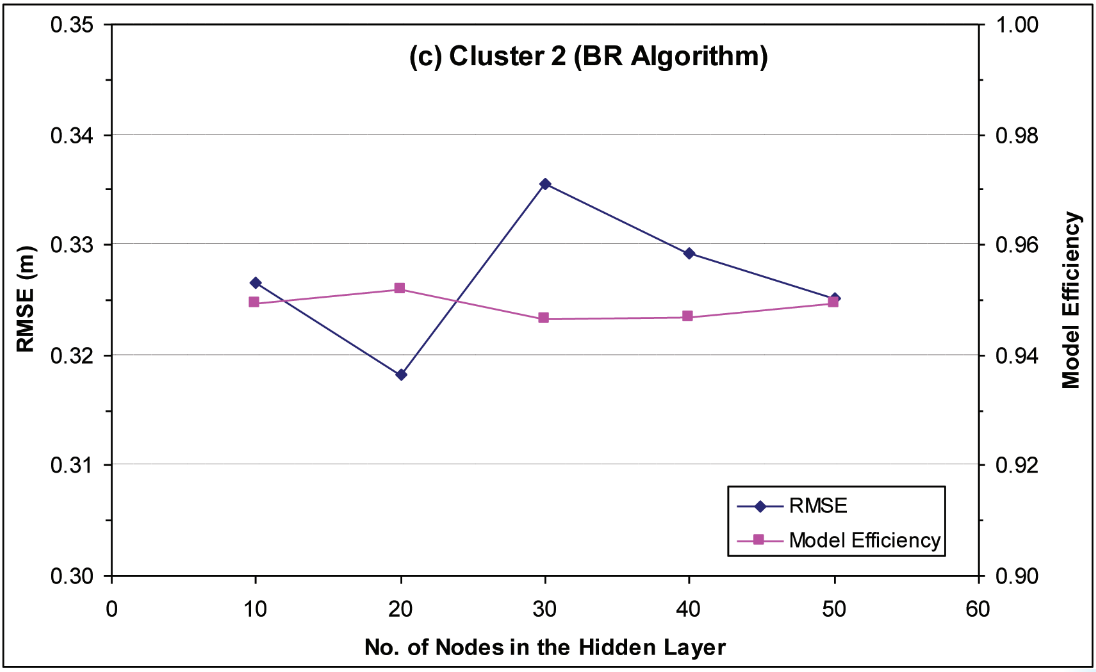

Fig. 5 (c) : Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the BR Algorithm in Cluster 2

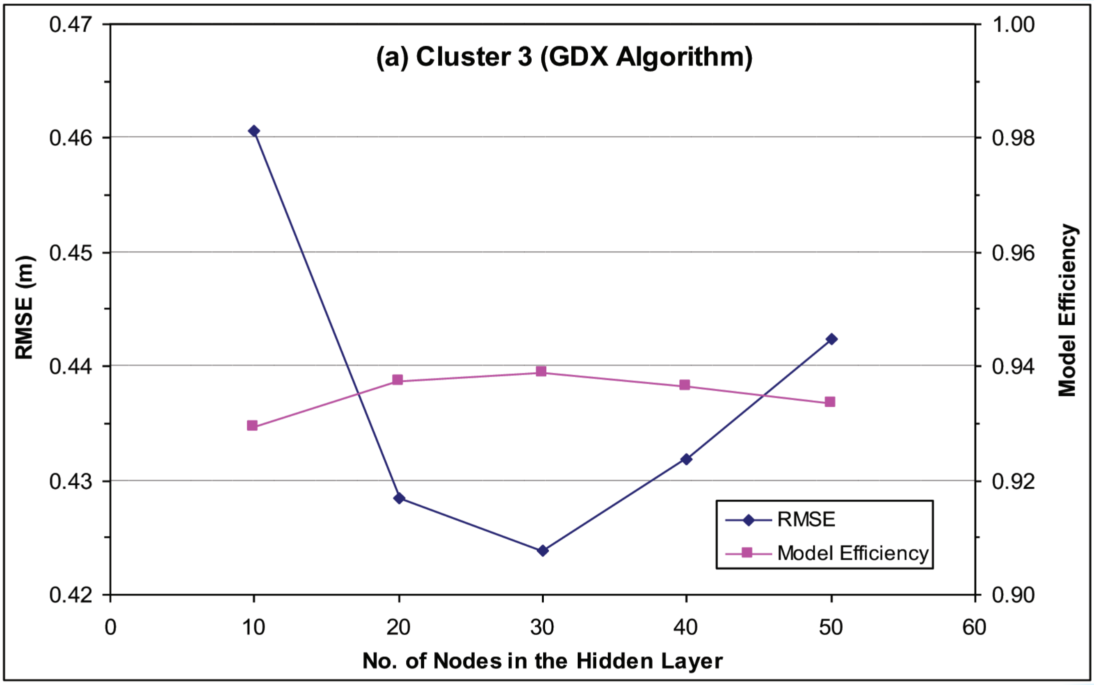

Fig. 6 (a): Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the GDX Algorithm in Cluster 3

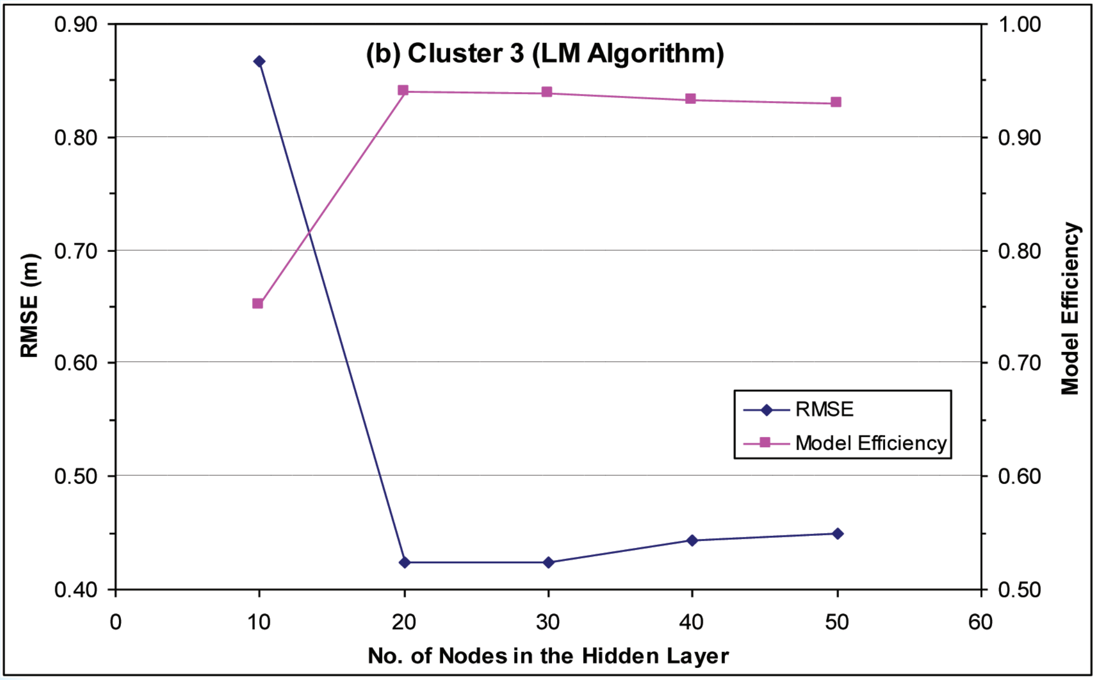

Fig. 6 (b): Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the LM Algorithm in Cluster 3

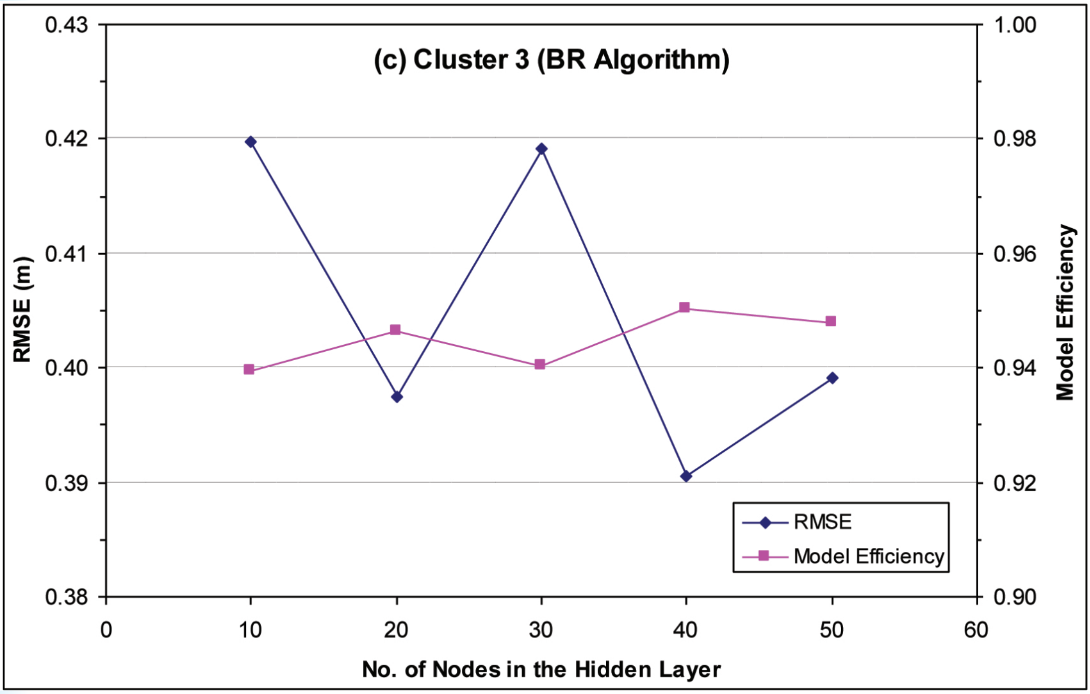

Fig. 6 (c) : Variation of RMSE and Model Efficiency with Number of Nodes in the Hidden Layer for the BR Algorithm in Cluster 3

4.5 Performance evaluation of the models

The performance evaluation of the three training algorithms was performed quantitatively by using statistical indicators and qualitatively by comparing the predicted groundwater levels with the observed groundwater levels. Four statistical indicators, i.e., mean error (ME), root mean squared error (RMSE), correlation coefficient (r) and Nash-Sutcliffe efficiency (NSE) were used to evaluate the effectiveness of three artificial neural network models developed in this study. The ANN model which yielded the lowest mean error, lowest RMSE, highest r and the highest NSE was selected for groundwater level forecasting in the study area.

The values of four statistical indicators of the three training algorithms for the three clusters are shown in Tables 4(a to c), respectively during training and testing periods. These statistical indicators have been obtained by taking the average of their values obtained at individual sites in each cluster. It can be seen from Tables 4(a to c) that the performance of all the three training algorithms is good during both training and testing periods, i.e., they are able to forecast groundwater levels one week in advance with a reasonable accuracy in all the three clusters. For the GDX training algorithm during testing period, the mean error values range from 0.016 to 0.062 m, RMSE values from 0.372 to 0.424 m, correlation coefficient (r) values from 0.9678 to 0.9756 and Nash-Sutcliffe efficiency (NSE) values from 0.9307 to 0.9388. For the LM training algorithm during testing period, the mean error values range from 0.029 to 0.081 m, RMSE values from 0.376 to 0.424 m, r values from 0.9697 to 0.9815, and NSE values from 0.9318 to 0.9380, whereas these figures for the BR algorithm are -0.003 m to 0.061 m, 0.318 to 0.390 m, 0.9721 to 0.9793 and 0.9366 to 0.9518 respectively.

Table 4(a): Goodness-of-fit Statistics for the GDX, LM and BR Algorithms for Cluster 1 (1-week Lead Time)

Algorithm	ME (m)		RMSE (m)		r		NSE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
GDX	-0.050	0.027	0.323	0.378	0.9739	0.9678	0.9460	0.9307
LM	-0.006	0.060	0.218	0.376	0.9881	0.9697	0.9743	0.9318
BR	-0.019	0.061	0.203	0.365	0.9895	0.9721	0.9785	0.9366

Table 4(b): Goodness-of-fit Statistics for the GDX, LM and BR Algorithms for Cluster 2 (1-week Lead Time)

Algorithm	ME (m)		RMSE (m)		r		NSE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
GDX	0.000	0.062	0.282	0.372	0.9766	0.9733	0.9536	0.9319
LM	0.003	0.029	0.127	0.378	0.9953	0.9772	0.9905	0.9321
BR	0.008	0.043	0.278	0.318	0.9773	0.9793	0.9546	0.9518

Table 4 (c): Goodness-of-fit Statistics for the GDX, LM and BR Algorithms for Cluster 3 (1-week Lead Time)

Algorithm	ME (m)		RMSE (m)		r		NSE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
GDX	0.004	0.016	0.413	0.424	0.9664	0.9756	0.9336	0.9388
LM	0.039	0.081	0.193	0.424	0.9935	0.9815	0.9856	0.9380
BR	0.032	-0.003	0.401	0.390	0.9695	0.9785	0.9378	0.9503

It is apparent from the above-mentioned quantitative performance criteria (i.e., statistical indicators) 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 Levenberg-Marquardt (LM) algorithm and the GDX algorithm.

Apart from the statistical indicators, the performance of the three algorithms was evaluated using visual checking of observed and calculated groundwater levels. Figs. 7(a to c) show the comparison of predicted groundwater levels (one week ahead) by the three training algorithms with the observed groundwater levels at three locations one each from the three clusters, i.e., Baulakuda (Site A) from the first cluster, Dahigan (Site K) from the second cluster and Chanduli (Site S) from the third cluster of the study area, respectively. These figures indicate that there is a very good matching between observed and simulated groundwater levels at the sites. Thus, based on the statistical indicators used in this study and the graphical comparison, it can be inferred that although all the three algorithms yield more or less similar results, the performance of the Bayesian regularization algorithm could be considered superior based on the statistical indicators. The GDX algorithm was found to be suitable for large neural networks with little less accuracy than the Levenberg-Marquardt algorithm and the Bayesian regularization algorithm, respectively. In practice, however, any of these three algorithms could be used for predicting groundwater levels one week advance in the study area.

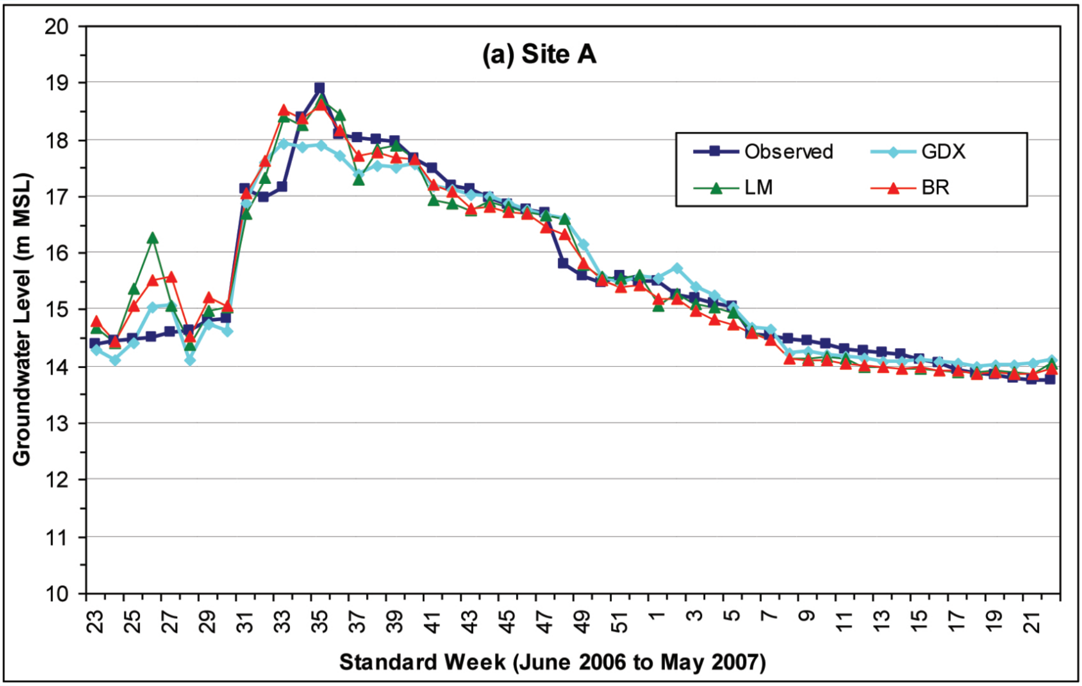

Fig. 7(a): Comparison between the Observed Groundwater Levels and the Groundwater Levels Predicted by GDX, LM and BR Algorithms at Site A during Testing Period

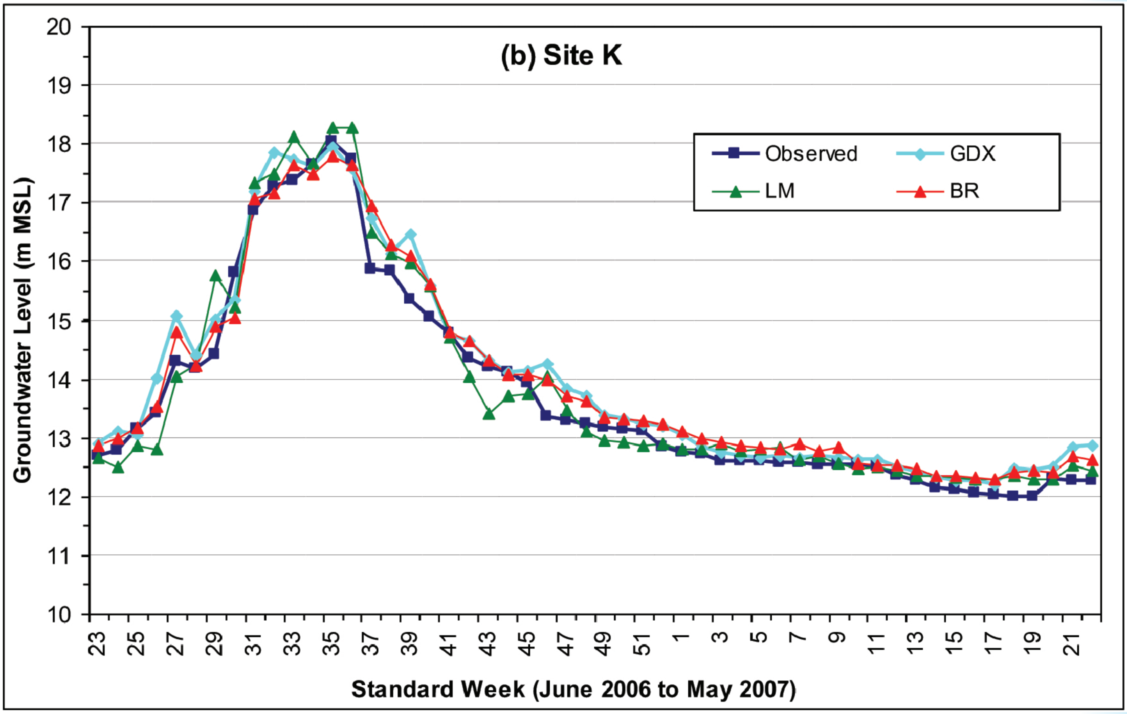

Fig. 7(b): Comparison between the Observed Groundwater Levels and the Groundwater Levels Predicted by GDX, LM and BR Algorithms at Site K during Testing Period

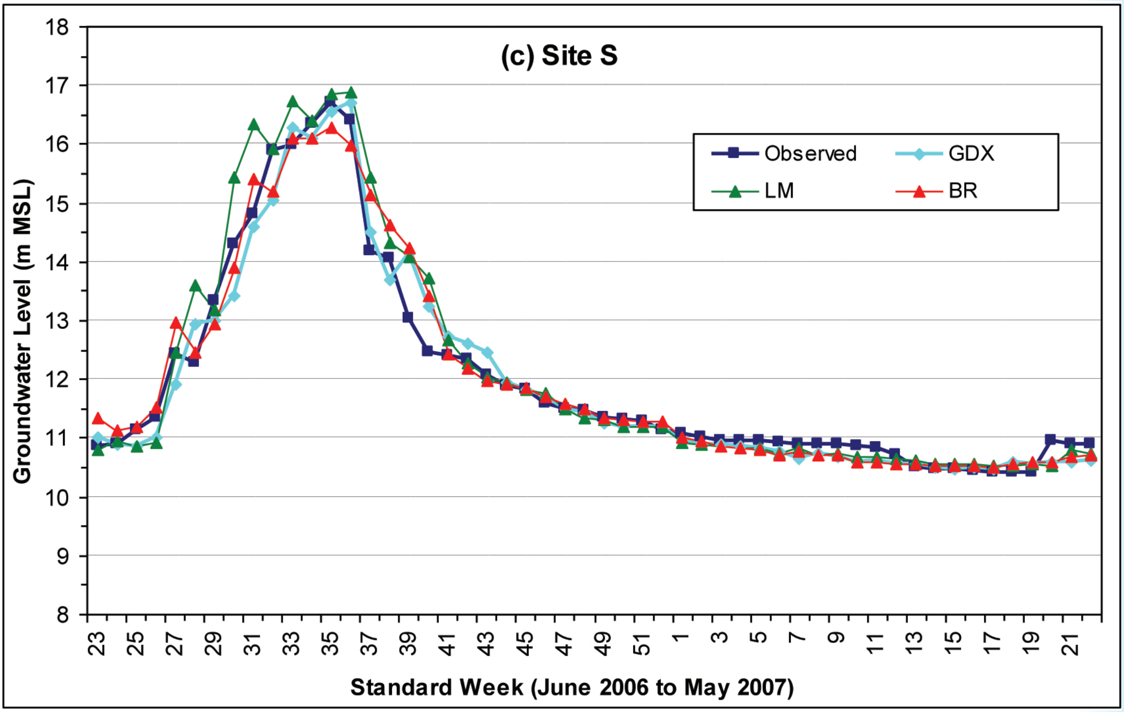

Fig. 7 (c) : Comparison between the Observed Groundwater Levels and the Groundwater Levels Predicted by GDX, LM and BR Algorithms at Site S during Testing Period

4.6 Effect of clustering on ANN model performance

Moreover, the GDX algorithm was used to forecast groundwater level at 18 sites at a time as it is suitable for large networks. Thereafter, performance of the GDX model, with and without clustering was compared using above-mentioned statistical indicators in order to study the effect of clustering on the accuracy of groundwater-level prediction. Table 5 shows the comparison of statistical indicators of the GDX model, with and without clustering respectively. It is evident that for the 'without clustering' model, the ME and RMSE values are lower and the r and NSE values are higher than the corresponding values of these statistical indicators for the 'with clustering' model during training period. However, it is quite opposite during testing period in which the ME and RMSE values are higher and r and NSE values are lower for the 'without clustering' model. It might be attributed to the overfitting of the 'without clustering' ANN model due to larger neural networks. This finding shows that the division of the study area into clusters improves the accuracy of model prediction. Therefore, it is recommended that clustering approach should be used to handle large number of inputs and sites in ANN modeling.

Table 5: Effect of Clustering on Goodness-of-fit Statistics for the GDX model

GDX Algorithm	ME (m)		RMSE (m)		r		NSE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
With Clustering	-0.015	0.035	0.340	0.392	0.9723	0.9722	0.9444	0.9338
Without Clustering	0.002	0.061	0.240	0.412	0.9861	0.9715	0.9722	0.9288

5. Simultaneous Forecasting of Groundwater Levels

As Lavenberg- Marquardt and Bayesian regularization algorithms has a great computational and memory requirement, the GDX algorithm was found suitable for forecasting groundwater level in a large group of wells simultaneously in a river basin. Hence this model was again used to simultaneously forecast groundwater level in 18 wells at a time. 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. Fig. 8 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 one week in advance with a reasonable accuracy.

Figs. 9(a) 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.

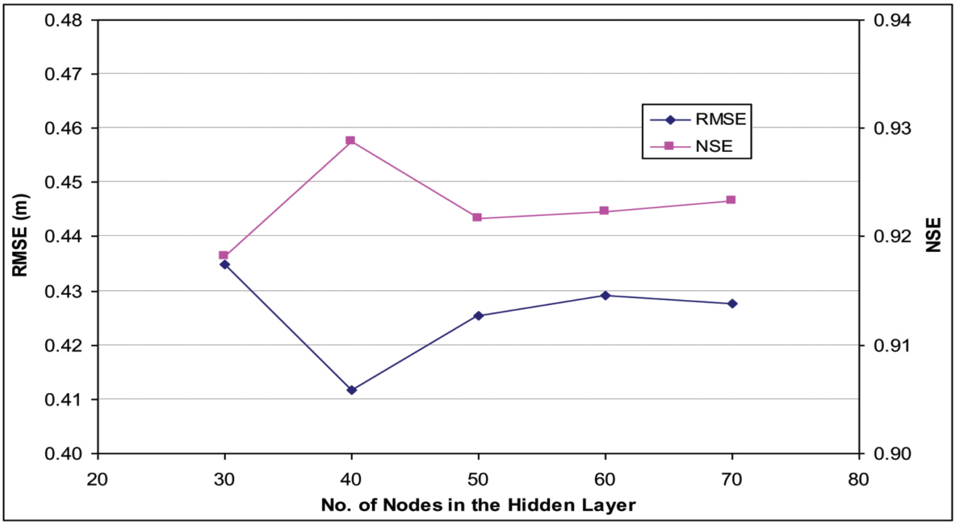

Fig. 8: Variation of RMSE and NSE with the number of nodes in the hidden layer

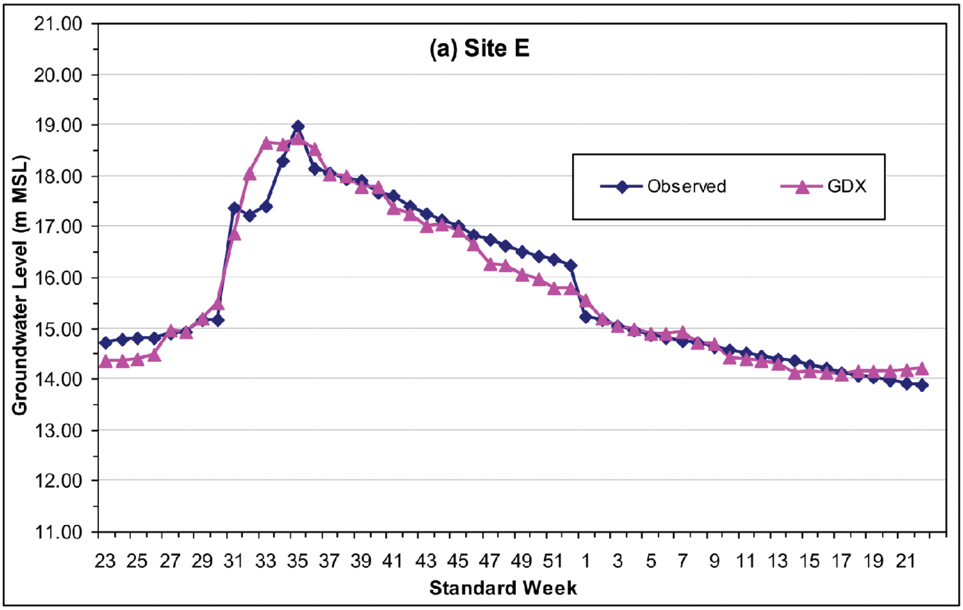

Fig. 9 (a): Comparison between observed and predicted groundwater levels at site E during testing period.

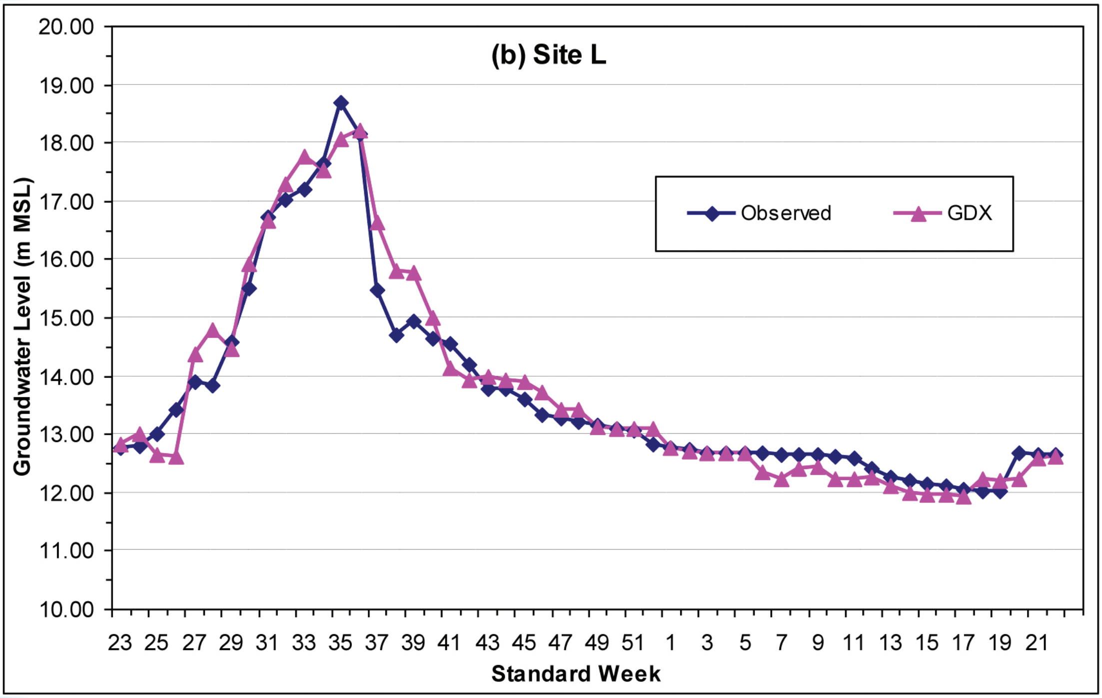

Fig. 9 (b): Comparison between observed and predicted groundwater levels at Site L during testing period.

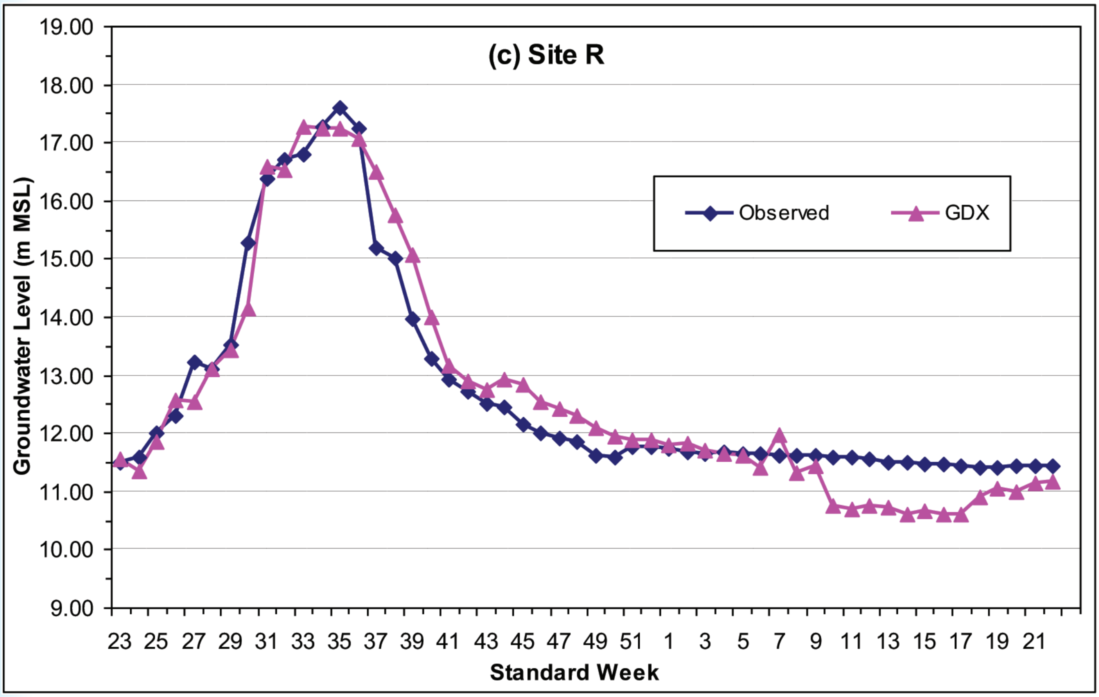

Fig. 9 (c) : Comparison between observed and predicted groundwater levels at Site R during testing period.

6. Groundwater Level Forecasting at Different Lead Times

The best-fit ANN model of the study area was used for groundwater level forecasting at 2-, 3- and 4-week in advance to examine the prediction accuracy of the model at different lead times. The inputs to all these ANN models were kept the same as that for the model predicting water level at 1 week in advance. The groundwater level forecasting at different lead times was performed quantitatively by using statistical indicators and qualitatively by comparing the predicted groundwater levels at different lead times.

The Bayesian regularization (BR) algorithm was used to forecast groundwater levels at 2-, 3- and 4-week in advance in Cluster 1 as an example. The inputs to these ANN models were kept the same as those for the ANN model predicting groundwater level at 1 week in advance. The performance of the BR algorithm at different lead time forecasts during testing period is shown in Table 6 in terms of ME, RMSE, r and NSE statistical indicators. As mentioned earlier, the statistical indicators shown in this table are the average of their values for the 7 sites of Cluster 1. It can be seen from Table 6 that the ME value varies from 0.061 m for the 1-week lead time forecast to 0.129 m for the 4-week lead time forecast, the value of RMSE varies from 0.365 m for the 1-week lead time to 0.546 m for the 4-week lead time, the value of r varies from 0.9721 for the 1-week lead time to 0.9389 for 4-week lead time, and the value of NSE varies from 0.9366 for 1-week lead time to 0.8647 for 4-week lead time. It is interesting to note that the performance of the 3-week lead time forecast model is slightly better than that of the 2-week lead time forecast model. The observed and simulated groundwater levels at different lead time forecasts are shown in Figs. 10(a to c) for three sites, Baulakuda (Site A), Dadhibamanpur (Site E) and Dhuleswar (Site J), respectively. These figures also indicate an improved matching between observed and simulated groundwater levels for the smaller lead times 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 (2 to 4 weeks) is also reasonably accurate in this study. On the whole, it could be inferred that despite the data constraints in this study, the developed ANN models predicted weekly groundwater levels over the river island reasonably well for 1-, 2-, 3- and 4-week lead times.

Table 6: Goodness-of-fit Statistics for Different Lead Time Forecasts

Lead Time	ME (m)		RMSE (m)		r		NSE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1 week	-0.019	0.061	0.203	0.365	0.9895	0.9721	0.9785	0.9366
2 weeks	0.001	0.084	0.361	0.492	0.9658	0.9469	0.9327	0.8866
3 weeks	-0.009	0.027	0.382	0.448	0.9617	0.9573	0.9245	0.9065
4 weeks	0.066	0.129	0.395	0.546	0.9604	0.9389	0.9199	0.8647

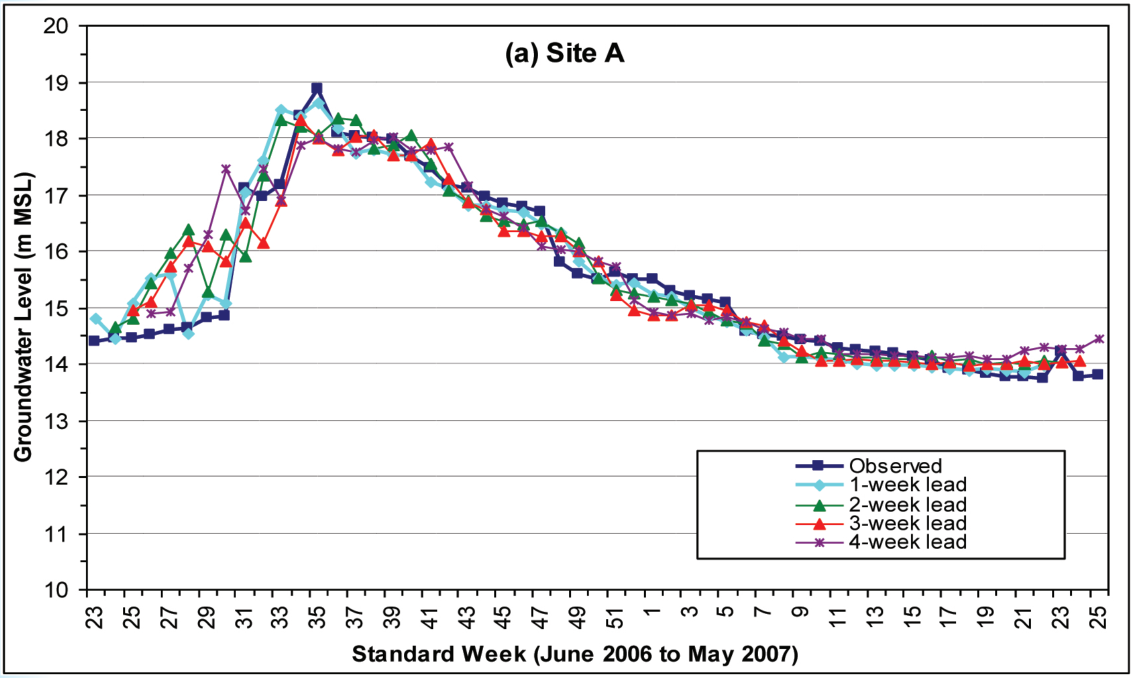

Fig. 10(a): Comparison between Observed and Simulated Groundwater Levels at Site A at Different Lead Time Forecast

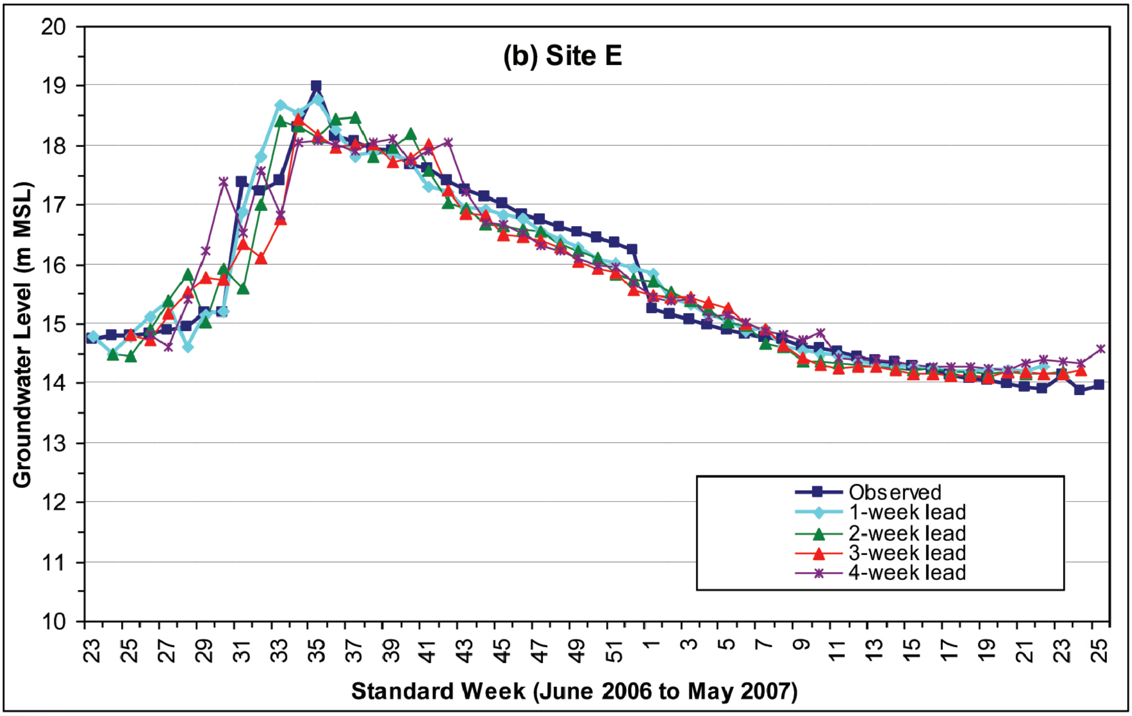

Fig. 10(b): Comparison between Observed and Simulated Groundwater Levels at Site E at Different Lead Time Forecast

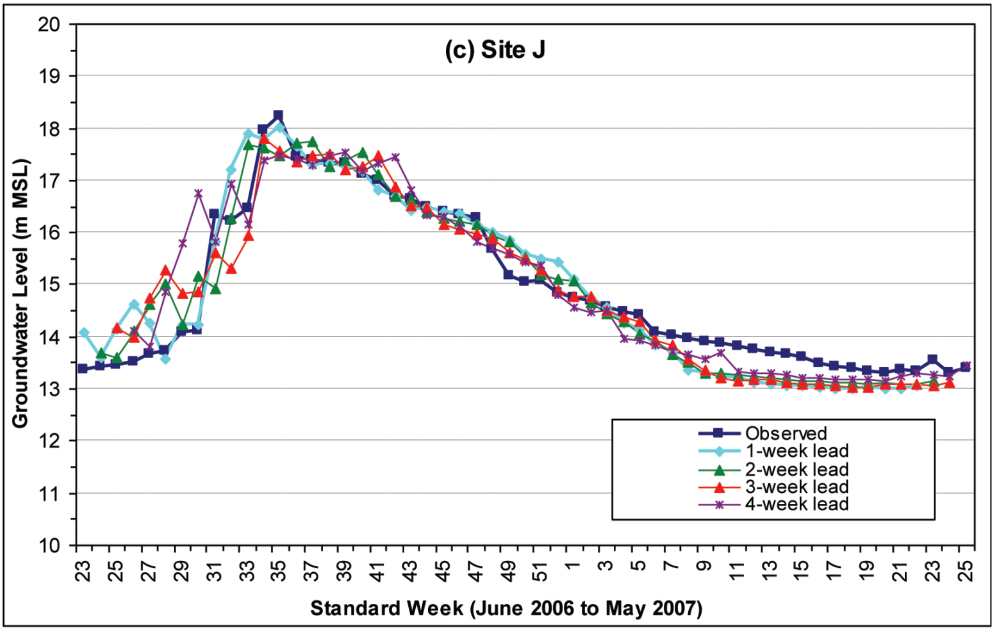

Fig. 10 (c) : Comparison between Observed and Simulated Groundwater Levels at Site S at Different Lead Time Forecast

7. Conclusion

Artificial neural network models were developed for groundwater level forecasting in Kathajodi-Surua Inter-basin within Mahanadi deltaic region of eastern India. Three ANN training algorithms namely gradient descent with momentum and adaptive learning rate backpropagation (GDX) algorithm, Levenberg-Marquardt (LM) algorithm and Bayesian regularization (BR) algorithm were evaluated for predicting groundwater levels in the study area. With the ANN model having 40 input nodes and 18 output nodes, the Levenberg-Marquardt and Bayesian regularization algorithms consumed lots of computer memory and were difficult to be evaluated by the trial-and-error method. In contrast, the GDX algorithm could effectively be evaluated by the trial-and-error procedure due to less requirement of computer memory. In order to run the LM and BR algorithms effectively, the entire study area was divided into three clusters and three cluster-specific ANN models were developed for predicting groundwater levels one week advance at the sites present in each cluster. The performance evaluation of training algorithms based on ME, RMSE, r and NSE showed that the BR algorithm performs somewhat better than the remaining two algorithms. On the other hand, the GDX algorithm can effectively be used for large neural networks with little less accuracy than the LM and BR algorithms. GDX algorithm was again successfully used to simultaneously forecast groundwater level at all the 18 tubewells at a time. The forecast of groundwater levels at 2-, 3- and 4-week in advance showed 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.

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