Journal of Geology & Geophysics
ISSN: 2381-8719
Lohani and Krishan, J Geol Geophys 2015, 4:3
DOI: 10.4172/2329-6755.1000206
Research Article
Open Access

Groundwater Level Simulation Using Artificial Neural Network in Southeast, Punjab, India

Lohani AK[1] and Krishan G[1,2]*

[1]*National Institute of Hydrology, Roorkee-247667, Uttarakhand, India*
[2]*IGB Groundwater Resilience Project, British Geological Survey, United Kingdom*

Abstract

This paper presents an efficient and stable artificial neural network (ANN) model for predicting groundwater level in south-east Punjab, India. After improving the model accuracy using different types of network architectures and training algorithms, it has been observed that best results can be achieved with a standard feed forward neural network trained with the Levenberg–Marquardt algorithm. Good estimation of groundwater level can be achieved by designing distinct networks for different sites and ANN method has been found to forecast groundwater level in Faridkot, Ferozepur, Ludhiana and Patiala districts of Punjab, India with reasonable accuracy.

Keywords: Artificial neural networks; Groundwater level forecasting; South-east Punjab; Aquifer exploitation

Introduction

For depicting hydrological variables and understanding the physical processes taking place in a hydrological system, conceptual and physically-based models are considered to be the main tools [1]. But these models do have practical limitations. Generally, when data are not sufficient, getting accurate predictions is more important than conceiving the actual physics of the system. In such situations, empirical models remain a good alternative method and generally provide useful results without a costly calibration time [2].

During the last decade, the Artificial Neural Network (ANNs) model has become popular in hydrological modeling and forecasting. Humans are able to do complex tasks like perception, pattern recognition, or reasoning much more efficiently and also able to learn from examples and neural systems of human brain are to some extent fault tolerant. Research and development in Artificial Neural Networks (ANNs) started with an attempt to model the bio-physiology of the human brain, creating models which would be capable of mimicking processes characteristics of human on a computational level. Neural networks are widely regarded as a potentially effective approach for handling large amounts of dynamic, non-linear and noisy data, especially in situations where the underlying physical relationships are not fully understood.

According to Firouzkouhi [3] groundwater always has been an important and reliable resource to supply drinking and agriculture water and considered to be a reliable resource for supporting consumption needs of different users. For the management of groundwater resources, prediction of groundwater level fluctuations with desired accuracy is very much required. Consequently, there is need for developing models which are capable of efficiently forecasting groundwater levels. In this regard, applications of soft computing techniques like ANN are more effective. An artificial neural network (ANN) model is such a 'black box' model having particular properties which are greatly suited to dynamic nonlinear system modeling [4]. Earlier the works of Minns and Hall, Coppolo et al., Imrie et al., Lekkas et al., Solomantine and Xue, Coulibaly et al., Dawson and Wilby [5-11] emphasized the application of artificial neural networks over other methods. A number of studies demonstrated the capability of ANN in hydrological modeling and forecasting [12-15]. Furthermore, Bisht et al., [16] demonstrated the capability of ANN in prediction groundwater level fluctuation in Ganga-Ramganga basin in Budaun District, Uttara Pradesh, India. Sethi et al., [17] developed ANN models for the prediction of groundwater table depths in Munijhara micro watershed in hard rock area of Nayagarh district, Orissa, India. Mayilvaganan and Naidu [18] applied ANN in groundwater level forecasting of Thurijapuram watershed, Thiruvannamalai district, Tamilnadu, India.

In this paper, an attempt has been made to identify a neural network structure for predicting groundwater level in Fardikot, Ferozepur, Ludhiana and Patiala districts of Punjab with a main purpose to apply ANNs particularly feed forward back propagation neural networks to simulate and forecast groundwater levels at desired lead period. Faridkot, Ferozepur, Ludhiana and Patiala districts of Punjab were chosen as the study area as the groundwater resources have been overexploited in south-east region of Punjab during the last two decades [19-22]. However, numerous studies carried out in different parts of Punjab and Indo-Gangetic basin emphasis that the groundwater level and quality in Punjab have been decreasing steadily [23-44] and using ANN groundwater level forecasting has been done in Amritsar and Gurdaspur districts of Punjab [45] but no such model was applied in south-east, Punjab. Therefore, for the planning and management of groundwater resources in the south-east region of Punjab accurate and timely forecasts of ground water levels are very much required. In this study ANN technique was used for forecasting the groundwater levels in Faridkot, Ferozepur, Ludhiana and Patiala districts based on the available groundwater level data of 2 blocks (Faridkot and Kotkapura) of Faridkot district; 3 blocks (Firozepur, Guruharsarai and Mamdot) of Firozepur district; 3 blocks (Machivara, Mangat and Pakhoval) of Ludhiana district and 5 blocks (Bhunerheri, Nabaha, Patiala, Rajpura and Samana) of Patiala district obtained from the Punjab Water Resources and Environment Directoate, Chandigarh.

The Study Area

Southeast region of Punjab also called 'Malwa'- comprises of eleven administrative districts of the Punjab, viz., Firozpur, Faridkot, Moga,

***Corresponding author:** Krishan G, IGB Groundwater Resilience Project, British Geological Survey, United Kingdom; E-mail: drgopal.krishan@gmail.com

Received May 01, 2015; **Accepted** May 20, 2015; **Published** May 22, 2015

Citation: Lohani AK, Krishan G (2015) Groundwater Level Simulation Using Artificial Neural Network in Southeast, Punjab, India. J Geol Geophys 4: 206. doi:10.4172/2329-6755.1000206

Muktsar, Bathinda, Sangrur, Mansa, Ludhiana, Patiala, Fatehgarh Sahib and Ropar and geographically lies in the Doaba region but the study was limited to 4 districts – Firozepur, Faridkot, Ludhiana and Patiala (Figure 1).

Malwa occupies 65.1 per cent of the total area and having 58.5 per cent of the total population with varying densities between 629 (Ludhiana) and 272 (Firozepur). The normal rainfall varies between 389 mm (Firozepur) to 681 mm (Ludhiana) in the 4 districts studied. Soil type is arid brown calcareous, loamy soil and desert soils. The cropping system is rice-wheat. Agricultural area is more than 80 percent in all 4 districts except Firozepur [19-22].

Data

The simulation of groundwater was done using monthly groundwater level (2006-13) and rainfall data (2006-10) On the basis of the studies carried out by Lallahem et al., [46] Nadiri [47] and Mirarabi [48] and these were introduced to the ANN as input with one-month time step. For the groundwater level forecasting model rainfall is considered as one of the important inputs and to design network, analogues output and input data of the same period with an equivalent time step were used.

Artificial Neural Network

Artificial neural networks (ANN), type of biologically inspired computational models [49] are being successfully used in the area of hydrology and water resources [14]. ANN model is a data driven model as it perform an input-output mapping via a series of simple processing nodes or neurons and in hydrology it is considered as black box model [12]. For the first time McCulloch and Pitts [50] presented a basic artificial neural network model. With the development of computational techniques, various researchers have suggested a different ANN structures to model various real life problems. The task of each individual neuron is in ANN model structure twofold (i) it integrates information from an external source or from other neurons, often via a linear function, and (ii) it outputs this value via a transfer function, such as the sigmoid. The ability to map a function is derived via the configuration of these neurons into a set of weighted, interconnected layers. Between the two external layers are one or more interconnected, hidden layers, which is the key to learning the relationships in the data. Hydrological processes are generally nonlinear in nature and the ability of ANN in modeling nonlinear processes [13] advocates their use in hydrology and water resources.

There are many ANN architectures and algorithms developed. Out

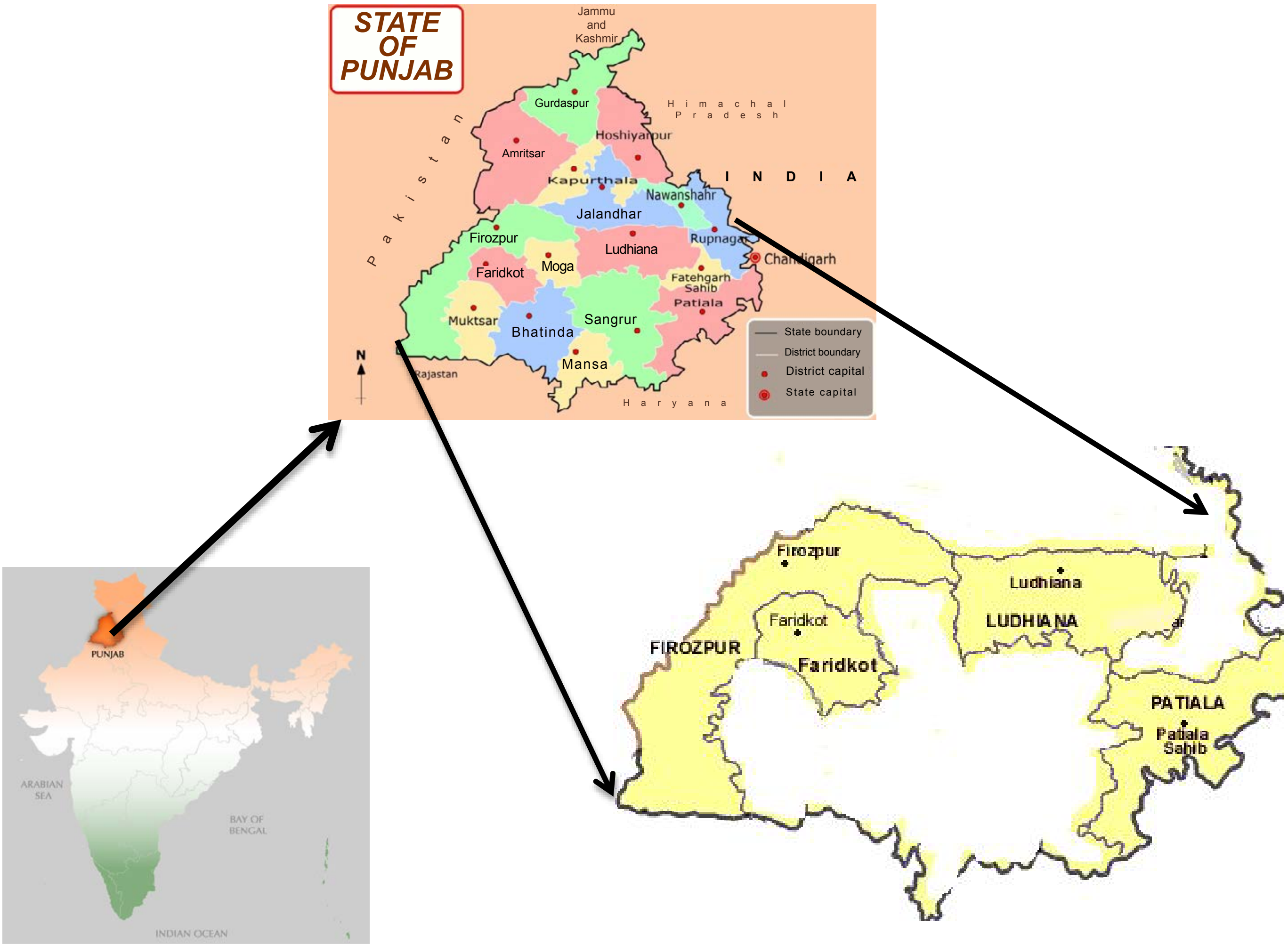

Figure 1: Study area.

of them most common are multi layer feed forward, Hopfield networks, Radial basis function network, recurrent network, Self organization feature maps, counter propagation networks [51]. Coppola et al., [6] showed that ANN has potential in predicting groundwater level fluctuations in an unsteady state of an aquifer influenced by pump and different weather conditions. They noted that predicted results of ANN are more accurate than quantitative models and also showed that ANN models are good at simulating karstic and leaky aquifers where other numerical models are weak in such cases. Taiyuan et al., [52] simulated the effects of hydrological, weather and humidity conditions on groundwater level by ANNs in lower part of Shenyang river basin, North West of china. The ANN model developed by them was able to predict groundwater levels with the average error of 0.37 m or lower with the high accuracy. Nadiri [47] had evaluated the ANN (FFN-LM) ability in modeling complex aquifer of Tabriz.

Applications of ANN in hydrological modeling is demonstrated in the studies carried out by Aziz and Wong, ASCE, Abd¨usselam, Agarwal et al., Gidson, Hagan et al., Lohani et al., Taslloti [4,14,53-59]. ANN is also very effective in hydrological forecasting as demonstrated in the works of Jones, Kar et al., Lohani et al., Maier and Dandy and Uddameri [51,60-62]. A number of studies demonstrated the capability of ANN in reproducing the unknown rainfall-runoff relationship, gauge-discharge relationship, discharge-sediment relationship [12-14], hydrological time series [15] etc. A three layer back propagation artificial neural network model was applied by Shaoyuan et al., [63] to investigate the effects of hydrological, meteorological and human factors on the ground water levels. Also, the use of ANN in ground water level forecasting is investigated by Jothiprakash and Suhasini, Zahra and Gholamreza, Kavitha and Naidu, and Bessaih et al., [64-67].

Application of neural networks

In this study, observed rainfall and ground water level data were used to train and validate an artificial neural-network. For ANN models, data sets are required for the training, validation and testing of the ANN networks. Inputs and outputs have been normalized in the range of (0–1) as NN works efficiently within this range. The back-propagation learning algorithm was applied to ANN model having a single hidden layer. Scaled conjugate gradient (SCG), Levenberg–Marquardt (LM), gradient descent with momentum (GDM), and back propagation were used for this purpose. The neural network model has been developed using the MATLAB Neural Network Toolbox. In the training stage, to model the output, the optimum numbers of neuron were identified by increasing the neurons one-by-one in the hidden layer and testing the model outputs. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function has been used in hidden layer while purelinear (purelin) transfer function has been used in output layer. After the successful training of the network, the finalized network was tested with the selected data. Further, the forecasting performance of ANN model results have been investigated by the statistical methods e.g. RMSE and coefficient of determination (R^2) between network output and network target outputs in training and validation groups.

Results and Discussions

The aim of the present study is to test the ability of ANN in forecasting groundwater level fluctuations in Fardikot, Ferozepur, Ludhiana and Patiala districts of Punjab. The network has input parameters such as rainfall of current and previous two months, groundwater level of current and two previous months and one output parameter i.e. forecasted groundwater level with 6 month lead period. Available monthly data were introduced to the ANN based ground water level forecasting model as input.

To design networks, analogues output and input data of the same period with an equivalent step time were used. Groundwater level of observation wells was available for the period 2006-2013. For the training and validation of the ANN models the data for the period 2006 to 2013 have been divided in parts. For obtaining the best desired model, several parameters, and variables such as number of neurons in hidden layers, percent of dividing data into training and validation sets, learning rate, number of repeating epochs and momentum coefficient were varied. Among these conditions, number of neurons are very effective in reaching to a desired state of network. In order to avoid overfitting of ANNs “early stopping” method has been applied. Optimal network architecture was selected based on the minimum root mean square error (RMSE).

For artificial neural network modelling input data were normalized and scaled between zero and one. For developing the ANN structure, rainfall of the study area and previous month and current month water level were selected as input to the model and six month ahead water levels in observation wells were selected as output. Then, to increase the predicting capability of the network, the input and output data were divided into two groups for each data set i.e. calibration data from 2006 to 2010 and validation data from 2011 to 2013.

Validation

In order to validate the developed neural networks models, new observation data were introduced to the networks and forecasted groundwater level were compared with actual groundwater of all observation wells in the study area (Figures 2-5). It is depicted from this figures that the neural networks can forecast six month ahead

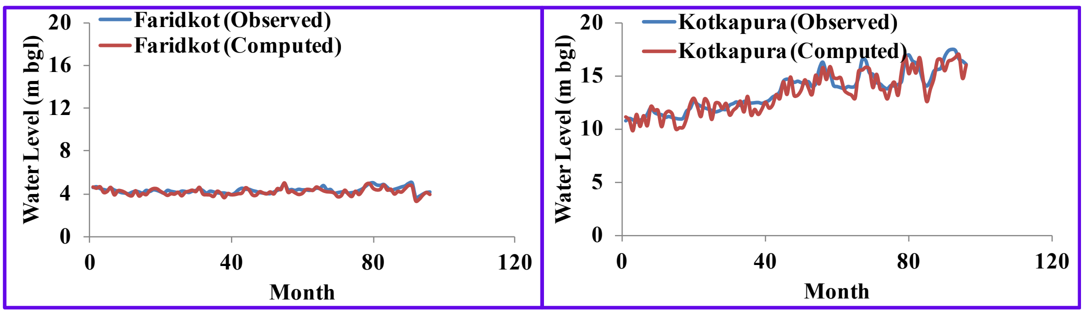

Figure 2: Observed and forecasted water level in Faridkot district (calibration, 1- 60 months & validation results, 61-96 months).

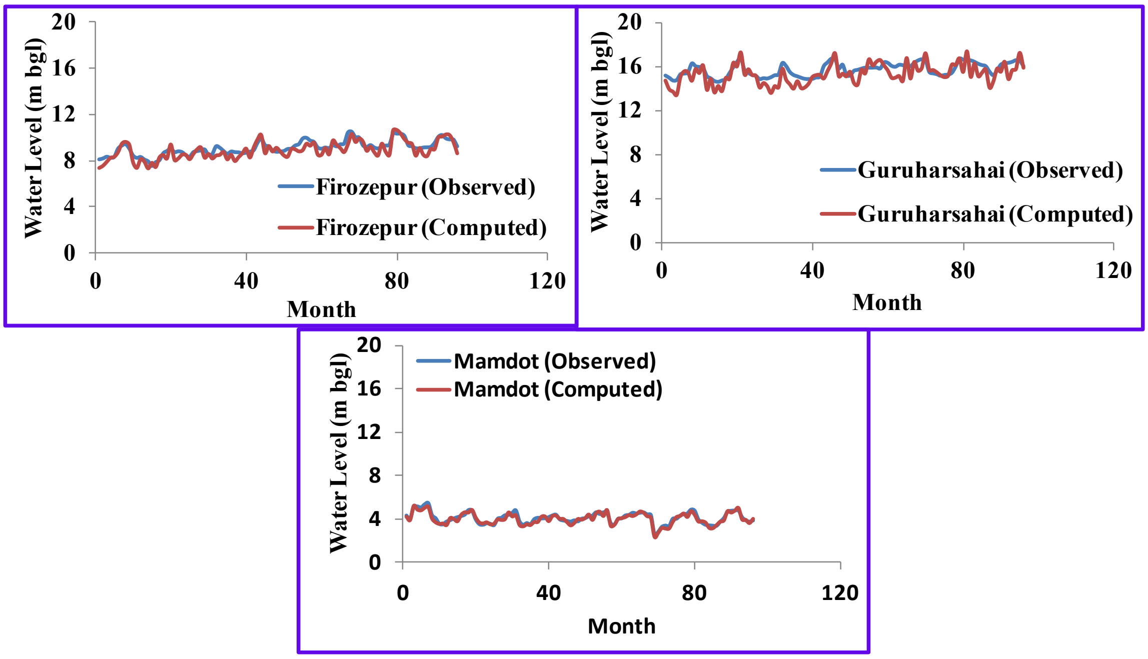

Figure 3: Observed and forecasted water level in Ferozepur district (calibration, 1- 60 months & validation results, 61-96 months).

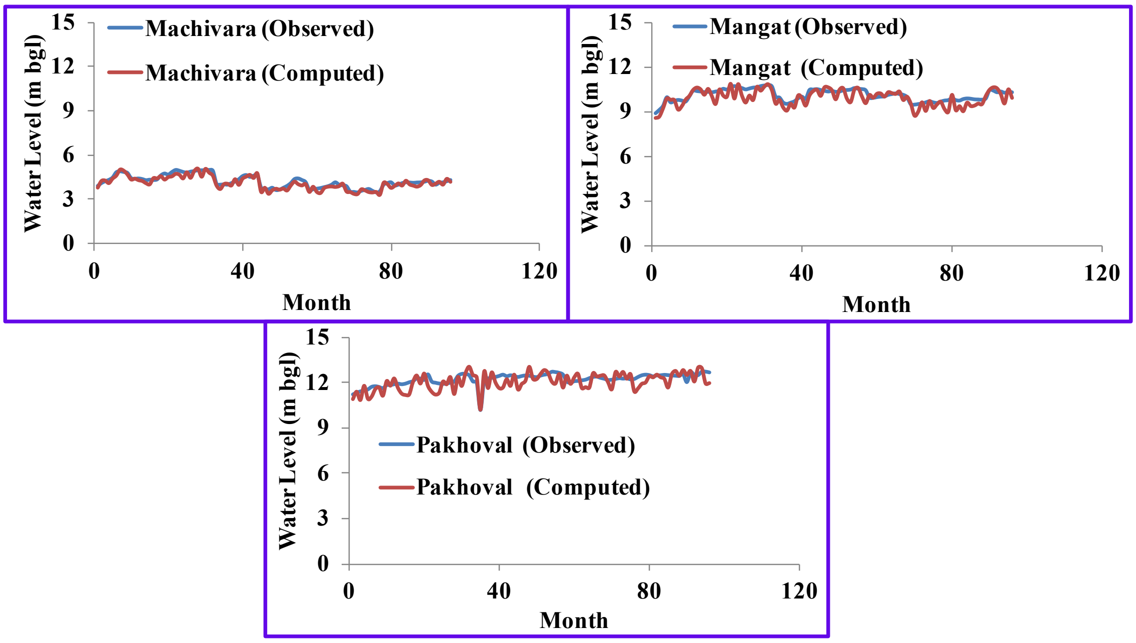

Figure 4: Observed and forecasted water level in Ludhiana district (calibration, 1- 60 months & validation results, 61-96 months).

groundwater levels with reasonable accuracy in most of the observation wells.

Forecasting capability of the ANN models have been evaluated by the RMSE and coefficient of determination of the observed and forecasted ground water levels of different wells. It is observed that (Table 1) the values of RMSE varies from 0.21 to 1.31 m during calibration and 0.20 to 1.49 m during validation. Furthermore, the coefficient of determination for both the calibration and validation data shows that the forecasted groundwater tables show reasonably good correlations.

Conclusion

The main aim of this study was to evaluate the capability of artificial neural network as a possible tool for forecasting groundwater level in Fardikot, Ferozepur, Ludhiana and Patiala districts of Punjab. In the developed ANN model structure, ground water levels with six month

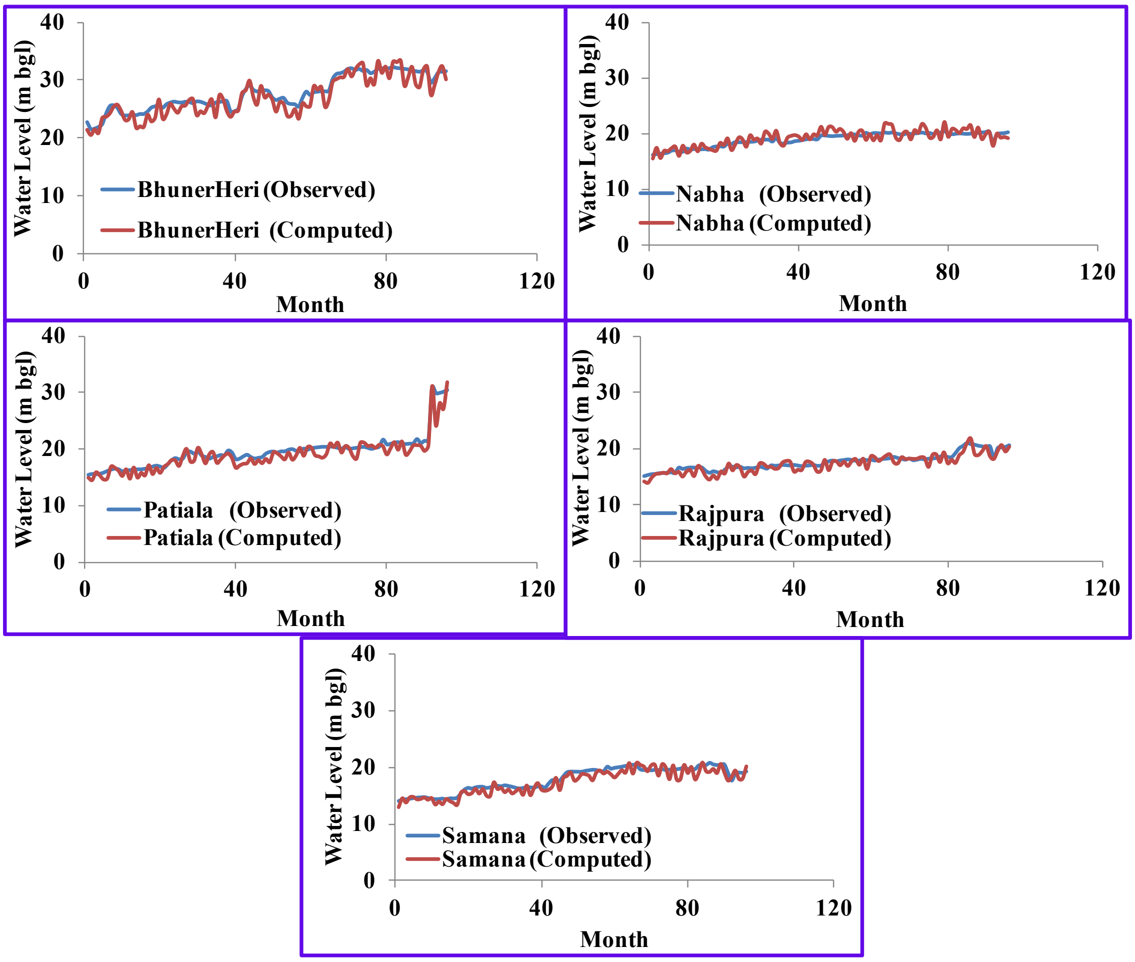

Figure 5: Observed and forecasted water level in Patiala district (calibration, 1- 60 months & validation results, 61-96 months).

Model	Training		Validation	
Location	**RMSE (m)**	**R^2**	**RMSE (m)**	**R^2**
Faridkot	0.579	0.826	0.22	0.23
Kotkapura	0.801	0.772	0.72	
Firozepur	0.820	0.792	0.40	0.43
Guruharsahai	0.785	0.418	0.78	0.78
Mamdot	0.918	0.953	0.24	0.20
Machivara	0.902	0.840	0.21	0.19
Mangat	0.826	0.734	0.35	0.37
Pakhoval	0.664	0.170	0.50	0.43
BhunerHeri	0.850	0.909	1.31	1.49
Nabha	0.868	0.251	0.77	0.95
Patiala	0.865	0.919	0.94	1.45
Rajpura	0.749	0.751	0.71	0.84

Table 1: RMSE and coefficient of determination.

lead period have been forecasted by using the rainfall of the study area and the previous month groundwater levels as input. Back propagation (BP) neural network model algorithms with one hidden layers have been studied. Number of neurons in the hidden layer has been varied to optimize network. To these neural networks, new observation data were introduced to the networks. Then, forecasted groundwater levels were compared with actual groundwater levels of all observation wells in the study area. Based on statistical indices (R^2 and RMSE), the best networks were selected for each of the stations (Table 1). The study concludes that there was reasonably good fit between observed and forecasted ground water level data in case of all the observation wells. Thus, the forecasted ground water levels obtained by the developed models can provide an input for the planning and management of the ground water resources in the region.

Acknowledgements

Authors wish to thank Director, National Institute of Hydrology for all his support and encouragement for this study. Dr. Gopal Krishan thanks Dr. Alan MacDonald, Dr. Dan Lapworth and Dr. Helen Bonsor (BGS-DFID) for their support during the study. Authors thank Er. K.S. Takshi & Er. J.P. Singh, Irrigation department, Punjab and Er. P.S. Bhogal, Director, Punjab Water Resources Environment Directorate, Chandigarh.

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