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Application of an artificial neural network to estimate groundwater level fluctuation

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ABSTRACT

This paper examines and compares the capability of an artificial neural network (ANN) with five different backpropagation (BP) algorithms, namely Gradient descent with momentum (GDM), Gradient descent with adaptive learning rate and momentum (GDX), The *Fletcher-Reeves* Conjugate gradient (CGF), Quasi-Newton (BGF) and Levenberg-Marquardt (LM), and a radial basis function (RBF) architecture for estimating groundwater level fluctuation (GLF). MATLAB was used to develop the ANN programming. Five-daily measurements of GLF in an observation well provided the data for analyzing the model. An input model using six time lags to estimate actual GLF and 10 hidden nodes gave an optimum result. In general, the work showed that an ANN could be used to estimate GLF even with relatively few data samples. The Levenberg-Marquardt (LM) algorithm was not only the best algorithm in the BP class but also delivered better results than RBF. This result may be very useful in helping developing countries develop groundwater monitoring and management systems. Such countries typically have very few observation wells and lack long-period time-series data due to budget limitations and government policy.

Keywords: *groundwater level fluctuation, estimating, artificial neural network, backpropagation algorithms, radial basis function, MATLAB.*

INTRODUCTION

Groundwater level is an indicator of groundwater availability, groundwater flow, and the physical characteristics of an aquifer or groundwater system. Groundwater-level monitoring is needed to maintain the groundwater equilibrium system and to prevent land subsidence. Monitoring of the groundwater level can be done by direct observation of monitoring wells or by forecasting using a simulation model such as an artificial-neural-network (ANN) model.

Several researchers have applied ANNs to groundwater problems, such as Ranjithan et al. (1993), who developed a neural network-based screening tool to simulate the pumping index for hydraulic conductivity realization for groundwater remediation under uncertainty. Scientists have also developed ANNs to estimate aquifer parameter values (Balkhair, 2002), to forecast the groundwater level using rainfall, temperature, and stream discharge as inputs (Daliakopoulos et al., 2005), and to evaluate the groundwater level in fractured media (Lallahem et al., 2004). In addition, Nayak et al. (2006) used ANN to forecast groundwater level in a shallow aquifer.

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In this study we developed ANNs using observed groundwater level for prediction and estimation of the groundwater level. The ANN, a "black-box model," is designed to identify the connection between input and output without going into analysis of the internal structure of the physical process. Selecting input variables is the most important step in ANN modeling. In this study we used a six time lag of five-daily GLF as the input model. We performed training and testing of the ANN models using MATLAB command-line. We investigated and compared the application of five different types of backpropagation neural-network (BPNN) algorithms and a radial-basis-function (RBF) neural network.

METHODOLOGY

ARTIFICIAL NEURAL NETWORK (ANN)

An ANN is an information-processing construct that consists of a number of interconnected processing elements called nodes, analogous to neurons in the brain. Each node combines a number of inputs and produces an output, which is then transmitted to many different locations, including other nodes. The difference between the various types of ANNs usually comes from the many different ways to arrange the nodes (architecture) and the many ways to determine the weights and functions for training the network.

A common type of ANN consists of three layers; an input layer, which is connected to a hidden layer, which is connected to an output layer. The activity of the input nodes represents the raw information that is fed into the network. The activity of each hidden node is determined by the activities of the input nodes and the weights on the connections between the input and the hidden nodes. The behavior of the output node depends on the activity of the hidden nodes and the weights between the hidden and output nodes. This simple type of network is interesting because the hidden nodes are free to construct their own representations of the input. The weights between the input and hidden nodes determine when each hidden node is active, and so by modifying these weights, a hidden node can choose what it represents.

"Feed-forward" means that all the interconnections between the layers propagate forward to the next layer. The type of node being used in the ANN determines the way that total input is calculated as well as the way that the node calculates its output as a function of its net input. In the present study, the activation function used for calculation is a sigmoid logistic function. Each node is a simple processing element that responds to the weighted inputs it receives from other nodes. The receiving node sums the weighted signals from all nodes to which it is connected in the preceding layer. The net input x_j to node j is the weighted sum of all the incoming signals:

$$Net\_input = x_j = \sum w_{ij} y_i \qquad (1)$$

Where x_j is the net input coming to node j, w_{ij} represents the weight between node i and node j, and y_i is the activation function at node i. The activation function, y_j, which is a nonlinear function of its net-input, is described by the sigmoid logistic function (eq. 2):

$$y_j = \frac{1}{1+\exp(-x_j)} \qquad (2)$$

The three-layer feed-forward neural network includes the inputs, weights, a bias, and an output as shown in Figure 1.

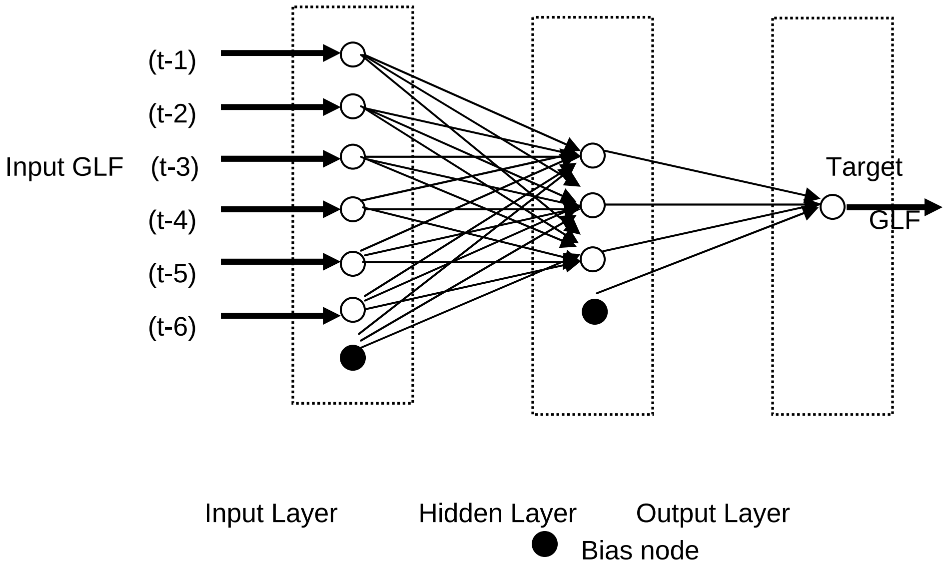

Figure 1. Topology of the three-layer feed-forward artificial neural network.

We used the *newff*, *train,* and *sim* MATLAB command lines to create, to train, and to obtain output from the networks. One hidden layer with 10 nodes was selected. We used a logistic sigmoid, *logsig*, as the activation function for input to the hidden layer and for hidden layer to an output. The backpropagation algorithm minimized the time between target and calculation output.

Backpropagation

Backpropagation is the most common algorithm used for prediction with neural networks. Lippmann (1987) analyzed learning and self-organization algorithms used in multilayer nets. A multilayer BPNN with gradient descent was described by Rumelhart et al. (1986). Details about BPNN for groundwater problems can be found elsewhere, such as in Ranjithan et al. (1993). The term *backpropagation* refers to the manner in which the gradient is computed for nonlinear multilayer networks. Input data and the corresponding target are used to train a network until it can approximate a function, associate input nodes with specific outputs, or classify input nodes in an appropriate way as defined.

After the output is calculated, the next step is the calculation of the error between actual outputs and desired output (target). If the error is less than the acceptable normalized error, the model is completed. If not, Error Back Propagation, one of the procedures used to adjust weights, is begun. The error for one input pattern is computed as follows:

$$E = 0.5\sum_{p=1}^{np}\sum_{j}^{nj}\left(t_{pj} - o_{pj}\right)^2 \qquad (3)$$

Where np is the number of training samples, t_{pj} is the target value of output node *j* of training sample *p*, o_{pj} is the output value of output node *j* of training sample *p*.

There are several variations of the backpropagation algorithm, five of which we applied and studied in this research. A detailed explanation of the algorithms below can be found in Demuth & Beale (2001).

- Gradient descent with momentum (GDM).

The training parameter was 0.5 for learning rate and 0.9 for momentum factor. The maximum iteration or epoch was 5000 with error goal 1exp(-5).

- Gradient descent with adaptive learning rate and momentum (GDX).

The initial learning rate was 0.01 with increment 1.05 and other parameters the same as GDM.

- The *Fletcher-Reeves* Conjugate gradient (CGF)
- Quasi-Newton (BGF)
- Levenberg-Marquardt (LM)

For CGF, BFG, and LM, we used a learning rate of 0.05.

Radial Basis Function (RBF)

The RBF network consists of only three layers similar to BP, namely input layer, a hidden layer or radial-basis layer, and an output layer or linear layer. The input layer collects the input information. The hidden layer consists of a set basis function, which applies nonlinear transformation to the input source. The most common transformation is a Gauss function as the nonlinearity of the hidden nodes (Demuth & Beale, 2001):

$$h(n) = exp\,(-n^2) \qquad (4)$$

where n is the vector distance between the input vector p and weight vector w, multiplied by the bias b value:

$$n = \|w - p\|b \qquad (5)$$

The output values of the network are computed as a linear combination of this basis function (hidden nodes).
The command-line function *newrb* in MATLAB iteratively creates a radial basis network one node at a time. Nodes are added to the network until the sum-squared error falls beneath an error goal or until a maximum number of nodes is reached. In this study the error goal was 1.0exp (-4), the maximum number of nodes was 10, and the spread chosen was 20.

STUDY AREA

To investigate the ANN as a robust method for solving non-linear problems such as groundwater level fluctuation (GLF), in this paper the ANN was used to estimate the GLF of Jakarta, Indonesia. Jakarta is the capital city of Indonesia and is located on Java Island. The temperature is almost always hot and to some extent humid. The average annual rainfall is about 1800-mm. Jakarta has two seasons: the wet season from October to April (with January being the rainiest month), and the dry season from May to September (with June through August being the driest months). Average daily temperatures range from 24 to 31 degrees Celsius.

The Jakarta groundwater basin is one of the 215-groundwater basins delineated in Indonesia. The boundaries of the system are the Cisadane River in the west, Bekasi River in the east and the Jakarta bay (Java Sea) in the north. The southern boundary is assumed close to Depok with very low permeability and thin aquifer (Tirtomihardjo, 1996). The bottom of the basin system is formed by impermeable Miocene sediment which also cropout at the southern boundary of the system. The basin fill consists of marine Pliocene and Quaternary sand and delta sediment up to 300 m thick. The thickness of the sandy aquifer layer is about 1 – 5 m interconnected with a predominantly silt/clay sequence and comprises only 20% of total sediment deposit. Fine sand and silt are very frequent components of aquifers. In general, the Quaternary aquifer can be divided into tree aquifer systems based on the hydraulic characteristics and depths: the unconfined aquifer system (0-40 m), the upper confined system (40-140 m), and the lower confined aquifer system (> 140 m) (Tirtomihardjo, 1996).

The location of the observation wells studied is spreading, as shown in Figure (2). They are representative of unconfined aquifer (J5), upper confined aquifer (J2), and lower confined aquifer (J1, J3 and J4). The characteristics of those wells are presented in Table 1. The range of GLF during seven years (1989-1995) for unconfined aquifer was 4.6 m for J5. The highest GLF range was J2 for 9.89 m. The range of J1, J3, and J4 were 5.35 m, 6.71 m, and 6.19 m, respectively.

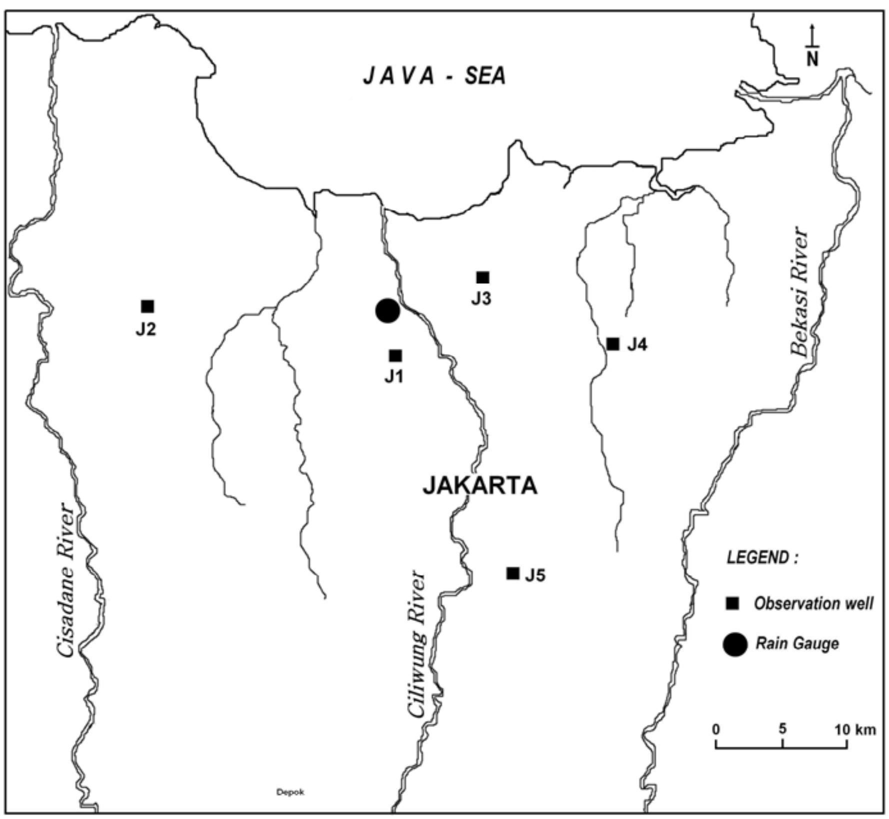

Figure 2. Map of study area and location of observation well used in this study

Table 1: Characteristic of the observation wells used in this study.

Well	Elevation from sea level (m)	Screen depth from land surface (m)	Aquifer
J1	5.8	177 - 193	lower confined
J2	6.9	76 - 79	upper confined
J3	2.4	235 - 241	lower confined
J4	6.0	231 - 237	lower confined
J5	40.8	16 - 18	unconfined

Under natural conditions, the recharge area of the deep aquifer is located in the hilly area at elevation between 25 m – 200 m. Discharge from the confined aquifer to the natural base level in the flat coastal area occurred mainly by upward leakage, evaporation, and outflow to the surface water system. Recharge to the deep aquifer system, other than horizontal inflow, may occur throughout the city area by downward leakage as the head level of the confined aquifer has dropped regionally below the water table of the unconfined aquifer (Tirtomihardjo, 1996; Sutrisno, 1999).

The groundwater contribution to the actual supply is about 250 million m^3/year and is mainly abstracted from innumerable shallow wells (80%) and more than 3,000 deep wells (20%). Between 1900 and 1950, groundwater abstraction was below 10 million m3 year-1, but since that time, mainly after 1970, it has steadily increased in step with the growth in population and industrial development. In the year 1994, deep groundwater abstraction was estimated to be 53 millions m^3/year, which was about 50% higher than could be accounted for by registered wells of 33.8 million m^3/year (Soetrisno, 1999).

DATA COLLECTION

The groundwater level fluctuation studied in this research was a time series of five daily groundwater-level readings obtained from five observation wells (Fig. 3). One of the most important steps in the development of any prediction model is the election of appropriate input variables. The main reason for this is that ANN belongs to the class of data-driven approaches (Maier and Dandy, 2000). We simulated a five-daily groundwater level fluctuation. After using the trial and error method and considering the length of the training sample, a six time lag of the well concerned (t-1 to t-6) gave an optimum result. The length of the training sample was 365, or 5-year data (1989-1993), and 146, or 2-year data (1994-1995), as a testing sample. Time lag not only helps overcome limitations of data but also helps to investigate the effect of time lag on the model. The optimal numbers of hidden neurons were determined by trial and error, which suggests that over-fitting does not occur if the number of training samples is at least 30 times the number of free parameters or weights (Maier and Dandy, 2000)

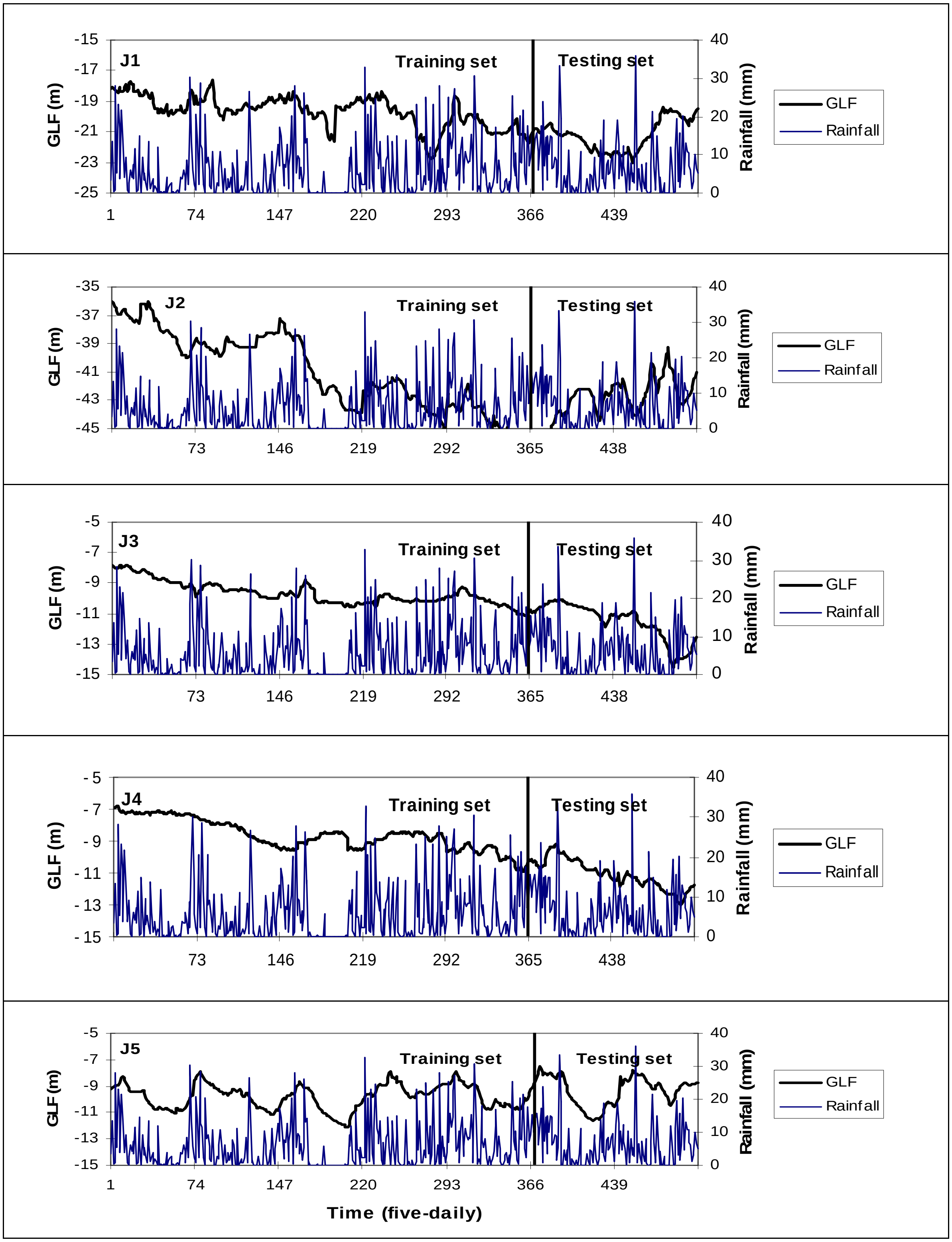

Figure 3. Five-daily groundwater level fluctuation and rainfall of Well J1 to J5.

It is important to determine the appropriate network architecture in order to obtain satisfactory results. In this study, one hidden layer with 10 nodes gave an optimal result. The activation function used was the sigmoid logistic function. Target data was scaled into the range of 0.1 to 0.9 by normalizing with respect to minimum and maximum data before feeding into the network. For convenience, input data was also scaled into the range of 0.1 to 0.9.

Normally, the data set for an ANN needs to be divided into three parts. The first part is for the training, the second part for validation and the third part for testing. However, because the length of our sample data was not very big, we considered only two parts: training and testing. The only difference between a testing phase and a validation phase is that if the error rate of the validation phase increases, then the training stops. In this study, those two terms are used synonymously.

RESULT AND DISCUSSION

The ANN programming was developed using MATLAB 6 for all training and testing phases. The training and testing period consisted of 365 samples (5 years) and 146 samples (2 years), respectively. Table 2 summarizes the performance of forecasting for all of the observation wells in terms of mean absolute error (MAE), mean relative error (MRE) root mean square error (RMSE) and maximum actual difference (MAD) during the training and testing period, which took place after a number of trial-and-error runs. In general, the results were satisfactory. Based on performance statistics for the BP algorithms, the Levenberg-Marquardt (LM) is the best algorithm, slightly better than RBF for calculating results in all cases studied during the testing period. However, the forecasting of the J3 and J4 observation wells seems poor compared with other observation wells. The J3 and J4 contain testing samples outside the range of values in the training period. Based on further analysis of prediction error, the three statistics' performance improved from the GDM algorithm to the LM algorithm and slightly decreased for the RBF algorithm.

Absolute error is the amount of physical error in an observation. The MAE is good during training and testing for BP and RBF model. A relative error gives an indication of how good a measurement is relative to the size of the thing being measured. The MRE, which measures accuracy with less sensitivity for outlying values than RMSE, is very good for predicting GLF. The highest value of MRE is about 6.395% for the training period of the J4 observation well using the GDM model. The RMSE, which is a measure of residual variance that shows the global goodness of fit between the predicted and observed GLF, is good during training and testing, except for the J3 observation well for BP models that have RMSE more than one meter.

Table 3 provides performance of model calculation in terms of determination coefficient (R-square) and efficiency index (EI). In general, the prediction result in the training set was satisfied. However, the values for the testing period of J3 and J4 were poor. Poor prediction can be expected when the validation or testing data contain values outside the range of those used for training, because ANNs are unable to extrapolate beyond the range of data used for training (Maier and Dandy, 2000). To overcome this problem, we added the part of testing data that is outside the range to the remaining training data, and we used the whole data set to retrain the network. Maier and Dandy (2000) used a similar procedure. The result of this procedure is shown in Table 4 and Table 5. From the calculation result, we can summarize that ANN is a powerful tool for forecasting GLF, even with relatively limited data.

Table 2: Performance of ANN model for six algorithms in term of MAE, MRE, RMSE and MAD for five years training and a two-year testing period.

Algorithms	J1 observation well		J2 observation well		J3 observation well		J4 observation well		J5 observation well	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
					MAE (m)					
GDM	0.200	0.158	0.235	0.251	0.492	0.620	0.529	0.569	0.132	0.180
GDX	0.189	0.150	0.209	0.271	0.159	0.621	0.337	0.434	0.139	0.167
CGF	0.234	0.148	0.190	0.205	0.123	0.584	0.153	0.405	0.128	0.150
BFG	0.217	0.140	0.189	0.211	0.156	0.670	0.087	0.379	0.103	0.121
LM	0.160	0.112	0.143	0.181	0.076	0.607	0.063	0.347	0.089	0.117
RB	0.156	0.124	0.138	0.201	0.060	0.222	0.062	0.125	0.091	0.123
					MRE (%)					
GDM	1.023	0.736	0.584	0.590	5.324	4.827	6.395	4.982	1.370	2.053
GDX	0.966	0.697	0.517	0.640	1.681	4.797	3.936	3.812	1.445	1.899
CGF	1.193	0.700	0.467	0.482	1.273	4.499	1.733	3.510	1.330	1.704
BFG	1.108	0.665	0.467	0.497	1.683	5.202	1.001	3.263	1.077	1.372
LM	0.819	0.528	0.351	0.426	0.778	4.652	0.725	2.927	0.929	1.321
RB	0.803	0.583	0.338	0.475	0.625	1.720	0.711	1.105	0.955	1.380
					RMSE (m)					
GDM	0.283	0.195	0.348	0.325	0.660	1.026	0.591	0.741	0.179	0.252
GDX	0.277	0.193	0.306	0.353	0.243	1.029	0.387	0.582	0.192	0.232
CGF	0.324	0.194	0.279	0.296	0.192	1.000	0.197	0.555	0.176	0.218
BFG	0.311	0.194	0.288	0.295	0.228	1.080	0.119	0.538	0.148	0.190
LM	0.242	0.155	0.239	0.275	0.113	1.045	0.090	0.535	0.129	0.188
RB	0.239	0.158	0.242	0.286	0.108	0.386	0.091	0.172	0.134	0.204
					MAD (m)					
GDM	2.435	0.556	1.643	0.977	1.712	2.962	1.049	1.995	1.038	1.296
GDX	2.323	0.685	1.582	1.206	1.312	2.990	1.328	1.637	1.081	1.074
CGF	2.391	0.648	1.594	1.549	1.152	2.957	0.949	1.656	1.072	1.173
BFG	2.392	0.579	1.587	1.317	0.989	3.154	0.663	1.627	1.057	1.256
LM	2.346	0.574	1.524	1.410	1.014	3.035	0.639	1.662	1.047	1.338
RB	2.296	0.572	1.567	1.448	0.947	1.432	0.685	1.036	1.116	1.321

Table 3: Performance of ANN model for six algorithms in term of R-square (Determination coefficient) and EI (efficiency index) for five years training and a two-year testing period.

	J1 observation well		J2 observation well		J3 observation well		J4 observation well		J5 observation well	
Algorithms	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
					R-sequare					
GDM	0.925	0.967	0.984	0.949	0.876	0.608	0.857	0.541	0.963	0.958
GDX	0.928	0.975	0.988	0.940	0.892	0.772	0.871	0.667	0.958	0.961
CGF	0.905	0.961	0.990	0.958	0.934	0.700	0.963	0.793	0.964	0.964
BFG	0.911	0.962	0.989	0.959	0.937	0.783	0.985	0.792	0.975	0.972
LM	0.945	0.977	0.993	0.964	0.979	0.721	0.991	0.840	0.981	0.972
RB	0.946	0.978	0.992	0.961	0.979	0.972	0.991	0.977	0.979	0.967
					Eff. Index (EI)					
GDM	0.925	0.960	0.984	0.947	0.206	0.285	0.614	0.340	0.963	0.949
GDX	0.928	0.961	0.988	0.937	0.892	0.280	0.835	0.593	0.957	0.957
CGF	0.902	0.961	0.990	0.956	0.933	0.320	0.957	0.629	0.964	0.962
BFG	0.909	0.961	0.989	0.956	0.905	0.206	0.985	0.652	0.975	0.971
LM	0.945	0.975	0.992	0.962	0.977	0.257	0.991	0.656	0.981	0.972
RB	0.946	0.974	0.992	0.959	0.979	0.899	0.991	0.965	0.979	0.967

Table 4: Performance of ANN model for retrain of J3 and J4 in term of MAE, MRE, RMSE and MAD (J3: 454 training samples; J4: 460 training samples; both: 146 testing samples).

	J3 observation well		J4 observation well	
Algorithms	Training	Testing	Training	Testing
		MAE (m)		
GDM	0.152	0.154	0.143	0.169
GDX	0.129	0.102	0.170	0.162
CGF	0.099	0.099	0.092	0.113
BFG	0.101	0.099	0.089	0.117
LM	0.058	0.054	0.063	0.078
RB	0.062	0.060	0.067	0.083
		MRE (%)		
GDM	1.497	1.306	1.524	1.541
GDX	1.312	0.869	1.855	1.473
CGF	0.972	0.817	0.983	1.024
BFG	1.006	0.841	0.945	1.051
LM	0.579	0.466	0.679	0.717
RB	0.614	0.509	0.717	0.754
		RMSE (m)		
GDM	0.240	0.206	0.199	0.227
GDX	0.187	0.149	0.229	0.216
CGF	0.167	0.154	0.132	0.163
BFG	0.168	0.134	0.126	0.166
LM	0.100	0.076	0.094	0.123
RB	0.111	0.084	0.101	0.128
		MAD (m)		
GDM	1.583	0.685	0.899	0.665
GDX	0.916	0.672	1.022	1.020
CGF	1.301	0.595	0.822	0.822
BFG	1.574	0.422	0.794	0.794
LM	0.962	0.335	0.828	0.828
RB	0.958	0.279	0.883	0.883

Table 5: Performance of ANN model for retrain of J3 and J4 in term of R-square and EI
(J3: 454 training samples, J4: 460 training samples)

	J3 observation well		J4 observation well	
Algorithms	Training	Testing	Training	Testing
		R-sequare		
GDM	0.966	0.972	0.982	0.940
GDX	0.979	0.985	0.977	0.946
CGF	0.984	0.984	0.992	0.970
BFG	0.984	0.988	0.993	0.967
LM	0.994	0.996	0.996	0.982
RBF	0.993	0.995	0.995	0.980
		Eff. Index (EI)		
GDM	0.966	0.971	0.982	0.938
GDX	0.979	0.985	0.977	0.944
CGF	0.983	0.984	0.992	0.968
BFG	0.983	0.988	0.993	0.967
LM	0.994	0.996	0.996	0.982
RBF	0.993	0.995	0.995	0.980

Figure 4 provides a scatterplot of predicted versus observed GLF for a test set of a two-year period (146 samples of data). The GLF of J3 and J4 were retrained with 454 and 460 data samples, respectively. The results showed that the ANN was successful in estimating the GLF. It is showed that the values are close to a diagonal line, which represents a perfect fit between prediction and observation GLF, even with some points slightly scattered. The result indicates that the model prediction can be used in groundwater monitoring in such areas without involving any groundwater parameter as an input model.

Figure 5 shows a comparison between estimated and observed GLF in the testing period of J1 to J5 observation wells using the LM algorithm. The mean absolute error or mean actual difference in observed and predicted values for each well, in general, did not exceed 0.2 meters, and the minimum average was 0.05 for J3 after retraining (see Table 4). High maximum actual difference occurred in J2 and J5 of 1.41 meters and 1.34 meters, respectively (Table 2). Positive deviation (actual difference) values indicate that the model overpredicts the GLF, whereas negative deviation values denote underprediction (Coulibaly et al., 2001). Figure 5 shows that the J1 and J3 are slightly underpredicted while J2 is slightly overpredicted. Interestingly, J4 and J5 are almost a balance. They have positive and negative deviation. It is investigated from Figure 5 that the ranges of actual difference are mostly less than ± 0.5 meters. All estimation results are acceptable within the range with minimum 94.52 % of J2.

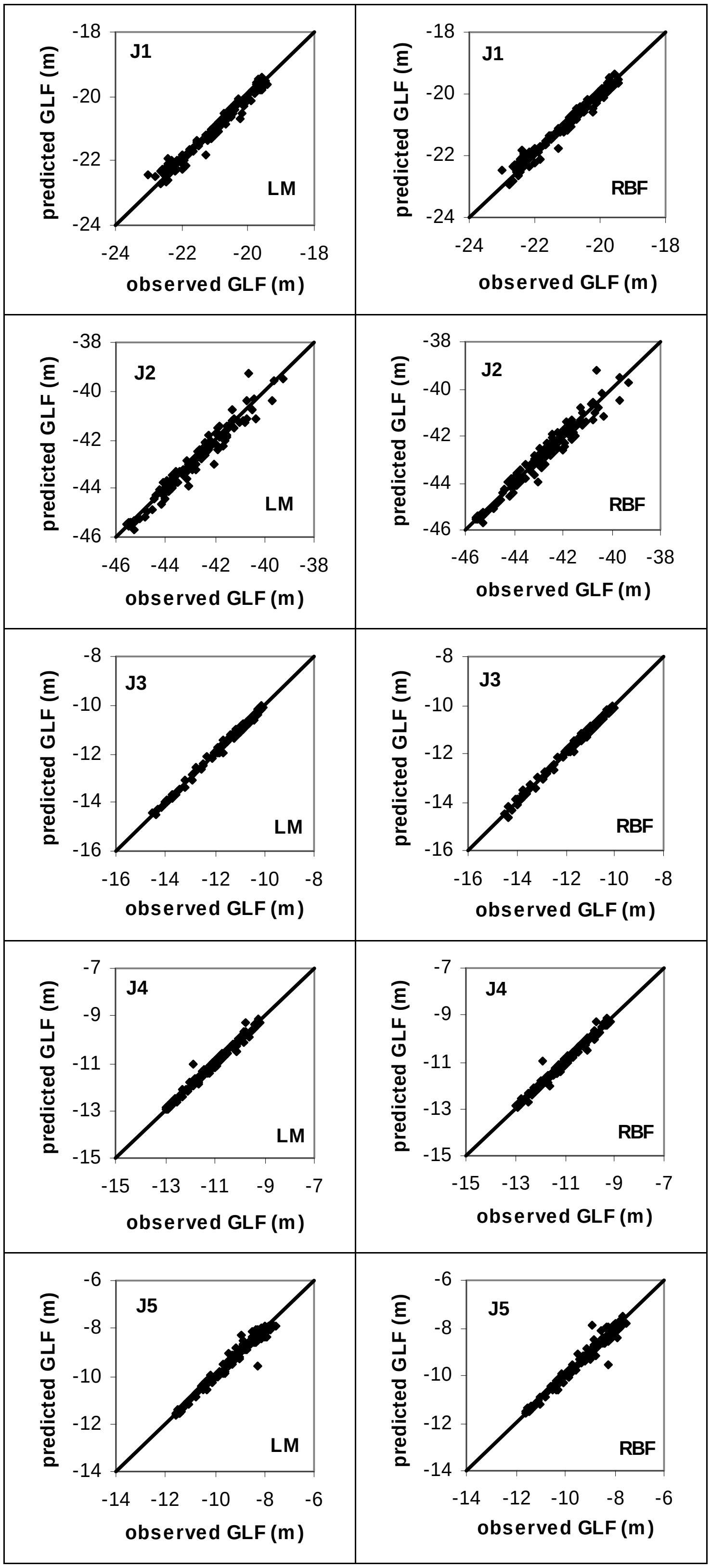

Figure 4. Scatterplot of model prediction versus observed GLF
(J3: 454 training samples, J4: 460 training samples)

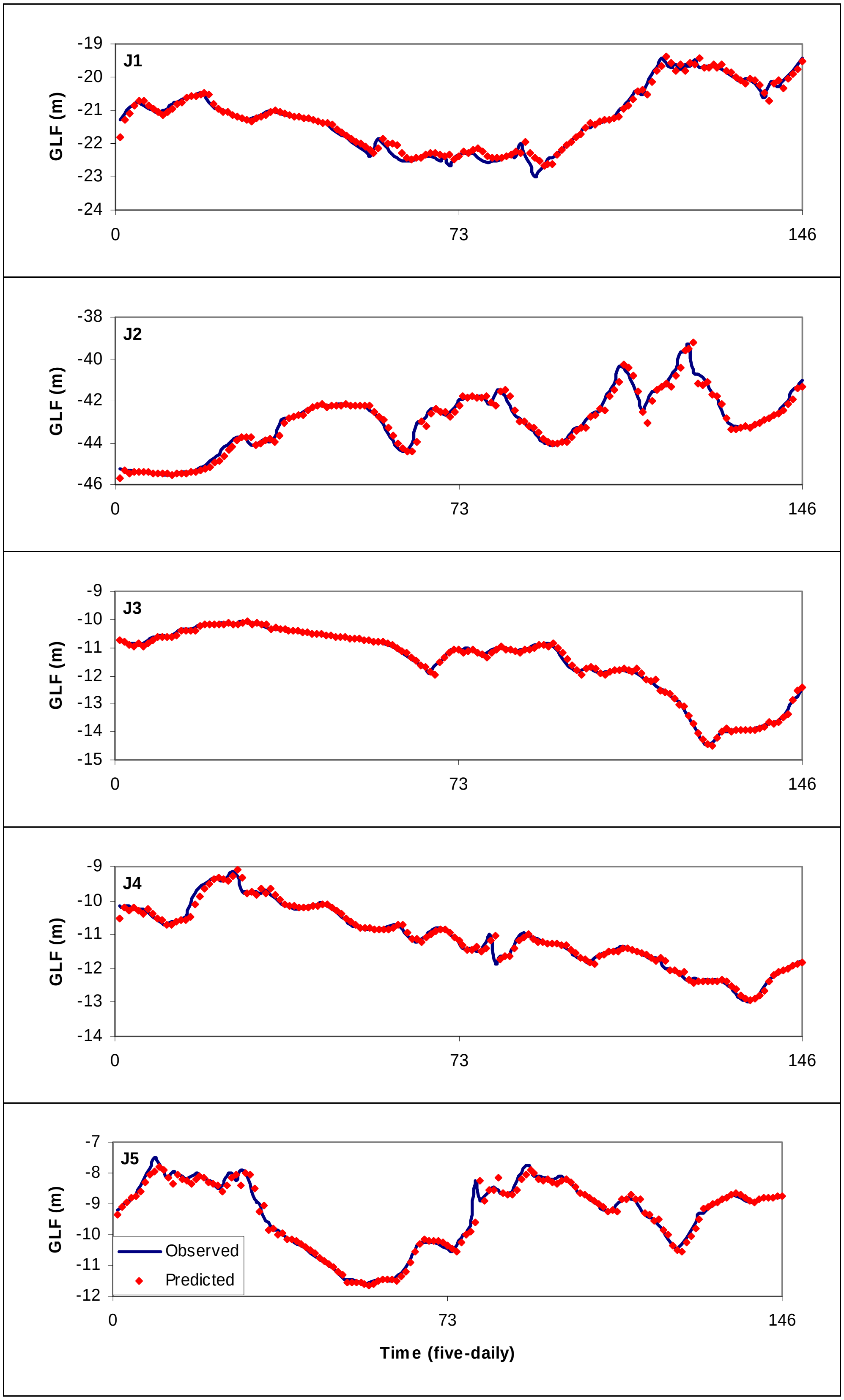

Figure 5. Comparison between GLF observation and prediction in testing period for J1 to J5 with 146 data samples using LM algorithm (J3: 454 training samples; J4: 460 training samples)

CONCLUSION

In this study, MATLAB programming was developed for an ANN model. The ANN, along with five BP algorithms and RBF, was applied and compared for GLF forecasting using six time lags of the GLF as the input model. In general, the results showed that an ANN is an effective tool for GLF forecasting, even though only limited data samples are available. The input set, which contained data from one month before (six time lag) the five-daily GLF measurements, still had a significant influence on the model. Among the different BP algorithms we found that the LM algorithm provided better results during the testing period than other BP algorithms and RBF. Based on these results, we believe an ANN can be used for forecasting GLF for the purposes of groundwater management.

In order to enhance the ANN model performance, we would consider the aquifer system by means of selecting input data from wells with the same strata of aquifer system. In addition, we would take into account the distance between input wells and output wells in order to maintain the continuous influent of groundwater level between them.

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