Daily groundwater level fluctuation forecasting using soft computing technique

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ABSTRACT: The study presented here deals with forecasting daily groundwater level fluctuation (GLF) for monitoring of GLF pattern. The calculation model is based on the adaptive neuro-fuzzy inference system (ANFIS) and two algorithms of artificial neural networks (ANN) models, namely Levenberg-Marquardt (LM) and radial basis function (RBF). The objective in this study is to predict daily GLF for monitoring purposes. The first step was to investigate the effect of the number time lags as inputs for one-day-ahead prediction using the ANFIS algorithm. It was found that three input nodes containing three time-lag of well studied gave good prediction results. The second experiment was to predict the GLF one to seven steps ahead using the three input nodes. In this experiment, the three soft computing techniques were applied. The results indicate that the performances were decreasing by increasing the time step ahead, and in general there was no significant difference between the three techniques used. The best accuracy was for one-day-ahead prediction. The results obtained in this study suggest that GLF monitoring can be conducted by a forecasting model with considering time-lag as inputs. [Nature and Science. 2007;5(2):1-10].

Keywords: groundwater level fluctuation, forecasting, soft computing, artificial neural network, Levenberg-Marquardt, radial basis function, adaptive neuro-fuzzy inference system.

INTRODUCTION

Groundwater is a highly valuable resource. Groundwater has agricultural, domestic, and industrial uses and is acquired by constructing and operating extraction wells. Measurement and analysis of groundwater level is needed for maintaining groundwater availability. Groundwater level modeling is important for environmental protection: maintaining the groundwater equilibrium system, controlling groundwater level fluctuation, and protecting against severe land subsidence. Groundwater management approaches based on a variety of simulation and prediction techniques and control measures have been proposed and adopted by researchers and relevant authorities to address the problem of providing long-term countermeasures against land subsidence and protection of groundwater resources. Recently, groundwater level fluctuation (GLF) analysis by means of forecasting or prediction has increased.

A common nonlinear method for groundwater problems is the artificial neural network (ANN). Many kinds of algorithms for training the network have been developed for GLF forecasting. A significant advantage of the ANN approach in system modeling is that one need not have a well-defined physical relationship for systematically converting an input to an output (Nayak et al., 2004). There have been various papers considering the application of ANN techniques in water resource problems. In surface hydrology, ANN applications have been used for runoff analysis (Gautam et al., 2000; Zhang & Govindaraju, 2003; Parida et al., 2006), rainfall forecasting (Luk et al., 2000; Toth et al., 2000; Trafalis et al., 2002; Ramirez et al., 2005), rainfall-runoff model (Sajikumar & Thandaveswar, 1999; Chiang et al., 2004; Lin & Chen, 2004; Rajurkar et al., 2004; Chen & Adam, 2006), and stream flow forecasting (Wang et al., 2006). In the groundwater domain, ANN has been used for groundwater reclamation (Ranjithan et al., 1993) and groundwater management (Coppola et al., 2003; Rao et al., 2003; Zaheer & Bai, 2003). Several papers have reported the use of ANN for groundwater level forecasting (Coulibaly et al., 2001; Daliakopoulos et al., 2005; Lallahem et al., 2005; Nayak et al., 2006). Gautam et al. (2004) reported that the groundwater table change before and after a bridge pier construction could be well analyzed by ANN. Many previous researchers have pointed out that ANN as non-linear model is a powerful tool to estimate a fluctuation of groundwater level with considering hydrological variables as inputs. A detailed theory and application of ANN in hydrology can be found in Govindaraju (2000a, b) and in Maier & Dandy (2000).

The application of a more promising soft computing technique, the fuzzy inference system (FIS), has recently been increasing in hydrology. Lu and Lo (2002) used self-organizing maps (SOM) and fuzzy theory for diagnosing reservoir water quality. Tayfur et al. (2003) developed fuzzy logic algorithms for estimating sediment loads from bare soil surface. Wong et al. (2003) predicted volume of rainfall using SOM, BPNN (Backpropagation neural networks), and fuzzy rule systems. Alvisi et al. (2006) predicted water level using fuzzy logic and ANN.

The combination of ANN and FIS into the adaptive neuro-fuzzy inference system (ANFIS) has advantages in a computational framework. The learning capability of ANN can be used effectively for automatic fuzzy if-then rule generation and parameter optimization (Nayak et al., 2004). Several researchers have used ANFIS in hydrology. Ponnambalam et al. (2003) used ANFIS for minimizing variance of reservoir systems operation. Nayak et al. (2004) applied it to hydrologic time series modeling. Kisi (2005) investigated the ability of ANFIS and ANN to model the relationship between streamflow and suspended sediment. Chang and Chang (2006) used it to construct a water level forecasting system for flood periods. Tutmez et al. (2006) developed an ANFIS model for groundwater electrical conductivity, based on the concentration of positively charged ions in water.

Most of the previous researches analyzed monthly GLF. However, in this paper we propose to predict daily GLF. The daily GLF time series from two observation wells in Saitama City, Japan were used as a case study. The groundwater in the study is abstracted from a multilayer aquifer and the aquifer layer system cannot be clearly defined. The main objective of this paper is to develop a reliable groundwater level fluctuation forecasting system to generate trend forecasts. The forecasts, based on ANFIS and ANN techniques, are then compared to actual measurements recorded during a subsequent monitoring period. The ANN models were developed based on backpropagation with Levenberg-Marquardt algorithms (LM) and radial basis function (RBF). The daily GLF of the past two years and two months was used as dataset.

MATERIAL AND METHODS

1. Artificial neural network

An artificial neural network (ANN) is different from a conventional system such as an analytical or statistical model. ANN is a network consisting of an arbitrary number of very simple elements called nodes. Each node is a simple processing element that responds to the weighted inputs it receives from other nodes (Lee et al., 2004). The arrangement of the nodes is referred to as the network architecture. There have been several types of ANN architecture and algorithm used successfully in groundwater level forecasting (Coulibaly, 2001; Daliakopoulos, 2005). The feed-forward neural network with Levenberg-Marquardt algorithm (LM) and radial basis function (RBF) will be presented. They are more reliable and faster to convergence.

Feed-forward neural network

A common type of feed-forward neural network (FFNN) consists of three layers: an input layer is connected to a hidden layer, which is connected to an output layer (Figure 1).

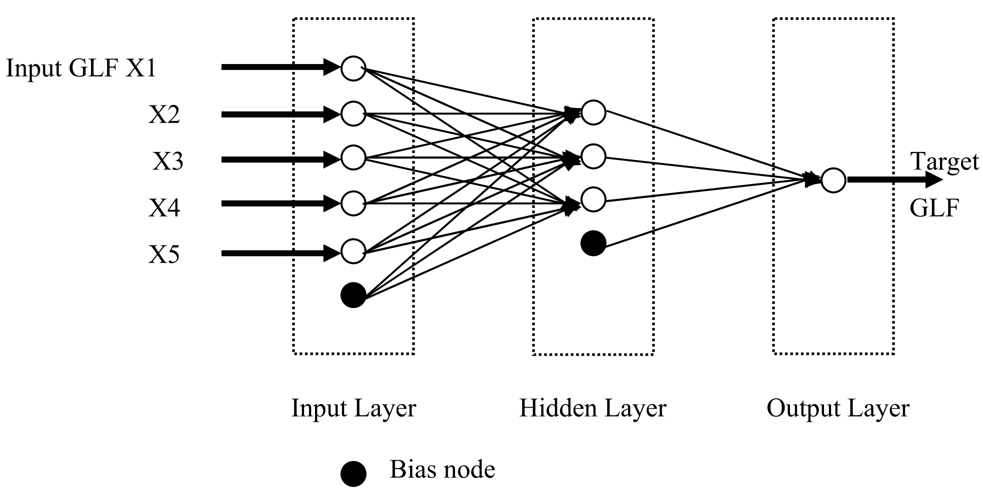

Figure 1. Topology of three-layer feed forward Artificial Neural Network

During this operation, each node j receives incoming signals from every node i in the previous layer. Each incoming signal (y_i) associates with a weight (w_{ji}). The net input, x_j, to node j is a sum of the incoming signal times the weight, as described in equation 1.

$$x_j = \sum_i y_i w_{ji} \qquad (1)$$

Note that this includes an extra node, called a *bias node*, which is assumed to have a value of 1 at all times. The weight on this extra node represents the bias as a threshold value.

The output signal $f(x_j)$, which is a non-linear function, is produced by a transfer function of its summed input. The most commonly used transfer or activation function is the logistic sigmoid and hyperbolic tangent functions. In this study, the logistic sigmoid (eq. 2) transfer function is used as activation function between the input layer and hidden layer, and between the hidden layer and the output layer.

$$f(x_j) = \frac{1}{1+e^{x_j}} \qquad (2)$$

The nonlinear nature of this logistic transfer function plays an important role in the performance of the ANN. Other functions can be used as long as they are continuous and possess a derivative at all points.

The backward pass is concerned with error computation and weight update. The algorithm normally used in this operation is a backpropagation algorithm. Backpropagation neural networks (BPNN) were introduced by Rumelhart et al. (1986), and a good description of the BPNN in groundwater problems can be found in Ranjithan et al. (1993) and Govindaraju (2000a, 2000b), among others. In a backpropagation algorithm, the difference between the calculated output of the output layer and the desired output is backpropagated to the previous layer and the weights are adjusted. In this study, the weight and bias values update according to the Levenberg-Marquardt (LM) algorithm. This process continuously proceeds until the criterion achieved. The LM algorithm is widely applied to many different domains. It works extremely well in practice and is considered the most efficient algorithm. Like Quasi-Newton methods, the LM algorithm was designed to approach second-order training speed without having to compute Hessian matrix. To update weights and biases, the LM algorithm uses an approximation of the Hessian matrix.

$$W_{k+1} = W_k - \left[J^T J + \mu I\right]^{-1} J^T e \qquad (3)$$

The W is weight and J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, the e is a vector of network errors, and μ is a scalar that controls the learning.

The Radial basis function network

The radial basis function (RBF) network also consists of three layers, namely an 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 of basis functions performing nonlinear transformations of the inputs. The most common transformation is Gauss function as the nonlinearity of the hidden nodes. The response of the j-th hidden node to x_i is given by

$$h_{ij}(x) = \exp\left(-\alpha \left\| x_i - c_j \right\|^2\right) \qquad (4)$$

where $\|\ldots\|$ is Euclidean norm, c_j is the center of the basis function and α is a positive constant that determines the width of the symmetric response of the hidden node.

The output values of the network are computed as linear combination of these basis functions (hidden nodes),

$$\hat{y}_i = \sum_{j=1}^{K} w_j h_{ij}(x) \qquad (5)$$

where w_j is the network connection weights and K is the number of hidden nodes. Assume that N samples of the signal are available for training. The center, c_j , $1 \le j \le K$, can be selected from the network training input x_i , $1 \le i \le N$. The weights can then be solved using the least squares method.

The RBF networks have been widely used for nonlinear system identification because of their simple topological structure and their ability to reveal in an explicit manner how the learning is proceeding (Lin & Chen, 2004). RBF networks have increasingly attracted interest for engineering applications due to their advantages over traditional multilayer perceptrons, namely faster convergence, smaller extrapolation errors, and higher reliability (Moradkhani et al., 2004). The architecture and training algorithms for radial basis function networks (RBF) are simple and clear.

2. ANFIS

Fuzzy logic, first introduced by Zadeh (1965), is about mapping an input space to an output space, and the primary mechanism of this mapping is a list of if-then statements called *rules*. Fuzzy rule-based modeling is a qualitative modeling scheme in which the system behavior is described using a natural language (Nayak et al., 2004). All rules are evaluated in parallel, rather than sequentially, and the order of the rules is unimportant. The rules refer to variables and the adjectives that describe those variables. The fuzzy components or steps are, in general: fuzzification of inputs, application of a fuzzy operator, application of an implication method, aggregation of all output, and defuzzification.

The fuzzy inference system (FIS) is based on the concept of fuzzy set theory and fuzzy reasoning. It is a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector. There are two types of fuzzy rule system being widely used, and these two were proposed by Namdani (1974) and Takagi-Sugeno (1985). Takagi-Sugeno has been adapted for ANFIS used in this paper. The Takagi-Sugeno method uses a composite procedure for fuzzy inference and output defuzzification (Alvisi et al., 2006).

ANFIS was originally proposed by Jang (1993). ANFIS is a fuzzy system trained by an algorithm derived from neural network theory. The algorithm is a hybrid training algorithm based on backpropagation and the least squares approach. In this algorithm, the parameters defining the shape of the membership functions are identified by a backpropagation algorithm, while the consequent parameters are identified by the least squares method. An ANFIS can be viewed as a special three-layer feedforward neural network. The first layer represents input variables, the hidden layer represents fuzzy rules, and the third layer is an output.

RESULT AND DISCUSSION

This paper investigates two schemes of soft computing technique, ANFIS and ANN models, for GLF forecasting. Records of daily GLFs were compiled from observation wells in the case study area for two years and two months (2003 to 2005). Two observation wells (Urawa1 and Urawa2) were analyzed. The daily GLFs that were missing for several days were interpolated using the cubic spline method. In order to ensure that all variables received equal attention during the calculation process, they were standardized (Maier & Dandy, 2000). By this consideration, the inputs and output desired were scaled in the range of 0.1 to 0.9 by normalizing with respect to minimum and maximum data before being fed into the calculation model. The training dataset of 730 daily records was used to train the network to obtain parameters. Another dataset consisting of 60 daily records was used as testing dataset.

The first set of analyses examined the impact of adding time lag by seven models (Model 1 to Model 7) on the ANFIS model for Urawa1 and Urawa2 data records. Model 1 contains two input nodes (time-lags *t* and *t-1*) and Model 7 have eight input nodes (time-lags *t*, *t-1*,… *t-7*).The simulated outputs (*t + 1*) were evaluated by such goodness of fit statistics as root mean square error (RMSE), mean absolute error (MAE), mean relative error (MRE), and coefficient of determination (R^2). The RMSE statistic measures the residual variances that show global goodness of fit between calculated and observed GLF. The mean absolute error is the average of the absolute values of the residuals. The mean relative error measures the accuracy that less sensitive for the outlying values than the RMSE. The coefficient of determination (r-square) is the ratio of the explained variation to the total variation. It represents the percent of data (observed-predicted) that is the closest to the line of best fit.

Table 1 shows the performance results obtained in the training and testing period of the ANFIS approach. The experiment showed that the R^2 values became higher with additional time lag for the training period. However, the largest R^2 values occurred for Model 2 and Model 3 on Urawa2 and Urawa1 during the testing period, respectively. The RMSE values were outstanding during training and testing period for all models studied. The biggest RMSE was 0.165 m for Model 1 in the training period and 0.159 m for Model 7 in the testing period. It also can be seen from the calculated results that Model 2 and Model 3 have the highest R^2 in the testing period for Urawa2 and Urawa1, respectively. For further analysis, we decided to use Model 2 to compare the performance of ANFIS with two ANN models (LM and RBF). The GLF predictions from one to seven ahead (daily) were performed.

Table 1. The performance results of ANFIS approach during training and testing period

	Training		Testing	
Model	RMSE	R2	RMSE	R2
		Urawa1		
1	0.165	0.972	0.139	0.799
2	0.161	0.973	0.137	0.805
3	0.155	0.975	0.134	0.814
4	0.144	0.978	0.138	0.805
5	0.131	0.982	0.145	0.791
6	0.114	0.986	0.151	0.779
7	0.099	0.990	0.159	0.755
		Urawa2		
1	0.115	0.980	0.077	0.934
2	0.110	0.982	0.075	0.941
3	0.105	0.983	0.077	0.938
4	0.100	0.985	0.079	0.936
5	0.094	0.987	0.078	0.938
6	0.085	0.989	0.077	0.938
7	0.074	0.992	0.079	0.932

Figure 2 shows the comparison results of three soft computing models using input Model 2 in the testing period. The general tendency of predictions shows that the determination coefficient (R^2) values decrease when predicting time-step increase and the prediction of one day ahead has the biggest R^2 values. It can thus be suggested that the model is good to predict one-day-ahead. The statistics indices of one-day-ahead prediction are presented in Table 2. The maximum value of mean absolute error (MAE) was 0.275 meters using the LM algorithm for Urawa1 in the training period. The mean relative error (MRE) values did not exceed 1.75% in the testing period. The coefficients of determination (R^2) were also good. It is clear that the soft computing approach has high predictive power.

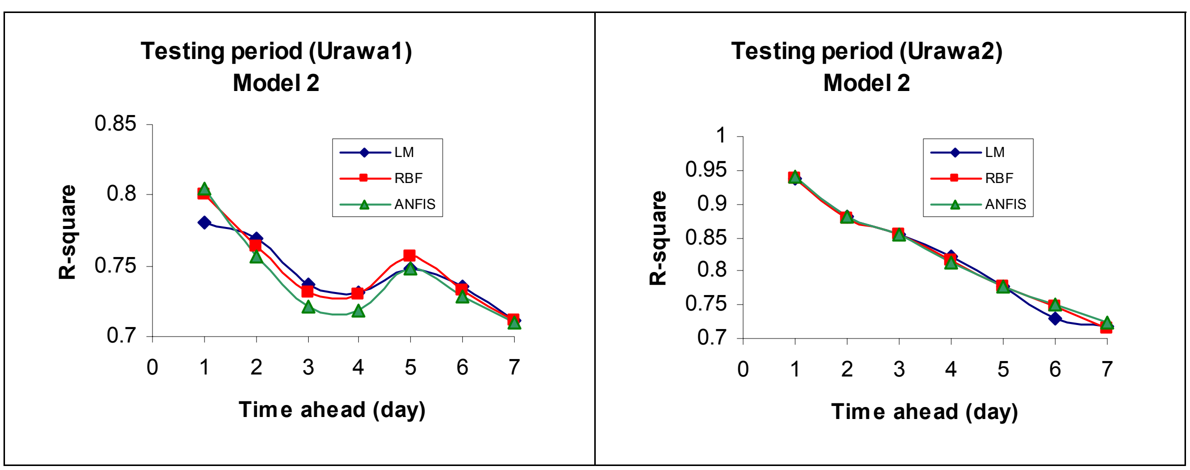

Figure 2. Comparison results of three different algorithms for lead time prediction using input Model 2.

Figure 3 shows the results of one-day-ahead prediction and observed GLF in the testing period using Model 2. The most striking result to emerge from the calculation is that there are no significantly different results among the three algorithms used. All predicted values tend to slightly underpredict groundwater level. (*Underpredicted* means that predicted values were shallower in depth than what was observed; *overpredicted* means they were deeper than the observed values.) The maximum positive deviation was 0.3746 meters for Urawa1 using the RBF algorithm and the maximum negative was 0.2938 meters for Urawa1 using the LM algorithm. It was observed that the prediction errors are falling around ± 0.2 meters. It can be seen from Figure 4 that of the predicted results, 85% are satisfactory. Based on these results, we can predict or monitor daily groundwater fluctuation with considering some time lag as inputs of the model.

Table 2. The performance of LM, RBF and ANFIS models during training and testing period

Algorithms	Training				Testing			
	MAE	RMSE	MRE	R2	MAE	RMSE	MRE	R2
					Urawa1			
LM	0.275	0.517	3.523	0.897	0.117	0.141	1.748	0.781
RBF	0.132	0.164	1.865	0.972	0.112	0.138	1.671	0.801
ANFIS	0.130	0.161	1.832	0.973	0.112	0.137	1.663	0.805
					Urawa2			
LM	0.088	0.110	0.913	0.982	0.059	0.073	0.622	0.941
RBF	0.089	0.112	0.930	0.981	0.060	0.075	0.637	0.938
ANFIS	0.088	0.110	0.916	0.982	0.060	0.075	0.632	0.941

CONCLUSION

This study has demonstrated the predictive value of soft computing techniques for groundwater level estimation. The groundwater level prediction for this study was done under two scenarios. First stage was one-day-ahead prediction with time lag input models using an ANFIS algorithm. It was found that Model 2, the (*lag t, t-1, t-2*) input model, gave satisfactory prediction results. The advanced study was designed to test predictions of groundwater level fluctuation for seven time steps ahead using input Model 2. In this second stage, we compared three soft computing techniques: the ANFIS, LM, and RBF algorithms. It was found that the three algorithms produced no significant differences in prediction results. In general, the results showed that the prediction accuracy was decaying by increasing time step ahead, with the best accuracy being for one day ahead. It was found that predicted values were close to the observed ones and 85% fell in the range of ± 0.2 meters. Overall, these results suggest that all three soft computing algorithms can predict daily groundwater level with high accuracy using time lag as inputs networks. Further studies are recommended, especially using a much larger number of observation wells, to cover regional variations and to allow more comprehensive analyses. Furthermore, the larger number of data samples is needed to assess the long term tendency of groundwater level.

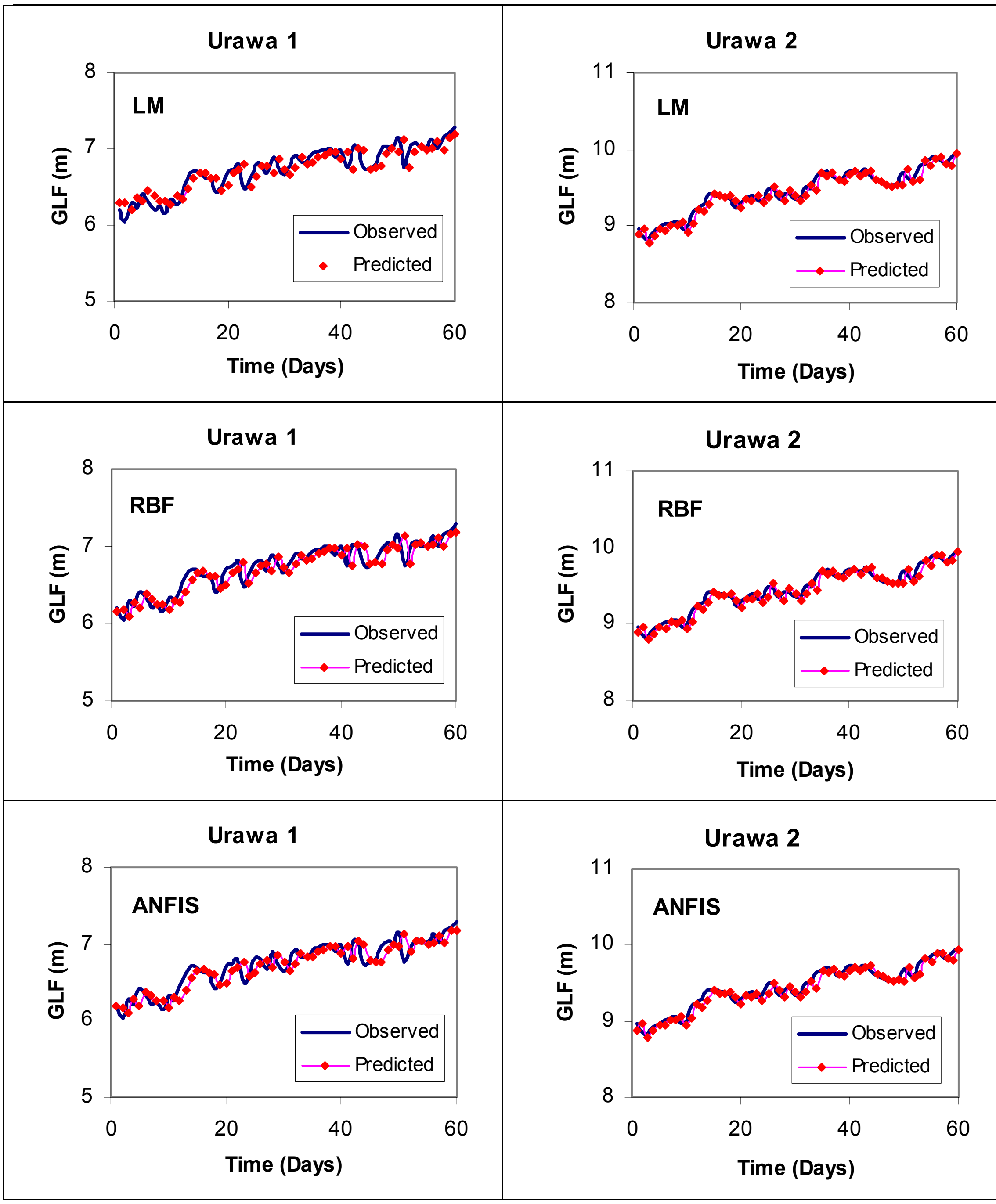

Figure 3. Comparison between observed and predicted GLF using ANFIS during testing period for input Model 2.

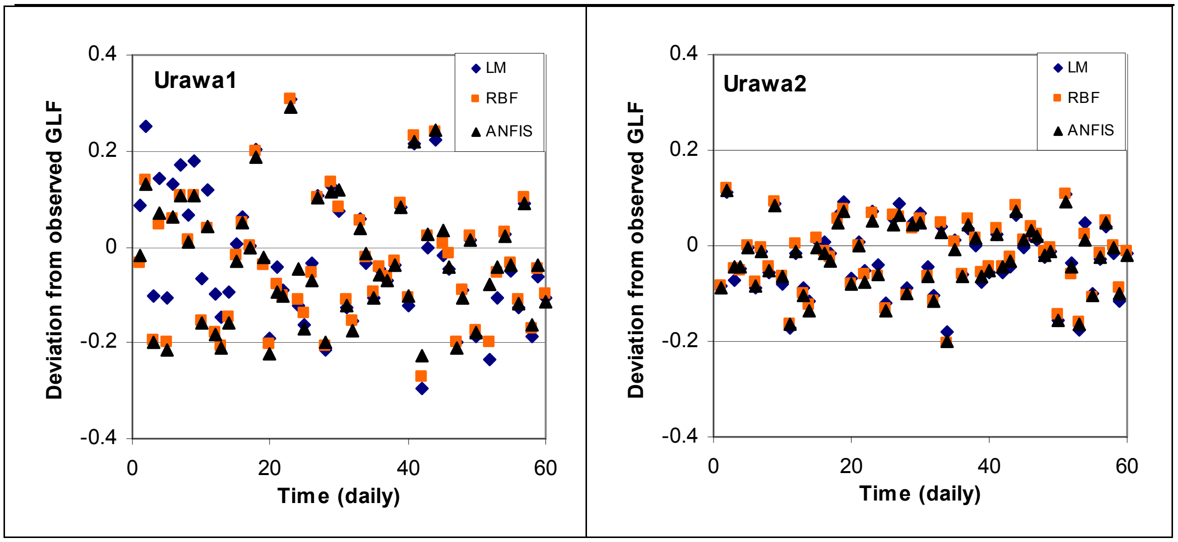

Figure 4. One day ahead prediction deviation from observed GLF during testing period

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