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Estimation of Groundwater Level Using Artificial Neural Networks: a Case Study of Hatay-Turkey

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Abstract. Groundwater, which is a strategic resource in Turkey, is used for drinking-use, agricultural irrigation and industrial purposes. Population increase and total water consumption are constantly increasing. In order to meet the need for water, over-shoots from underground water have caused significant falls in groundwater level. Estimation of water level is important for planning an efficient and sustainable groundwater management. In this study, groundwater level, monthly mean precipitation and temperature observations of Turkish General Directorate of State Hydraulic Works (DSI) in Hatay, Amik Plain, Kumlu district were used between 2000 and 2015 years. The performance evaluation was done by creating Multi Linear Regression (MLR) and Artificial Neural Networks (ANN) models. The ANN model gave better results than the MLR model.

Keywords: Groundwater level, prediction, Amik plain, artificial neural networks.w

Conference Topic: Water engineering.

Introduction

Determination of change in groundwater level, in terms of planning and operating their resources is important. Existing data usually require more reliable decisions, so they need to be modeled in the process. The correct model to define time series can be more realistic and reliable for the future. It is possible to produce scenarios and make more accurate decisions. The total amount of water in the world is 1.4 billion km^3. 97.5% of these waters are in the oceans and the seas and 2.5% is in fresh water. Sweet waters; 0.3% is in lakes and rivers, 30.8% in ground water, soil necropsy and marsh, 68.9% in the form of ice and permanent snow. It is understood that the amount of available fresh water that humans can easily use because of the fact that 90% of the fresh water resources are so small and in the underground (DSI 2015). A large amount of usable water is formed in groundwater. Therefore, the determination of groundwater exchange is of great importance.

When we look at the past literature, it is seen that various studies have been made using artificial neural networks (ANN) method. Until today, ANN has been used in many different disciplines and areas ANN has been successful in many researches on water resources management (Rizzo, Dougherty 1994; Cigizoglu, Kisi 2005).

Tokar and Johnson (1999) show that ANN technology can be applied to daily flows; Daily rainfall, temperature and snowfall data as a function of their data. Campolo *et al.* (1999) used ANN for river flow estimation during heavy precipitation and low flow processes. Coppola *et al.* (2003) investigated groundwater level fluctuations under different weather conditions using artificial neural networks in unsteady aquifer state and ANN was also used in different groundwater problems (Ranjithan *et al.* 1993; Rogers, Dowla 1994). Raman and Sunil (1995) examined the utility of ANN in the derivation of synthetic reservoir flow series. Boogaard *et al.* (1998) developed autoregressive neural networks and applied them to nonlinear analysis and modeling of time series.

In this study, Kumlu region in the north-east of the Amik plain of Hatay -Turkey was investigated. The Amik plain, located in the basin of Asi, is between 36 ° 13'–36 ° 30' North latitudes and 36 ° 12 '–36 ° 33' East longitudes and has an area of approximately 65 000 ha. Kırıkhan county is located to the north of Amik plain, Antakya and Reyhanlı county to the east and Nur mountains to the west (Figure 1).

Monthly total rainfall and monthly average temperature data measured at the Antakya-Hatay Meteorological Station, Turkish General Directorate of State Meteorology (DMI), and the static groundwater level monthly measurement data of the observation well No. 474 belonging to DSI in Kumlu region. Data were used between 2000 and 2015 years in this study. The DSI observation well is located at 36.21981 latitude and 36.29114 longitude, with a depth of 80 m.

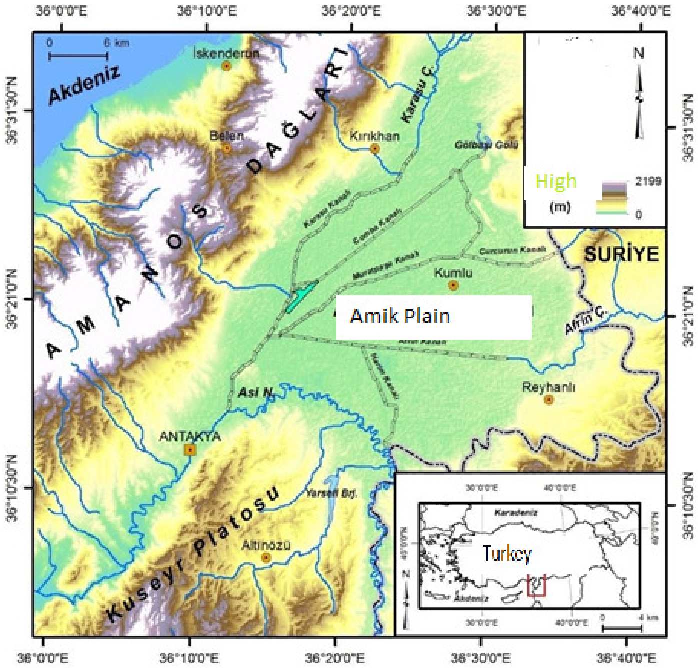

Fig. 1. Map of Amik plain

Methodology

Artificial neural networks (ANNs)

Artificial neural networks (ANNs) are based on the present understanding of the biological nervous system, though much of the biological detail is neglected. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights. The methodology used here for adjusting the weights is called "momentum back propagation", and is based on the "generalized delta rule", as presented by Rumelhart *et al.* (1986). Throughout all ANN simulations, the adaptive learning rates were used for increasing the convergence velocity. The sigmoid and linear functions are used for the activation functions of the hidden and output nodes, respectively. It seems necessary that non-linear methods, such as artificial neural networks (ANNs), which are well suited to complex non-linear models, can be used for the analysis of real world temporal data. Recently, ANNs have begun to be frequently used in the water resources engineering and in many different disciplines and areas. ANNs lead to practically acceptable results in many research subjects of the water resources management.

The data cover a 15-year period, from 2000 to 2015, and are collected on a daily basis. Meanwhile, the precipitation time series are provided by DMI for two rain gauge stations for the same time period. The monthly average input and output values are calculated from these daily values, which were used in both methods and comparisons. The monthly groundwater level fluctuation during this period is used present study. In this region, high precipitations occur in the early and late spring. On the other hand, the drought season comes between July and September. It is observed that consequent groundwater level fluctuations are entirely dependent on meteorological conditions, which affect the drainage basin. For model development (training stage) the first 150-month data are used, whereas the remaining 42-month data are used to validate (test) the model.

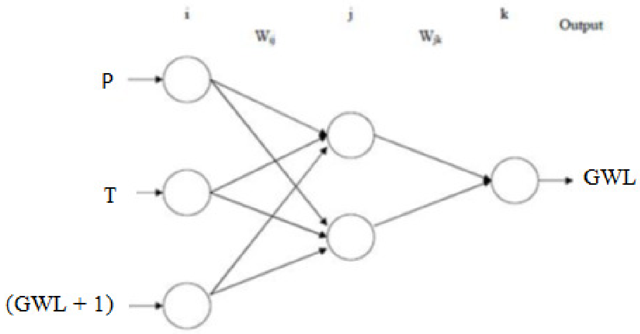

Fig. 2. An ANN architecture used for groundwater level estimation

Of the many ANN paradigms, the backpropagation network is by far the most popular (Lippman 1987). The network consists of layers of parallel processing elements, called neurons, with each layer being fully connected to the proceeding layer by interconnection strengths, or weights, W. Figure 2 illustrates a three-layer neural network consisting of layers i, j and k, with the interconnection weights Wij and Wjk between layers of neurons.

Results

MLR model results

The monthly groundwater level data of DSI and the monthly total rainfall and monthly average temperature data of Antakya Meteorological Station were used to determine groundwater level. In this study, modeling was carried out using 192 data of monthly ground water level, monthly total precipitation and monthly average temperature values measured for 16 years between 2000 and 2015. 150 data were evaluated in the training and 42 data were used for the test. The distribution and scatter graphs for the testing data are shown in Figure 3 and Figure 4.

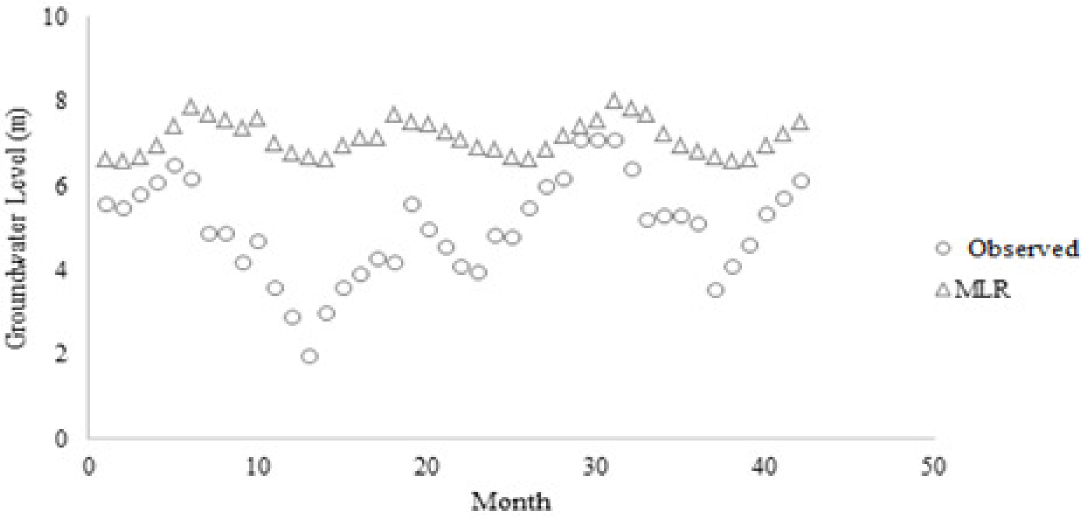

Fig. 3. Measurement and MLR distribution chart for underground water level for test data.

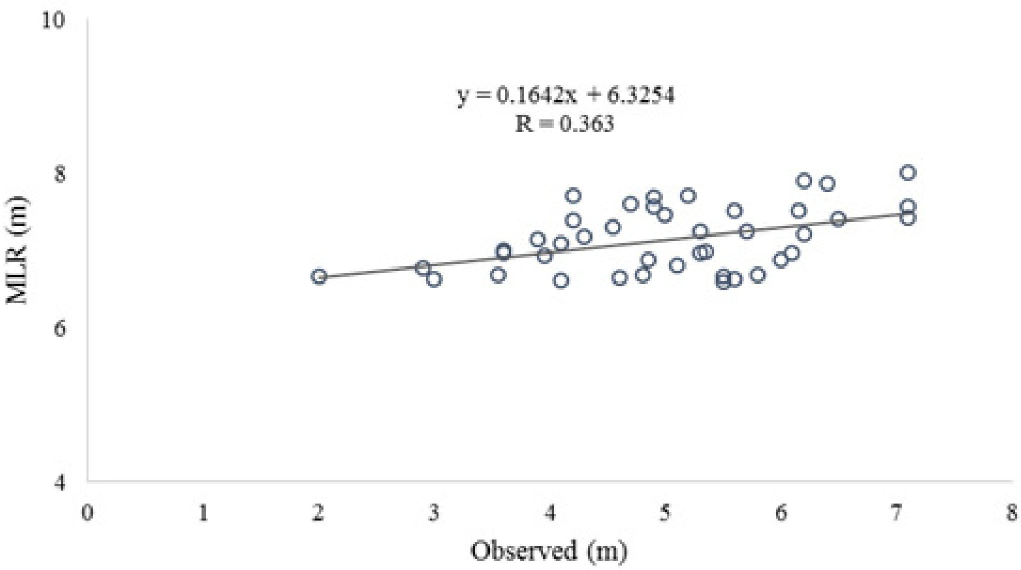

Fig. 4. Measurement and MLR scatter graph for ground water level for test data.

The MLR estimates in the test phase also show that the underground water level estimate is larger than the actual values as seen the Figure 3. The correlation coefficient R = 0.363 was obtained very small for MLR model as seen the Figure 4.

ANN Model Resuls

In the artificial neural networks (ANN) model, 150 data of 192 were used training and 42 data were analyzed for the test. As a result of the analysis, it was seen that the correlation coefficient was very low and the high error values appeared as in the MLR model. Therefore, when ANN is applied in this study, additional time data of groundwater level in the data used is added as additional data (GWL + 1) for the test data, Figure 5. And scatter graphs are shown in Figure 6.

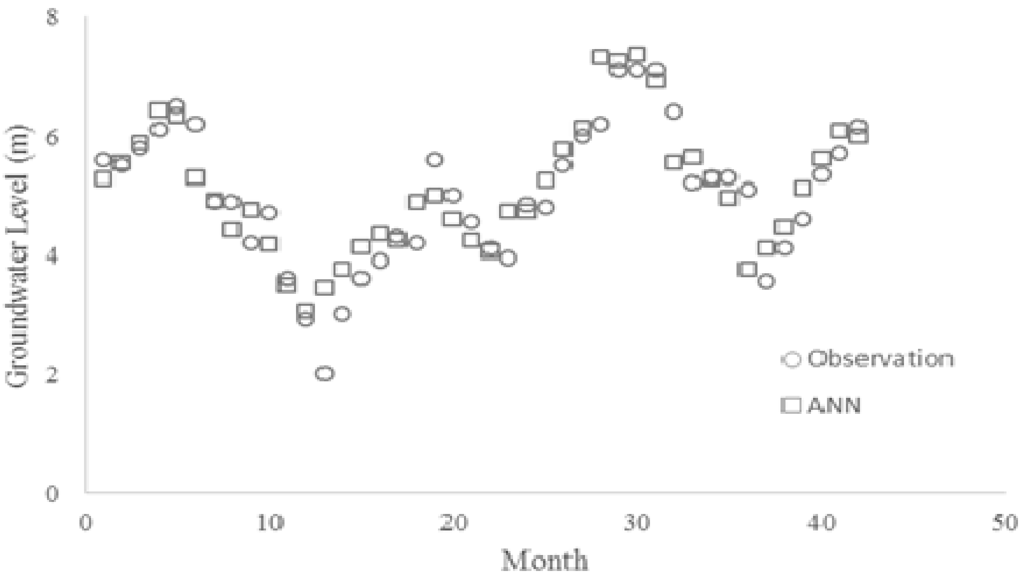

Fig. 5. Distribution graph of monthly ANN results

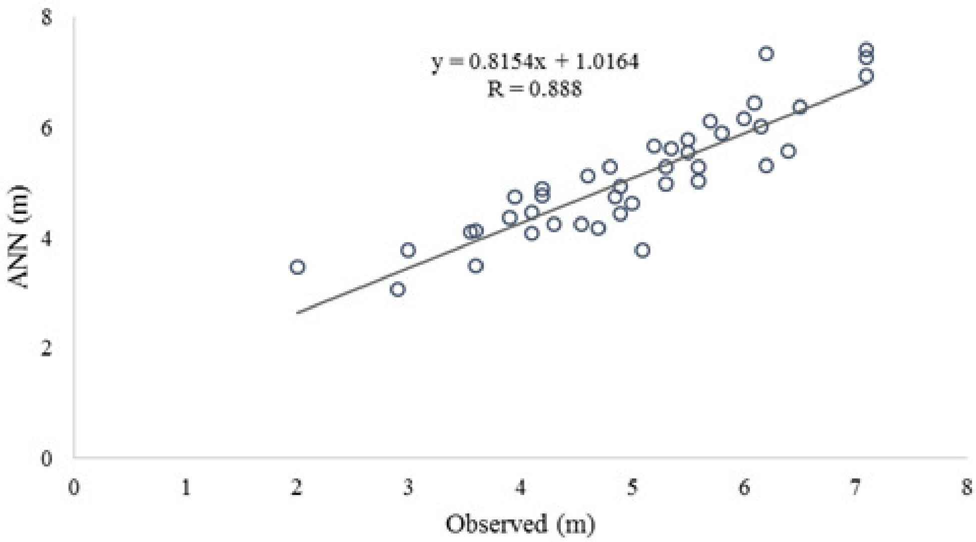

Fig. 6. Scatter graph of ANN and observed values

Monthly Mean Precipitation (MP), Monthly Average Temperature (MT), Monthly Ground Water Level (GWL+1) were used for the groundwater level estimate. ANN model results data are close to the actual values shown in Figure 5. The correlation coefficient R = 0.888 was obtained very high for ANN model as seen the Figure 6.

General Evaluation

The correlation coefficient (R), mean square error (MSE) and absolute mean error (MAE) for the performance evaluation of the MLR and ANN models are calculated. For each model, mean square error (MSE) and mean absolute error (MAE) are computed as follows

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Yi_{observed} - Yi_{forecast}\right)^2; \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Yi_{observed} - Yi_{forecast}\right|, \tag{2}$$

where: N and Yi denote the number of data sets and dam reservoir level, respectively.

The results are also used to compare the performance of model estimates and observations. The comparison of the MSE, MAE and R parameters obtained for the test data in the models with two data sets are shown in Table 1.

Table 1. MSE: Mean square error, MAE: Absolute mean error, R: Correlation coefficient

Model	MSE	MAE	R
MLR	0.746	0.457	0.363
ANN	0.348	0.419	0.888

The best model is MSE, the MAE is the smallest, and the R is the largest model. The ANN model gave better results than the MLR model for MSE, MAE and R values.

Conclusion

In this study, the performance of multi linear regression (MLR) and artificial neural networks (ANN) methods underground water level predictions was investigated for Hatay region. Monthly total rainfall, monthly mean temperature, monthly groundwater level data of Kumlu region were used to compare which model gave better results. Neural Networks (ANNs) are compared with the measured groundwater levels and conventional MLR model results.

The ANN correctly adapts to the changing input conditions, such as water demand policy changes in the groundwater operation. The advantages of ANNs over conventional methods in the prediction of groundwater levels can be explained by saying that ANN structure includes the non-linear dynamics of the problem in the whole data set. This is quite important since similar sudden changes can be observed on the related time series within the reservoir operation management studies.

The presented ANN model provides better estimates of the groundwater level fluctuations than the other MLR model. Finally, these results show that ANN is a useful alternative method for groundwater level prediction.

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