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Ground Water Level Estimation for Dörtyol region in HATAY

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Abstract— *Accurate and reliable estimation of groundwater level is important for the development and management of water resources. In this study, models of adaptive neuro-fuzzy inference system (ANFIS) with multiple linear regression (MLR) method and its performance in predicting groundwater level were investigated. As a field of application, it was applied for General Directorate of State Hydraulic Works (DSİ) 5512 well of Dörtyol region of Hatay province. In the study, 147-month data sets between 2000 and 2015, including hydrological parameters such as Precipitation (P), average air temperature (T), relative humidity (RH), wind speed (W) groundwater level (GWL) time series, predict the groundwater level used. The determinant coefficient (R^2), mean square error (MSE) and mean absolute error (MAE) were used as the statistical performance evaluation criteria. As a result of this study, MLR and ANFIS models performed well for GWL estimation. In particular, the ANFIS model yielded better results than the MLR model.*

Keywords— ***Estimation, groundwater level, Dörtyol, MLR, ANFIS.***

I. INTRODUCTION

Groundwater is vital for humanity, it is an important for fresh water source worldwide. It is usually found more easily than other sources of drinking water and is cleaner. More than 2 billion people are dependent on groundwater for drinking water resources. It is therefore essential to develop sustainable water resource management measures to ensure the supply of drinking water in a region. Accurate and reliable estimates of groundwater levels play a decisive role as it provides basic information about the groundwater conditions of an aquifer. Common practice in modeling groundwater variables is the application of numerical models that use physical relationships to define a particular area. Such models require a lot of data and their development, implementation and maintenance is time consuming and expensive. However, artificial intelligence methods are an alternative, data-driven approach commonly used to estimate water resource variables over the last decade. ANFIS, which is one of the artificial intelligence methods, can assign all possible rules according to the structure created for the problem. ANFIS's ability to form a rule or allow for the creation of a rule means that it can benefit from expert opinions. For this reason, it is possible to obtain better results according to the error criterion as it provides the opportunity to benefit from expert opinions on artificial neural networks in many estimation problems. it becomes a valuable tool for complex scenarios, which are difficult to define by methods..

Recently, artificial intelligence methods have begun to be frequently used in modeling the rainfall-runoff [1-2], suspended sediment [3-6], dam reservoir level [7-10], density flow plunging [11], dam reservoir volume [12-15], sand bar crest [16], evaporation [17-18], and groundwater level [19-25].

In the two hydrometer stations in Hajighoshan and Tamar on the Gorgan River, Vafakhah [26] compared ANNs, ANFIS and ARMA model forflow estimations using flow 1 day, 2 days and 3 days-time series. The results showed that ANNs are superior to ANFIS and ARMA for current flow estimations 1 day, 2 days and 3 days ago. Nourani et al. [27]used feed-forward neural network (FFNN), Automatic Regressive Moving Average (ARIMAX) models for the prediction of GWL in the plain Ardabil of northwestern Iran. Unes et al. [28], predicted evapotranspiration (ET) in their study. They used ANFIS model has better performance than the empirical formulas for the estimation of daily ET.

The aim of this study is to investigate the monthly ground water level (GWL) fluctuation estimation by using Multiple Linear Regression (MLR) and Adaptive network fuzzy inference system (ANFIS) models.

II. STUDY AREA

In this study, the groundwater level of Dortyol region of Hatay province was examined. Monthly groundwater level data obtained from General Directorate of State Hydraulic Works (DSI) data and monthly total rainfall (R) recorded by Antakya Meteorology Station, monthly average temperature (T), monthly average wind speed (WS) and monthly relative humidity (RH) data were used

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to determine ground water level (GWL).

Figure 1 shows the location of the selected probe well on the map in this study.

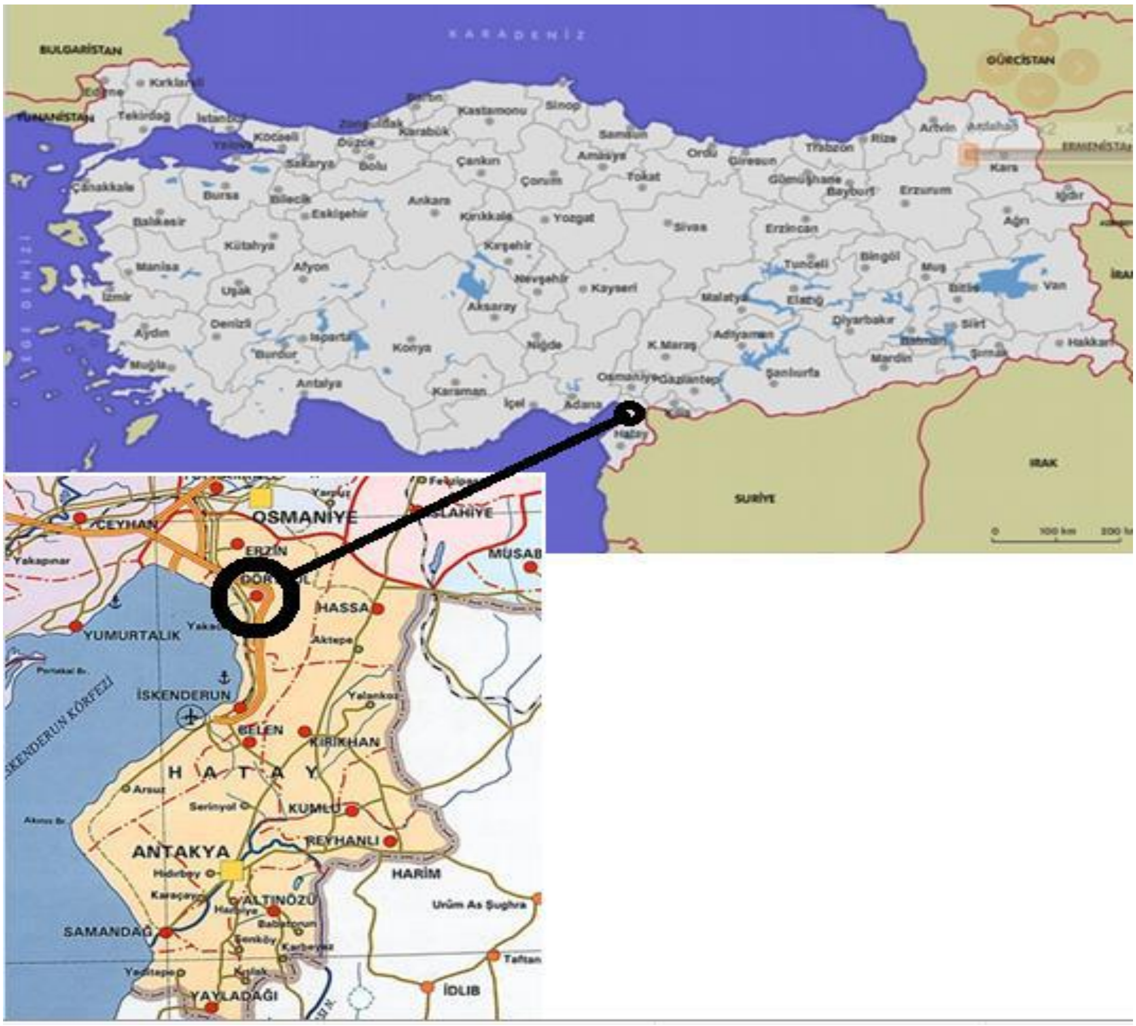

Fig. 1: Dortyol GWL station used in the study

III. METHODOLOGY

In this paper, Multiple Linear Regression (MLR) and Adaptive network based fuzzy inference system (ANFIS) models were used. In the all models, monthlyPrecipitation (P), average air temperature (T), relative humidity (RH), wind speed (W) groundwater level (GWL) time series were used for the Ground Water Level Estimations. All data obtained from Dortyol region in HatayProvincein the Turkey.

3.1. Multi-Linear Regression (MLR) Model

An MLR model is a method used to model the linear relationship between a dependent variable and one or more independent variables. The dependent variable is sometimes called a prediction, and arguments are called predictors. With these models, it is considered that the effects associated with a limited time period at some point can be approximated with the equality value.

The general equation of the MLR model is expressed as follows:

$$y=a+b_1x_1+b_2x_2+...............+(b_mx_m) \qquad \textbf{(1)}$$

In this equation, y represents the expected value of y when independent parameters (x1 = x1), (x2 = x2) ...., (xm = xm)

3.2. Adaptive Neuro Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a hybrid artificial intelligence method that uses the ability of parallel neural network to calculate and learn artificial neural networks and the inference of fuzzy logic. The NF model developed in 1993 by Jang [29] uses the fuzzy inference model and Hybrid learning algorithm. Adaptive networks consist of directly connected nodes. Each node represents a processing unit. The connections between the nodes indicate an undetermined interest (weight) between them. All or part of the nodes can be adaptive.NF is a universal approximation methodology and is capable of

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approximating any real continuous function on a compact set to any degree of accuracy.NF with first-order Sugeno fuzzy model which used in this study. For more information, researchers can access Jang [20].

IV. MODEL RESULTS AND ANALYZE

4.1. Model Results

To see the relationship between created MLR model and observed values distribution graph are drawn in Figure 2 and scatter chart of this model was drawn in Figure 3.

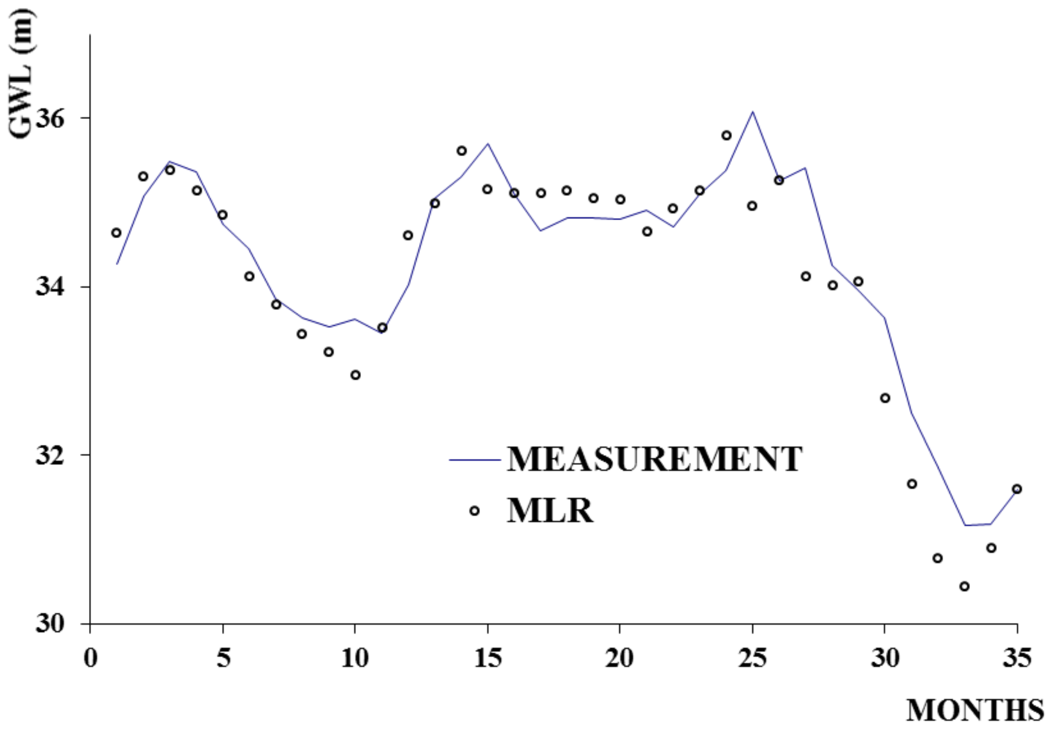

Fig.2: Distribution of MLR model

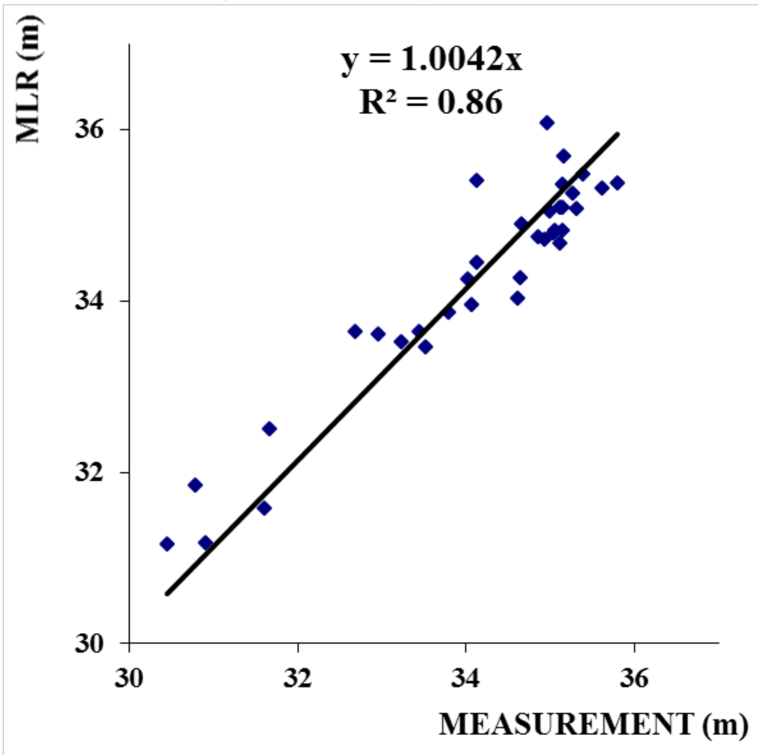

Fig.3: Scatter chart of MLR model

Figure 2. shows that distribution of NF model test results are quite close to observed values of groundwater level for the study area.As it is seen in Figure 3, determination coefficient is calculated as 0.86 for test set of MLR method. In distribution and scatter charts, values are close to the actual values. Distribution of ANFIS method results and scatter chart is given with Figure 4. and Figure 5., respectively.

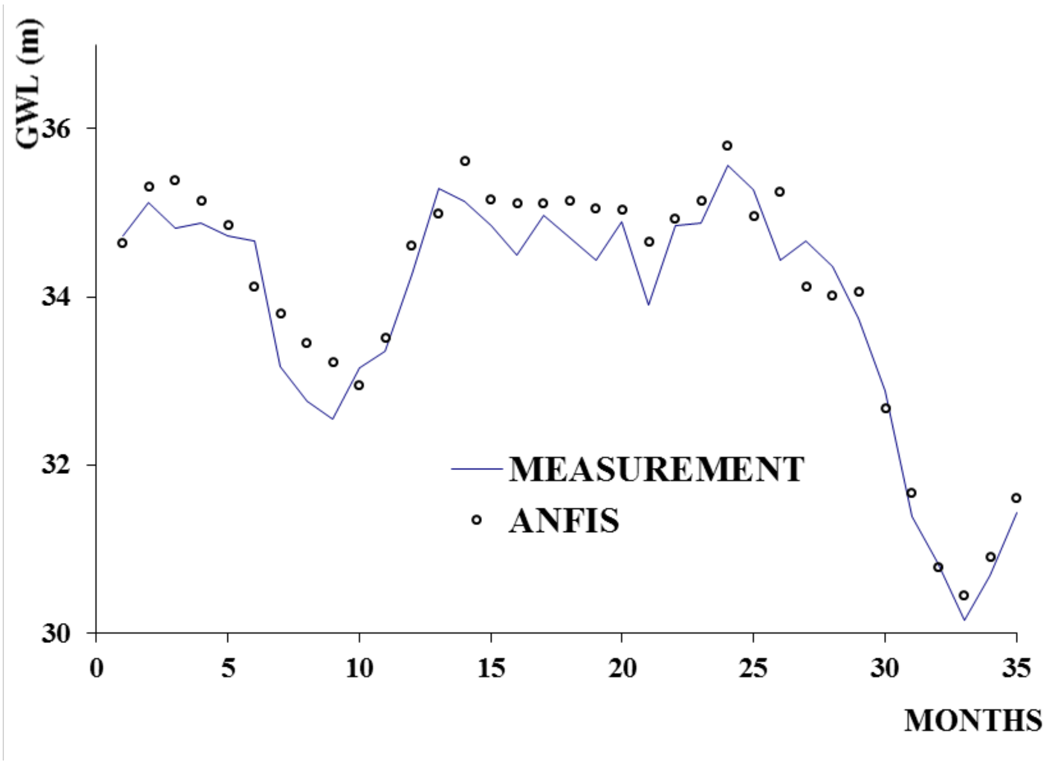

Fig.4: Distribution of ANFIS model

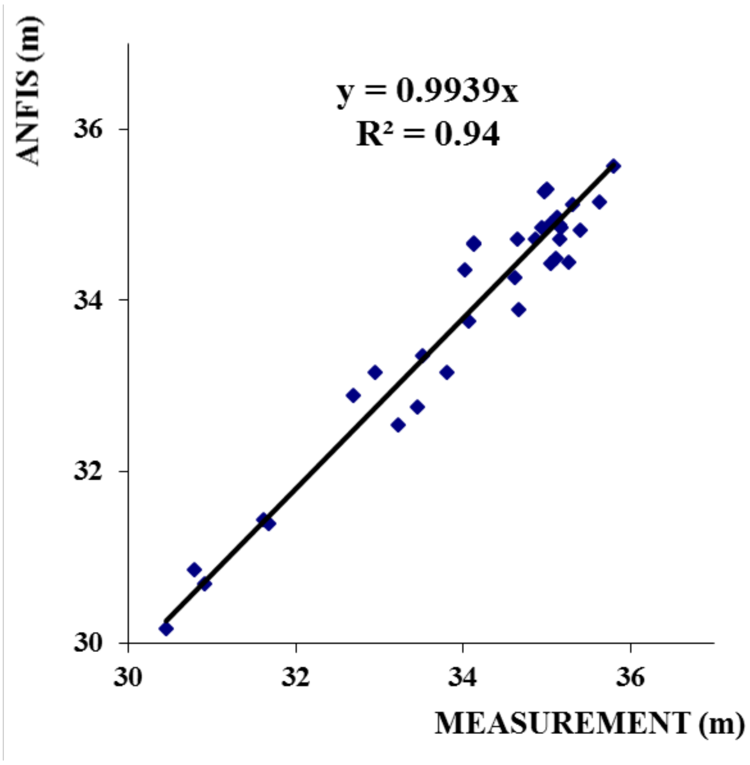

Fig.5: Scatter chart of ANFIS model

Results of ANFIS model show that the determination coefficient is high and the groundwater level estimationsarecloser to the actual values shown in Figure 4. Determination coefficient is calculated as 0.94 for ANFIS results as it is seen in Figure 5.

3.2. Model Analyze

Models were created using 151 data. 70% of the data were trained as training and 30% as test data. Model results were evaluated according to the coefficient of determination (R^2), mean squared error (MSE) and mean absolute error (MAE). Mean squared error (MSE) and mean absolute error (MAE)measures the magnitude of the error. MSE and MAE are used to diagnose the possibility of errors. MSE, MAE can take values from zero to infinite. Low values mean it is more useful.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|GWL_{Measure} - GWL_{predict}\right| \quad \textbf{(2)}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(GWL_{Measure} - GWL_{predict}\right)^2 \quad \textbf{(3)}$$

Here, n is the number of data and GWL means the monthly average groundwater level (m).

The result parameters of the MSE, MAE and R^2 obtained from the test data will be shown in tabular form. The results will be used to compare estimates and performance.The statistical results of the models are given in Table 1.

Table.1: Comparison of MLR and ANFIS model performances

MODEL NAMES	MODEL INPUTS	MSE(m^2)	MAE(m)	R^2
MLR	$P_{(t)},T_{(t)},RH_{(t)},WS_{(t)}, GWL_{(t+1)}$	0.25	0.44	0.86
ANFIS	$P_{(t)},T_{(t)},RH_{(t)},WS_{(t)}, GWL_{(t+1)}$	0.17	0.35	0.94

MSE: Mean squared error, MAE: Mean absolute error R^2: Determination coefficient.
P (t): monthly total precipitation, T (t): monthly average Temperature, RH (t): monthly Relative Humidity, WS (t): monthly average Wind Speed, GWL (t + 1): monthly groundwater level

According to Table 1, when MSE, MAE and R^2statistical criteria were compared, all models were good. All models are evaluated separately; MLR (0.25 - 0.44-0.86) and ANFIS (0.17 - 0.35 - 0.94) models were found to perform well. Nevertheless, it is observed that the ANFIS model has a low error rate with high correlation.

In addition, the MLR model are close to ANFIS prediction performance. When the results were examined, MLR and ANFIS models were found to perform better in GWL estimations.

V. CONCLUSION

In this study, multiple linear regression (MLR) and Adaptive network based fuzzy inference system (ANFIS) models' performanceson groundwater level is investigated. As a field of application, the province of Hatay was applied to the GWL well of the Dörtyol region. 147-month data sets between 2000 and 2015, including hydrological parameters such as precipitation (P), mean air temperature (T), relative humidity (RH), wind speed (WS) groundwater level (GWL) time series, to estimate the groundwater level as input data. The determinative coefficient (R^2), mean square error (MSE), mean absolute error (MAE) were used as the statistical performance evaluation criteria. As a result of this study, MLR and ANFIS models performed well for GWL estimation. In particular, the ANFIS model has shown better results than the MLR model.

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