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Estimation of Groundwater Level Fluctuations Using Neuro-Fuzzy and Support Vector Regression Models

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Abstract— *Estimation of Ground Water Level (GWL) is important in the determination of the sustainable use of water resources and Ground Water resources. Groundwater level fluctuations were investigated using the variable of groundwater level, precipitation, temperature. In the present study, GWL estimation studies were conducted via Neuro-Fuzzy (NF), Support Vector Regression with radial basis functions (SVR-RBF) and Support Vector Regression with poly kernel (SVR-PK) models. The daily data of the precipitation, temperature and groundwater level are used which is taken from Minnesota, United States of America. The results were compared with NF and SVR methods. According to this comparison, it was observed that the NF and SVR models gave similar results for observation.*

Keywords— Ground water level, Neuro-Fuzzy, Support Vector Regression, Kernel, Modeling.

I. INTRODUCTION

Estimation of groundwater level is important for effective planning and sustainable groundwater management. Since the available data generally do not fully reflect the sum of the process, the process needs to be modeled in order to make more reliable decisions. Models can be used to generate data for planning and design, or to estimate the future value of processes. In addition to increasing population-related water use, climate change, agriculture and industrialization, taking into account factors such as the need for water in the future, modeling studies are done. The precipitation-evaporation relationship, the interaction between groundwater and surface waters and the quantity, storage and nutritional potentials of the modeling studies should be determined accurately. In the estimation of these parameters, the determination or prediction of the groundwater in the region is important in determining the other parameters of the hydrological cycle.

Groundwater level; It is an indicator of the interaction between groundwater and surface water, aquifer feeding and water use. Regular measurement of groundwater levels, which is an important variable in determining these mechanisms, is expensive and difficult. However, it is possible to determine the groundwater potential in a region by using meteorological data and ground water levels of previous days. In order to monitor the groundwater level regularly, it is necessary to estimate either directly by means of observation wells or by using different methods for non-observable or missing locations.

Artificial intelligence methods collect information about the samples, make generalizations and then make decisions about the samples by using the information they have learned compared to the samples they have never seen before. Recently, artificial intelligence methods have begun to be frequently used in modeling the suspended sediment [1-4], dam reservoir level [5-7], density flow plunging [8], dam reservoir volume [9-11], sand bar crest [12], evaporation [13-14], and groundwater level [15-16], and in many different disciplines-areas [17-26]. Mohanty et al [27] investigated that artificial neural network (ANN) approach to the weekly forecasting of groundwater levels at river basin. Gong et al [28] used three nonlinear time-series intelligence models for prediction of the groundwater level. They studied 10 years data-sets including hydrological parameters such as precipitation, temperature, past groundwater level and lake level to forecast groundwater level. Guzman et al [29] used nonlinear autoregressive with exogenous inputs (NARX) artificial neural network (ANN) and support vector regression (SVR) methods for daily groundwater level predictions. According to their results, SVR method had a better modeling in prediction of groundwater level. In this study, daily of temperature, precipitation and

In this study, Neuro-Fuzzy (NF), Support Vector Regression with radial basis functions (SVR-RBF) and Support Vector Regression with poly kernel (SVR-PK) models were used estimate groundwater level. Ground-water level data belong to Prairie Island well reservoir

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station (PI98-14). Well reservoir station is in the Goodhue County- Minnesota, hydrologic unit is 07040001. All data were taken from United States Geological Survey (USGS).

II. METHODOLOGY

In this paper, Neuro-Fuzzy (NF), Support Vector Regression with radial basis functions (SVR-RBF) and Support Vector Regression with poly kernel (SVR-PK) models were used. In the all models, daily Mean Precipitation (MP), Mean Temperature (MT), Ground Water Level (GWL+1) were used for the Ground Water Level Estimations. All data obtained from Minnesota in the United States of America.

2.1. Neuro Fuzzy (NF)

Adaptive Neuro-Fuzzy System (NF) 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 [30] 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 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 [30].

2.2. Support Vector Regression

Support vector (SVR) is machine-learning approach in data-driven research fields which founded by Cortes and Vapnik [31]. SVR is based on statistical learning theory. SVR are mainly used to best distinguish between two classes of data. For this purpose, the decision limits or hyper planes are determined. In a non-linear dataset, SVRs cannot draw a linear hyper-plane. Therefore, kernel tricks are used. The Kernel method greatly increases machine learning in nonlinear data. The process of an SVR estimator (y) can be expressed as :

$$y = (K_{xi} \cdot W_{jk}) + b \qquad (1)$$

where the Kernel function is K_{pi} , b is bias term of SVM network and W_{jk} is called as the weight vector. Kx and W show Lagrange multipliers. K_{xi} is a nonlinear function that maps the input vectors into a high-dimensional feature space. The inner product of the inputs is calculated by using kernel functions. Lagrange multipliers show the weights. The output value for a sample in the SVR is equal to the sum of the inner product of the inputs and the independent combinations of Lagrange multipliers. The non-linear Kernel functions used in this study are Poly kernel and radial basis function kernels. Details about SVM can be found in Vapnik [32], Haykin [33], Vapnik [34].

2.2.1. Support Vector Regression with radial basis functions (SVR-RBF)

Lagrange multipliers that obtain the significance of the training data sets for the output data. The kernel function of non-linear radial basis (Hsu et al [35]) is:

$$K_{xi} = e^{-\gamma \|p_i - y_i\|^2} \qquad \gamma > 0 \qquad (2)$$
$$\text{and} \quad i = 1,2,3,\ldots n$$

where K_{xi} is a nonlinear function , γ is a user-defined parameter, pi and yi are vectors in input space.

2.2.2. Support Vector Regression with poly kernel (SVR-PK)

The kernel function of polynomial (Hsu et al [35]) is:

$$K_{xi} = (p.y + c)^d \qquad i = 1,2,3,\ldots n \qquad (3)$$

where K_{xi} is a nonlinear function, pi and yi are vectors, c is the free parameter in input space.

III. MODEL RESULTS AND ANALYZE

3.1. Model Results

To see the relationship between created NF model and observed values distribution graph are drawn in Figure 1 and scatter chart belong to this model was drawn in Figure 2.

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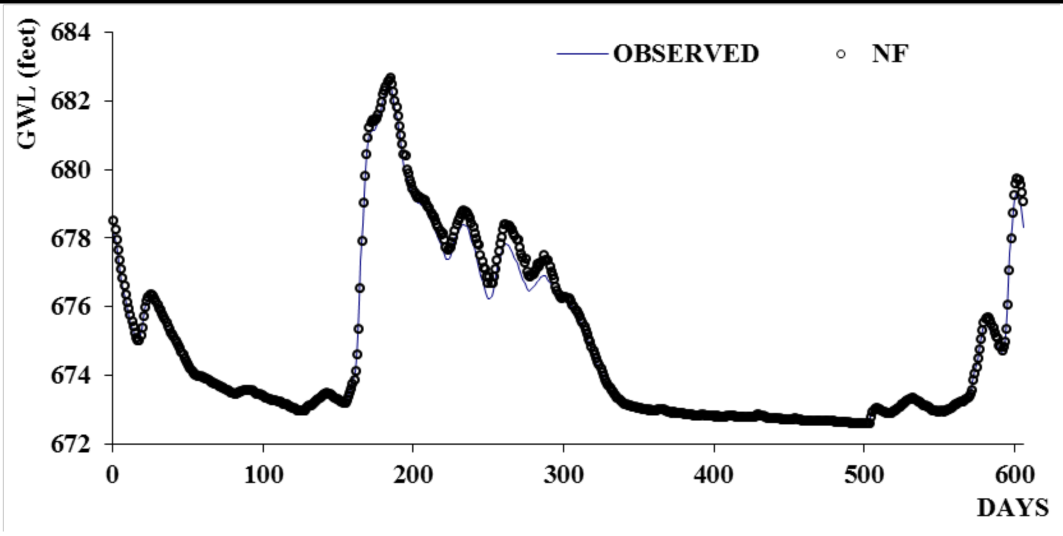

Fig.1: Distribution of NF model

Figure 1. shows that distribution of NF model test results are quite close to observed values of groundwater level for the study area.

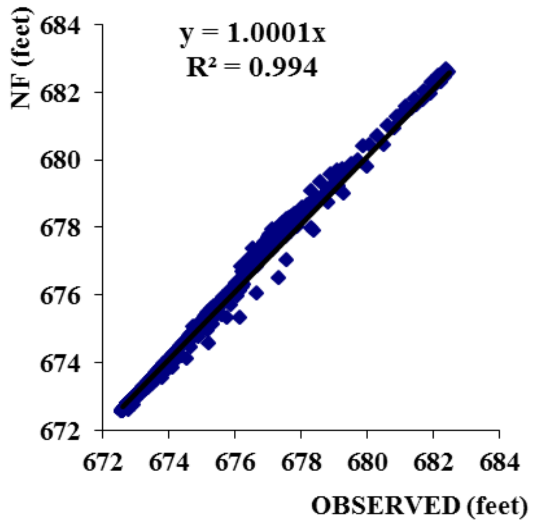

Fig.2: Scatter chart of NF model

As it is seen in Figure 2, determination coefficient is calculated as 0.994 for test set of ANN method. In distribution and scatter charts, values are close to the actual values.

Distribution of SVR RBF method results and scatter chart is given with Figure 3. and Figure 4., respectively.

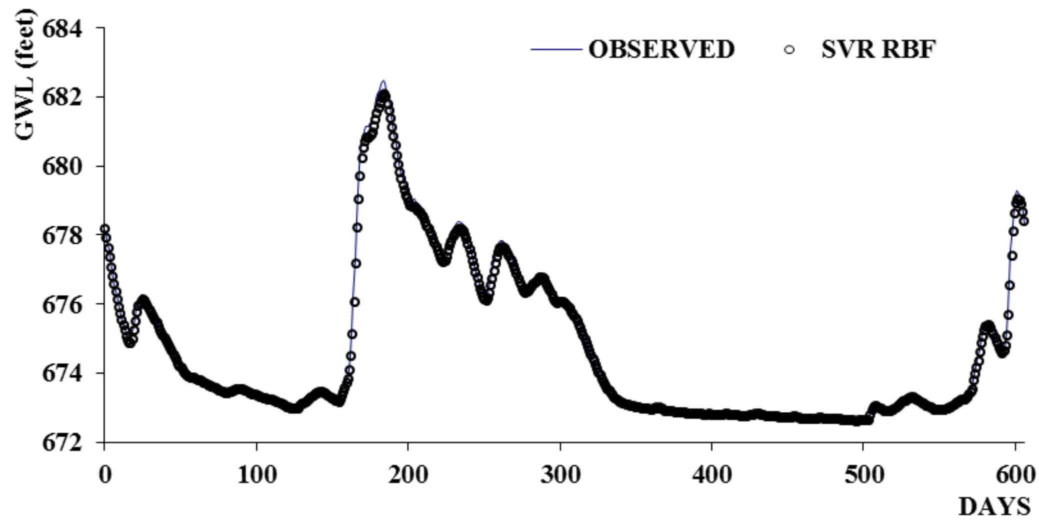

Fig.3: Distribution of SVR RBF model

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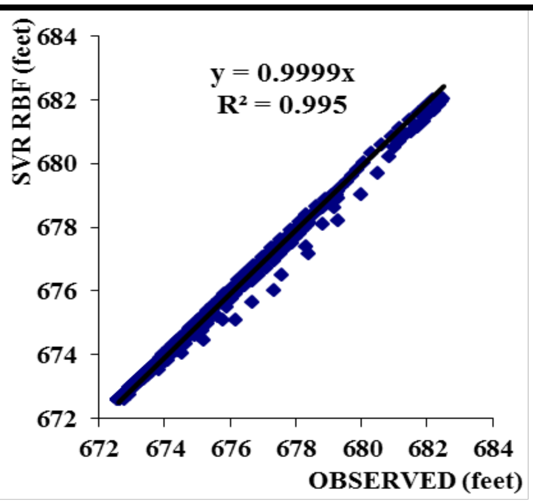

Fig.4: Scatter chart of SVR RBF model

Results of SVR RBF model show that the determination coefficient is high and the groundwater level estimate is closer to the actual values shown in Figure 3. Determination coefficient is calculated as 0.995 for SVR RBF results as it is seen in Figure 4.

Distribution of SVR PK method results and scatter chart is given with Figure 5. and Figure 6., respectively.

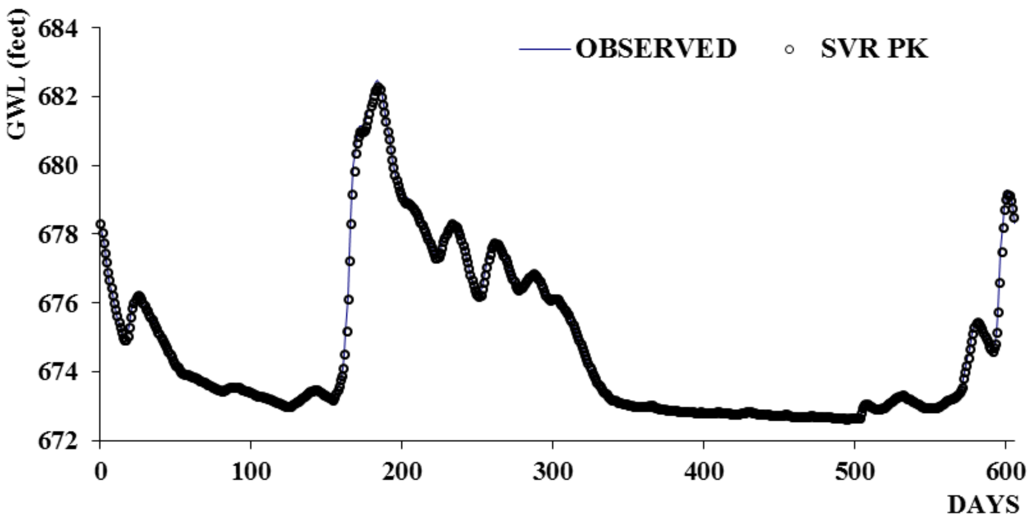

Fig.5: Distribution of SVR PK model

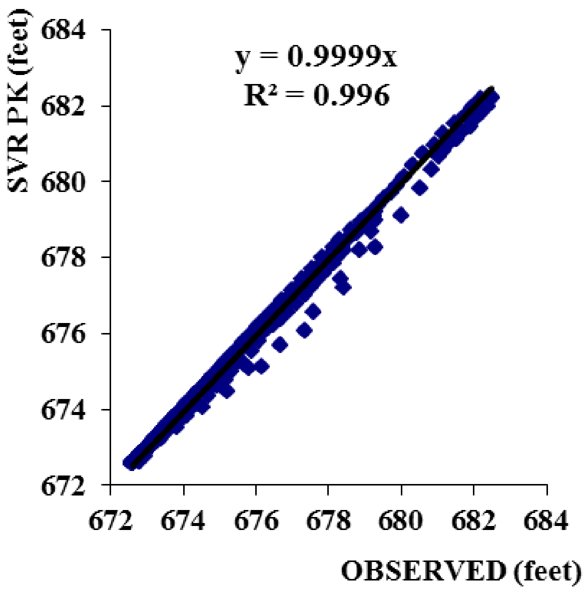

Fig.6: Scatter chart of SVR PK model

Results of SVR PK model show that the determination coefficient is high and the groundwater level estimate is closer to the actual values shown in Figure 5. Determination coefficient is calculated as 0.996 for SVR PK results as it is seen in Figure 6.

3.2. Model Analyze

Within the scope of the study conducted for the relationship between Precipitation, Temperature and Ground Water Level, a total of 2025 daily data was used. 1419 daily data are used for training models and remaining 606 daily data are used for testing. Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and determination coefficient (R^2) statistics are calculated for comparison of methods used. NF, SVR RBF and SVR PK results are compared in Table 1.

Table.1: Comparison of NF and SVR model performances

MODEL NAMES	MODEL INPUTS	RMSE	MAE	R^2
NF	MP,MT, GWL+1	0.227	0.139	0.994
SVR RBF	MP,MT, GWL+1	0.192	0.090	0.995
SVR PK	MP,MT, GWL+1	0.168	0.074	0.996

RMSE: Root Mean square error, MAE: Mean absolute error, R^2: Determination coefficient

According to Table 1, it is observed that all models have good results for the test data. When the table is analyzed, we can express the good results with the high coefficient of determination (R^2) and the lowest error amount (RMSE, MAE). Accordingly, the best estimation and low error rate of the SVR PK model and the highest number of determinations (R^2 = 0.996) and the lowest RMSE (0.168 feet) and MAE (0.074 feet) error is seen. In addition, the NF and SVR RBF models are close to SVR PK prediction performance. When the results were examined, NF, SVR RBF and SVR PK models were found to perform better in GWL estimations.

IV. CONCLUSION

In this paper, Neuro-Fuzzy (NF), Support Vector Regression with radial basis functions (SVR-RBF) and Support Vector Regression with poly kernel (SVR-PK) models were used for the relationship between the precipitation, temperature and groundwater level. 2025 data of Minnesota observation station was studied model prediction analyze. NF and SVR methods results were compared with the observed real GWL values. When the determination coefficients and error calculations are evaluated it is understood that NF and SVR models gave good and similar results.

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