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Academic Analysis and Discussions in Engineering

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Prof. Dr. Mustafa BOZDEMİR • Doç. Dr. Rukiye UZUN ARSLAN



ÖZGÜR YAYINLARI

Mühendislik Alanında Akademik Analiz ve Tartışmalar

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Prof. Dr. Mustafa BOZDEMİR

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INTRODUCTION

Water is an essential source for all living creatures as one of their basic components. Both life and environmental activities rely on water quality and quantity. Rapid population growth has led to decreased water resources and increased water pollution (Yücel et al., 2022). In particular, groundwater, which is clean, high-quality, and suitable for use in many areas, suffers from the abovementioned situation. Groundwater is an important resource for people living in developing countries or rural areas to carry out daily activities (Carrard et al., 2019). However, GWL monitoring and assessment studies are insufficient in these regions due to both financial inadequacies and lack of awareness (Ruybal et al., 2019). It is necessary for

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regional development that decision-makers and local governments develop strategies by considering the existing regions' supply-demand relations by continuously monitoring GWL and evaluating water quality. Considering the importance of the subject, there are many statistical, mathematical and physics-based conventional prediction model studies for GWL prediction (Henriksen et al., 2008; Dalkılıç and Gharehbaghi, 2021). However, this traditional approach's major disadvantage is its reliance on a large amount of physical data and the difficulty of predicting the comprehensive mechanism (Kovács et al., 2015). For this reason, with the developing computer algorithms, data-driven models require less data and provide faster, more efficient and more precise solutions, as well as time-saving. Artificial intelligence approaches have been used by many researchers, especially in hydrological studies, due to their high predictive capacity with available data on non-linear and chaotic time series, independent of the main mechanism of physical processes (Gezici and Şengül, 2023; Başakın et al., 2021). Bisht et al. (2009) stated that computer-based machine learning models such as fuzzy logic rule-based and ANFIS produced more successful results than traditional methods in predicting groundwater levels, with adaptive-network-based fuzzy inference systems (ANFIS) having the most successful predictive ability. Mohanty et al. (2013) compared the artificial neural network (ANN) algorithm and MODFLOW-based numerical models for GWL forecasting. As a result of the study, ANN is more suitable for short-time-interval forecasts and numerical models are more suitable for long-term forecasts and emphasized that the type of problem is critical in selecting the method to be applied. Bowes et al. (2019) evaluated two different neural network models, namely Recurrent Neural Network (RNN) and long-short-term memory (LSTM), to investigate hourly variations in groundwater levels during storms in coastal regions. The authors highlighted that LSTM provides more accurate prediction results compared to RNN. Moosavi vd. (2021) created hybrid models by combining the group method of data handling (GMDH) with various signal decomposition models (ensemble empirical mode decomposition (EEMD), wavelet transform (WT) and wavelet packet transform (WPT) in two different basins to monitor monthly groundwater level changes. The results show that all signal decomposition methods improve the prediction capacity and EEMD-GMDH is the most successful model. Kardan Moghaddam et al. (2021) evaluated three machine learning algorithms, namely GMDH, BN and ANN, for ten scenarios for GWL estimation in eastern Iraq. The results showed that the GMDH method with rainfall, GWL in the previous month and aquifer exploitation as input parameters produced the most

successful results. Vadiati et al. (2022) evaluated ANN, SVM, ANFIS and FL algorithms for monitoring the GWL change in the Tehran-Karaj plain and used monthly precipitation, temperature, evapotranspiration, river discharge and maximum of three-time delays for groundwater data as input. Although the prediction capacity of all models is high, the most successful model is ANFIS. Ali et al. (2022) established convolutional neural network (CNN) - bidirectional LSTM model as a hybrid neural network model to monitor the hourly change of GWL. As a result of the model, they found that the prediction performance was successful in both training and testing phases and proposed Bayesian optimization for the most suitable model. Samani et al. (2022) evaluated the forecasting performance of 5 different data-driven methods, namely ANN, FL, ANFIS, GMDH and LSSVM, depending on the basic meteorological parameters of precipitation, temperature and ET. While satisfactory results were obtained in all models, LSSVM was proposed as the most successful model. Considering the existence of a number of machine learning algorithms, the hybrid operation of these methods with optimization techniques and signal decomposition methods, and the large number of different input parameters, the number of data-driven GWL estimation studies has been quite high, especially in the last 10 years (Rajaee et al., 2019; Tao et al., 2022).

This study used a Deep learning algorithm consisting of a combination of CNN-RNN and GMDH techniques to estimate GWL values. The modeling was carried out according to the time series approach.

2. MATERIAL AND METHODS

2.1. Study Area and Data

Modeling of the groundwater level, which acts as a security in arid and semi-arid regions, is critical in agricultural production and utility water. Within the scope of this study it is aimed to model the groundwater level in Erzurum, which is in an important position in terms of agricultural production. Figure 1 presents the geographic coordinates of the study area and the digital elevation model. Accordingly, due to the high altitude of the study areas, snowfall is generally dominant. Therefore, it can be thought that the effect of meteorological parameters in GWL modeling is low. In this respect, the time series approach has been tried to estimate the working GWL values.

Table 1. Characteristics of groundwater wells used in the study area

Well Name	Well No	Ground Level	Coordinate in decimal degrees		Well Depth (m)	Province	Village / Neighborhood
			X (D)	Y (K)			
University	1353	1801	39.92	41.23	149.55	Erzurum	University
Şıh village	15820	1800	39.94	41.28	159.20	Erzurum	Şıh village

Table 1 presents the topographic and geographical features of the groundwater wells used in the study area. Accordingly, groundwater data were measured from wells at 1800 m elevation. The water level in the wells was taken relative to the ground reference plane.

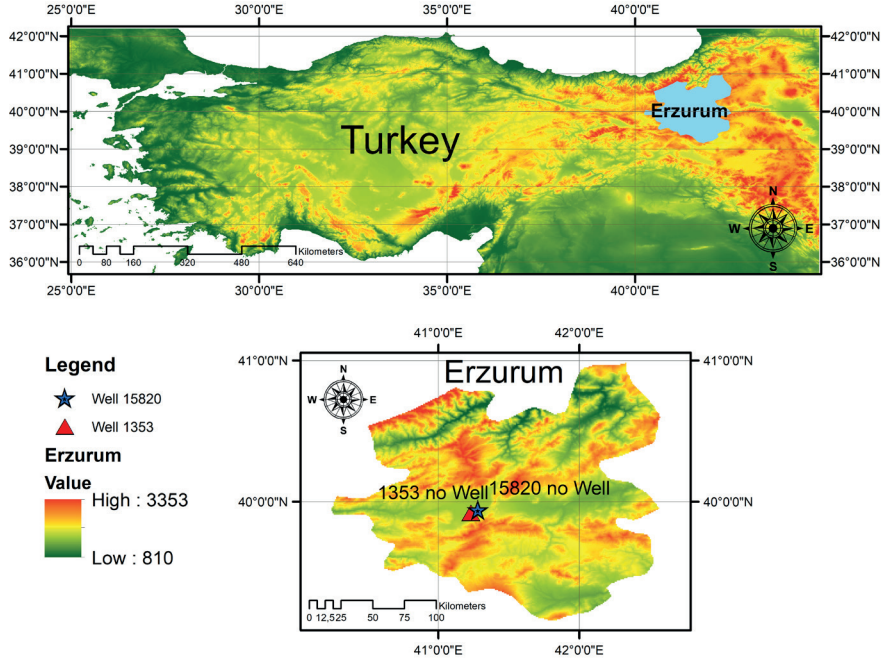


Figure 1. Location map of the study area

2.2. Group Method of Data Handling

Ivashshenko suggested this method in the 70s of the last century, and it is distinguished by its hierarchical structure, where models are trained and refined at each hierarchical level. This characteristic allows it to solve complex scientific problems in several fields, such as engineering, economics, etc.

The GMDH is characterized by many advantages, including its ability to deal with complex non-linear data (Akbarizadeh et al., 2013; Atashrouz et al., 2014), as well as flexibility concerning the functional form of relationships, as it does not require prior assumptions, in addition, and to avoid overflow pitfalls the GDMH model separates the assembly and control kits, also for model validation, it may use the objective function. Finally, complex interactions are captured through the iterative process of adding variables and combining them.

2.3. Convolutional Neural Network

CNNs are a special kind of neural network that derive their work from the biological processes present in the visual section of the human brain. The main component of CNNs is the convolutional layers; their task is to find the important features in the image (He et al., 2016; Krizhevsky et al., 2012). CNN's model consists of four essential layers; we find that the first layer is convolutional and its task is to extract features and apply filters; the second layer collects important features and reduces dimensions; the third layer is called a flattening whose task is to convert the vital information taken from the second layer into a one-dimensional data matrix. Finally, we find the whole connection layer. The latter is building all the connectors in the hidden network.

2.4. Recurrent Neural Networks

RNNs are a type of deep learning proposed by (Rumelhart et al., 1986; Werbos, 1988), containing loops within their networks that use previous information to estimate the following values. These networks greatly benefit from recognizing the subsequent sequencing of certain data as they retain some important features of the sequential data. In theory, RNN should hold information for a long time; however, it is challenging to publish all this information when the time step is too long. When the network contains many deep layers, it becomes untrainable. This problem is called the vanishing gradient problem. It is known that the neural network updates the weight using an algorithm of gradient ratios. Gradients grow as the network progresses to the lower layers. If the gradient remains constant, there is no room for improvement. The model can detect changes in the gradient that affect the network's output. But if the gradient difference is too small, the network's learning process will be adversely affected. To overcome this problem of the vanishing gradient problem faced by RNN, The researchers (Hochreiter et al.. 2001) improved RNNS with an architecture called LSTM. The latter provides to the network with past information relevant to

a more recent time, and the network uses a better architecture to locate and transfer information to a later time.

2.5. Performance Metrics

2.5.1. Root Mean Square Error (RMSE)

Among the model validation indicators, which are characterized by ease of calculation, we find the RMSE, This last is an indicator that makes it possible to check the accuracy of the models, and this is done by studying the deviations between the observed values and the predicted values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \quad (1)$$

The value given by RMSE is always positive, the closer it is to zero, the more accurate the model (Katipoğlu, 2023a, b).

Correlation coefficient (R)

To study the correlation between two or more variables, it is necessary to study the strength of the relationship between them. The connection sought is a relation whose graphical representation is a straight line. The value of this correlation is obtained numerically by the calculation of the correlation coefficient based on the following equation:

$$r_p = \frac{\sum_{i=1}^{N}(x_i - \bar{x}) * (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2} * \sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \quad (2)$$

RESULTS

This study used a Deep learning algorithm consisting of a combination of CNN-RNN and the GMDH technique to estimate groundwater level values. The modeling was carried out according to the time series approach. For this purpose, measurement data were used from two wells (University-WELL ID 1353; Şıh village- WELL ID 15820) in Erzurum province in northeastern Turkey. Monthly, 70% of the available data is allocated for training and 30% for testing. Partial autocorrelation plots are presented in Figure 2 for both wells as a measure that controls for the effect of autocorrelation in time series data at a given lag, excluding other lags. When Figure 2 is analyzed, GWL_{t-1} and GWL_{t-2} were selected as input in the University well for the GMDH model, while GWL_{t-1}, GWL_{t-5}, GWL_{t-9}, and GWL_{t-11} monthly lags were

selected for the Şıh village well. For the GMDH model in GWL estimation, a structure with five layers and 25 neurons in each layer was created.

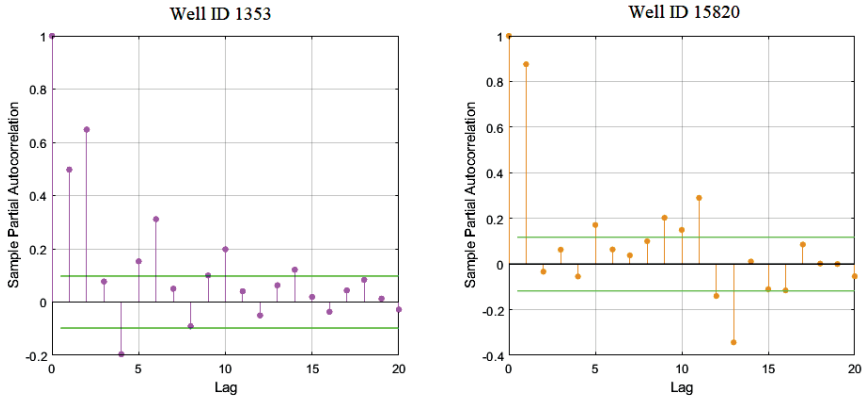
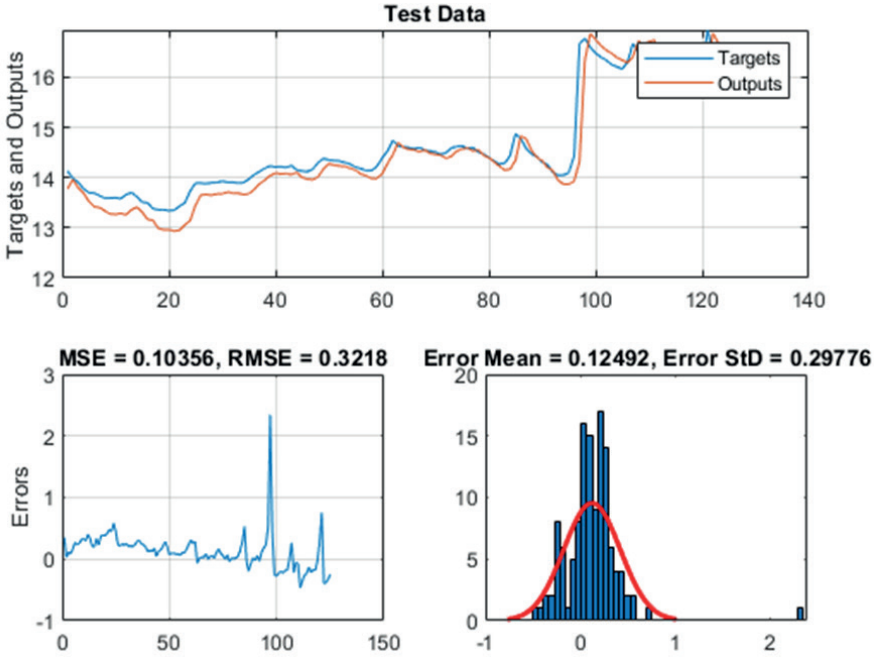
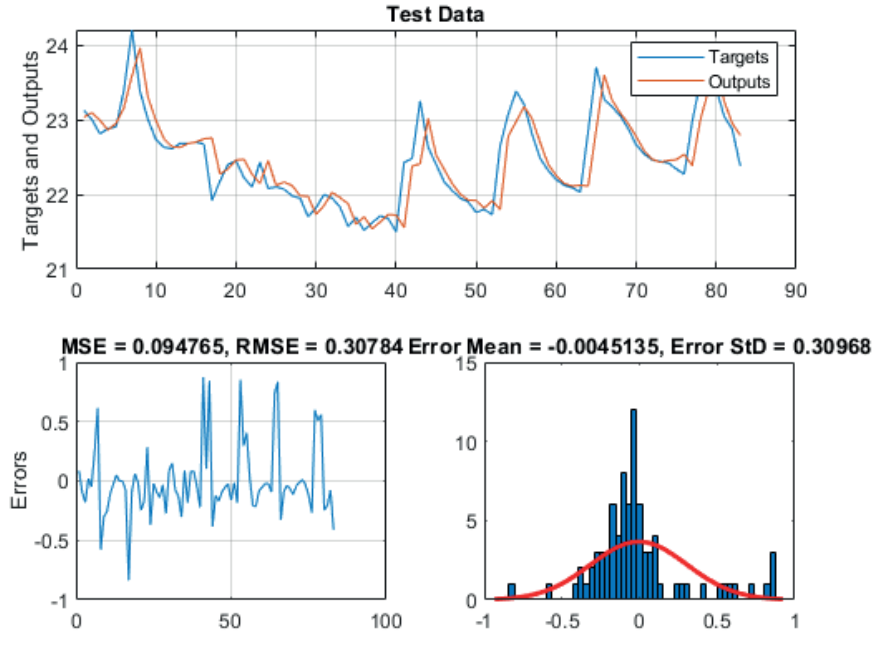


Figure 2. Partial autocorrelation (PACF) for monthly GWL prediction

GMDH model results for test data for both wells are presented in Figure 3. Since the test data consists of data that a model does not see, it is critical to evaluate its predictive capacity. The error values and histogram for both wells are also presented in Figure 3. While the coefficient of determination of the test data for the GWL estimation of the University well is R^2=0.935, this value for Şıh village is R^2=0.731. In particular, very successful prediction results were obtained for the University well, while relatively unsuccessful results were obtained for the Şıh village well. Figure 4 shows the observation and prediction data of both training and test data in a scatter plot. The production of successful prediction results for both test and training data in both wells shows that the GMDH model will be suitable for predicting the monthly groundwater level.

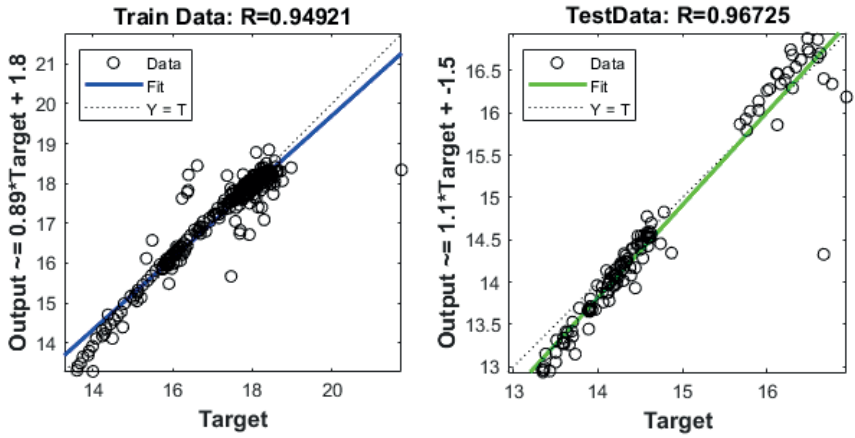


(a)

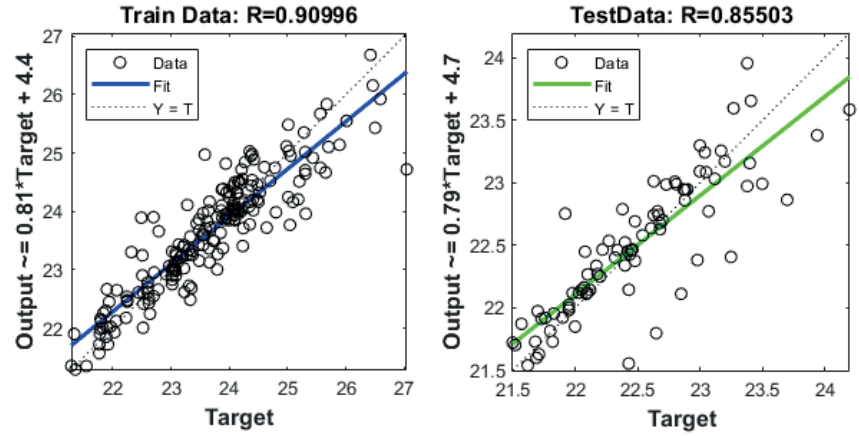


(b)

Figure 3. Test data results of the GMDH model. (a) University Well, (b) Şıh Village Well



(a)

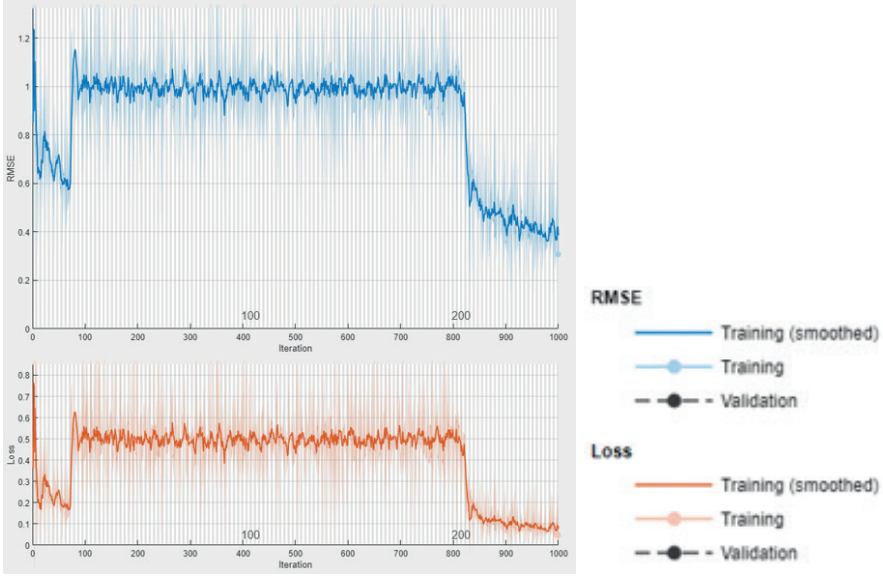


(b)

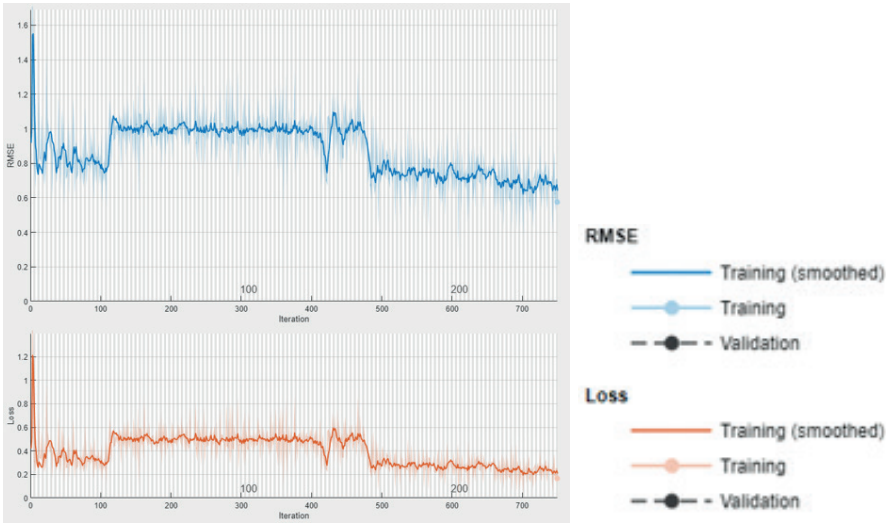
Figure 4. Scatter plot for training and test data results of the GMDH model. (a) University Well, (b) Şıh village Well

In this study, a CNN-RNN hybrid model was also used for groundwater level prediction and a graph showing the loss in the training process is given in Figure 5. In Figure 5a, for the University well, we observe how the loss changes depending on the number of iterations of the model. At first, the model learned quickly and reduced the loss rapidly, but then there was a point where the loss quickly increased. This point may indicate that the model encountered some difficulties in the training process or showed

signs of overfitting. Then, the loss value remained almost constant for a long iteration, indicating that the model improved less with more iterations. Finally, it is observed that the loss decreases again rapidly and the model continues to improve. This graph visualizes the training process of the CNN-RNN hybrid model for groundwater level prediction, showing that the model initially learns quickly, encounters some difficulties and then improves. After 1000 iterations, it is observed that the loss is considerably reduced. When Figure 5b is analyzed, while the loss decreased rapidly at the beginning of the training process, an increase in the loss value was observed at a certain point. Afterward, the loss value remained constant, and the model showed a stable performance during the training process. Then, around the middle stages, there was a decrease, indicating that the model was adapting better and started to make more accurate predictions. In the next iterations, the loss value remained almost constant and the training process was terminated. Based on these observations, it can be concluded that the model learns quickly, optimizes, and does not make significant progress in the final iterations.



(a)



(b)

Figure 5. Training process in monthly GWL estimation for CNN-RNN model. a) University well, b) Şıh village well

Figure 6 shows the observed and predicted monthly GWL estimates. Figure 6a indicates that the coefficient of determination R^2= 0.828. It is seen that the model is particularly successful in capturing the dynamic change of groundwater over time and sudden ups and downs. In addition, the model's success in predicting high GWL values is also quite high. It is seen that the data predicted by the CNN-RNN model for the University well are higher than the observation data. However, it was observed that higher predictions were realised with small deviations. When Figure 6b is analyzed, the coefficient of determination R^2=0.44. The appearance of large scatter in the prediction data and the failure of the CNN-RNN model in predicting the continuously increasing and decreasing change trend in the relevant well. The production of quite different model results for two different wells shows that the dynamic characteristics of the aquifer and the well are highly effective in GWL estimation studies. It is seen that the CNN-RNN model produces successful results for relatively stationary time series where GWL fluctuations occur less for time. Still, the model success decreases in time series where GWL is highly variable and extremum values appear in short periods.

In the present study, two different approaches, GMDH and CNN-RNN, were tested for GWL prediction success for two different wells in the northeast of Turkey. It was observed that both models produced more

successful results, especially for the University well. GMDH method has higher accuracy values in estimating continuous and non-stationary GWL time series for both wells. It was observed that the GMDH method produced lower predictions with small deviations from the observed values, whereas the CNN-RNN method produced higher predictions. When the prediction success of the same models for different wells is evaluated, it can be emphasized that the well's utilization status and the aquifer's physical properties may be an essential factor affecting the prediction success.

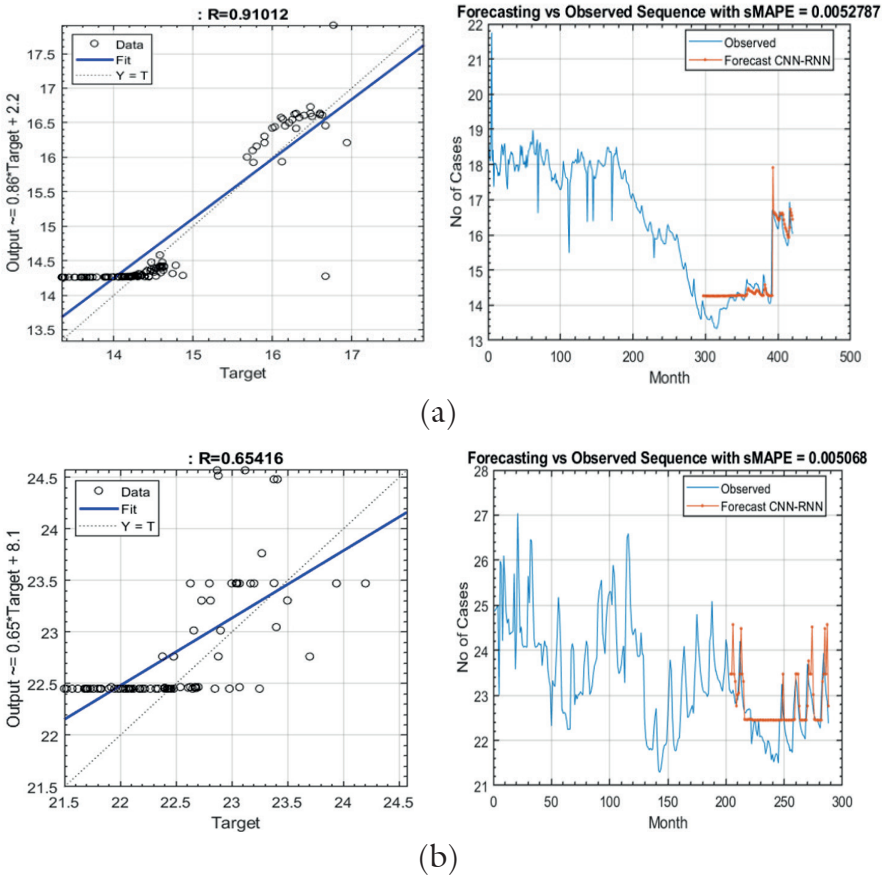


Figure 6. Monthly GWL values observed and predicted by the CNN-RNN model. a) University Well, b) Şıh Village Well

4. DISCUSSION

In this study, various machine learning and deep learning algorithms are compared to predict groundwater time series. As a result of the study, promising results were obtained. Although many time series studies have been carried out with the GMDH model in the literature, groundwater-level forecasting studies are limited. Barzegar et al. (2017) used the wavelet signal decomposition method with two different algorithms, the wavelet-group method of data handling (WA-GMDH) and wavelet-extreme learning machine (WA-ELM), to predict GWL in 1, 2 and 3 months. It is emphasized that the WA-ELM method produces results with higher accuracy. Moosavi et al. (2021) used three different signal decomposition methods, namely EEMD, WT and WPT, and created hybrid models with GMDH to predict the GWL in 1 month. They emphasized that all signal decomposition methods increase the forecasting capacity and the WPT-GMDH hybrid model is the most successful. However, considering the high computational cost of this model, the EEMD-GMDH model is more suitable for GWL forecasting studies. Amiri-Doumari et al. (2022) created a groundwater potential map using 3 different optimization algorithms (GMDH-PSO, GMDH-GWO, GMDH-ACO and GMDH), including particle swarm optimization (PSO), grey wolf optimizer (GWO), and ant colony optimization (ACO) and single GMDH. As a result of the study, it was emphasized that precipitation, topography and land cover are critical parameters regarding GWL potential. He suggested that the GMDH-PSO algorithm is the most successful model. When the studies are analyzed, it is seen that GMDH is influential in determining groundwater level and potential. However, it is emphasized that the estimation capacity increases with various optimization algorithms and signal decomposition methods.

Akhshandehroo et al. (2012) investigated the prediction of monthly GWL in Shiraz Plain using different neural network models (RNN, FNN, RBF and Generalized regression). The input data included precipitation, GWL, temperature, evaporation, and runoff. The FNN and RNN networks exhibited the most successful results among the models tested. Bowes et al. (2019) used two machine learning methods, Long Short-term Memory (LSTM) and RNN, to forecast GWL in a coastal area in Norfolk, Virginia. Compared to RNN, LSTM produced more successful forecasting results both in the whole time series and in the time series cases only during storm periods. Ali et al. (2022) analyzed hourly GWL changes using the CNN-BiLSTM hybrid model. As a result, they obtained a high $R^2 = 0.917$ in the training phase and a lower $R^2 = 0.632$ in the testing phase. Especially in deep learning studies, the high number of data causes the model performance to

increase in the training phase. Considering that the models used in the studies produce successful results in GWL time series forecasting, the creation of hybrid models by considering the machine learning methods, which have been increasing and successful in recent years, can increase the success rate. In particular, the success of models built with signal decomposition methods or optimization algorithms in forecasting dynamic and continuous time series should be considered.

5. CONCLUSION

This study compared the performances of the GDMH and CNN-RNN algorithms for modeling the underground levels in 2 Erzurum wells. For model input combinations, lagged values exceeding 95% were selected from the PACF charts. According to the analysis results, the GDMH model performed more effectively in both wells. As a result of the analysis, both models produce promising results in GWL time series estimation. The study's outputs are essential for effective water management for water resource managers, decision-makers, and planners.

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