

Evaluation of the Capability of NARX Neural Network in Predicting Ground Water Level Changes [†]

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Abstract: Efficient monitoring and tracking of groundwater level changes are critical for the sustainable management of water resources, especially in light of population growth and climate change. This study evaluates the ability of the Non-linear Autoregressive with exogenous input (NARX) model to simulate groundwater level trends in Ajabshir, Iran, using groundwater level data from 2006 to 2019 as the baseline period. The model was trained using time, groundwater levels, and delay times between 1 to 2 as the input training samples. The results indicate that the NARX model performed exceptionally well in simulating historical trends of groundwater levels, achieving a Coefficient of Determination (DC) value of 0.87 and a Root Mean Squared Error (RMSE) of 0.215.

Keywords: groundwater levels; non-linear autoregressive with exogenous input (NARX); simulation; sustainable water management

1. Introduction

Groundwater is a valuable natural resource, and its accurate prediction plays a significant role in various fields such as agriculture, urban planning, and water supply management. Groundwater level (GWL) prediction is a crucial aspect of water resource management, environmental monitoring, and sustainable development. With the advent of Artificial Intelligence (AI) technologies, in recent years, Artificial Neural Networks (ANNs) have emerged as powerful tools for forecasting GWL due to their ability to simulate complex non-linear relationships. In response, researchers have turned to ANN, a data-driven modeling technique capable of capturing complex relationships within data, to improve GWL prediction accuracy [1]. The investigation conducted by Zhao et al., (2016) [2] is centered on the prediction of GWL in regions that are prone to landslides. This methodology combines classification and regression techniques to comprehensively analyze the relationships between GWLs and the potential for landslide occurrences. The primary objective of this approach is to advance the understanding of the intricate dynamics governing landslide events in these specific geographical areas. conducted a research study on predicting GWL in seashore reclaimed land using a hybrid model based on wavelet and ANN. The study highlights the application of this novel hybrid approach to enhance the accuracy of predictions in coastal reclamation areas. Ref. [3] conducted a study on the prediction of monthly GWL in Kerman plain, Iran, employing ANN and neuro-fuzzy models. The research focuses on developing accurate forecasting models to assist in managing groundwater resources in the region. Ref. [4] conducted a study on GWL prediction utilizing ANN and M5 Tree models. The research focuses on comparing the effectiveness of these models for accurate GWL forecasting. The study contributes to

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the advancement of predictive modeling techniques in groundwater management and resource planning. A wavelet neural network conjunction model for GWL forecasting was done by Adamowski and Chan, (2011). In this paper, a new method based on coupling discrete wavelet transforms and ANN for GWL forecasting applications is proposed, and the results of the study demonstrated that the wavelet neural network is potential in GWL forecasting. Daliakopoulos et al., 2005 proposed a GWL forecasting method using ANNs. Their study aims to leverage the capabilities of neural networks to predict groundwater levels accurately. The research explores the potential of this approach in enhancing water resource management and environmental monitoring efforts. Ref. [5] explore GWL variations through the simulation of a combined model utilizing wavelet, neural network, linear regression, and support vector machine techniques. The research aims to assess the effectiveness of this integrated approach in accurately predicting GWL, thereby contributing to improved water resource management and environmental monitoring. Emamgholizadeh et al., (2011) conducted a study on predicting the GWL of Bastam Plain, Iran, employing ANN and adaptive neuro-fuzzy inference system. The research explores the application of these advanced modeling techniques to enhance the accuracy of GWL forecasts. Ref. [6] investigated the impact of input feature selection on GWL prediction using a multi-layer perceptron neural network. The research delves into the significance of selecting appropriate input features to improve the accuracy of groundwater level forecasts. Ref. [7] explored machine learning algorithms for modeling groundwater level changes in agricultural regions of the U.S. The research aims to assess the effectiveness of various machine learning techniques in predicting groundwater level fluctuations.

In this study, an assessment has been conducted to evaluate the effectiveness of the NARX model in simulating GWL trends in Abshir, Iran. GWL data from the period of 2006 to 2019 was conducted as the baseline period.

2. Materials and Methods

2.1. Study Area and Data Set

Ajabshir is a county located in the northwest of Iran, within East Azerbaijan province, with an approximate area of 700 square kilometers (1.6% of the province's total area). It is bordered by Azarshahr and Osku to the north, Lake Urmia to the west, Maragheh to the east, and Bonab to the south. Due to its location in a mountainous region, the area experiences moderate summers and snowy cold winters, as shown in the Figure 1.

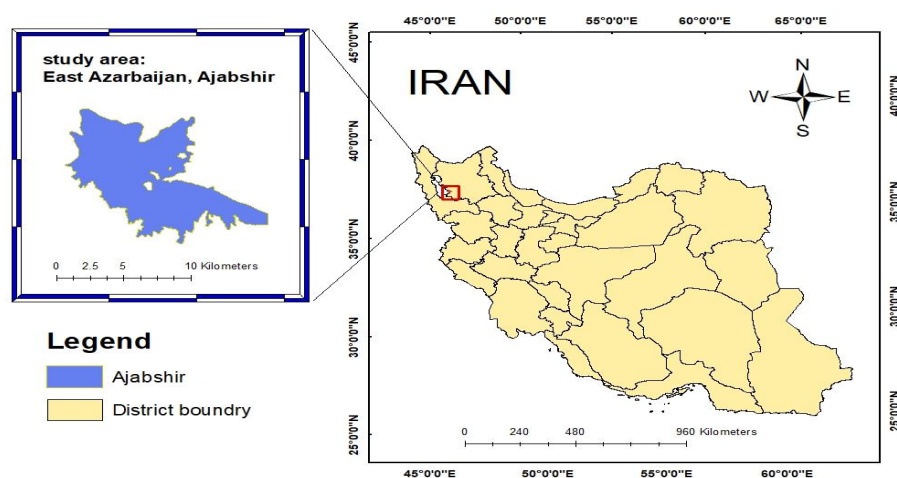


Figure 1. Location of study region.

GWL data spanning the baseline period of 2006 to 2019 is collected for the study area. Figure 2 illustrates the monthly changes in GWL for the baseline period.

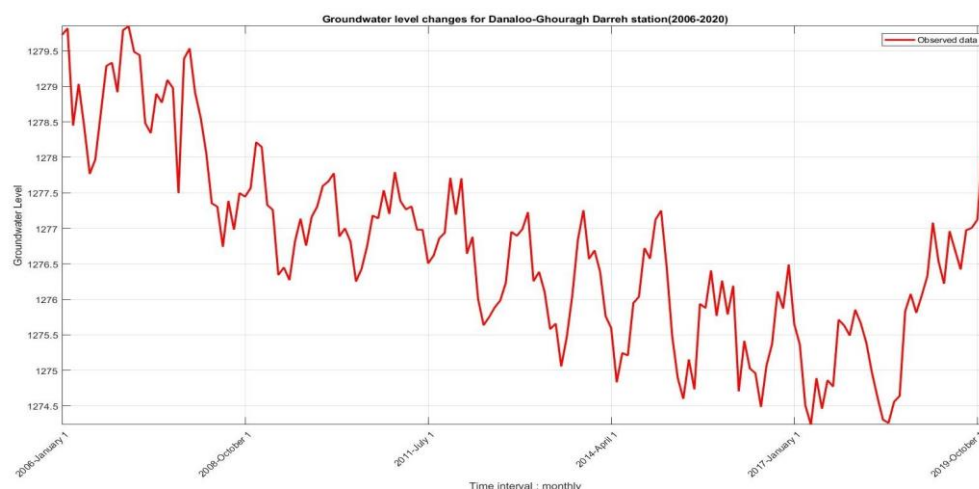


Figure 2. Observed GWL monthly time series data.

2.2. ANN (Artificial Neural Networks) Non-Linear Autoregressive with Exogenous Input NARX

ANN (Artificial Neural Networks) and NARX models have gained significant popularity in time-series prediction due to their ability to model complex non-linear relationships. NARX networks are particularly recurrent dynamic type of ANNs [14]. NARX neural network can be used for effective nonlinear time series forecasting. The time series of NARX neural network can be defined as follows [15]:

$$y(t) = f(y(t - 1), y(t - 2), \dots, y(t - d), x(t - 1), x(t - 2), \dots, x(t - d)) \quad (1)$$

where, the future values of a time series, denoted as $y(t)$, are forecasted based on its past values with a delay time of d , as well as an external series $x(t)$. The model operates by capturing the non-linear dependencies between $y(t)$ and its historical values while incorporating the influence of the external series $x(t)$ to enhance prediction accuracy. By considering both the autoregressive nature of the target series with a delay of d and the impact of external factors, the NARX model offers a robust framework for time-series forecasting in various domains.

This study investigates the capability of the NARX model for GWL data prediction, utilizing time ($x(t)$) as the input variable and GWL ($y(t)$) as the target variable. The research employs a neural network architecture with one hidden layer and utilizes 1000 iterations for model training. The scaled conjugate gradient was used in the case of the training network. The scaled conjugate gradient method is an optimization algorithm commonly used in training ANNs, including models like the NARX. The SCG method efficiently minimizes the error function by updating the network’s weight parameters during the learning process. The data were divided into the training (70%) and test (30%) data. The delay time is set to 1:2.

2.3. Evaluation Criteria

To assess the precision of the predicting models, Root Mean Squared Error (RMSE) and Correlation Coefficient (R) metrics was utilized [16].

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - o_i)^2}{n}} \quad (2)$$

$$R = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{3}$$

where x_i , \bar{x} , y_i , and \bar{y} represent the values of the x-variable within a sample, the average of x-variable values, the values of the y-variable within a sample, and the average of y-variable values, respectively.

4. Results and Discussion

Based on the information mentioned in the previous section, in this study, the NARX neural network model used to simulate the GWL changes. Figure 3 illustrates the comparison between the actual monthly GWL time series and the predicted values using the NARX model. According to the results of the analysis, The RMSE resulted in a value of 0.215, while the DC yielded a value of 0.85. Additionally, the R-values for the training data and test data were determined to be 0.92 and 0.87, respectively (Figures 5 and 6).

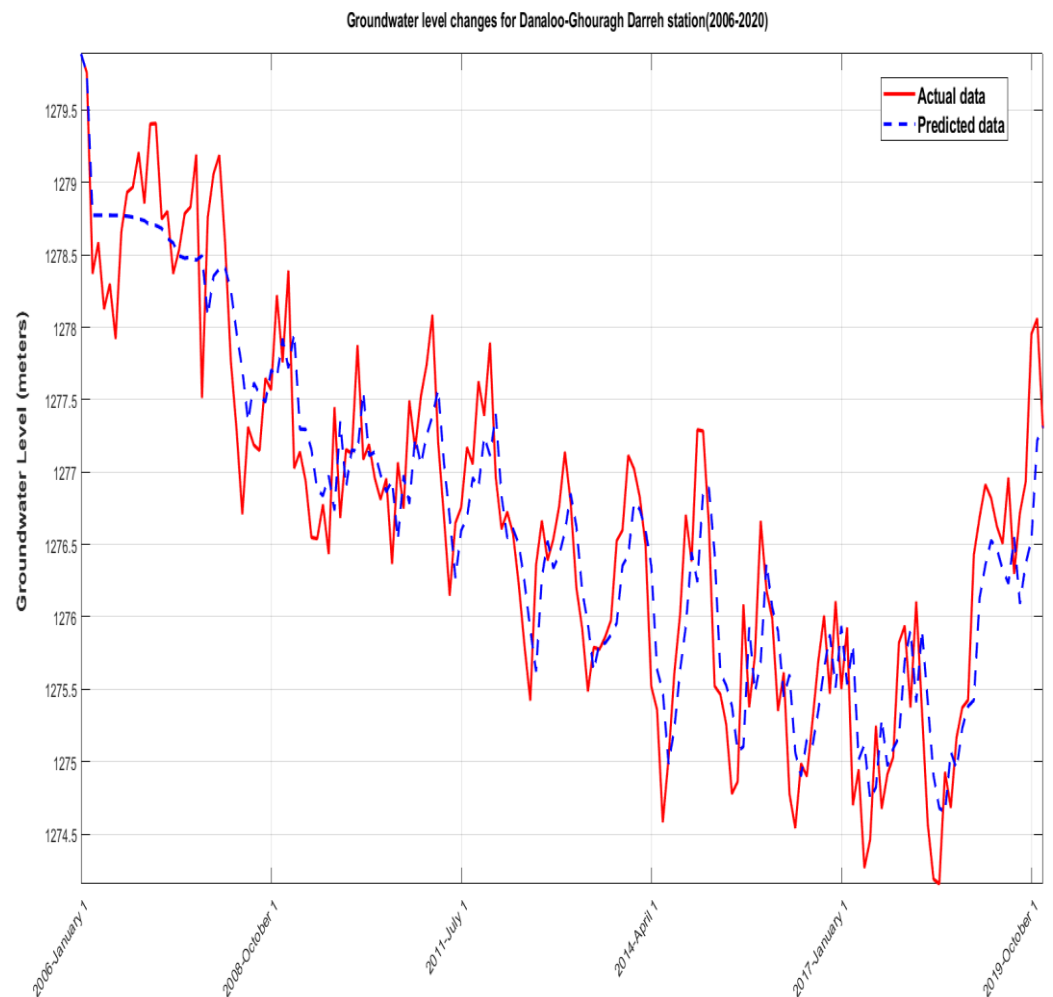


Figure 3. The observed (Actual) and predicted groundwater levels.

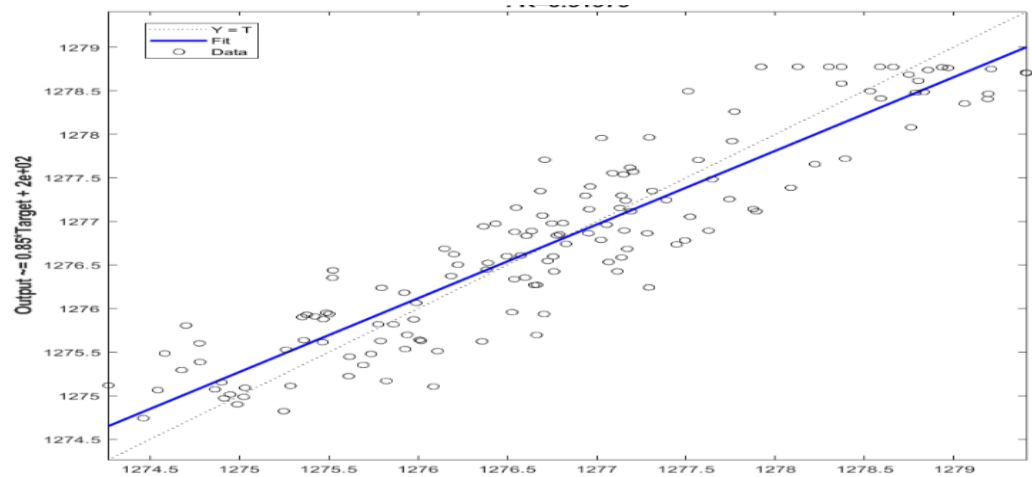


Figure 4. Correlation values (R) for train data.

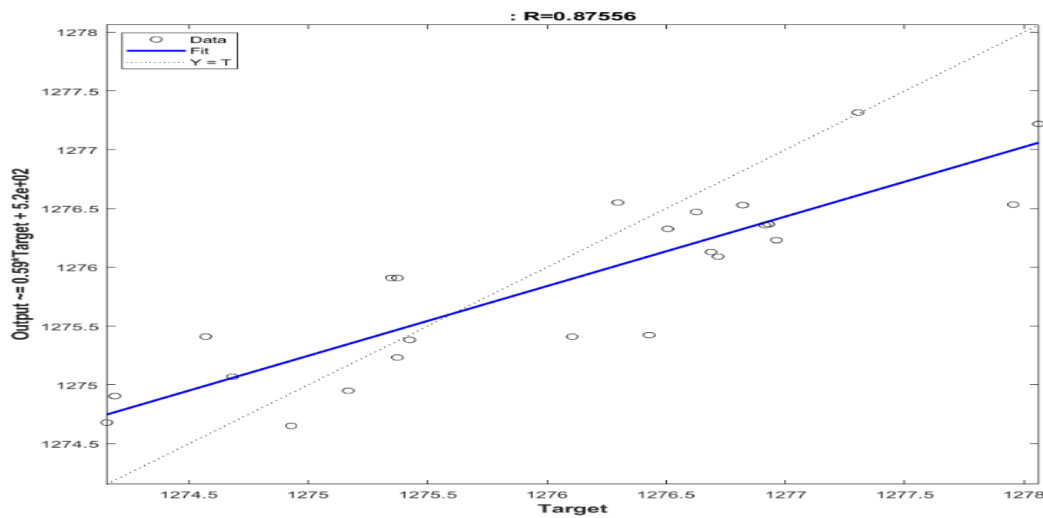


Figure 5. Correlation values (R) for test data.

The results obtained from the NARX model demonstrate its promising capability in predicting GWL variations. The DC of 0.86 indicates a reasonably good fit between the predicted and observed GWL values. Additionally, the relatively low RMSE of 0.215 suggests that the NARX model is capable of providing accurate predictions, with the deviations between predicted and observed values being relatively small. Moreover, the high R-values of 0.92 and 0.87 for the training and test data, respectively, indicate that the NARX model exhibits good performance in capturing the underlying non-linear dependencies in the data and has the potential for generalizing well to unseen data. However, despite these positive outcomes, the NARX model has some limitations that need to be addressed in future studies.

5. Conclusions

The accuracy of the model heavily relies on the availability and quality of the input data, including both the time series GWL data and relevant exogenous variables. Furthermore, the NARX model’s success may vary with different delay times (d) and the number of hidden layer nodes. Fine-tuning these hyperparameters could potentially enhance the model’s predictive capabilities and should be explored in future research.

For future studies, incorporating more domain-specific features and environmental factors could improve the NARX model’s performance. Consideration of factors like

groundwater recharge rates, geological characteristics, and land use can enhance the model's ability to capture complex hydrological interactions.

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References

1. Tao, H.; Hameed, M.M.; Marhoon, H.A.; Zounemat-Kermani, M.; Heddami, S.; Kim, S.; Sulaiman, S.O.; Tan, M.L.; Sa'adi, Z.; Mehr, A.D. and Allawi, M.F. Groundwater level prediction using machine learning models: A comprehensive review. *Neurocomputing* **2022**, *489*, 271–308.
2. Nourani, V.; Mogaddam, A.A.; Nadiri, A.O. An ANN-based model for spatiotemporal groundwater level forecasting. *Hydrol. Process. : Int. J.* **2008**, *22*, 5054–5066.
3. Zhao, Y.; Li, Y.; Zhang, L.; Wang, Q. Groundwater level prediction of landslide based on classification and regression tree. *Geod. Geodyn.* **2016**, *7*, 348–355.
4. Sadat-Noori, M.; Glamore, W.; Khojasteh, D. Groundwater level prediction using genetic programming: the importance of precipitation data and weather station location on model accuracy. *Environ. Earth Sci.* **2020**, *79*, 37.
5. Zhang, J.; Zhang, X.; Niu, J.; Hu, B.X.; Soltanian, M.R.; Qiu, H.; Yang, L. Prediction of groundwater level in seashore reclaimed land using wavelet and artificial neural network-based hybrid model. *J. Hydrol.* **2019**, *577*, 123948.
6. Jalalkamali, A.; Sedghi, H.; Manshouri, M. Monthly groundwater level prediction using ANN and neuro-fuzzy models: a case study on Kerman plain, Iran. *J. Hydroinformatics* **2011**, *13*, 867–876.
7. Kaya, Y.Z.; Üneş, F.; Demirci, M.; Taşar, B.; Varçin, H. Groundwater level prediction using artificial neural network and M5 tree models. *Aerul Si Apa. Compon. Ale Mediu.* **2018**, 195–201.
8. Adamowski, J.; Chan, H.F. A wavelet neural network conjunction model for groundwater level forecasting. *J. Hydrol.* **2011**, *407*, 28–40.
9. Daliakopoulos, I.N.; Coulibaly, P.; Tsanis, I.K. Groundwater level forecasting using artificial neural networks. *J. Hydrol.* **2005**, *309*, 229–240.
10. Ebrahimi, H.; Rajaei, T. Simulation of groundwater level variations using wavelet combined with neural network, linear regression and support vector machine. *Glob. Planet. Change* **2017**, *148*, 181–191.
11. Emamgholizadeh, S.; Moslemi, K.; Karami, G. Prediction the groundwater level of bastam plain (Iran) by artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). *Water Resour. Manag.* **2014**, *28*, 5433–5446.
12. Kaya, Y.Z.; Üneş, F.; Demirci, M.; Taşar, B.; Varçin, H. Impact of input feature selection on groundwater level prediction from a multi-layer perceptron neural network. *Front. Water* **2020**, *2*, 573034.
13. Sahoo, S.; Russo, T.A.; Elliott, J.; Foster, I. Machine learning algorithms for modeling groundwater level changes in agricultural regions of the US. *Water Resour. Res.* **2017**, *53*, 3878–3895.
14. Di Nunno, F.; Granata, F. Groundwater level prediction in Apulia region (Southern Italy) using NARX neural network. *Environ. Res.* **2020**, *190*, 110062.
15. Ruiz, L.G.B.; Cuéllar, M.P.; Calvo-Flores, M.D.; Jiménez, M.D.C.P. An application of non-linear autoregressive neural networks to predict energy consumption in public buildings. *Energies* **2016**, *9*, 684.
16. Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models part I—A discussion of principles. *J. Hydrol.* **1970**, *10*, 282–290.

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