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J. N. Reddy · Chien Ming Wang ·
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Water Resource and Hydraulic Session

An Application of ANN on Groundwater Level Prediction of the Fractured Aquifers in the Nhue—Day River Basin

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Abstract. Groundwater level (GWL) varies periodically or non-periodically with various factors including rainfall (RF), evaporation (ET), number of sunny hours (NS), humidity (HM), air temperature (AT), and topographic elevation (TE). This study presents an implementation of an Artificial Neural Network (ANN) to predict groundwater level in the fractured aquifers of Nhue—Day River basin, Vietnam. In this regard, the monthly historical time series climatological data (rainfall, temperature, humidity, and evaporation) during 2018–2019 and hydrogeological parameters at seven observation wells have been used as input variables to estimate GWL. The statistical performance of the developed Levenberg-Marquardt back-propagation artificial neural network (ANN) models was evaluated using three criteria: Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). Results showed that the ANN model predicted groundwater level with reasonable errors. The average root mean square prediction error was 1.77 m for groundwater level prediction at seven observation wells. The training results revealed that monthly precipitation and evaporation are important variables that have a strong influence on groundwater level prediction. Based on these values, the seasonal groundwater level and fluctuation were mapped using the geo-statistical toolbox in ArcGIS 10.8. Finally, the present study as a pioneer approach provides significant contributions to groundwater management and development of Nhue—Day River basin.

Keywords: ANN · Groundwater level · Fractured aquifer · Nhue-Day River basin

1 Introduction

Groundwater, which refers to water stored beneath the Earth's surface, is a precious and limited natural resource [8, 11]. To make informed decisions regarding water resources in the present and future, it is crucial to monitor and assess the availability of groundwater.

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One direct and straightforward measure used for this purpose is the groundwater level (GWL), which indicates the depth of water below the land surface [13]. However, GWL consists of an integrated response to several climatic, topographic, and hydrogeological factors and their interactions, which makes the simulation of GWL a challenging task [1, 13]. Several studies were carried out for forecasting the groundwater levels using conceptual/physical models that are not only laborious, but also have practical limitations [4, 9] as many inter-related variables are involved. Several studies have reported that artificial neural networks demonstrate remarkable accuracy in predicting fluctuations in groundwater levels, particularly excelling in simulating karstic and leaky aquifers, where other numerical models are inadequate for such environments. [3, 10]. Considering existing limits and a review of the literature, an approach combining Artificial Neural Networks (ANN) and Geographic Information Systems (GIS) is proposed to estimate the spatial and temporal groundwater level distribution in fractured aquifers within the Nhue-Day River basin, where limited observation data and other hydrogeological parameters are available.

2 Materials and Methods

2.1 Study Area

The study focused on the Nhue-Day River sub-basin, which is situated in the northeastern part of Vietnam. The Nhue-Day River basin covers a total area of 7,958 square kilometers and spans across six provinces: Hanam, Namdinh, Ninhbinh, Hanoi, and Hoabinh. The basin experiences a wet-hot monsoon-tropical climate characterized by a dry-cold winter and a rainy-hot summer. The average annual temperatures range from 24 to 27 degrees Celsius. The region receives an average annual rainfall of 1,500 to 2,200 mm, with the highest precipitation occurring at Ba Vi Mountain in the upper catchment of the Tich River. The Nhue-Day River basin contains two major aquifer types. There are alluvial sediment aquifers located in narrow valleys between steep valley walls of the mountain massif. These aquifers encompass the middle and upper reaches of the mountain-fed rivers in the region. Secondly, there are fractured rock aquifers characterized by a thick sequence of hard sedimentary rocks, predominantly fractured sandstones, covering an outcrop area of 2,471 square kilometers. These fractured rock aquifers are primarily found in the southwestern part of the Nhue-Day River basin. In fractured rock aquifers, groundwater is primarily stored within fractures, joints, bedding planes, and cavities within the rock mass. Abstractions in these aquifers are limited and groundwater level is strongly dependent on surface elevation (Fig. 1).

2.2 Required Data

In this study, elevation values from 104 boreholes were gathered from the project to map the GWL of the fractured aquifers. There is a significant spatial interaction between groundwater levels and surface topographic in fractured aquifer ($R^2 > 0.9$). Monthly GWL time series data at 7 observation wells (Fig. 2) from January to December in 2019 were collected from the NAWAPI project “Investigation and research sources of

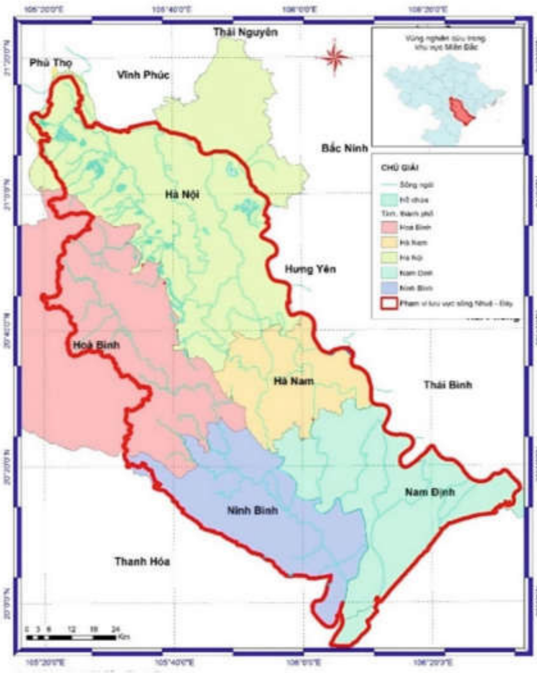

Fig. 1. Location of study area

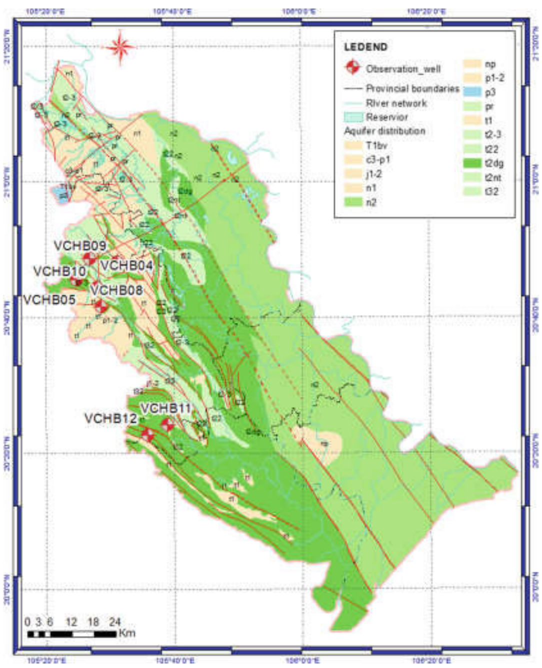

Fig. 2. Hydrogeological map of study area

groundwater supply in highland and water-scarce areas". Other data collected during the study period included rainfall, evaporation, sunny hours, humidity, and air temperature, which were used as inputs for the ANN model. The study used regression analysis to find an adequate relationship between groundwater level and climate variables (X_1 is monthly rainfall, X_2 is monthly evaporation (ET), X_3 is number of sunny hours, X_4 is humidity, X_5 is air temperature). The multi-regression equation is written as below:

$$Y = \beta + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + u$$

Analysis of the above results shows that the groundwater in the fissure aquifers in the study depends closely on climatic factors, with high values of the multiple correlation coefficients (R > 0.9) (Table 1).

Table 1. Multiple-regression analysis results

No	Wells	Slope coefficient					Determination coefficient (R)
		β_1	β_2	β_3	β_4	β_5	
1	VCHB04	0.0070	0.1369	−0.0338	0.8609	10.316	0,940
2	VCHB05	0.0061	0.1180	−0.0260	0.8032	10.417	0,953
3	VCHB08	0.0063	0.1826	−0.0320	10.624	0.9282	0,936
4	VCHB09	0.0011	0.0485	−0.0152	0.0637	0.2541	0,951
5	VCHB10	0.0051	0.2304	−0.0323	0.8298	0.8480	0,942
6	VCHB11	0.0017	0.0247	−0.0008	0.0386	0.0020	0,959
7	VCHB12	0.0016	0.0216	−0.0002	0.0375	0.0031	0,961
Average		**0,0041**	**0.1090**	**−0.0200**	**0.5280**	**0.5870**	**0.949**

2.3 Artificial Neural Network Model (ANN)

The Artificial Neural Network (ANN) is an advanced soft-computing technique that encompasses diverse available procedures [5]. Based on previous research reviews, it was found that a feedforward backpropagation neural network using the Levenberg-Marquardt algorithm (LMA) stands out as one of the most promising choices for water level prediction [4, 7, 14]. An Artificial Neural Network (ANN) was utilized to forecast groundwater levels (GWL) by considering several variables representing the physical phenomena of groundwater/climate interaction. These variables included monthly variations in rainfall (RF), evaporation (ET), number of sunny hours (NS), humidity (HM), temperature (TP), and topographic elevation (TE) (Fig. 3).

The initial crucial decision involves determining the appropriate network architecture, which includes the number of layers and nodes in each layer. In this research, the input layer consists of 6 neurons representing RF, ET, NS, HM, AT, and TE, while the output layer comprises 1 neuron representing GWL. To account for the random nature of ANNs, various backpropagation feedforward neural network (BPFNN) models were tested, altering the number of neurons in both the input and hidden layers. The Levenberg-Marquardt optimization technique was employed in this study.

To train the neural network and allow it to learn patterns from the data, 70% of the data were allocated to the training set, 15% to the testing set, and 15% to the validation

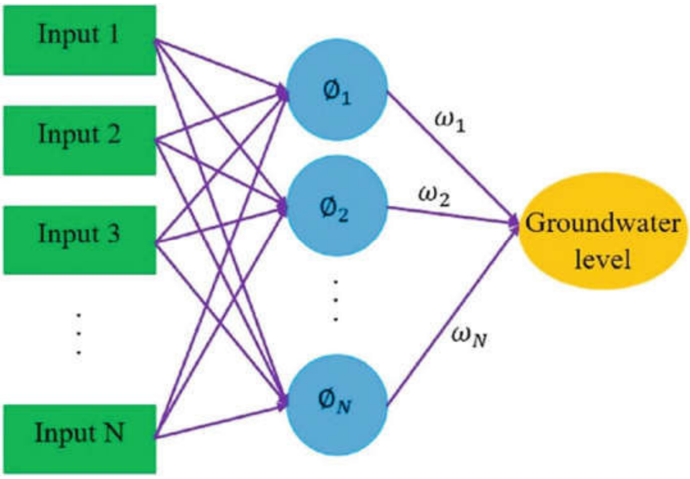

Fig. 3. ANN network to estimate groundwater levels

set. This study used several error evaluation techniques, such as Mean Square Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2), which are widely employed by researchers to provide quantitative measures of the model's performance [6, 12, 14].

3 Results

3.1 Groundwater Level Prediction

Figure 4 illustrates the regression coefficient (R) plot for the optimal architecture consisting of 3 hidden layers. During the training phase, the neural network effectively aligns the data points along the blue line, resulting in a high R value of 0.9987, which is close to 1, indicating a strong fit between the actual network outputs and their corresponding target values. Similarly, in the testing phase, the neural network fits the data along the red line, yielding an R value of 0.998, further affirming the accurate prediction of groundwater levels. The validation data also exhibit a good fit represented by the green line, with an R-value of 0.9945. When considering all the training, testing, and validation data together, the overall R-value is 0.98731. The proximity of these R-values to 1 signifies that the model adequately captures the data patterns and provides precise groundwater level predictions.

The comparison is depicted in Table 2 and Fig. 5, which visually illustrates the agreement or discrepancy between the observed and predicted groundwater levels for the selected wells. The evaluation metrics, including RMSE, MSE, and efficiency (R^2), were used to assess the performance of the estimated GWLs compared to the actual values for all seven observation wells in the ANN models. The results obtained from these metrics indicate reasonable accuracy and reliability of the estimation.

3.2 Groundwater Level Mapping

Based on the obtained results, the trained models were applied to predict GWLs from January 2022 to December 2022 at 1,191 different locations. The observations revealed

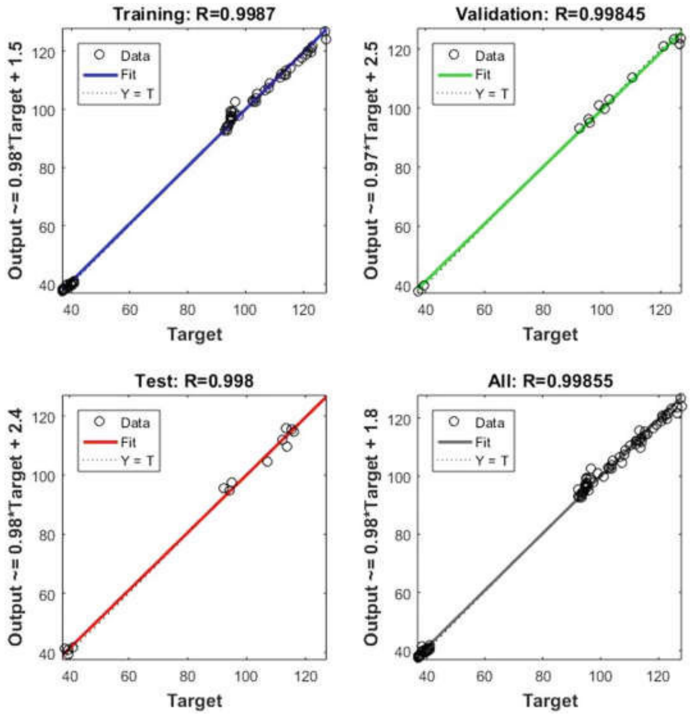

Fig. 4. Regression plot for neural network

Table 2. Error results

Well ID	RMSE (m)	MSE (m^2)	R^2
VCHB04	3.24	1.80	0.91
VCHB05	2.43	1.56	0.91
VCHB08	3.33	1.83	0.88
VCHB09	0.15	0.39	0.90
VCHB10	3.22	1.79	0.89
VCHB11	0.03	0.16	0.92
VCHB12	0.02	0.15	0.92

that the depth to groundwater tends to increase with higher elevation, and it is generally shallower towards the river. During the dry season, the static water levels (SWL) were found to be deeper compared to the wet season, while the GWLs was higher during the wet season than the dry season. The depth from the ground surface to the GWLs ranged from 38 to 120 m in the dry season and 56 to 120 m in the wet season (Fig. 6).

3.3 Discussion

In the highlands of the Nhue-Day River basin, the most influence of groundwater level fluctuation are the monthly precipitation and evaporation based on ANN model results

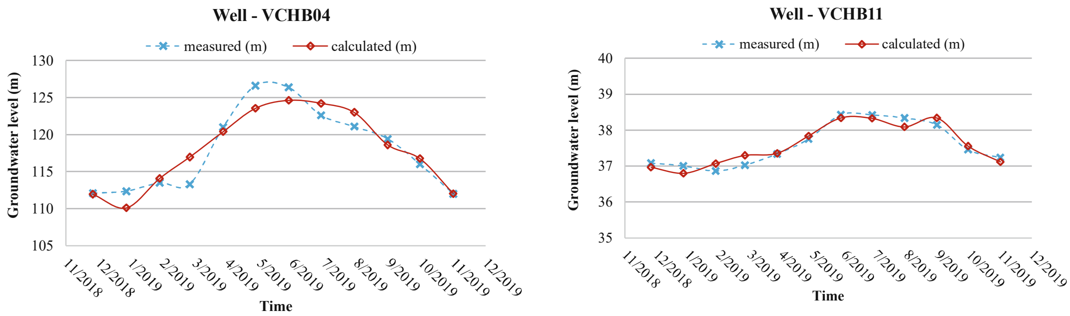

Fig. 5. Measured and calculated of GWLs at observed wells (VCHB04, VCHB11)

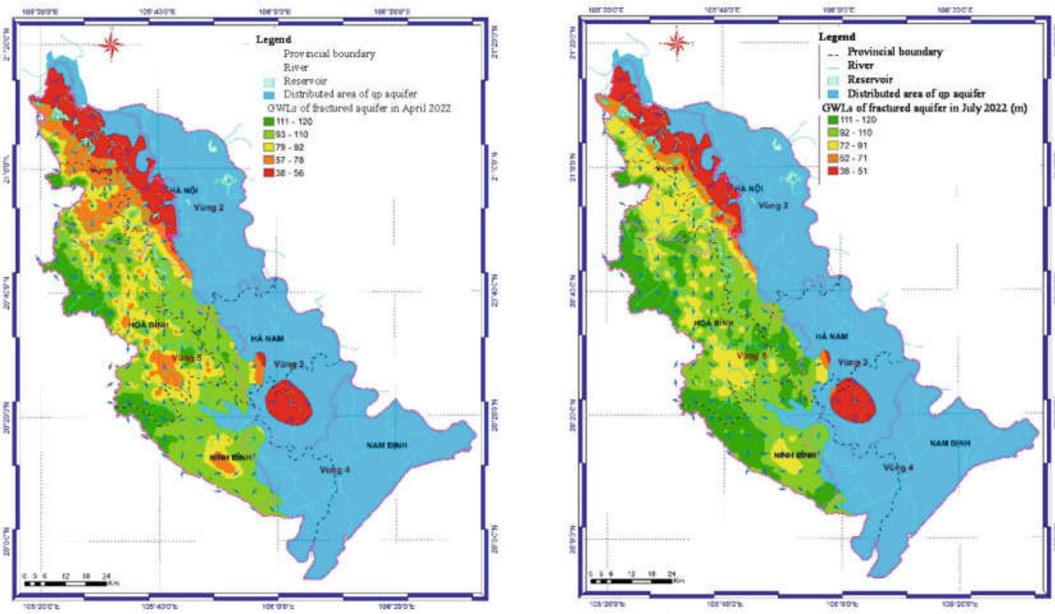

Fig. 6. GWL distribution of fractured aquifers in the Nhue—Day river basin: lelft—dry season; right—wet season.

of all seven observation wells. Due to limited data from well fields, there is insufficient information regarding the variable lithology of the aquifer and a comprehensive understanding of how external factors impact groundwater levels and flow directions within the aquifer. The lack of detailed information on the aquifer's lithology hinders a complete characterization of its properties and behavior. Additionally, the influences of external forces, such as precipitation patterns, land use changes, and human activities, on groundwater levels and flow directions are not fully understood. Further research and data collection efforts are needed to gather more comprehensive information about the lithology of the aquifer and to study the effects of various external factors on groundwater dynamics. This knowledge would contribute to a better understanding of the aquifer system and enable more accurate assessments and management of groundwater resources in the Nhue-Day River basin.

4 Conclusions

This article investigated the feasibility of utilizing a feedforward backpropagation artificial neural network (ANN) for predicting groundwater levels. The study revealed a significant influence of precipitation and evaporation variations on well groundwater level fluctuations. The performance evaluation of the ANN model during training, testing, and validation yielded regression coefficients (R) of 0.9987, 0.998, and 0.99845, respectively. Regarding the prediction accuracy, the ANN model achieved accuracies of 0.15 m, 0.03 m, and 0.02 m for observation wells VCHB09, VCHB11, and VCHB12, respectively. These findings indicate the ANN's capability to accurately forecast groundwater levels in the mentioned observation wells. And for other four observation wells, the prediction accuracy ranges from 2.43 m to 3.33 m. The findings of this study highlight the effectiveness of soft computing techniques in accurately estimating groundwater levels in fractured aquifers. In this study, the ANN model was trained without incorporating groundwater abstraction information. The assumption made was that the patterns of groundwater abstraction observed during the training period would remain consistent in the future. Nevertheless, despite this drawback, ANN models remain valuable tools for estimating GWLs when complete hydrological and hydrogeological data are not accessible, and a physically based hydrologic model cannot be applied.

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