Hindawi
International Journal of Geophysics
Volume 2022, Article ID 2487656, 12 pages
https://doi.org/10.1155/2022/2487656

Research Article

Groundwater Level Forecasting in the Jakarta Groundwater Basin

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Received 5 September 2022; Revised 21 October 2022; Accepted 25 October 2022; Published 9 November 2022

Academic Editor: Angelo De Santis

Groundwater is an important source of fresh water worldwide. Jakarta, the capital city of the Republic of Indonesia, is a large city with a population of more than 10 million and the center of the country's economy and urban development. However, Jakarta has many challenges related to groundwater management. Changes in well GWL serve as a direct indicator of the effects of groundwater evolution, and GWL time series usually contain important information about aquifer dynamics. Therefore, water managers and engineers must model and predict GWL, identify and measure groundwater resources, and maintain a balance between supply and demand. Measuring and analyzing the groundwater table (GWL) of an aquifer are an important and valuable activity in the management of groundwater resources, and information on GWL variability can be used to determine groundwater availability. Accurate and reliable groundwater level estimation is very important because it provides important information about the quantitative groundwater status of an aquifer. The main advantage of AI models is their ability to reproduce nonlinear and complex processes without a full understanding of the underlying physics. As a result, the use of AI techniques in GWL modeling continues to grow, attracting the attention of scientists around the world. Using a nonlinear autoregressive network with extrinsic input (NARX) with a timestep of 14 days, this study is aimed at predicting the volatility of Jakarta's GWL. Based on the research results, both JKT-01 and JKT-03 show a linear downward trend. On the other hand, JKT-02 and JKT-04 show a stable linear trend. GWL increases the linear trend of JKT-05. Variable results are generated by model performance. Model performance (R) varied between 0.2 and 0.9 during the training phase and between 0.2 and 0.9 during the validation phase. The overall performance of the model varies from 0.3 to 0.9. The diverse lithology and high pumping capacity in Jakarta are the reasons for the different modeling results. Forecasts for 14 days (14 timesteps) show that GWL remains constant at certain well locations, while GWL decreases at other locations. This is a consideration that stakeholders can consider to reduce the small effect of the daily GWL pattern as a result of NARX modeling.

1. Introduction

Groundwater is a necessary resource for daily needs [1]. More than 2 billion people use groundwater for drinking water and daily needs [1–3]. This is because the quality of groundwater is usually cleaner when compared to surface water (Arfanuzzaman and Atiq Rahman 2017). The need for groundwater resources will increase in the coming years due to the high demand for groundwater. The use of groundwater as a raw material is also needed by industry. In agriculture, groundwater plays an important role in meeting daily needs [4, 5]. With the many uses of groundwater, groundwater management requires serious attention. This is to prevent the impact of geological disasters caused by the lack of serious groundwater management such as land subsidence [2, 6]. Research on groundwater continues to be developed by several researchers [7–9]. Groundwater management should be a serious concern for stakeholders [10]. Scholars also use GIS for analysis in their study [11].

Jakarta, the capital city of the Republic of Indonesia [12], is a megalopolis with a population of over 10 million [13, 14] and the center of economic and urban development in Indonesia. However, Jakarta has many difficulties in groundwater management, such as land subsidence, flooding, and seawater intrusion [13, 15–20]. The Indonesian federal government and the Jakarta provincial government are striving to

achieve groundwater sustainability to protect the city from disasters caused by excessive groundwater consumption. Previous steps included the issuance of a Governor's Decree concerning restrictions on the use of groundwater by Jakarta residents, as well as the termination of new permits for groundwater drilling and the closure of boreholes in the city of Jakarta. Therefore, it is very important to manage the existing water resources in Jakarta, especially groundwater, which as a source of clean water for most of humanity, which is a major concern for the citizens of Jakarta.

Groundwater level is one indicator of the impact of groundwater utilization. Groundwater level data provides information about the condition of the aquifer in an area. Aquifer dynamics can be seen clearly through fluctuations in groundwater level [21]. Relevant stakeholders can use data from the groundwater level to make policies related to management in an area. Stakeholders can also create models to predict future groundwater conditions to ensure the availability of groundwater. Groundwater availability can be indicated from groundwater level fluctuation data through certain measurements and analysis. Thus, both groundwater level measurement and analysis are valuable and important information [21]. The quantitative condition of groundwater can be obtained if the groundwater level prediction is carried out carefully and accurately [1]. In predicting groundwater level, there are many techniques used by researchers around the world [22–24]. One of the commonly used techniques to predict groundwater level is artificial intelligence (AI) [25]. The main advantage of AI models is their ability to reproduce nonlinear and complex processes without a full understanding of the underlying physics [26]. As a result, the use of AI techniques in GWL modeling continues to grow, attracting the attention of scientists around the world. Conceptual or physics-based models have historically been the main tool for GWL modeling. However, there are some serious practical limitations: the need for large amounts of data and input parameters. In certain situations, data is scarce and making accurate predictions is more important than understanding the underlying mechanisms. Therefore, the artificial intelligence (AI) black box model can be a viable alternative [21]. AI methods have been used in recent years due to their simplicity and acceptable results, Although there are various methods for modeling and predicting aquifer GWL, including conceptual, physical, numerical, and statistical. AI methods have been used in recent years because of their simplicity and acceptable results, and many studies have evaluated the performance of AI models for GWL modeling in various regions.

In groundwater variable modeling, the use of numerical models that utilize physical relationships to describe certain areas is a common practice [27]. These models require significant amounts of data, and their development, implementation, and maintenance are time-consuming and expensive. However, artificial neural networks (ANN) provide a data-driven alternative that has gained popularity in the last decade for forecasting water resource problems [28]. Using specific training algorithms on accessible data, they were able to identify correlations between variables that resembled human brain activity. This adaptability makes ANN a useful tool for analyzing complex scenarios that are difficult to explain using conventional methods, especially when the results are more important than a complete explanation of the underlying process or when only limited system knowledge is available [29]. ANN is suitable for studying hydrological systems, which often display considerable spatiotemporal fluctuations, due to their capacity to capture system dynamics and nonlinearities [30]. Despite the widespread use of different model architectures in hydrology [28], feedforward and repeat networks remain the most common [21]. A number of studies have used artificial neural networks (ANN) to predict water resource variables (such as discharge or water level) in river systems [28]. In addition, ANN is applied in a large number of studies to estimate groundwater levels [4, 23, 29, 31–39]. Although the NARX model is used for groundwater level prediction [5, 22, 40], feedforward networks are used most often [5, 22, 40]. Izady et al. [22] investigated the effectiveness of feedforward networks and NARX for predicting groundwater levels in alluvial plains of Iran. By comparing the results of the validation period, they identified a strong benefit of NARX over static neural networks. Guzman et al. [5] applied the NARX model to examine alluvial aquifers in the United States, and several training approaches were evaluated to make daily groundwater level estimates with promising results. Chang et al. [40] used the NARX model and self-organizing map (SOM) to predict regional mean groundwater levels in alluvial fans in Taiwan.

These studies demonstrate the superiority of the NARX model in predicting groundwater levels. However, this model has been criticized in various ways, including its potential for overtraining and the difficulty in estimating parameters using a heuristic approach [41].

The Jakarta aquifer shows lithophacological and hydrostratigraphic problems. NARX modeling is aimed at reducing the complexity of the model. The main objective of this project is to predict the groundwater level in a groundwater basin in Jakarta 14 days in advance. The modeling strategy was simplified because only one water table dataset was used in this study.

2. Theory of the Nonlinear Autoregressive Network with Exogenous Input (NARX) Neural Network

ANNs are often utilized in both surface and groundwater hydrology due to their capacity to describe nonlinear interactions ([42–45]. Maier and Dandy [46] conducted a comprehensive analysis of the hydrological applications of ANNs [28].

ANNs, like their biological counterparts, are composed of neurons that are organized and interconnected in a particular fashion, [27] as specified by the network's architecture. Throughout the learning process, data is displayed on the network, and unique training algorithms seek to suit the target data by altering the weights of neural connections. Transmission functions, which are basic, predefined functions (such as linear or sigmoid), dictate the computations performed by neurons during data processing. The nonlinear,

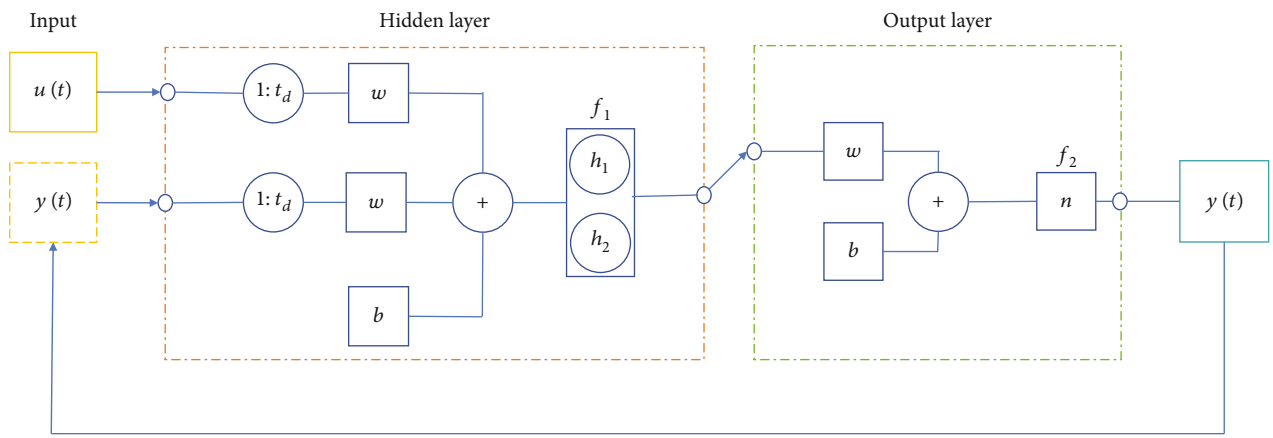

Figure 1: Architecture of the NARX model.

graded response of sigmoid transfer functions enables ANN to identify nonlinear relationships within the training data.

The multilayer perceptron (MLP), which is classified as a feedforward network (FFN), is a fundamental and commonly employed artificial neural network. These FFNs consist of multiple layers, including one for all hidden layers (HL) and another for all hidden layers (HL) (HL). The connection configuration between the levels is uncommon in that only the output layer can receive information. Recurring networks (RNN) are networks that use feedback links to facilitate lateral or reverse information flow inside the network [27]. Exogenous nonlinear autoregressive input (NARX) RNNs utilize an input-output global feedback connection. Consequently, they may be appropriate for modeling nonlinear systems. NARX can be viewed as a neural network employing the linear ARX model, a typical technique for analyzing time series. A neural network is utilized by the ARX structure to capture nonlinearities [22]. NARX converges faster than other recurrent neural networks and has greater prediction performance [47], as a result of their ability to retain information two to three times longer than other recurrent neural networks [47]. They are commonly utilised in nonlinear time series forecasting and filtering. While RNNs struggle to map long-term dependability, NARX frequently surpasses standard RNNs [47]. The output of NARX is often returned to the input layer. In consequence, the subsequent output value recalculates not only the independent input signal but also the preceding output signal [48]. This is known as a closed-loop structure, and it is commonly used to predict many steps to improve training results NARX may be taught in an open-loop scenario. In this case, the actual output, which is the observed target time series, is used as input rather than the anticipated output (closed loop). It is more accurate to display the objective rather than network outputs, which makes training significantly more effective and in most situations permits near-perfect fitness [49]. The conventional feedforward design without feedback connections facilitates training due to the network's dynamic nature, which reduces the need to modify learning methods. NARX is frequently learned in an open-loop environment and implemented in a closed-loop configuration for multistep prediction tasks.

NARX networks are a type of dynamic ANN with a high frequency of recurrence. ANNs consist of a collection of interconnected nodes known as "artificial neurons," which contain biological neurons. Each neuron can have multiple input-output connections, but each output neuron has only one input neuron. There are numerous classifications of ANNs based on the direction of information flow and processing. While the node in FNNs is positioned in layers with one-way information flow, information travels both forward and backward in recurrent networks such as NARX, allowing linkages between neurons in the same or preceding levels of FNNs [27]. Fewer input parameters are necessary to make the NARX model more efficient, which is a benefit over the FNN model [5].

$$y(t) = f\left(y(t-1), y(t-2), \cdots, y\left(t-n_y\right), u(t-1), u(t-2), \cdots, u(t-n_u)\right), \tag{1}$$

where $u(t)$ and $y(t)$ are the input and output values at time t , n_u and n_y are the input and output network layers, and f is the approximated nonlinear function. Neural Net Time Series code in MATLAB®2021a was used to implement the NARX model (Figure 1).

Using XCF cross-correlation, the temporal lag t_d between precipitation and groundwater levels has been determined. t_d was determined to be the highest point of the crosscorrelation function following the calculation of the time series [50].

$$t_{d,c} = \max\,(XCF) = \max\left(\int_0^s P(t)\mathrm{GWL}(t+\tau)d\tau\right). \tag{2}$$

s is identical for the time series P and GWL and is the delay [51]. The forecasts with a computed time delay $t_{d,c}$ were compared with those derived at four time delay values t_d typically considered in the literature and equal to 5, 25, 50, and 100 days [5]. As the time delay grows, the performance of the models can be evaluated. The number of nodes hidden was 2 and, respectively, h1 and h2, and the literature offers the optimal GWL forecasts [32].

A sigmoid f_1 was utilized for the hidden layer, while a linear f_2 was employed for the output layer using a single neuron n. The NARX designs return the output $y(t)$ to the input values. Additionally, weight w and bias b have been optimized using the subsequent training procedures. Figure 1 depicts the model architecture for NARX.

Levenberg-Marquardt (LM), often used for time series prediction with ANNs, is a popular algorithm [52, 53]. The convergence is rapid and constant [54]. Typically, it is employed to tackle nonlinear least squares issues. The Hessian matrix approximates the LM method via the following equation:

$$\Delta w = \left[J^T(w)J(w) + \lambda I\right]^{-1} J^T(w)e(w). \tag{3}$$

w is the weight vector, J is the Jacobian matrix, J^T is the transpose, I is the identity matrix, e is the error vector, and λ is the learning constant.

3. Validation Model

Based on Di Nunno and Granata [50], validation evaluates the network's ability to recognize a particular pattern. There are four commonly employed error calculations: coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and relative absolute error (RAE). The error calculation is formulated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(f_i - y_i)^2}{\sum_{i=1}^{m}(y_a - y_i)^2}, \tag{4}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{m}|f_i - y_i|}{m}, \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{m}(f_i - y_i)^2}{M}}, \tag{6}$$

$$\mathrm{RAE} = \sqrt{\frac{\sum_{i=1}^{m}|f_i - y_i|}{\sum_{i=1}^{m}y_a - y_i}}. \tag{7}$$

The primary purpose is to minimize the error value by continually modifying the weight values of each neuron in the network. Each iteration involves calculating the error associated with every neuron in the output and hidden layers to estimate the amount of weight change (Istiqomah and Setiyono 2015).

4. Hydrogeology of the Jakarta Groundwater Basin

According to Turkandi et al. [55], the study area consists of alluvium (Qa), beach ridge deposits (Qbr), alluvial fan (Qav), and dan Banten Tuff (QTvb) formation (Figure 2). Alluvium (Qa) consists of clay, silt, sand, gravel, pebble, and boulder. Beach ridge deposits (Qbr) consist of coarse sand, well sorted, with mollusc shells. Alluvial fan (Qav) consists of bedded fine tuff, sandy tuff, and conglomeratic tuff interbedded. Banten Tuff (QTvb) consists of tuff, pumice tuff, and tuffaceous sandstone.

The study area was categorized to the aquifer group with flow through the intergrain space [56]. These aquifers generally have moderate productivity with a large distribution. Poespowardoyo [57] stated that the basement of the Jakarta groundwater basin is a Tertiary-aged claystone layer with a depth of about 300 m, while Assegaf [58], Hutasoit et al. [59], and Harsolumakso [60] stated that the depth of the Tertiary-Quaternary rock boundary in the Jakarta groundwater basin varies at a depth of less than 300 m. These Tertiary-aged rocks can also act as aquifers.

The aquifer system in the Jakarta groundwater basin consists of multilayer aquifer which is grouped into four aquifer systems based on their hydraulic properties, including an unconfined aquifer system with an average depth < 40 m, an upper confined aquifer system with an average depth of 40-140 m, the middle confined aquifer system with an average depth of 140-250 m, and the lower confined aquifer system with an average depth of >250 m [57].

The aquifer system is generally composed of Quaternary deposits and underlaid by Tertiary deposits which are relatively impermeable. Assegaf [58] concluded that based on the hydraulic type, the Jakarta groundwater basin aquifer is divided into unconfined aquifer systems at a depth of <20 m and confined aquifers at a depth of 20–300 meters which are divided into seven groups. Fachri et al. [61] divided the hydrostratigraphic zone of the Jakarta groundwater basin into four zones, namely, Zone 1 in the form of aquifers composed of sandstone, conglomerate, and claystone; Zone 2 in the form of aquitars composed of claystone with sand intercalation; Zone 3 in the form of aquifers composed of sandstone with breccia intercalation and claystones, and Zone 4 is an aquitar composed of sandstone and claystone intercalation.

5. Materials and Methods

The dataset utilized in this work was collected from the Groundwater Research Division of MONAS (http://bkat.geologi.esdm.go.id/monas) (Balai Konservasi Airtanah/BKAT in Indonesian; see Figure 3). JKT-02 and JKT-05 can be found in the alluvial fan geological formation. JKT-04 is composed of alluvium (Qa). The beach ridge deposit (Qbr) formation contains JKT-01. JKT-03 can be found within the alluvium (Qa) geological formation. The daily depth to water table records of five wells are used to generate a time series (JKT-01 to JKT-05). Groundwater level information varied at each well. For JKT-01, the GWL data was used from August 8th to November 17th, 2020. For JKT-02, the GWL data was used from September 19th to October 15th, 2019. For JKT-03, the GWL data was used from August 23rd to October 15th, 2019. For JKT-04, the GWL data was used from September 2nd 2019 to July 19th, 2020. The data on the water table was utilized to train and assess NARX models. 70% of each well's initial data was used to train the models, while the remaining 30% was used for testing. The training and testing data were collected from the same seasons. The daily statistical characteristics of the

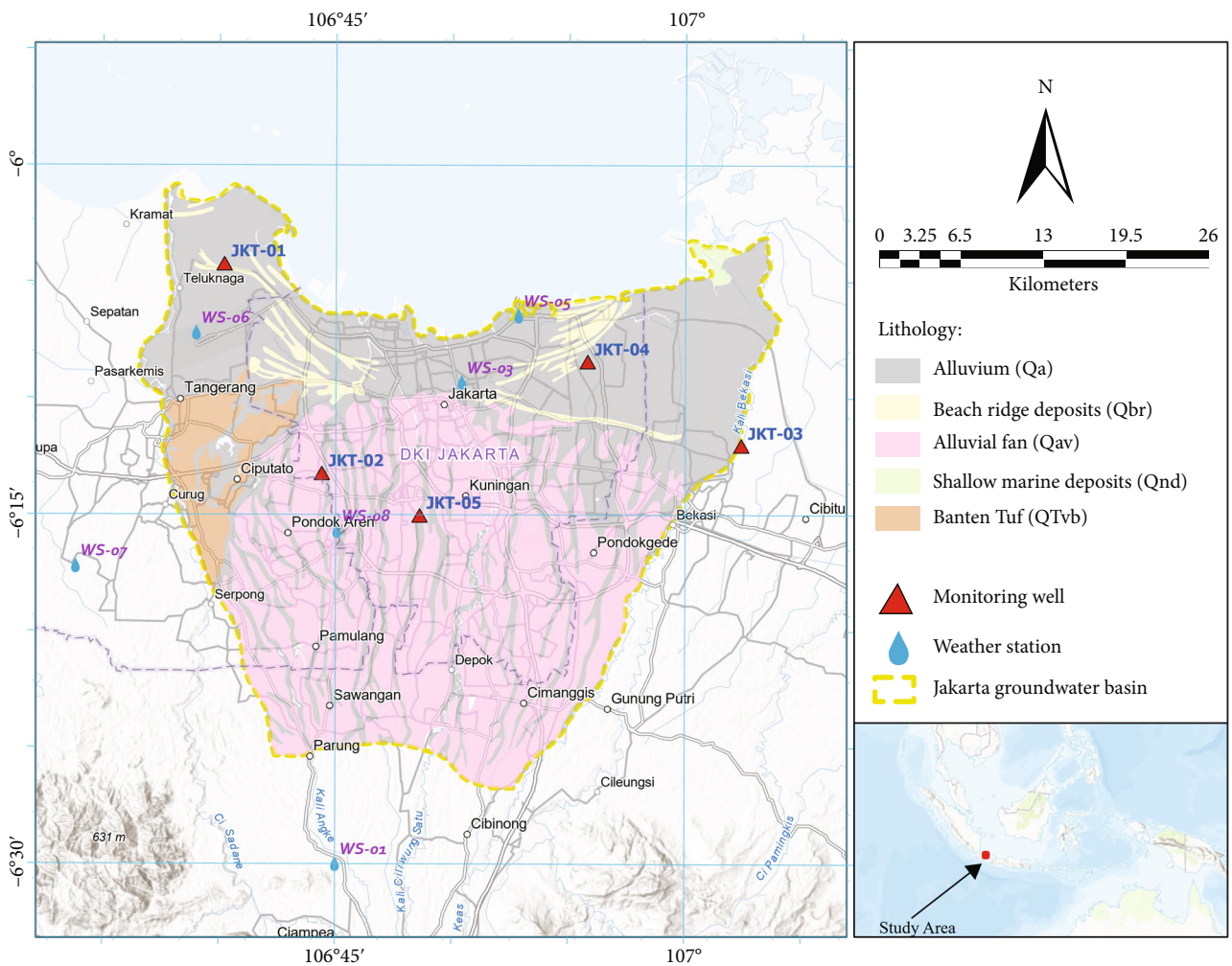

Figure 2: Study area.

Figure 3: MONAS from BKAT.

water table data will be reported in the section entitled Result and Discussion.

Figure 4 shows the flow chart of this study. Groundwater levels were the sole input parameters for modeling and forecasting (GWL). GWL can be used as easily measurable input parameters. The target data consist exclusively of groundwater level record data. After collecting input and target data, a customized dataset for each observation well is compiled. This includes collecting daily data on the groundwater level. The arithmetic mean is utilized to calculate daily GWL values. The observation wells' data time spans are chosen to have very little data gaps. Almost every gap contains a time series of groundwater level measurements. Due to the rarity and small size of the gaps, missing values were

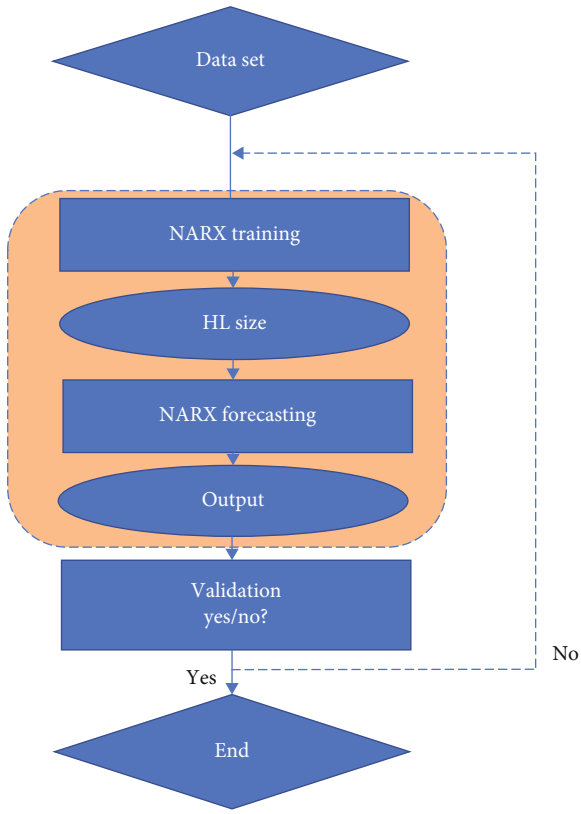

Figure 4: Flow chart.

interpolated using a linear method (maximum of four values). The subsequent phases are the time series determination of key modeling parameters (ID, FD) and the NARX training and forecasting technique.

6. Result and Discussion

6.1. JKT-01. JKT-01 has a total of 102 data (August 8th to November 17th 2020). JKT-01 has an average groundwater level value of -2.54 m. The minimum groundwater level value is -2.63, while the maximum groundwater level is -2.42 m. As for the standard deviation of the groundwater level data, JKT-01 is 0.03 m. 72 data were used as training data (70%), and 30 data were used as testing data (30%). The hidden layer size in JKT-02 is 2. The time delay in the JKT-01 model is 5. The prediction is made for 13 timesteps (13 days). The JKT-01 model uses a Bayesian regularization backpropagation algorithm.

The training results show an R value of 0.83. Test results show an R value of 0.77 (Figure 5) while the overall model shows an R value of 0.81. The test results show an R value that is smaller than the training value; however, the overall modeling results show an acceptable value.

6.2. JKT-02. JKT-02 has 39 data points (September 19th to October 15th 2019). JKT-02 has an average groundwater level of -28.61 m. The minimum groundwater level value is -28.65, while the maximum groundwater level is -28.60 m. As for the standard deviation of the groundwater level data, JKT-01 is 0.01 m. 27 data were used as training data (70%), and 12 data were used as testing data (30%). The hidden layer size in JKT-02 is 2. The time delay in the JKT-01 model is 5. Predictions are made for 14 timesteps (14 days). The JKT-02 model uses a Bayesian regularization backpropagation algorithm.

The training results show an R value of 0.4. The test results show an R value of 0.2 (Figure 6) while the overall model shows an R value of 0.32. The test results show that the R test value is smaller than the training value; however, the modeling results show an acceptable value.

6.3. JKT-03. JKT-03 has a total of 54 data (August 23rd-October 15th 2019). JKT-03 has an average groundwater level value of -21.06 m. The minimum groundwater level value is -21.52, while the maximum groundwater level is -20.63 m. As for the standard deviation of the groundwater level data, JKT-03 is 0.2 m. 38 data were used as training data (70%), and 16 data were used as testing data (30%). The hidden layer size in JKT-03 is 2. The time delay in the JKT-03 model is 5. Predictions are made for 14 timesteps (14 days). The JKT-03 model uses a Bayesian regularization backpropagation algorithm.

The training results show an R value of 0.9 (Figure 7). The test results show an R value of 0.9, while the overall model shows an R value of 0.9. The NARX model on JKT-03 shows very good results when compared to other wells.

6.4. JKT-04. JKT-04 has a total of 322 data (September 2nd 2019–July 19th 2020). JKT-04 has an average groundwater level value of -25.76 m. The minimum groundwater level

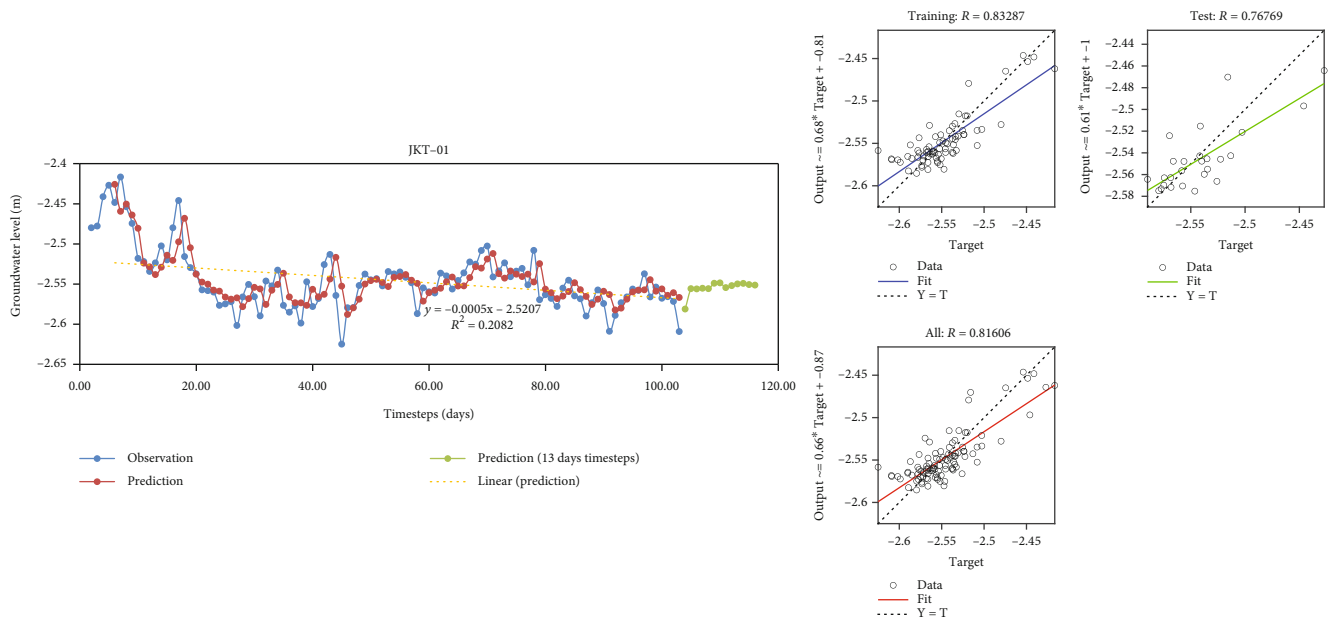

Figure 5: NARX prediction and model performance for JKT-01.

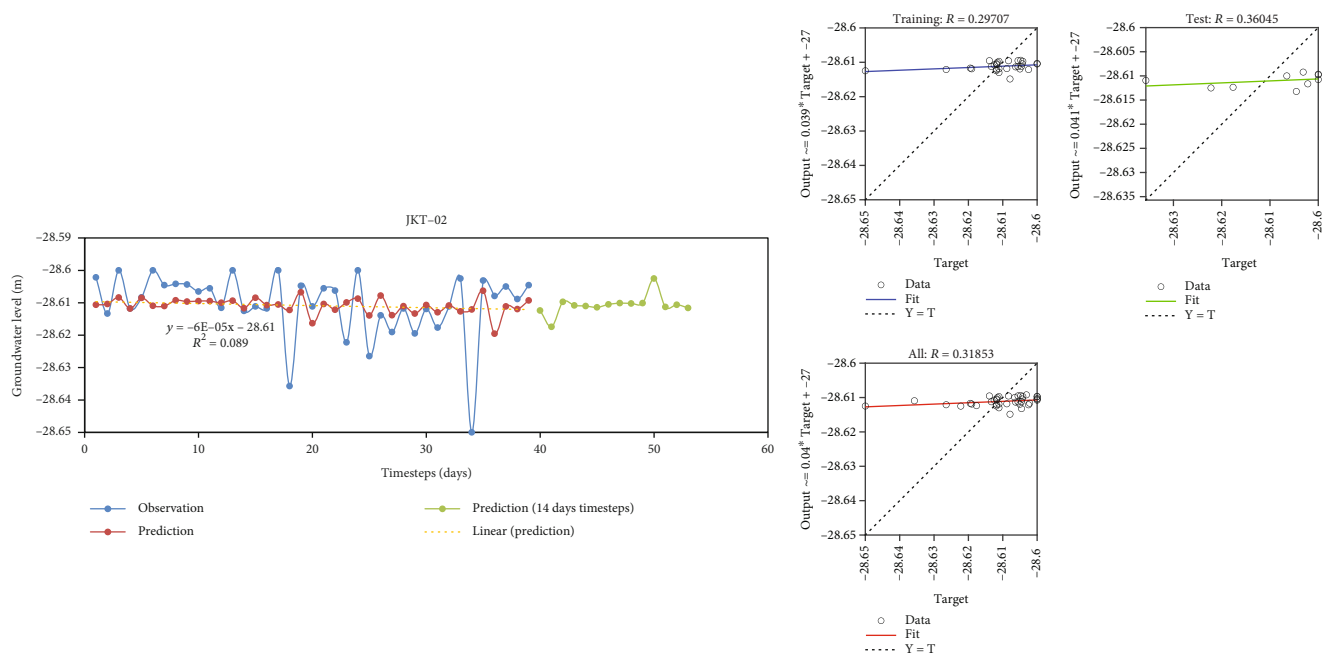

Figure 6: NARX prediction and model performance for JKT-02.

value is -31.63, while the maximum groundwater level is -9.12 m. As for the standard deviation of the JKT-04 groundwater level data, it is 6.2 m. 225 data were used as training data (70%), and 97 data were used as testing data (30%). The hidden layer size in JKT-04 is 2. The time delay in the JKT-04 model is 5. Predictions are made for 14 timesteps (14 days). The JKT-04 model uses a Bayesian regularization backpropagation algorithm.

The training results show an R value of 0.83. The test results show an R value of 0.74 (Figure 8) while the overall model shows an R value of 0.8. The NARX model on JKT-08 shows good results when compared to other wells.

6.5. JKT-05. JKT-05 has a total of 220 data (September 27th 2019–May 3rd 2020). JKT-05 has an average groundwater level value of -25.96 m (Figure 9). The minimum groundwater level value is -25.98, while the maximum groundwater level is -25.90 m. As for the standard deviation value for groundwater level, JKT-05 is 0.01 m. 154 data were used as training data (70%), and 66 data were used as testing data

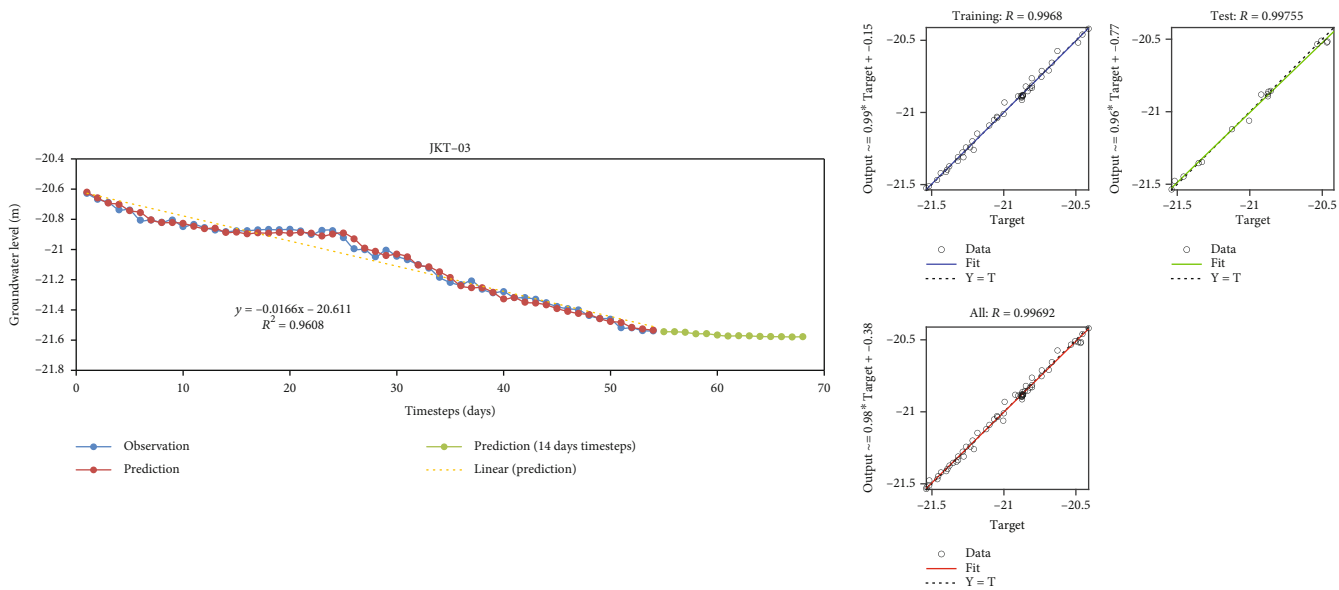

Figure 7: NARX prediction and model performance for JKT-03.

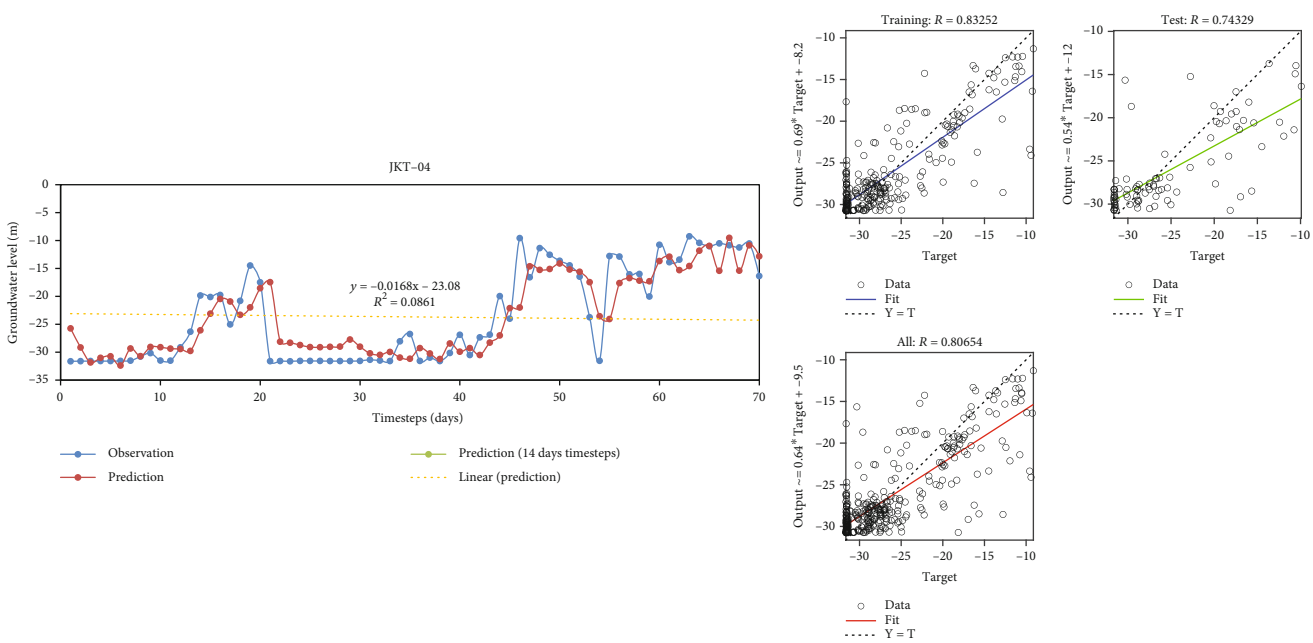

Figure 8: NARX prediction and model performance for JKT-04.

(30%). The hidden layer size in JKT-05 is 2. The time delay in the JKT-05 model is 5. Predictions are made for 14 timesteps (14 days). The JKT-04 model uses a Bayesian regularization backpropagation algorithm.

The training results show an R value of 0.9. The test results show an R value of 0.6 while the overall model shows an R value of 0.87 (Figure 9). The NARX model on JKT-05 shows good results when compared to other wells.

Well JKT-05 shows an increasing trend of GWL. JKT-05 is located in the southernmost part of the study site compared to other wells. Meanwhile, other wells in the south, i.e., JKT-02, shows a consistent trend and does not show a graph of a decline in GWL. The results of these two wells have shown a significant condition of GWL conditions in Jakarta. This result shows the positive result of what has been done by the government and stakeholders. Groundwater conservation efforts in the southern part of the study area show that groundwater in the southern part of Jakarta is recovering. Some of the challenges faced in this study are that each well has a different time span, making it difficult to compare one well with other wells at the same time. JKT-01 well is a well located in the northernmost part of the research location. This well shows a downward trend for 102 days of GWL modeling. This could be due to the

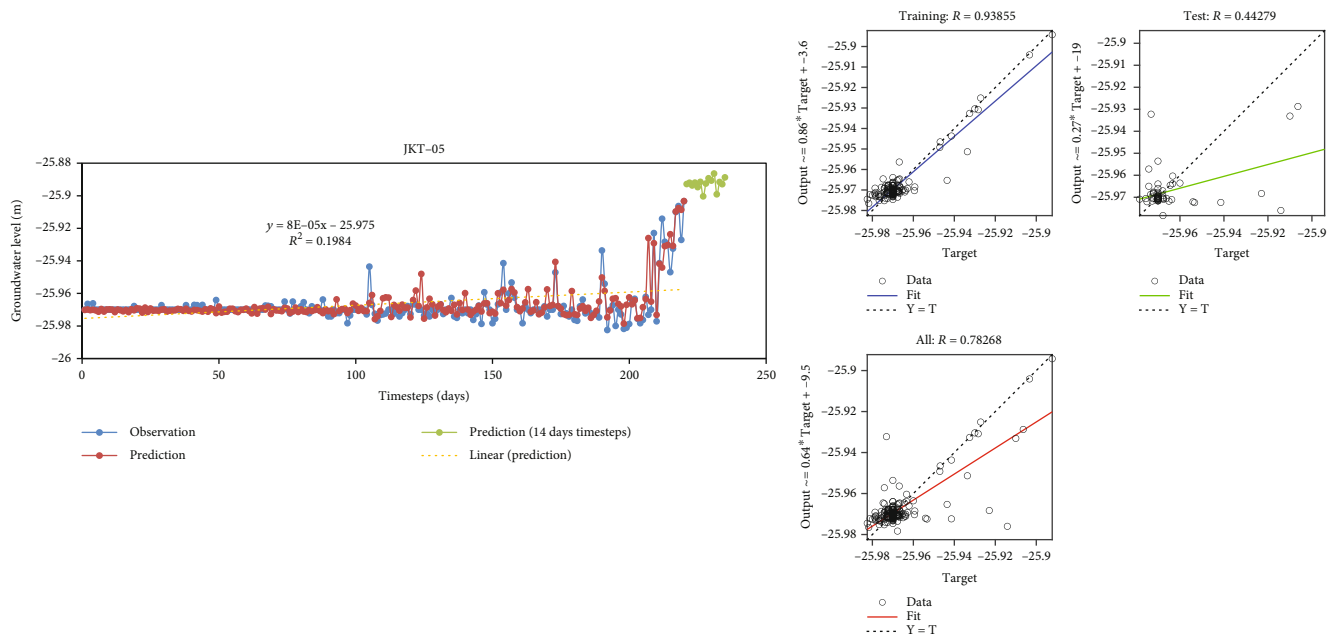

Figure 9: NARX prediction and model performance for JKT-05.

high activity of pumping groundwater in this area. This condition must be a serious concern for the government and related stakeholders. This also shows that the groundwater conditions in the northernmost area are still in critical condition. Well JKT-03 showed the most significant reduction in GWL modeling for 54 days. This can be caused by several things. The first is the lack of data for GWL modeling. Secondly, groundwater pumping activity is still high at this location. This requires serious attention from the government in the midst of groundwater conservation efforts in Jakarta. This also shows that there are still many industries that use groundwater as the main source of meeting raw water to support their activities. Well JKT-04 shows a consistent trend. At some time, JKT-04 showed an upward trend. JKT-04 well is located near the boundary of the Jakarta groundwater basin. This shows that the condition of groundwater in the recharge area tends to recover. However, the government still needs to monitor industrial activities in this area to avoid overpumping and it would be better if the industry did not use groundwater as raw water to support their industrial activities.

From all the results of the NARX modeling applied to the JKT-01 to JKT-05 well data, the results showed varied results. Generally, the modeling results show good results. Only JKT-02 has poor results ($R = 0.32$ for the overall model). Several things can cause this to happen. First, the observation data on the JKT-02 well have extreme fluctuations in the groundwater level. This could be due to the high groundwater pumping discharge around the JKT-02 well. Second is the selection of setting values for FD (feedback delay), HL (hidden layer), and algorithms unsuitable for extreme conditions in the JKT-02 well. The solution to the first problem is to check the sensor on the JKT-02 well. The second problem's solution is optimizing the parameter settings in the JKT-02 well. Of course, other anthropogenic factors around JKT-02 could have influenced the behavior of the groundwater table in the well.

JKT-03 has the best performance model compared to the other four wells. This is very likely to happen because the groundwater level data in JKT-03 tends to be stable, and there are no extreme fluctuations in the data. This causes the value of the modeling and observation results to have an excellent R value. Other than that, the location of monitoring well JKT-03 is in an area with relatively small anthropogenic effects compared to the other four wells.

7. Conclusion

This study has successfully modeled and predicted the GWL in Jakarta city using NARX. Modeling results show a good overall performance. Several wells showed poor performance due to the diversity of Jakarta's subsurface lithology and the high pumping volume in Jakarta. There is an increase in GWL in several places based on NARX forecasting; this is a good sign for stakeholders to continue the program that has been running. Meanwhile, several wells showed a decreasing pattern of GWL. This should be a serious concern for relevant stakeholders to reevaluate groundwater conditions in Jakarta. The result shows that JKT-01 and JKT-03 have a decreased linear trend. Meanwhile, JKT-02 and JKT-04 show a constant linear trend. JKT-05 shows an increased linear trend of GWL. The model performance shows result that vary. For training stage, the model performance (R) ranges from 0.2 to 0.9. For the testing stage, the model performance (R) ranges from 0.2 to 0.9. Overall model performance shows the range from 0.3 to 0.9. The various modeling results are caused by the variety of lithologies in Jakarta and the high pumping volume in this city. Prediction results for 14 days (14 timesteps) showed that some well points were at constant GWL while others showed

a decrease in GWL. This can be a consideration for stakeholders to mitigate the impact of a decrease in the daily GWL pattern as a result of the NARX modeling.

This study has several limitations, including monitoring wells used only in the northern part of the Jakarta groundwater basin. Apart from that, the distance between the monitoring well points is quite sparse, causing a wide gap. Another limitation is that the distribution of monitoring well points does not cover all geological formations suspected to be aquifers in the Jakarta groundwater basin. Apart from problems with monitoring well data as the basis for the NARX analysis, another problem in this study is the predictive ability which only covers a maximum of 14 timesteps. Exploration of other hybrid AI methods is highly encouraged for further research. This is to maximize the potential of AI. Apart from that, related to the primary data, new monitoring wells are needed in the Jakarta groundwater basin and form a network of groundwater monitoring wells. This is very important for providing primary groundwater level data. This study has proven that groundwater level fluctuations have occurred in Jakarta. Some places show an upward trend in groundwater, and in other places, it shows a downward trend in groundwater level. In places with a downward trend in groundwater level, an evaluation of groundwater use in the area must be carried out. This is intended to avoid other impacts of groundwater subsidence in the Jakarta groundwater basin, such as land subsidence. In places with a trend of rising groundwater levels, serious monitoring must still be carried out so that groundwater level decline does not occur again. The installation of new groundwater monitoring well in the southern part of the Jakarta groundwater basin is urgent. This new monitoring well is to provide the primary data of groundwater level data for groundwater analysis.

Data Availability

Most of the data used herein were collected and analyzed by the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors are grateful to the Dean of Geological Engineering Faculty, Universitas Padjadjaran, for the support.

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