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Analysis of Groundwater level in Kouhdasht Plain of Lorestan using Metaheuristic Models

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Abstract

Prediction of groundwater levels (GWL) using machine learning techniques has gained substantial attention over the past few decades. Several researchers have reported the advances in this field and provided clear understanding of the state-of-the-art machine learning models implemented for GWL modeling. In this research, a new hybrid model based on artificial neural network approaches has been developed to estimate the groundwater level. For this purpose, three optimization algorithms, including wavelet, innovative gunner, and black widow spider, were employed for modeling the groundwater level. The study utilized statistical data from four piezometers in Kouhdasht Plain of Lorestan Province, Iran, as a case study over five combined scenarios of input parameters from 2002 to 2022. To evaluate the performance of the models, correlation coefficient, root mean square error, mean absolute error, and Nash-Sutcliffe efficiency coefficient were used as assessment criteria. Additionally, time series charts and box plots were employed to analyze the model results. The findings indicated that the combined scenarios in the models improved the model's performance. Moreover, the evaluation results showed that the wavelet-support vector regression model exhibited higher accuracy than the other models across all the examined piezometric wells. Overall, the results demonstrated that the use of intelligent models based on the hybrid approach of artificial neural networks can be an effective factor in water resource management.

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Introduction

The groundwater level (GWL) is of critical importance, especially in arid and semi-arid countries. In many areas, the overexploitation of GWL has led to irreparable damage to the groundwater sources (Alfarrah and Walraevens, 2018; Bovolo et al., 2009; Priyan, 2021). Predicting GWL is a key challenge in hydrogeological investigations, effective aquifer management, and assessment of subterranean water volume (Sun et al., 2022; Barzegar et al., 2017). Hydrogeological studies have been conducted to estimate the potential of underground water, predict changes in the GWL, and examine the current state of underground water resources (Hay and Mimura, 2005; Russo and Taddia, 2009). Empirical time series models have been extensively used to predict GWL levels (Eriksson, 1970). The ability of empirical or numerical models such as finite element groundwater flow system (FEFLOW) (Ma et al., 2022), modular finite-difference flow model (MODFLOW) (Hughes et al., 2022), and HydroGeoSphere (Kang et al., 2017) to estimate the GWL has made these models helpful in predicting the GWL (Trefry and Muffels, 2007; Wang et al., 2008; Brunner and Simmons, 2012).The prediction of GWL is crucial for sustainable water resource management, as accurate forecasts contribute to understanding the availability and distribution of groundwater, essential for purposes such as agriculture, drinking water supply, and ecosystem maintenance (Singh et al., 2021a; Pragnaditya et al., 2021; Khan et al., 2023). In recent years, due to the non-linear and complex nature of hydrogeological issues, models based on artificial intelligence approaches have been utilized. These models are inspired by the nature of living organisms and are capable of solving problems with great complexity and extent. These models have gained attention from researchers in the field of groundwater level prediction, which can be referred to with the following points:

Mirzania et al. (2023) developed a hybrid model combining artificial neural networks (ANN) with the Harris Hawk optimization algorithm to predict groundwater levels in the Shabestar plain. Using data from 21 piezometric wells (2001–2019), their results demonstrated that integrating optimization algorithms with ANN significantly enhances model performance. Similarly, Saroughi et al. (2023) evaluated hybrid models—Support Vector Regression (SVR) with the Badger algorithm and ANN with the Badger algorithm—for groundwater simulation in the Shabestar plain. Analyzing data from 20 wells (2001–2022), they found that coupling intelligent models with optimization algorithms improves predictive accuracy.

Mirboluki et al. (2024) compared multiple models—Long Short-Term Memory (LSTM), ANN, Grey Wolf-optimized ANN, and LSTM-Grey Wolf—for groundwater prediction in the Mashhad plain. Based on data from 86 wells, their study identified the Grey Wolf-optimized ANN as the top-performing model. Feng et al. (2024) assessed traditional and deep learning models—including CNN, RNN, SVM, Decision Trees, Random Forests, and GAN—for groundwater forecasting in Izeh County, Khuzestan. Using precipitation, discharge, and extraction data (2018–2022), they concluded that Convolutional Neural Networks (CNN) outperformed other models.

Elmotawakkil et al. (2024) tested Gradient Boosting Regression, SVR, Random Forest, and Decision Trees for groundwater estimation in Morocco's Rabat plain. Incorporating GRACE/MODIS satellite data and environmental variables (e.g., temperature, soil moisture, vegetation index), their results highlighted Gradient Boosting Regression as the most accurate model. Artificial neural networks have proven effective for groundwater estimation, but recent advancements emphasize hybridizing ANN with metaheuristic algorithms to enhance performance. This study introduces a novel approach by integrating ANN with Wavelet Transform (WT), the Innovative Gunner algorithm, and the Black Widow Spider algorithm to predict groundwater decline in the Kuhdasht Plain, Lorestan Province.

The Kuhdasht Plain, classified as a prohibited plain due to severe depletion, faces critical challenges:

- Excessive groundwater extraction for agriculture, drinking, and industry.
- Illegal well drilling and climate change exacerbating resource depletion.
- Land subsidence and well drying as direct consequences.

While ANN models have been applied in the region, no prior research has explored the efficacy of Wavelet Transform, Innovative Gunner, or Black Widow Spider algorithms for groundwater prediction. This study aims to bridge this gap by:

1. Developing hybrid ANN models coupled with the aforementioned algorithms.
2. Evaluating their performance using climatic data, historical groundwater levels, and extraction records.
3. Providing actionable insights for sustainable water resource management in Kuhdasht

Materials and Methods

Study Area

The Kuhdasht Plain is one of the main aquifers located in the western part of the Lorestan Province at geographical coordinates 33°26′ to 33°36′ North and 47°16′ to 47°27′ East. This plain has an area of 1,129 square kilometers and is one of the study areas of the Karkheh River Basin. The climate is relatively warm, with an annual precipitation of 443 millimeters. The groundwater table in this plain is of the unconfined type and is oval-shaped, located in alluvial deposits in the northern part of the study area. The extent of this aquifer is equivalent to 248.8 square kilometers, and the average altitude of the plains and mountains is 1,261 meters and 1,396 meters, respectively, with an overall average elevation for the entire study area of 1,360 meters above sea level. The location of the study area is shown in Figure 1.

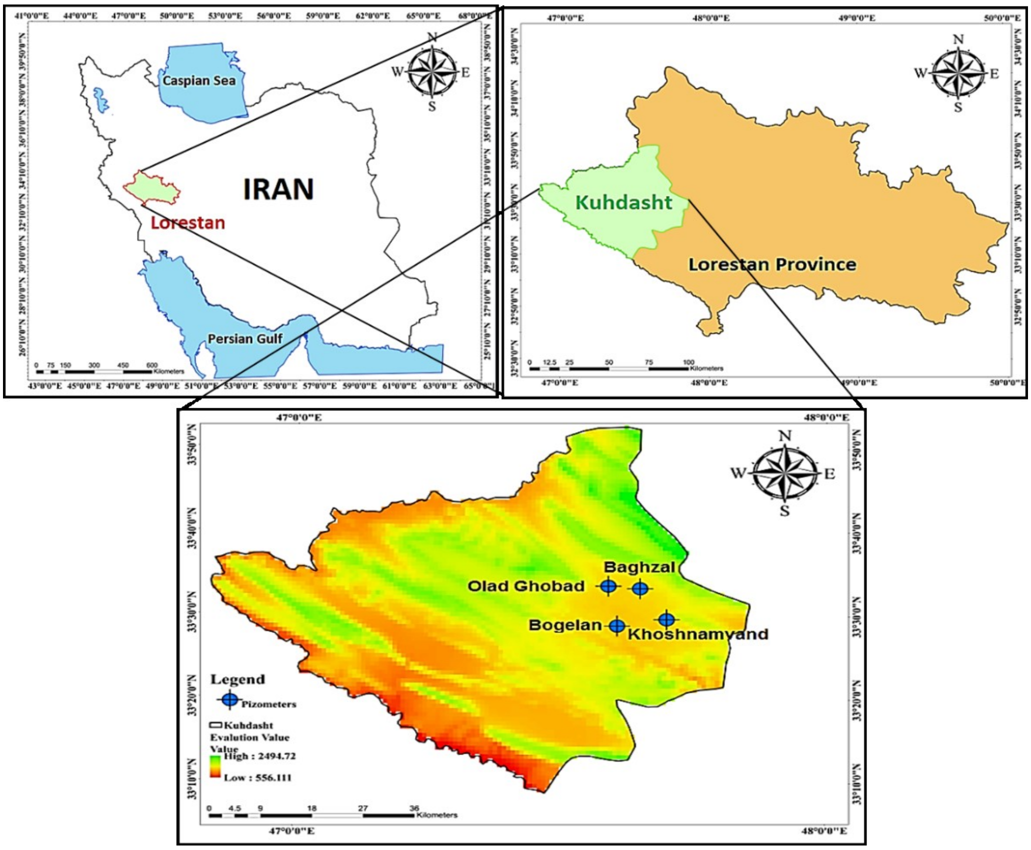

Figure 1. Location of the study area in Lorestan Province of Iran

In this research, data from four piezometric wells with long-term records and no missing data were utilized. For modeling, monthly parameters including precipitation §, temperature (T), groundwater level (H), and water extraction (q) were used, obtained from the Lorestan Regional Water Company for the period from 2002 to 2022. Of the data, 70% was used for modeling and model creation (training), while 30% was reserved for model validation and evaluation (testing) (Khosravi et al., 2018). Table 1 presents the geographical location of the studied piezometric wells, and Table 2 shows the statistical characteristics of groundwater levels in the studied piezometers.

Table 1. Geographical location of the study stations

Number	Name of Pizometers	Longitude	Latitude	Elevation(m)
1	Baghzal	47˚38' 57"	33˚33' 15"	1226
2	Khoshnamvand	47˚41' 59"	33˚29' 33"	1209
3	Olad Ghobad	47˚35' 21"	33˚33' 31"	1215
4	Bogelan	47˚39' 52"	33˚28' 38"	1188

Artificial Neural Network

Artificial neural networks (ANNs) have become a fundamental tool in hydrology and water resource management (Hornik, 1998). A typical ANN structure comprises three layers:

1. Input layer: Receives and preprocesses data
2. Hidden layer(s): Performs computations through interconnected nodes
3. Output layer: Produces the network's predictions

The practical implementation of ANNs advanced significantly with multilayer perceptrons (Dehghani & Torabi Poudeh, 2021). Research has demonstrated that feedforward networks using backpropagation learning algorithms with three-layer architectures can effectively solve complex engineering problems and model hydrological time series (Nourani et al., 2009). Common activation functions in these networks include sigmoid and hyperbolic tangent functions (Nourani et al., 2011). Figure 2 illustrates this network architecture.

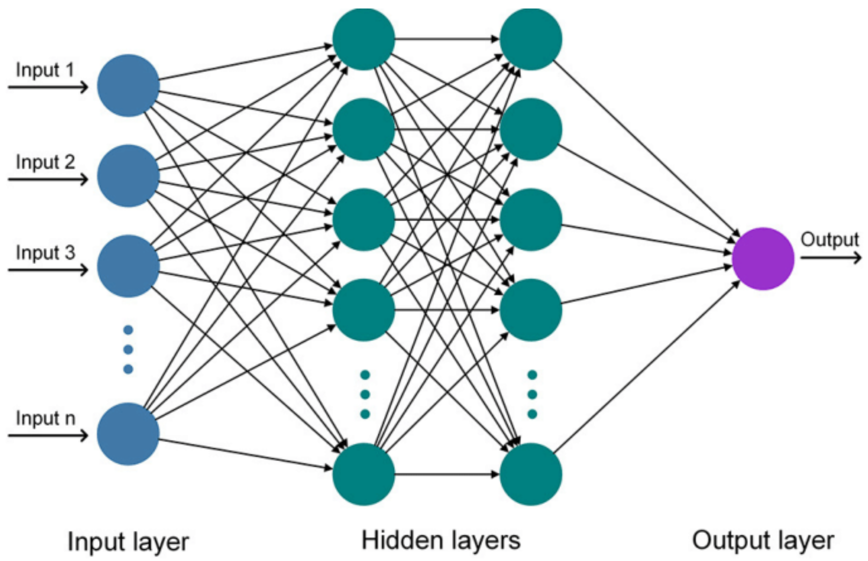

Figure 2. General view of an artificial neural network

Wavelet Transform

The Wavelet Transform is presented as an alternative method to the Short-Time Fourier Transform, designed to address limitations in frequency resolution inherent to the Short-Time Fourier Transform. Similar to the Short-Time Fourier Transform, the signal of interest is divided into windows, with the wavelet transform applied separately to each window (Wang et al., 2000). The most significant distinction between these methods lies in the wavelet transform's ability to adapt both frequency resolution and window width (or scale) according to the frequency characteristics of the signal. Rather than operating solely on frequency, the wavelet transform functions on a scale basis, making it fundamentally a time-scale transformation.

Through wavelet transform, high-scale analysis expands the signal, enabling detailed examination of its features, while low-scale analysis compresses the signal, facilitating the study of its broader characteristics. The term "wavelet," meaning "little wave," refers to a localized segment of the original signal where energy is temporally concentrated. Wavelet analysis decomposes a parent signal or time series into constituent wavelets of varying resolution levels and scales. These wavelets represent translated and scaled versions of the parent signal, characterized by finite-duration oscillations and rapid decay (Noorani et al., 2018). This critical property of wavelet transform allows for effective local analysis of non-stationary and transient time series (Shin et al., 2005).

The Algorithm of Innovative Gunner (AIG)

The algorithm of innovative gunner is one of the latest meta-innovative optimization algorithms proposed by Pijarski & Kacejko (2019). The steps for implementing this algorithm are summarized as follows:

1. Start the model at a starting point (the initial value for the first bullet determined randomly);
2. Determine the firing distance (firing distance of the bullet from the gun to the target point);
3. Calculate the produced bullet (the second bullet in the third stage taken from the first bullet);
4. Check the possibility of a bullet hitting the target (the location shot - did the bullet hit the target correctly?);
5. Select N random bullets as the main bullets (in case of hitting the target correctly);
6. Check and update the position where the bullet hits the target (if the bullet hits the center of the target, the termination condition will be fulfilled and the work will be completed; however, if it does not, the initial value must be redetermined);
7. Determine the best registered position;
8. Finish.

Figure (3) shows the general flowchart of the algorithm of the innovative gunner.

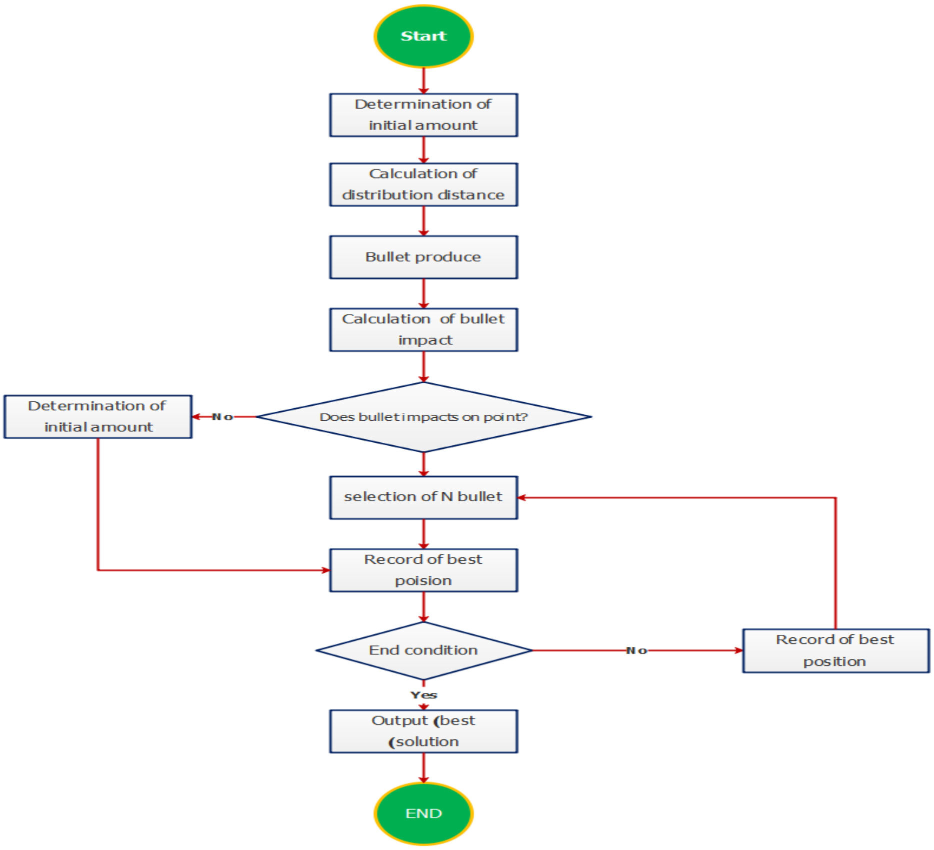

Figure 3. General flowchart of the AIG

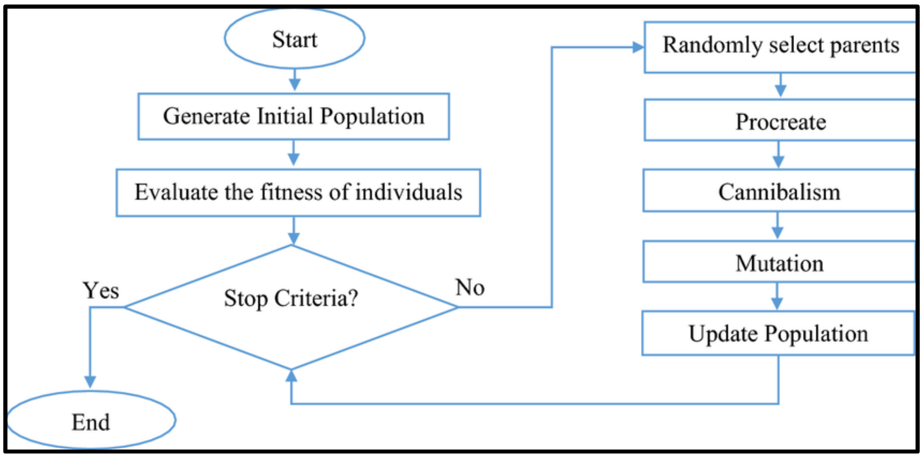

Figure 4. General flowchart of the BWO

Black Widow Optimization (BWO)

This algorithm was first introduced by Sebastian and Peter (2009) based on the survival of the superiors or natural selection. In this algorithm, primary spiders mate and attempt to reproduce a new generation. The female black widow swallows the male mate during/after the mating process. Then, it carries the stored sperms in its sperm sack and releases them in its ovule sack. To solve an optimization problem, the values for variables must be identified in a proper structure. This structure is known as "chromosome" and "particle location" in genetic algorithm and particle swarm optimization, respectively, and "widow" in BWO. In the BWO algorithm, the potential solution to any problem is considered as a black widow spider. Figure (4) shows the general flowchart of the algorithm of the black widow optimization.

Evaluation Criteria

In this study, the following evaluation indicators were used to evaluate the models under study for estimating groundwater levels.

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

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\ (x_i-y_i)^2} \qquad (2)$$

$$MAE=\frac{\sum_{i=1}^{n}|x_i-y_i|}{n} \qquad (3)$$

$$NS=1-\frac{\sum_{i=1}^{N}\ (x_i-y_i)^2}{\sum_{i=1}^{N}\ (x_i-\bar{y})^2}\quad \infty\leq NS\leq 1 \qquad (4)$$

In the above relations, R is the correlation coefficient, RMSE is the root mean square error in terms of m, NS is the Nash-Sutcliffe criterion, x_i and y_i are the observed and calculated values at the i-th time step, N is the number of time steps, x¯and y¯are the average of the observed and calculated values, respectively. In addition to the above criteria, scatter plots and time series of the observed-calculated values over time are also used for further comparison and analysis.

Results and Discussion

In this research, a hybrid artificial neural network model incorporating wavelet algorithms, the Innovative Gunner method, and the black widow spider optimization technique was employed to model groundwater levels in the Kouhshad Plain of Lorestan Province, Iran. The model utilized precipitation (P), temperature (T), and groundwater extraction (q) as input parameters, with groundwater level (H) serving as the output variable. Monthly data from 2012 to 2022 for four piezometric wells were analyzed. The fundamental objective of intelligent modeling approaches is to characterize relationships between variables where natural complexities create significant uncertainty. Groundwater level, being a crucial hydrogeological parameter, holds particular importance for future projections. This study employed advanced hybrid methods to minimize estimation errors and achieve high predictive accuracy using minimal input parameters, demonstrating superior performance compared to conventional approximation techniques.

The primary research aim was to capture the inherent complexity among hydrological parameters and develop a robust predictive model. Given the paramount importance of groundwater levels among hydrogeological variables, this parameter was selected as the target output. For model development, the dataset was partitioned with 70% randomly selected for training and the remaining 30% reserved for testing, ensuring comprehensive coverage of data variability (Nagy et al., 2002; Kisi and Karhan, 2006). A critical modeling phase involves selecting optimal input variable combinations. In intelligent modeling frameworks, choosing appropriate initial inputs that effectively represent the underlying phenomena significantly enhances model performance. Accordingly, for groundwater level prediction, careful selection was made of the most representative observational data for training purposes (Dehghani et al., 2020). Multiple input parameter combinations were evaluated to identify the optimal configuration for groundwater level estimation, as detailed in Table 2.

Table 2. Combinations of input variables for the selection of the best model

Number	Input	Output
1	P(t)	H(t)
2	T(t)	H(t)
3	P(t), T(t)	H(t)
4	T(t), P(t), q(t)	H(t)
5	T(t), P(t), q(t), H(t-1)	H(t)

To model the groundwater level, a hybrid artificial neural network model was employed, utilizing wavelet algorithms, Innovative Gunner and black widow spider. Additionally, different activation functions were used in the artificial neural network model, with the hyperbolic tangent function providing suitable accuracy compared to other functions. The artificial neural network model has tuning parameters, including weights and biases, which are typically selected randomly by the model in conventional models. However, today, optimization algorithms are used to predict these values to their best possible estimates in order to enhance model accuracy. In this research, values were estimated using wavelet algorithms, Innovative gunner, and black widow spider. Therefore, after entering the input parameters into the model and optimizing the tuning parameters, the structure of the hybrid model is formed, leading to the computational response of the model. Since the stopping criterion in training artificial intelligence models is based on the level of error, the model stops at the lowest possible error, resulting in the final output.

As shown in Table 3, hybrid models in scenario number 5, which includes all input parameters to the model, have less error compared to other scenarios. Therefore, increasing the number of effective parameters in hybrid models based on artificial neural networks leads to improved model performance. The results of the models examined in scenario number 5 are presented in Table 3. As indicated in the table, in all investigated wells, the artificial neural network-wavelet model demonstrated better performance. For instance, in the piezometric well of Baghzal, the highest correlation coefficient is 0.970, the lowest root mean square error (RMSE) is 0.231, the lowest mean absolute error (MAE) is 0.021, and the highest Nash-Sutcliffe efficiency coefficient is 0.980. Similarly, in the piezometric well of Khoshnamvand, the highest correlation coefficient is 0.970, the lowest RMSE is 0.177, the lowest MAE is 0.091, and the highest Nash-Sutcliffe efficiency coefficient is 0.978. For the piezometric well of Bogelan, the parameters are the same: highest correlation coefficient of 0.982, lowest RMSE of 0.124, lowest MAE of 0.068, and highest Nash-Sutcliffe efficiency coefficient of 0.990. Finally, in the piezometric well of Olad Ghobad, similar results were observed with the highest correlation coefficient of 0.975, lowest RMSE of 0.195, lowest MAE of 0.093, and highest Nash-Sutcliffe efficiency coefficient of 0.982. Overall, better performance was shown during the validation phase. In Figures 5-8, the time series chart of observed and computed values is shown. As observed, the artificial neural network-wavelet model demonstrates acceptable accuracy in estimating most points, including minimum, maximum, and median values, compared to the hybrid models of artificial neural network-Innovative gunner, artificial neural network-black widow spider, and the traditional artificial neural network. The artificial neural network-Innovative gunner model also shows good performance in estimating most points. However, the artificial neural network-black widow spider and the traditional artificial neural network have shown relatively satisfactory performance in estimating median values but performed poorly in estimating minimum and maximum values. In Figure 6, a box plot of the models under investigation is presented. As seen, the artificial neural network-wavelet model shows better performance in estimating the first quartile and median values compared to the observational data, while the artificial neural network-black widow spider performed poorly, and the artificial neural network-Innovative gunner achieved satisfactory accuracy, ranking second. Figure 9 shows the box plots of the models under consideration. As can be seen, the WANN model shows better performance than the observed data in estimating the first quartile and median values, while the AIG-ANN model has acceptable performance and ranks second. The BWO-ANN and ANN models, however, show poor performance. As shown in Figure 9, in the piezometric wells of Baghzal, Khoshnamvnd, Olad Ghobad, and Boogalan, the WANN model has performed well in estimating the first quartile, third quartile, and median values.

All models also have good accuracy in estimating the minimum and maximum values. The single ANN model also performed well in estimating the median values, but performed poorly in estimating the first and third quartiles. Therefore, according to this box plot, the new AIG-ANN model has good accuracy in estimating the groundwater level. Therefore, the artificial neural network-wavelet model exhibits better performance than the other models under investigation, and these results are consistent with the studies of Zeidalinejad and Dehghani (2023) and Dehghani and Babaali (2023). Analyzing these results reveals that the superiority of this model is due to the wavelet transform, which divides the received signals into two categories: high-pass and low-pass. In the high-pass category, the resolution power is increased, allowing for the maximum values of the signal to be analyzed with satisfactory accuracy. The artificial neural network-Innovative Gunner model combines continuous and discrete optimization, reducing the time to find an optimal solution in a broad search area by avoiding local optimum solutions. This makes the algorithm suitable for solving nonlinear problems in high dimensions with an appropriate convergence speed towards a satisfactory optimal answer. This characteristic results in this model having higher accuracy compared to other models. Overall, it is recommended to use the hybrid artificial neural network-wavelet and Innovative gunner model as a model with minimal error for solving nonlinear problems in high dimensions, with an appropriate convergence speed towards an optimal solution. It can also be considered a novel approach for predicting groundwater levels to make suitable management decisions for improving water resources.

Table 3. Performance evaluation of models for simulation of piezometer wells

Baghzal								
Model	**Training**				**Testing**			
	R^2	**RMSE**	**MAE**	**NS**	**R^2**	**RMSE**	**MAE**	**NS**
WANN	0.945	0.422	0.235	0.960	0.970	0.231	0.021	0.980
AIG-ANN	0.940	0.694	0.462	0.955	0.950	0.435	0.214	0.960
BWO-ANN	0.920	0.876	0.683	0.930	0.935	0.654	0.324	0.940
ANN	0.910	0.944	0.724	0.915	0.920	0.710	0.458	0.930

Khoshnamvand								
Model	**Training**				**Testing**			
	R^2	**RMSE**	**MAE**	**NS**	**R^2**	**RMSE**	**MAE**	**NS**
WANN	0.960	0.348	0.184	0.966	0.970	0.177	0.091	0.978
AIG-ANN	0.935	0.593	0.345	0.942	0.955	0.336	0.154	0.962
BWO-ANN	0.920	0.725	0.548	0.928	0.936	0.535	0.266	0.944
ANN	0.910	0.915	0.722	0.917	0.925	0.706	0.357	0.932

Olad Ghobad								
Model	**Training**				**Testing**			
	R^2	**RMSE**	**MAE**	**NS**	**R^2**	**RMSE**	**MAE**	**NS**
WANN	0.955	0.393	0.211	0.962	0.975	0.195	0.093	0.982
AIG-ANN	0.922	0.642	0.321	0.947	0.950	0.352	0.164	0.965
BWO-ANN	0.915	0.853	0.432	0.934	0.937	0.525	0.277	0.947
ANN	0.907	0.964	0.538	0.921	0.926	0.742	0.361	0.935

Bogelan								
Model	**Training**				**Testing**			
	R^2	**RMSE**	**MAE**	**NS**	**R^2**	**RMSE**	**MAE**	**NS**
WANN	0.965	0.237	0.118	0.974	0.982	0.124	0.068	0.990
AIG-ANN	0.950	0.484	0.240	0.968	0.971	0.178	0.112	0.980
BWO-ANN	0.932	0.636	0.322	0.947	0.946		0.397	0.950
ANN	0.921	0.822	0.420	0.933	0.935	0.428	0.208	0.940

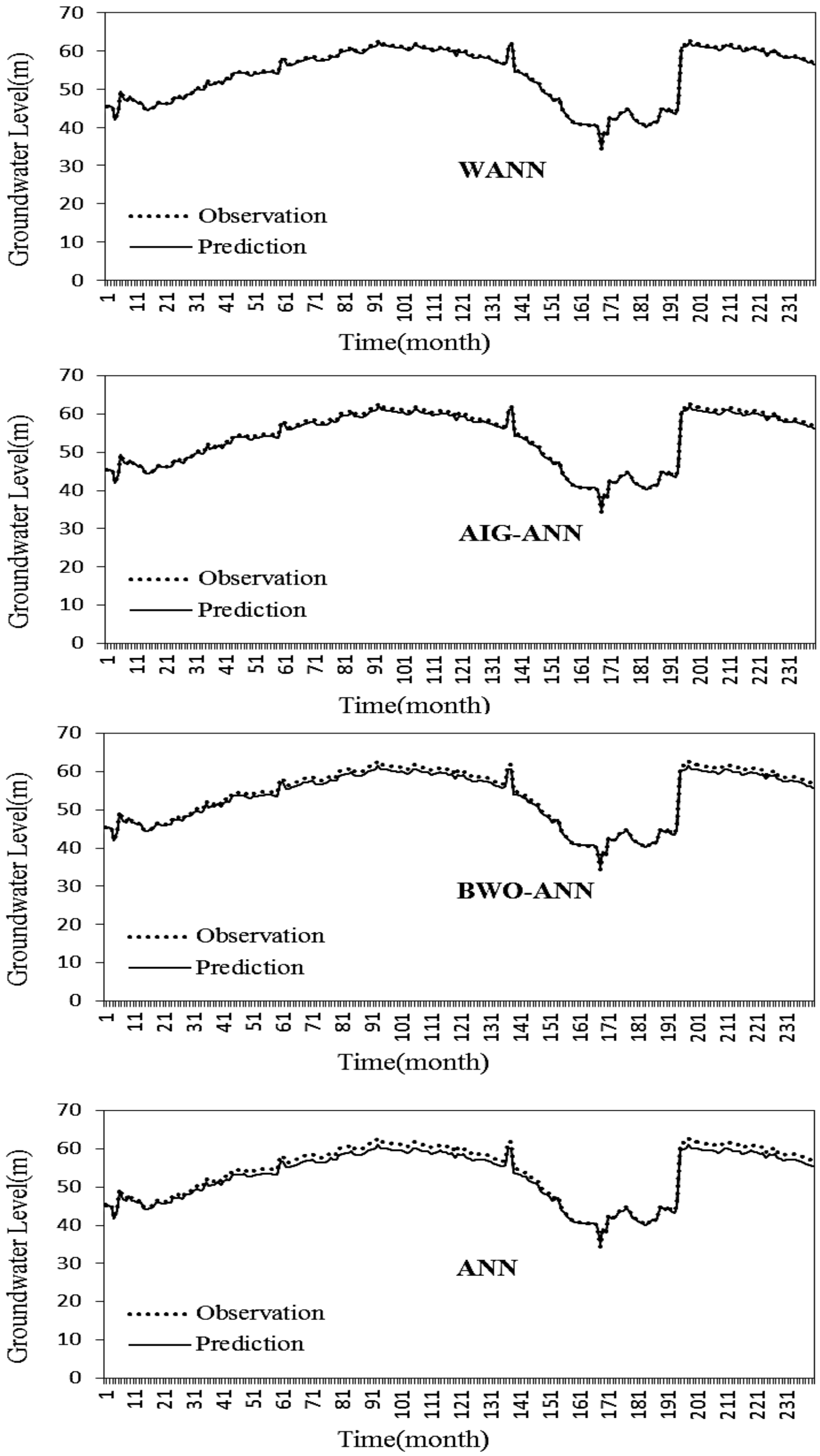

Figure 5. Time series plot of the Baghzal pizometer

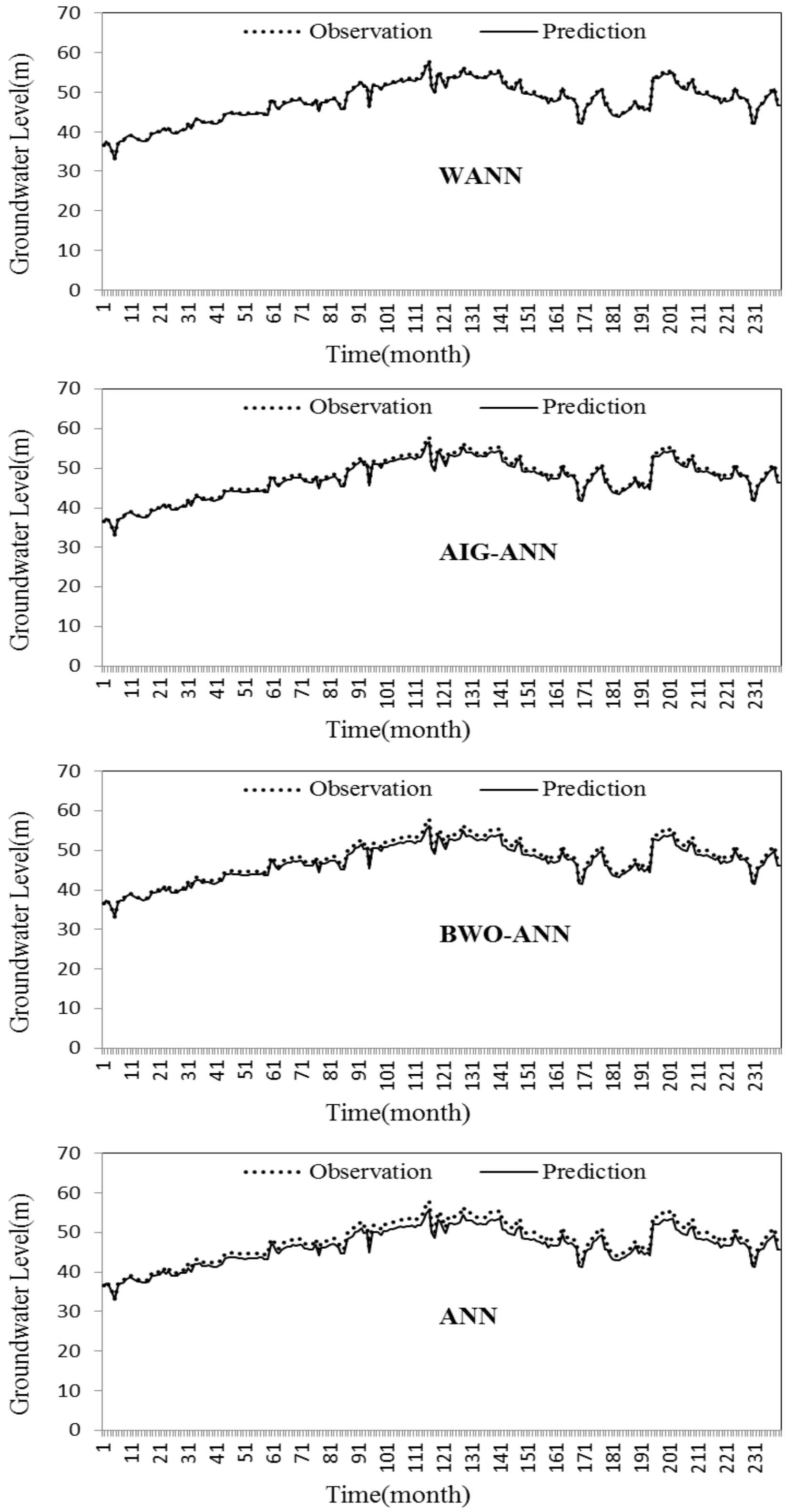

Figure 6. Time series plot of the Khoshnamvand piezometer

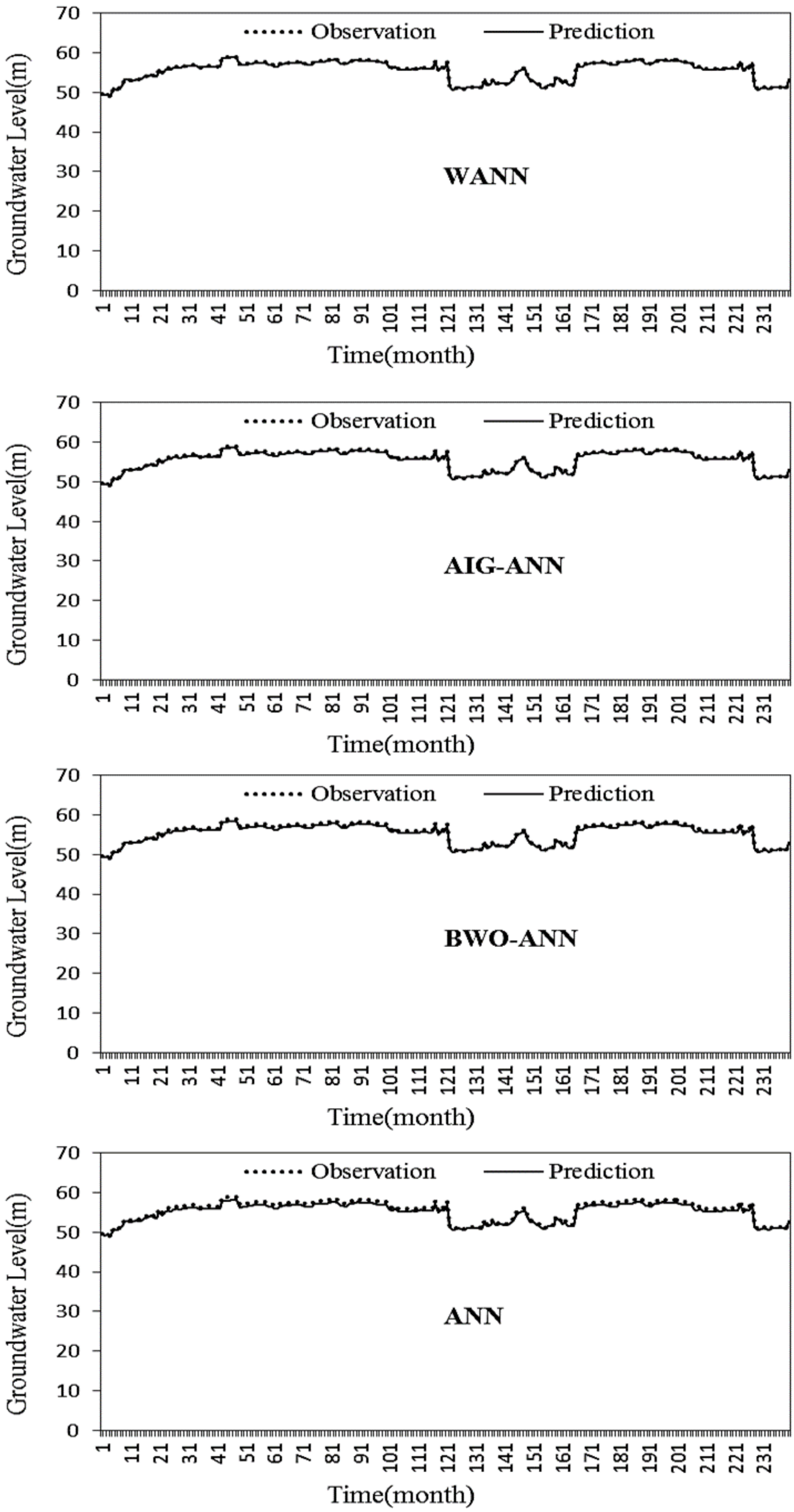

Figure 7. Time series plot of the Olad Ghobad piezometer

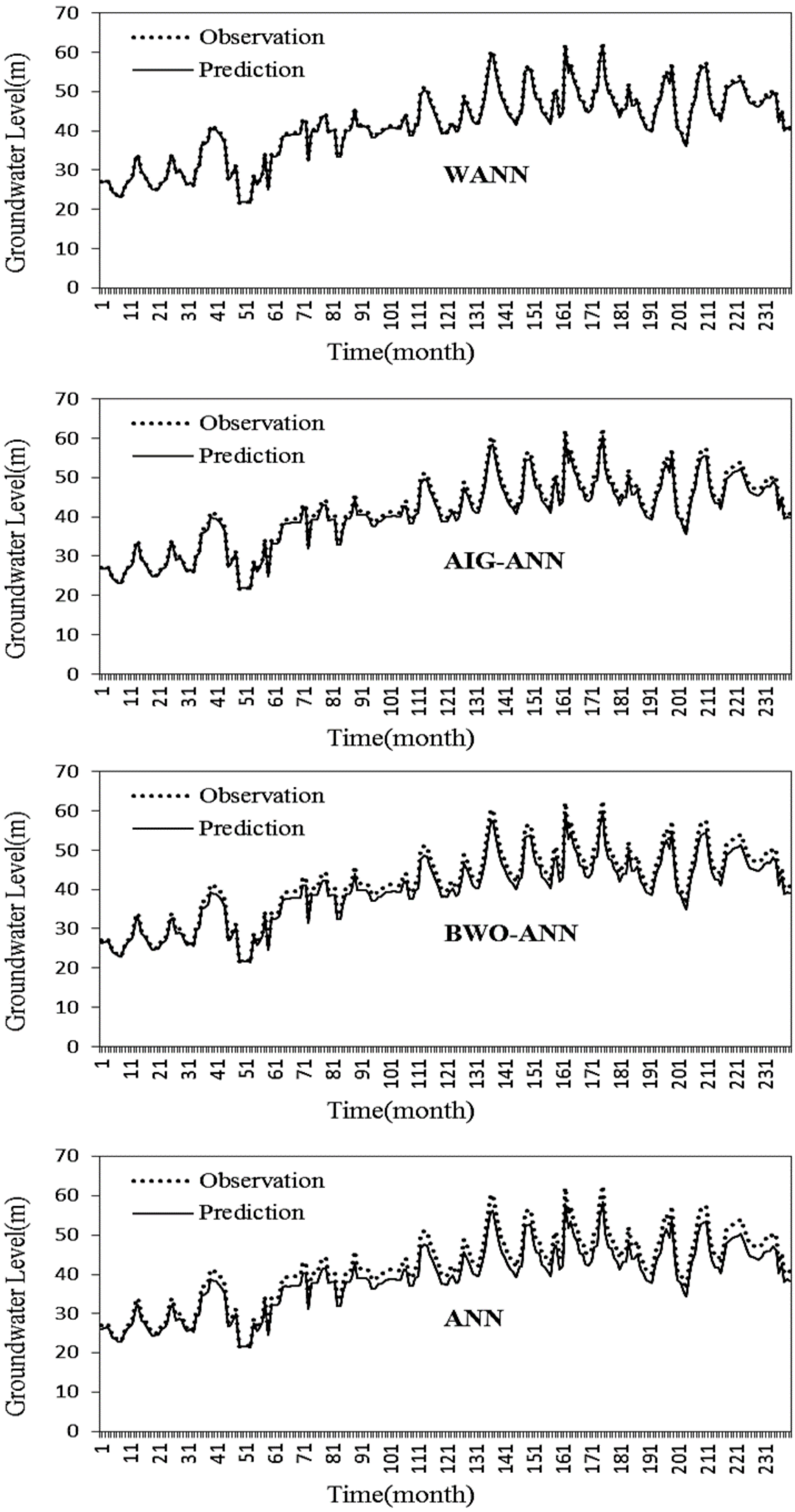

Figure 8. Time series plot of the Bogelan piezometer

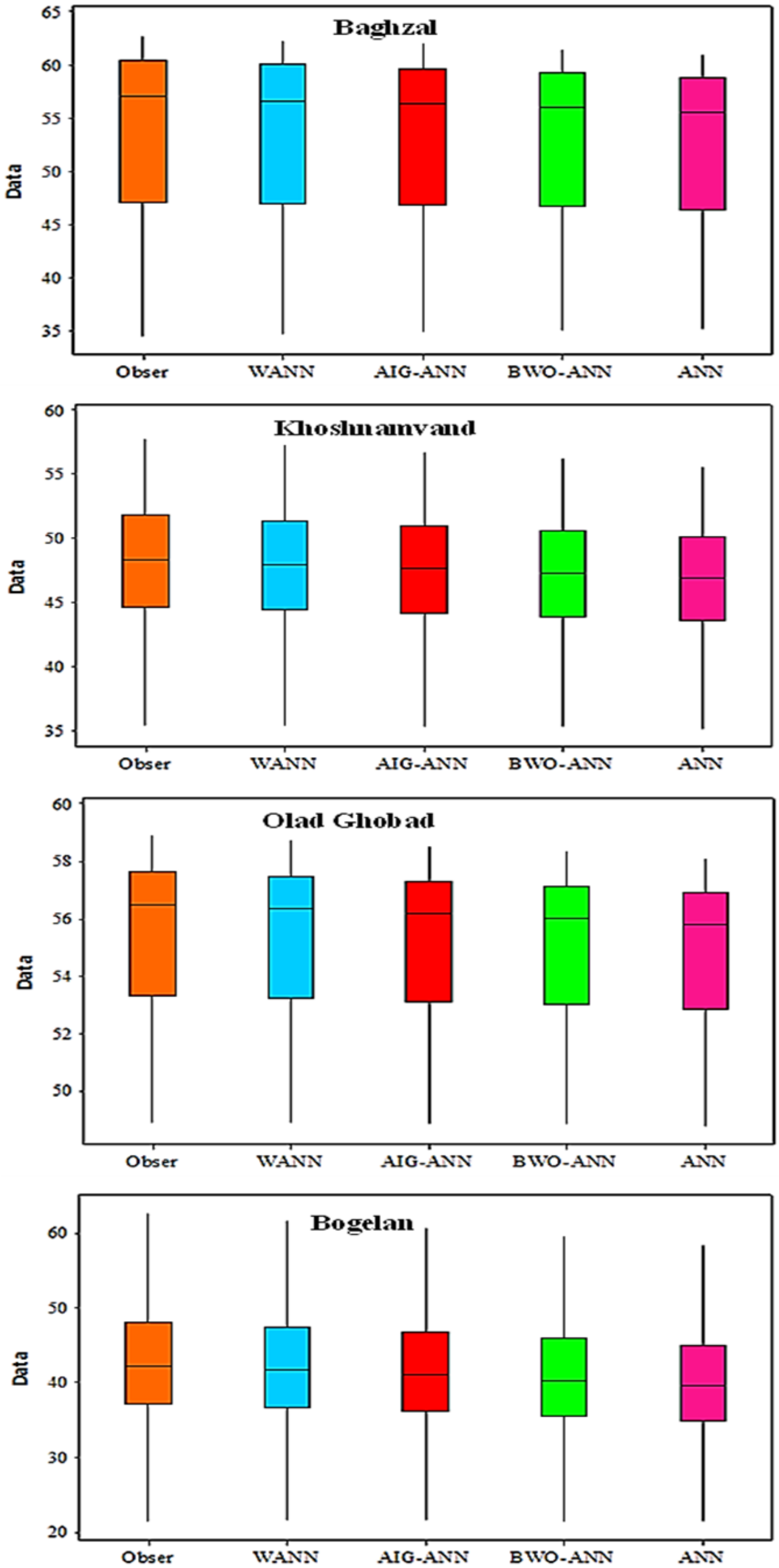

Figure 9. Box plot for the measured and predicted values

Conclusion

Estimating groundwater levels using hybrid models based on artificial neural networks has proven to be an effective approach in hydrogeology. In this study, we evaluated the performance of a hybrid metaheuristic artificial neural network model for groundwater level estimation in the Kuhdasht Plain of Lorestan Province, Iran. The hybrid model integrated nature-inspired optimization algorithms—wavelet transform, the Innovative Gunner algorithm, and the Black Widow Spider algorithm—with an artificial neural network framework. For the modeling process, precipitation (P), temperature (T), and groundwater withdrawal (q) were used as input parameters, while groundwater level (H) served as the model output. The dataset was partitioned such that 70% was allocated for model training and the remaining 30% for testing and validation. Model performance was assessed using statistical metrics, including the correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), and the Nash-Sutcliffe efficiency coefficient (NSE). Additionally, time series plots, box plots, and Taylor diagrams were employed to analyze the results.

The findings revealed that across all tested models, incorporating additional input parameters improved groundwater level estimation accuracy. Evaluation of the hybrid models demonstrated that the artificial neural network–wavelet (ANN-WT) model achieved the highest predictive accuracy with minimal error. The box plots and time series analysis further confirmed that the ANN-WT model produced estimates closely aligned with observed groundwater levels. In conclusion, this study highlights the efficacy of artificial intelligence–based models, particularly the hybrid ANN-WT approach, for groundwater level estimation. The methodology can be extended to other regions with long-term hydrological data, providing valuable insights for sustainable groundwater management and decision-making.

References

Alfarrah, N., and Walraevens, K. 2018. Groundwater overexploitation and seawater intrusion in coastal areas of arid and semi-arid regions. Water. 10(2), 143-154.

Barzegar, R., Fijani, E., Moghaddam, A. A., and Tziritis, E. 2017. Forecasting of groundwater level fluctuations using ensemble hybrid multi-wavelet neural network-based models. Science of The Total Environment. 599(3), 20–31.

Bovolo, C. I., Parkin, G., and Sophocleous, M. 2009. Groundwater resources, climate and vulnerability. Environmental Research Letters . 4(1), 125-142.

Brunner, P., and Simmons, C.T. 2012. HydroGeoSphere: a fully integrated, physically based hydrological model. Ground water. 50(2), 170–176.

Dehghani, R., and Dehghani, F. 2022. Application of wavelet neural network in estimation of average air-temperature. Environmental Resources Research.10(2),1-10

Dehghani, R., and Torabi Poudeh, H. 2022. The effect of climate change on groundwater level and its prediction using modern meta- heuristic model. Groundwater for Sustainable Development. 16(4),224-238.

Dehghani, R., and Torabi Poudeh, H. 2021. Application of novel hybrid artificial intelligence algorithms to groundwater simulation. International Journal of Environmental Science and Technology. 19(3),4351-4368.

Dehghani, R., Babaali, H. R., and Zeidalinejad, N. 2022. Evaluation of Statistical Models and Modern Hybrid Artificial Intelligence in Simulation of Runoff Precipitation Process. Sustainable Water Resources Management . 8(5), 154-176.

Dehghani, R., Torabi Poudeh, H., and Izadi, Z. 2021. Dissolved oxygen concentration predictions for running waters with using hybrid machine learning techniques. Modeling Earth Systems and Environment. 8(2),2599-2613.

Elmotawakkil, A.,Sadiki, A., and Enneya, N. 2024. Predicting groundwater level based on remote sensing and machine learning: a case study in the Rabat-Kénitra region .Journal of Hydroinformatics . 26 (10), 2639–2667

Eriksson, E. 1970. Groundwater time series: an exercise in stochastic hydrology. Hydrology Research. 1(1), 181–205.

Feng, F., Ghorbani, H., and Radwan, A. 2024. Predicting groundwater level using traditional and deep machine learning algorithms.Frontiers in Environmental Science.12(3), 442-461.

Hay, J. E., and Mimura, N. 2005. Sea-level rise: implications for water resources management. Mitigation and Adaptation Strategies for Global Change.10(3), 717–737.

Hornik, K. 1998. Multilayer feed-forward networks are universal approximators, Neural Networks . 2(5), 359–366.

Hughes, J. D., Russcher, M. J., Langevin, C. D., Morway, E. D., and McDonald, R.R. 2022. The MODFLOW Application Programming Interface for simulation control and software interoperability. Environmental Modelling & Software. 148(4), 105-122.

Kang, D.-h., So, Y. H., Kim, I. K., Oh, S.-b., Kim, S., and Kim, B.W. 2017. Groundwater flow and water budget analyses using HydroGeoSphere model at the facility agricultural complex. Engineering Geology. 27(2), 313–322.

Khan, J., Lee, E., Balobaid, A. S., and Kim, K. 2023. A comprehensive review of conventional, machine leaning, and deep learning models for groundwater level (GWL) forecasting. Applied Sciences . 13(2), 274-289.

Kisi, O., Karahan, M., and Sen, Z. 2006. River suspended sediment modeling using fuzzy logic approach. Hydrological Processes. 20(2), 4351-4362.

Ma, J., Liu, H., Shi, Y., and Zhang, H. 2022. Study on the numerical simulation of groundwater "drainage and recharge in open pit coal mine based on FEFLOW," in 2022 8th International Conference on Hydraulic and Civil Engineering: Deep Space Intelligent Development and Utilization Forum (ICHCE). Xi'an, China, November, 1–8.

Mirboluki, A., Mehraein, M., Kisi, O., Kuriqi, A., and Barati, R. 2024.Groundwater level estimation using improved deep learning and soft computing methods. Earth Science Informatics.17(2), 2587–2608

Mirzania, E., Ghorbani, M.A., and Asadi, E. 2023.Enhancement groundwater level prediction using hybrid ANN-HHO model: case study (Shabestar Plain in Iran).Arabian Journal of Geosciences.16(4), 464-482.

Nagy, H., Watanabe, K., and Hirano, M. 2002. Prediction of sediment load concentration in rivers using artificial neural network model. Journal of Hydraulics Engineering. 128(4), 558-559.

Nourani, V., Kisi, Ö., and Komasi, M. 2011. Two hybrid artificial intelligence approaches for modeling rainfall–runoff process. Journal of Hydrology. 402(2), 41–59.

Nourani, V., Tajbakhsh, A.D., and Molajou, A. 2018. Data mining based on wavelet and decision tree for rainfall-runoff simulation. Hydrology Research. 50:75–84. Nourani, V., Alami, M. T., Aminfar, M. H. (2009). A combined neural-wavelet model for prediction of Ligvanchai watershed precipitation. Engineering Applications of Artificial Intelligence . 22(2),466–472.

Pijarski, P., and Kacejko, P. 2019. A new metaheuristic optimization method: the algorithm of the innovative gunner (AIG). Engineering Optimization. 51(12),2049-2068.

Pragnaditya, M., Abhijit, M., Bhanja, S. N., Kumar, R. R., Sudeshna, S., and Anwar, Z. 2021. Machine-learning-based regional-scale groundwater level prediction using GRACE. Hydrogeology Journal. 29(3), 1027–1042.

Priyan, K. 2021. Issues and challenges of groundwater and surface water management in semi-arid regions. Groundwater Resources Development and Planning in the Semi-Arid Region. 4(1),1–17.

Russo, S.L., and Taddia, G. 2009. Groundwater in the urban environment: management needs and planning strategies. American Journal of Environmental Sciences. 5(2), 494–500.

Saroughi, M., Mirzania, E., Vishwakarma, D.K., Nivesh, S., Charaan Panda, K., and Aghaee Daneshvar, F. 2023. A Novel Hybrid Algorithms for Groundwater Level Prediction. Iranian Journal of Science and Technology, Transactions of Civil Engineering. 47(3), 3147–3164

Sebastian, P.A., and Peter, K.V. 2009. Spiders of India. Universities press.2(3), 70-115.

Shin, S., Kyung, D., Lee, S., Taik & Kim, J., and Hyun, J. 2005. An application of support vector machines in bankruptcy prediction model. Expert Systems with Applications.28(4),127-135.

Singh, S. K., Shirzadi, A., and Pham, B.T. 2021a. Application of artificial intelligence in predicting groundwater contaminants. Water Pollution and Management Practices .8(4),71–105.

Sun, J., Hu, L., Li, D., Sun, K., and Yang, Z. 2022. Data-driven models for accurate groundwater level prediction and their practical significance in groundwater management. Journal of Hydrology. 608(3), 127-142.

Trefry, M. G., and Muffels, C. 2007. FEFLOW: a finite-element ground water flow and transport modeling tool. Groundwater. 45(3), 525–528.

Wang, S., Shao, J., Song, X., Zhang, Y., Huo, Z., and Zhou, X. 2008. Application of MODFLOW and geographic information system to groundwater flow simulation in North China Plain, China. Environmental Earth Sciences. 55(7), 1449-1462

Wang, W., and Ding, J. 2003. Wavelet Network Model and Its Application to the Prediction of Hydrology. Nature and Science.1(1), 67-71.