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Analysis and evaluation of the drop in the groundwater level of Khorramabad plain

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Abstract

In recent years, the indiscriminate extraction of groundwater has led to a significant decline in groundwater levels, causing problems such as land subsidence. Therefore, it is crucial to reliably predict groundwater levels for effective resource management. In this study, the groundwater levels in the Khorramabad plain were simulated using hybrid models, including support vector regression-wavelet, support vector regression-bat, and support vector regression-gray wolf. These models were applied to four piezometric wells, incorporating parameters such as temperature, precipitation, and aquifer withdrawals over the period from 2004 to 2024. The models' performance was evaluated and compared using the correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), and the Nash-Sutcliffe efficiency (NS) coefficient. The results indicated that the hybrid models outperformed other approaches across all models investigated. Among them, the support vector regression-wavelet model demonstrated the best performance, with values of R=0.985R = 0.985-0.9780.978, RMSE=0.101RMSE = 0.101-0.2210.221, MAE=0.007MAE = 0.007-0.0110.011 m, and NS=0.985NS = 0.985-0.9950.995, making it the most reliable model compared to the others.

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Introduction

Considering the ever-increasing population growth and the necessity of optimal use of water resources, providing the maximum possible amount of groundwater water to meet the needs of all humans is of particular importance. Indiscriminate exploitation of groundwater resources in recent years has disturbed the natural balance and has negatively affected the level of groundwater in aquifers in many parts of the country (Zeidalinejad and Dehghani,2023, Dehghani and Torabi,2022). To know the status of these resources and their optimal management, it is necessary to accurately predict the fluctuations of the groundwater level. Most of the hydrological time series, such as changes in the groundwater level, always include unpredictable and complex processes that cannot be well described and modeled using conventional and classic linear models. Therefore, in order to model these hydrological phenomena, it is necessary to use non-linear models. Nowadays, intelligent systems are widely used to predict nonlinear phenomena (Mirzania et al,2023: Dehghani and Babaali,2022). In recent years, the use of smart methods in the quantitative studies of groundwater has attracted the attention of researchers, among which the following can be mentioned:

Moravej et al. (2020) used meta exploration algorithms combined with the SVR model to simulate the groundwater level of the Karaj plain located in Iran. In this research, the parameters of the groundwater level, precipitation and evaporation using the internal search algorithm-minimum support vector regression (ISA-LSSVR) and Genetic Algorithm-Least Vector Regression (GA-LSSVR) compared to Genetic Programming (GP) and Adaptive Neural Fuzzy Inference System (ANFIS). The results showed that the ISA-LSSVR model has a better performance than other studied models. Also, the results of the defined scenarios showed that precipitation and evaporation parameters play a significant role in increasing the accuracy of the models.

Lam et al. (2021) investigated the effect of climate change on groundwater resources in a coastal area of Vietnam using the distributed hydrological model (PANTA RHEI) and the finite element subsurface flow system model (FEFLOW). The results showed the amount of precipitation in the coming years. Especially the dry and wet seasons have a decreasing trend, also the results showed that precipitation is the most effective parameter on GWL.

Bahmani et al (2021) used hybrid artificial intelligence techniques to predict the groundwater water level of Delfan plain located in Lorestan province of Iran. In this research, in order to simulate the groundwater level, gene expression program (GEP) and decision tree (M5) models were used with group experimental mode analysis (EEMD) and experimental group experimental mode analysis (CEEMD) to pre-process the input data to produce composite models. . The results showed that pre-processing can improve the performance of simple models and the combined model of WT and CEEMD has shown good performance compared to EEMD.

In general, the research highlights the need for effective solutions and accurate forecasts of groundwater resources to prevent subsidence and drought phenomena in Iran. The Khorramabad Plain, located in Lorestan province, is particularly important for both drinking water and agriculture. It is one of the most significant agricultural areas in the province, with its crops relying heavily on groundwater for growth and development. However, unauthorized groundwater extraction and the drilling of unregulated wells have caused a sharp decline in groundwater levels in recent years. Given this situation, monitoring changes in groundwater levels and implementing management measures to address the decline are crucial. The aim of this research is to simulate the groundwater level of Khorramabad Plain using an integrated model that combines support vector regression-wavelet, support vector regression-bat, and support vector regression-grey wolf. The model is based on climatic parameters, groundwater levels, and aquifer withdrawal data.

Materials and methods

Study area

Khorramabad plain is located in the center of Lorestan Province in Iran between latitudes 33 degrees and 13 minutes to 33 degrees and 35 degrees north and longitudes from 47 degrees and 52 minutes to 48 degrees and 46 minutes east. The maximum height of the area is 1903 meters and the minimum is 929 meters, and the area of this study area is 2517 square kilometers. Also, the average annual precipitation of Khorramabad study area is 509 mm and its average temperature is 17.2 degrees Celsius. The main aquifer of Khorramabad Plain is formed by alluvial sediments. This plain has 4 piezometer wells with homogeneous statistics and lacks statistics and missing information, which can be seen in Figure 1. Also, for modeling, the parameters of precipitation (P), temperature (T), groundwater level (H) and withdrawal from water sources (q) were used every month, which were available in the Lorestan Regional Water Company during the period of 2004-2024. Table (1) shows the geographic location of the investigated piezometer wells.

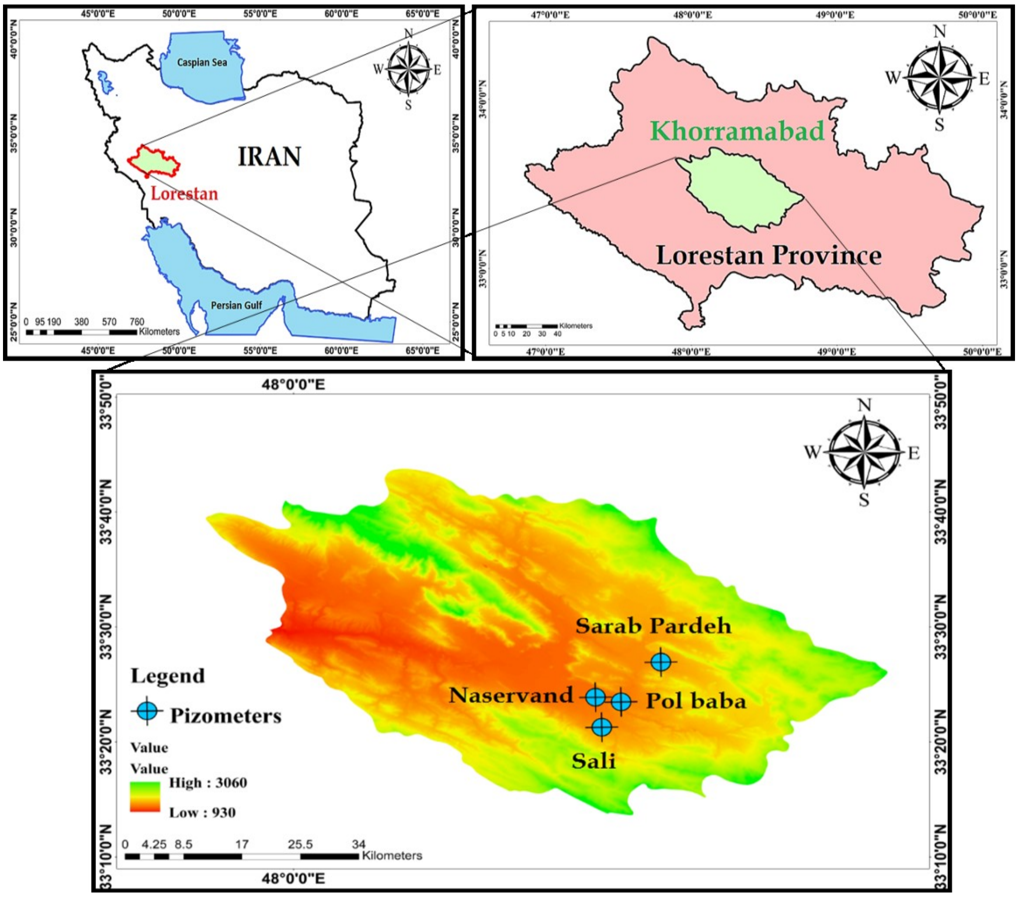

Figure 1. Study area

Table 1. Geographical location of the studied stations

ID	Type of station	Name of station	Longitude	Latitude	Elevation(m)
1	Piezometer well	Sarab Pardeh	48˚28' 49"	33˚26' 57"	1376
2	Piezometer well	Naservand	48˚23' 41"	33˚23' 53"	1234
3	Piezometer well	Sali	48˚24' 10"	33˚21' 16"	1302
4	Piezometer well	Pol baba	48˚25' 41"	33˚23' 29"	1267

Wavelet Transform

The wavelet transform is one of the transforms that replace the short-time Fourier transform and its purpose is to reduce the problems related to resolution. In wavelet conversion, the signal is divided into cells and the conversion is done on the cell individually (Vapnik, 1998). The most important difference between this transformation and their short-time Fourier transformation is that in simultaneous wavelet transformation, the width of the cell also changes according to the type of frequency (Shin et al, 2005). In other words, there is scale instead of frequency in this transformation. That is, wavelet transform is a kind of time-scale transform. Therefore, in the wavelet transform, the details of the time series can be checked at high scales, and the generalities of the time series are checked at low scales (Wang et al, 2000).

Support Vector Regression

Support vector machine is an efficient learning system based on the theory of constrained optimization, which uses the inductive principle of structural error minimization and leads to a general optimal solution (Vapnik, 1995). In the SVM regression model, a function associated with the dependent variable Y, which is itself a function of several independent variables x, is estimated. Similar to other regression problems, it is assumed that the relationship between the independent and dependent variables is determined by an algebraic function such as f(x) plus some disturbance (allowable error (ε)) (Vapnik, 1998: Hamel, 2009).

$$f(x)=W^{T}.\emptyset(x)+b \quad (1)$$

$$y=f(x)+noise \quad (2)$$

Different kernel functions can be used to construct different types of ε-SVM. The types of kernel functions that can be used in the regression SVM model are polynomial kernel, radial basis functions kernel (RBF) and linear kernel, respectively, calculated according to the following relations(Misra et al,2009). The figure below shows the structure of the support vector machine model. Considering that one of the most widely used kernel functions is the radial, linear, and polynomial basis kernel (Basak et al., 2006: Vapnik and Cheronsky, 1991). In this research, these three kernel functions are used. It is worth mentioning that the calculation process of the support vector machine was done based on coding in MATLAB environment, and parameters of kernel functions were optimized through trial and error.

$$k(x,x_j)=(t+x_i.x_j)^d \quad (3)$$

$$K(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \quad (4)$$

$$k(x,x_j)=x_i.x_j \quad (5)$$

Gray wolf scenario

Gray wolf GWO is a simulation algorithm that takes advantage of the social behavior of gray wolves and the hierarchical process (Oustu, 1979). This algorithm is population-based and can be easily extended to problems with scalable dimensions. In this algorithm, the top hunters are the gray wolves that are placed on top of the pyramid. These wolves are in a pack, with each pack having an average of 5-12 members. Wolves located at the top of the pyramid have special duties and have a strict social dominance hierarchy. There are 4 levels of hunting in each pack of wolves. In this optimization scenario, the behavior of gray wolves and their leadership hierarchy and hunting method are taken. In this scenario, four types of gray wolves including alpha (∝), beta (β), delta (δ) and omega (ω) are used to simulate leadership hierarchy. (∝alpha: the most appropriate answer, β beta: the most appropriate answer by factoring ∝, delta: the most appropriate answer by factoring ∝ and β, omega: the rest of the candidate solutions).

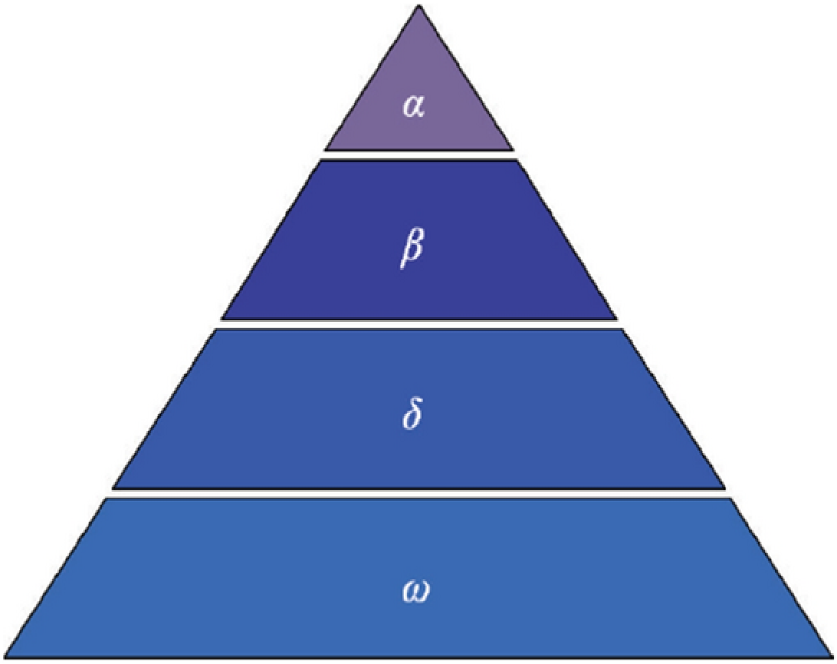

Figure 3. Hierarchical structure of wolves

Bat scenario

Collective intelligence is one of the most desirable optimization processes that is inspired by group behavior (Amuda, 2013). The bat scenario is inspired by the collective behavior of bats in the natural environment. This scenario is based on the property of reflecting the sound of bats. Bats find the exact path and location of their prey by sending sound waves and receiving their reflection. When the sound waves return to the bat, it can draw a sound image of the obstacles around it and see the surroundings clearly in the dark. Using this process, bats can distinguish moving and stationary objects (Amuda, 2013). The bat scenario is based on echolocation of tiny bats. There are two types of bats in general, the first type is the big bat and the second type is the small bat. Small bats use the mentioned feature at night and for hunting.

The rules of the bat scenario These rules can be stated in simple language as follows: All bats use echolocation to identify the distance and difference between prey and obstacles.

Evaluation and performance of models

In this research, to evaluate the accuracy and efficiency of the models, the coefficient of explanation (R^2), root mean square error (RMSE), mean absolute value of error (MAE) and Nash Sutcliffe coefficient (NS) were used according to the following relationships. The best value for these four criteria is one, zero, zero, one and zero respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(M_{oi}-\bar{M}_0)(M_{ei}-\bar{M}_e)}{\sqrt{\sum_{i=1}^{n}(M_{oi}-\bar{M}_0)^2 \cdot \sum_{i=1}^{n}(M_{ei}-\bar{M}_e)^2}}\right]^2, 0 \leq R^2 \leq 1 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_{ei}-M_{oi})^2}, 0 \leq RMSE \leq +\infty \quad (7)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|M_{ei}-M_{oi}|, 0 \leq MAE \leq +\infty \quad (8)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(M_{ei}-M_{oi})^2}{(M_{ei}-\bar{M}_e)^2}, -\infty < NSE < 1 \quad (9)$$

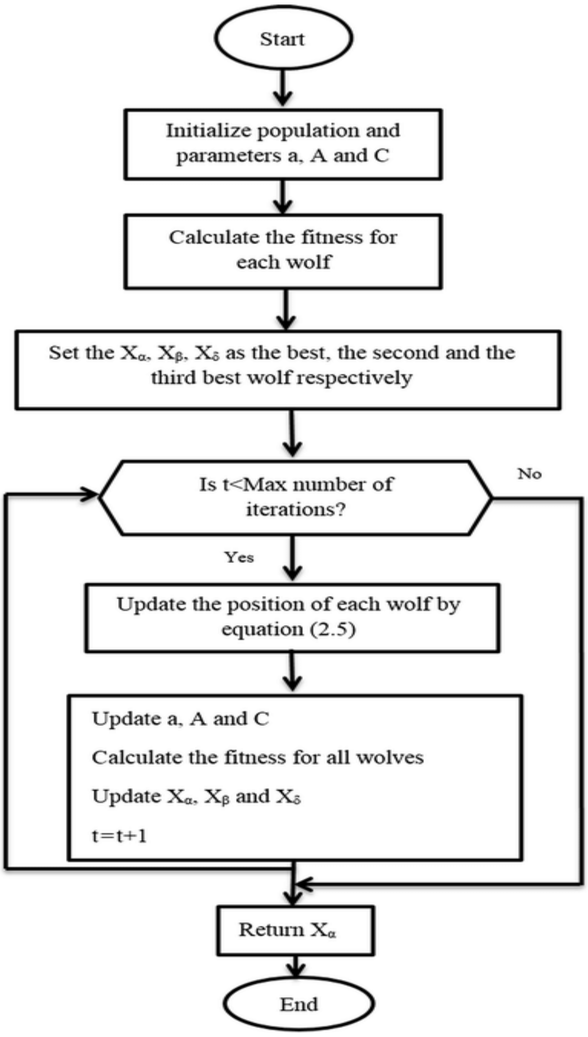

Figure 4. Flow diagram of the gray wolf scenario

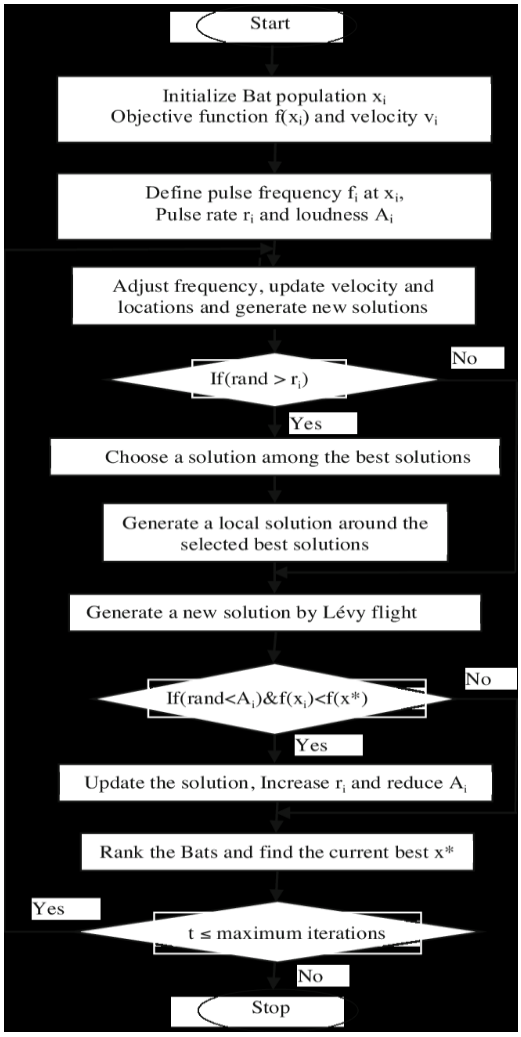

Figure 5. flow diagram of bat optimization scenario

Discussion and results

One of the most important steps in modeling is choosing a suitable combination of input variables (Dehghani and Torabi,2021: Dehghani et al,2020). In intelligent models, choosing appropriate and effective initial inputs in the phenomenon to teach the nature of the mechanism governing the phenomenon will improve the performance, therefore, in modeling the fluctuations of the groundwater water level, we tried to select the most effective parameters for training the models, which is shown in Table 2. is In this research, to simulate the fluctuations of the groundwater water level, the statistics and monthly data of four piezometric wells located in Khorramabad Plain, which had homogeneous statistics and no missing data, were used. For modeling, the parameters of precipitation (P), temperature (T) and groundwater level (H) and withdrawal from water sources (q) were used as input to the models. It should be noted that 80% of the data for training and the remaining 20% for testing were randomly selected to cover a wide range of data types (Kisi and Karhan, 2006; Nagy et al., 2002). In the following, the results of the used models are presented.

Table 2. Selected combinations of input parameters of the investigated models

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

To estimate the fluctuations of the groundwater level in Khorramabad Plain, Lorestan province, meta-exploration models and algorithms were evaluated with an observational data set and the efficiency of the models was checked. To model, different patterns were considered as input to the model, which is presented in table (2) of the best patterns of input compounds. Also, for each hybrid model including support vector regression-wavelet, support vector regression-bat, support vector regression-gray wolf, all four models are used in the training and testing stages. In summary, after choosing the best input combination for each model, the simulation of the groundwater level of piezometric wells, according to Table 3, shows that for all four piezometric wells, the hybrid model of support vector regression-wavelet performs better than other hybrid models, including support vector regression- Bat, regression of the support vector - gray wolf has such that according to the evaluation indices of the models, this model has values of R=0.978, RMSE=0.221 m, MAE=0.011 m, NS=0.985 in the piezometric well of Sarab Pardah and also in the piezometric well of Naservand it has values of R =0.981, RMSE=0.168 m, MAE=0.008 m, 0.991 NS= and also the Sally piezometric well with values of R=0.980, RMSE=0.186 m, MAE=0.010 m, 0.986 NS= and finally the piezometric well of Baba Hossein with values of R =0.985, RMSE=0.101 m, MAE=0.007 m, NS=0.995. In general, it can be stated that the wavelet-support vector regression model has the best performance, and the bat-support vector regression model, the gray wolf-support vector regression model has the weakest performance. These results are consistent with the results of Dehghani and Torabi (2021).

Also, in Figure 4, the error and accuracy graph of the investigated hybrid models shows that the support vector-wavelet regression model has a better performance than the bat-support vector regression models, gray wolf-support vector regression, as shown in the figure, it has the lowest an error.

A box diagram was used to analyze and evaluate the models used in the research. The advantage of a boxplot is that it can show how well a model predicts extreme values, medians, and quartiles. The box plot of groundwater level fluctuations in Fig 5 shows that the support vector-wavelet regression model is in good agreement with the observed groundwater level fluctuations. Also, support vector regression-bat, support vector regression-gray wolf have the least agreement. The same result was observed for predicting the minimum fluctuations of the observed groundwater level. These two results show that, although support vector regression is one of the smart and accurate models, it cannot predict the maximum values well. But when it is combined with meta-exploratory algorithms or models such as wavelet transform, its performance in predicting the maximum values is greatly improved, which is consistent with the results of Bahmani et al.'s (2020) research.

Also, according to Figure 5, in Sali and Naservand and Baba Hossein Bridge piezometric wells, the support vector-wavelet regression model had better performance in estimating all values (minimum, maximum, median, first and third quartile) than other models because these values were close It is estimated to calculated values. As can be seen, the support vector-wavelet regression model performed better because the WT wavelet transformation by separating the signal into high and low frequencies has the multi-scale characteristics of the signal and increases the accuracy of the model to a significant extent. The high-pass and low-pass signals obtained from the wavelet analysis have a very good fit with the sinusoidal sum equations, as the number of levels of these equations increases, the accuracy of the work increases. Is reduced and the signal becomes softer (Wang et al., 2000: Dehghani et al,2020: Dehghani and Torabi,2021), therefore the WSVR model is preferable to other models.

Table 3. Evaluation of the performance of the models to simulate the investigated piezometer wells

Sarab Pardeh								
Model	Training				Testing			
	R^2	RMSE(m)	MAE(m)	NS	R^2	RMSE(m)	MAE(m)	NS
WSVR	0.95	0.418	0.231	0.968	0.978	0.221	0.011	0.985
GWO-SVR	0.935	0.684	0.455	0.954	0.951	0.425	0.201	0.97
BA-SVR	0.916	0.862	0.671	0.938	0.933	0.526	0.315	0.947

Naservand								
Model	Training				Testing			
	R^2	RMSE(m)	MAE(m)	NS	R^2	RMSE(m)	MAE(m)	NS
WSVR	0.966	0.344	0.171	0.975	0.981	0.168	0.008	0.991
GWO-SVR	0.941	0.582	0.341	0.962	0.964	0.236	0.108	0.978
BA-SVR	0.925	0.714	0.546	0.947	0.945	0.487	0.264	0.958

Sali								
Model	Training				Testing			
	R^2	RMSE(m)	MAE(m)	NS	R^2	RMSE(m)	MAE(m)	NS
WSVR	0.957	0.386	0.201	0.973	0.98	0.186	0.01	0.986
GWO-SVR	0.926	0.631	0.37	0.958	0.957	0.344	0.155	0.975
BA-SVR	0.918	0.843	0.588	0.941	0.942	0.512	0.272	0.953

Pol Baba								
Model	Training				Testing			
	R^2	RMSE(m)	MAE(m)	NS	R^2	RMSE(m)	MAE(m)	NS
WSVR	0.971	0.233	0.188	0.984	0.985	0.101	0.007	0.995
GWO-SVR	0.953	0.472	0.231	0.976	0.972	0.157	0.111	0.98
BA-SVR	0.937	0.623	0.472	0.952	0.955	0.394	0.221	0.961

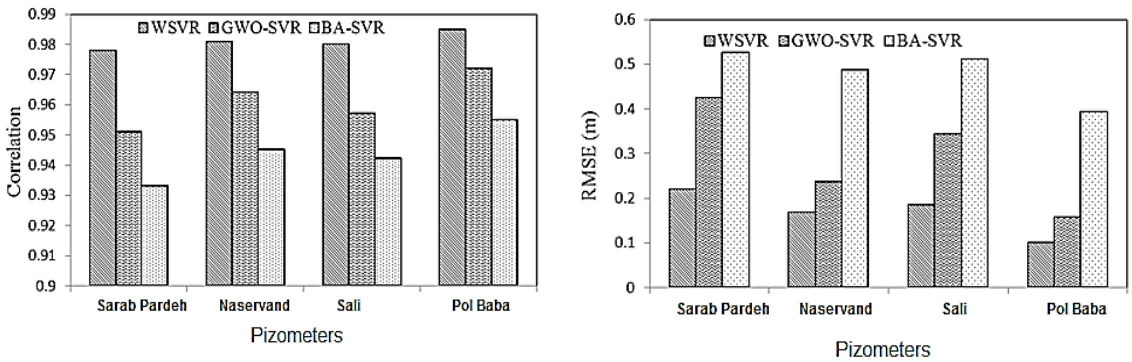

Figure 4. Accuracy and error diagram of the investigated hybrid models

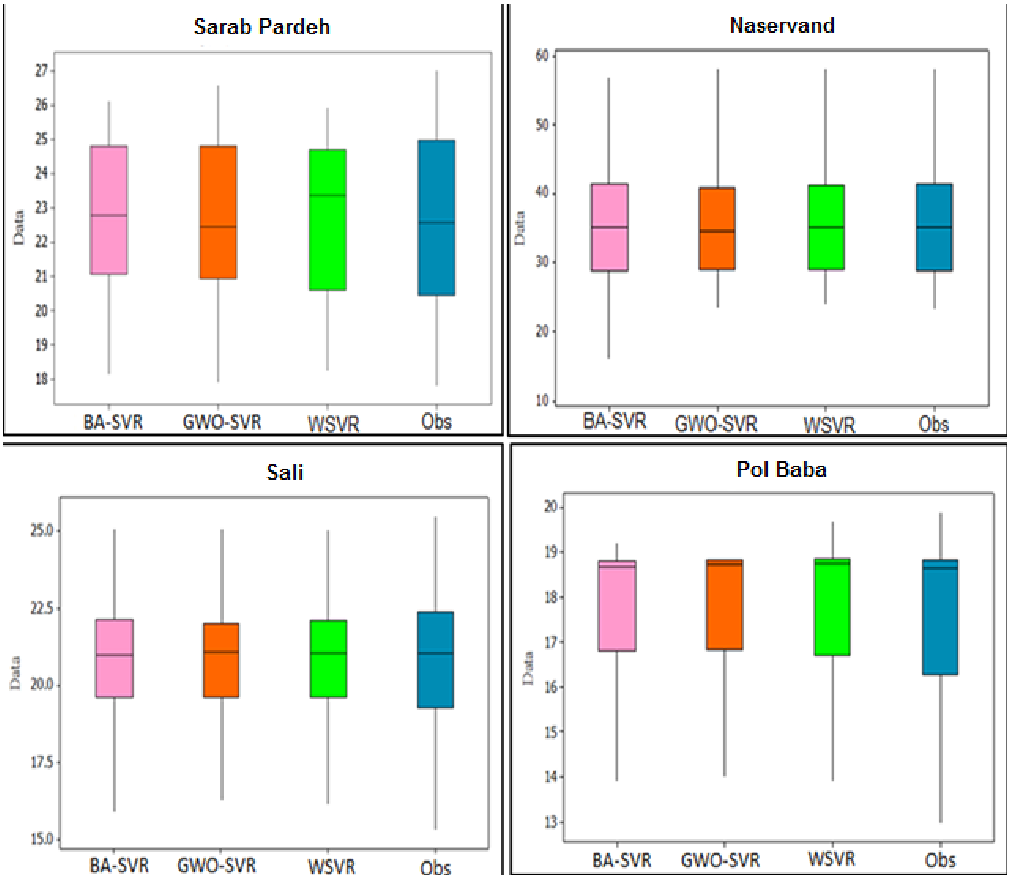

Figure 5. Box plot diagram of the examined models

Conclusion

In this study, the performance of three hybrid models—support vector regression-wavelet, support vector regression-bat, and support vector regression-gray wolf—was evaluated to simulate the groundwater levels of four piezometric wells in the Khorramabad Plain, located in Lorestan province. The models used precipitation, temperature, and flow rate parameters to predict groundwater levels during the statistical period from 2004 to 2024. The observed groundwater level values were compared with the estimated values produced by these models using various evaluation criteria.

The results showed that the hybrid models, particularly when using a combined structure with all input parameters, outperformed other approaches due to enhanced memory capabilities. Among these, the support vector regression-wavelet model demonstrated the highest accuracy and lowest error. This can be attributed to the wavelet transformation, which separates the signals into high-pass and low-pass components, allowing for more precise predictions.

Given the decline in groundwater levels over the past 20 years, it is recommended to install smart meters on all agricultural and industrial wells, prevent the drilling of unauthorized wells, and discourage the cultivation of water-intensive crops through awareness campaigns targeting well owners. These measures would facilitate the development and implementation of effective groundwater management strategies and support informed decision-making to improve the sustainability of groundwater resources.

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