GEOPERSIA

Accepted Manuscript

Predicting Groundwater Capture Zone Characteristics Using Fuzzy Inference System (FIS), Case study: Abarkooh Aquifer

Sajjad Moradi Nazar Poor, Hadi Jafari

DOI: 10.22059/GEOPE.2025.382188.648788

Receive Date: 23 November 2024
Revise Date: 06 March 2025
Accept Date: 05 April 2025

Predicting Groundwater Capture Zone Characteristics Using Fuzzy Inference System (FIS), Case study: Abarkooh Aquifer

Sajjad Moradi Nazar Poor [1,*], Hadi Jafari [2]

[1] Faculty of Earth Sciences, Shiraz university, Shiraz, Iran
[2] Faculty of Earth Sciences, Shahrood University of Technology, Shahrood, Iran

Received: 23 November 2024, Revised: 06 March 2025, Accepted: 05 April 2025

Abstract
Groundwater is a vital resource for human water supply, which makes studying well capture zones critical, particularly for anthropogenic water sources and water quality management. Capture zones, also known as wellhead protection areas, are influenced by numerous factors, including pumping rate, hydraulic conductivity, groundwater gradient, and other hydrogeological parameters. Various methods exist for calculating capture zones, ranging from analytical approaches to advanced numerical models, and these methods continue to evolve. This research introduces, for the first time, the application of a Fuzzy Inference System (FIS) to predict both the size and elongation of capture zones. Key input parameters include annual well discharge (measured in million cubic meters, MCM), hydraulic conductivity, groundwater gradient, and aquifer thickness. Results from the WhAEM software were used as target values to validate the FIS predictions. The findings reveal strong correlations between the FIS predictions and the WhAEM results, with correlation coefficients (R) of 0.92 for capture zone size and 0.73 for elongation coefficient. These results underscore the effectiveness of fuzzy logic in accurately predicting critical hydrogeological parameters, offering a robust alternative method for capture zone analysis.

Keywords: Fuzzy inference system, Elongation coefficient, Capturer zone, Abarkooh.

Introduction

The water table is a critical component of groundwater systems, playing a pivotal role in environmental dynamics and resource management, particularly concerning water quantity and quality (Goodarzi & Eslamian, 2019). Its intricate influence on various environmental phenomena underscores the importance of understanding and modeling groundwater systems. To this end, a wide range of methodologies has been developed, with groundwater modeling emerging as an indispensable tool.

Protecting drinking water sourced from groundwater is also a significant issue. Groundwater protection strategies are typically implemented in two forms: first, by safeguarding groundwater pumping areas, and second, by controlling source areas (Siarkos and Latinopoulos, 2012). Effective modeling of the water table is foundational to comprehending groundwater dynamics and their interactions with the surrounding environment. By examining the complex mechanisms governing groundwater flow and distribution, modeling facilitates in- formed decision-making for resource optimization and sustainable management. The dynamic nature of the water table-shaped by factors such as recharge rates, anthropogenic activities, and climatic variations-necessitates the development of accurate and robust modeling approaches.

In recent years, fuzzy logic has emerged as a versatile and powerful tool across diverse scientific domains, including artificial intelligence, aerospace, automotive, defense, electronics,

* Corresponding author e-mail: s.moradi1989@yahoo.com

and hydrology (Gupta, 2021). Its application in water table modeling and groundwater quality analysis has demonstrated significant potential. For instance, Javadi et al. (2022) introduced a novel approach to clustering groundwater pollution using fuzzy logic techniques, underscoring the importance of advanced analytical methods in addressing groundwater contamination complexities. By incorporating expert knowledge and accommodating inherent uncertainties, fuzzy logic provides a nuanced framework for data analysis and decision-making. The integration of fuzzification, fuzzy rule bases, fuzzy inference, and defuzzification within fuzzy inference systems facilitates the transformation of complex, imprecise inputs into actionable insights (Fukuda et al., 1993). This process enriches the interpretability of modeling outcomes, blending qualitative reasoning with quantitative analysis.

Fuzzy logic is particularly well-suited to managing uncertainty in hydrological studies. For example, Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been employed to predict lake water levels with high accuracy and reliability (Pham et al., 2023; Chen et al., 2017; Esbati et al., 2018). Moreover, fuzzy logic has been utilized to calculate well losses and compare them with the Rorabaugh technique, showcasing its ability to minimize error margins (Altunkaynak, 2010). Similarly, hydrological time series forecasting using ANFIS has demonstrated superior accuracy and reliability (Firat and Gϋngӧr, 2008). In another study, flow prediction methods combining ANFIS and stochastic hydrological models have proven effective in modeling complex hydrological systems (Keskin et al., 2006).

Further advancements include integrating fuzzy logic with data mining techniques to assess groundwater vulnerability using the DRASTIC model. This approach has been shown to enhance reliability and practicality in vulnerability assessments (Nourani et al., 2024). Additionally, the impact of dams on aquifers has been quantified using fuzzy logic, emphasizing its utility in capturing intricate hydrological interactions (Moradi Nazarpoor et al., 2024).

While several methods exist for calculating capture zones, fuzzy logic stands out as a particularly promising approach. However, a significant research gap remains in incorporating slope and water table elevation into fuzzy logic frameworks for capture zone calculation. This study aims to address this gap by developing a novel methodology that integrates fuzzy logic with key hydrogeological parameters, such as hydraulic conductivity, aquifer thickness, groundwater gradient, and related factors. This comprehensive approach is expected to provide more accurate and actionable insights for groundwater resource management.

Materials and method

Area of Study

The Abarkhooh Plain is looked in the center of Iran, in the Yazed province. It covers an area of $929 Km^2$ an lies between 52°58` N to 31°14` N and 31°14` W to 30°50` W. This plain is surrounded by the Shoor River in the northern part of the area and the Abarkhooh Desert to the east.Investigation of the iso-potential map shows that the main groundwater flow direction is from west to east of the plain.Therefore, the main recharge zone for Abarkhooh is the eastern elevation of the plain. The main discharge from the Abarkhooh aquifer occurs through well exploitation for agriculture.Overall, there are 575 wells in the Abarkhooh Aquifer, which are extracting approximately 99 million cubic meters (MCM) of water from the aquifer (Fig. 1).

Methodology

To gain appropriate insight and comprehensive understanding of all processes, several methodological frameworks are proposed. Specifically, three steps are involved, which are outlined as follows: Step 1: Inputting data Step 2: Fuzzy inference system Step 3: Interpreting results (Fig. 2).

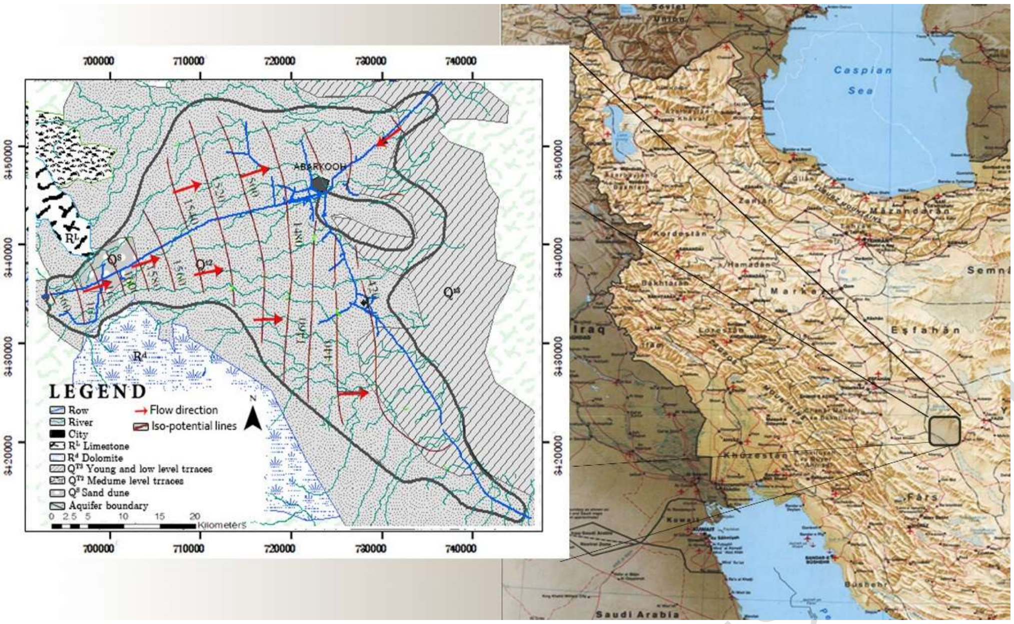

Figure 1. The area of Study

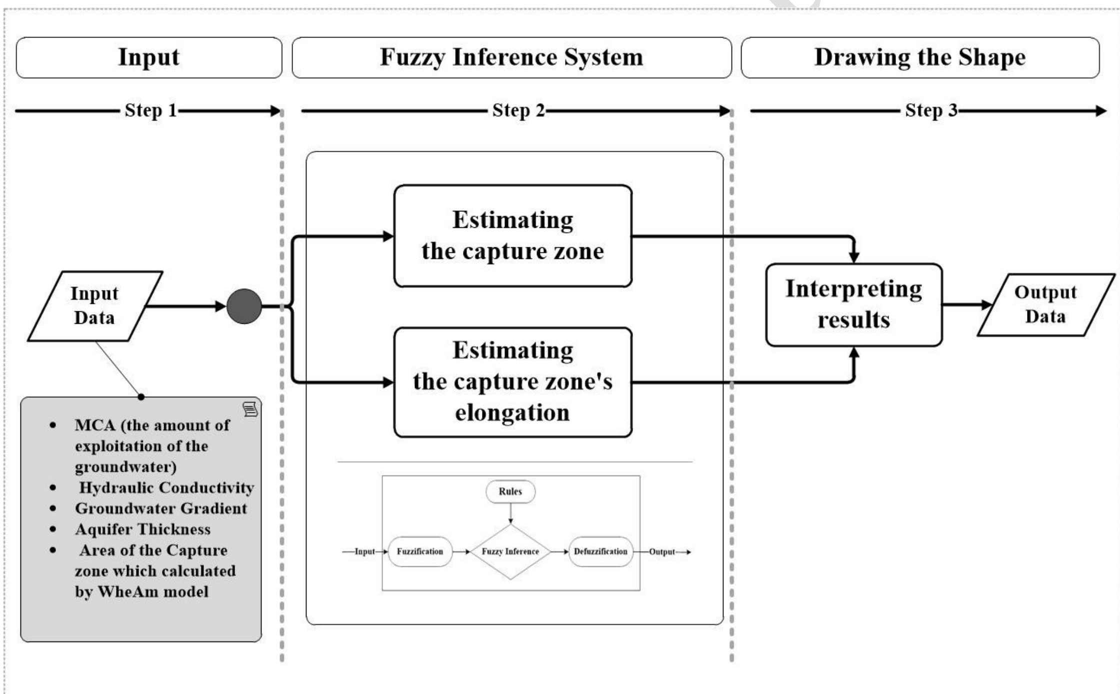

Figure 2. This is road map for study

Step1: Preparing Data

Data collection and analysis are crucial components of this research. The study employs multiple layers, including annual well discharge in million cubic meters (MCM), hydraulic conductivity, groundwater gradient, aquifer thickness, and area of the capture zone, to recalculate the capture zone. These layers were adapted from Jafari et al. (2023) who attempted to delineate the capture zone using the WhAEM model. For the application of fuzzy logic, all data mentioned were obtained for 540 wells using ArcGIS.

To apply fuzzy logic, it is necessary to identify the dependent and independent variables. In this study, the size and elongation of the capture zone are the dependent variables, (Altunkaynak, 2010; Firat & Gu¨ngo¨r, 2008) million cubic meters (MCA), hydraulic conductivity, groundwater gradient, and aquifer thickness serve as the independent variables.

Calculating the elongation coefficient of oval is the ratio of the major axis to the minor axis Eq.1. As the elongation coefficient approaches 1, the shape becomes more circular. When this value deviates from 1, the shape becomes increasingly elongated confession (EC).

$$EC = Ma\ j\ or\ L/Minor\ L \quad (1)$$

In which MajorL and MinorL are Major axis length and minor axis length respectively. In this study, the capture zone was assumed to be oval-shaped for measuring the elongation coefficient. Subsequently, the elongation coefficient was calculated for 540 samples (Fig.3).

Step2: Fuzzy Inference System (FIS)

A fundamental component of fuzzy logic is the membership function, which defines the degree of input and output elements. This function can also represent the imprecise relationship between input and output variables. The fuzzy inference system (FIS) operates on nonlinear algorithms for complex systems (Nourani et al., 2024). Additionally, Sugeno introduced a new type of FIS, complementing existing approaches (Sugeno, 1985) which used in this study. In the next step, Using the Adaptive Neuro-Fuzzy Inference System (ANFIS), 80% of the wells were designated as the training set and 20% as the testing set. This division was used to develop and evaluate the model. Through this process, the optimal membership function was identified, allowing for an accurate determination of the relationship between the input variables and the corresponding outputs. For the Abarkooh aquifer, the relationship between inputs and outputs is characterized by a Membership Function.(i.e., capture zone Fig. 4 and Elongation coefficient Fig. 5). This membership function is designed based on the best and most ideal predictions. Next, so that predictions of the elongation coefficient for the capture zone area, all input variables were recalculated.

Results and Discussion

In fact, the results of the WhAEM software in this case study depend on various input parameters, including groundwater head gradient, hydraulic conductivity, aquifer thickness, and discharge rate. The outcomes of the WhAEM analysis are illustrated in the accompanying figure 6 and also it's descriptive statistics in the table 1.

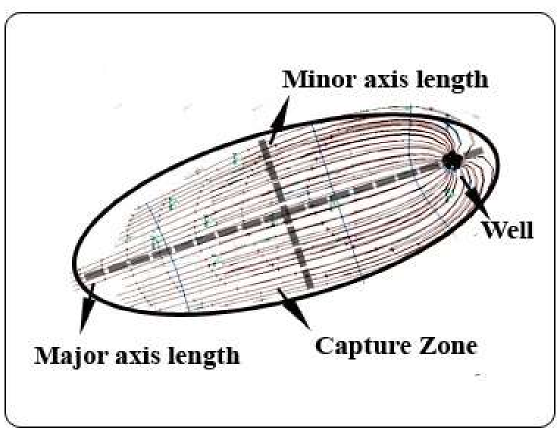

Figure 3. The conceptual form of capture zones and ovals

Table 1. Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
MCA	540	0.471	0.002	0.473	0.12	0.088	1.13	0.10	1.21	0.21
Area (m^2)	540	409362	7991	4173535	216205	90554	-0.12	0.10	-0.68	0.21
Length (m)	540	1622	261	1884	804	354	0.47	0.10	-0.62	0.21
Width (m)	540	602	17	620	283	97	0.17	0.10	1.14	0.21
Hydraulic Conductivity	540	8.36	3.36	11.73	7.53	1.66	-0.13	0.10	-0.33	0.21
Gradient	540	0.17	0.003	0.17	0.06	0.03	0.60	0.10	-0.36	0.21
Aquifer Thickness	540	385.29	35.9	421.2	128	83	1.73	0.10	1.9	0.21
Elongation	540	48	1	49	3.64	3.59	5.6	0.10	55	0.21
Valid N (listwise)	540									

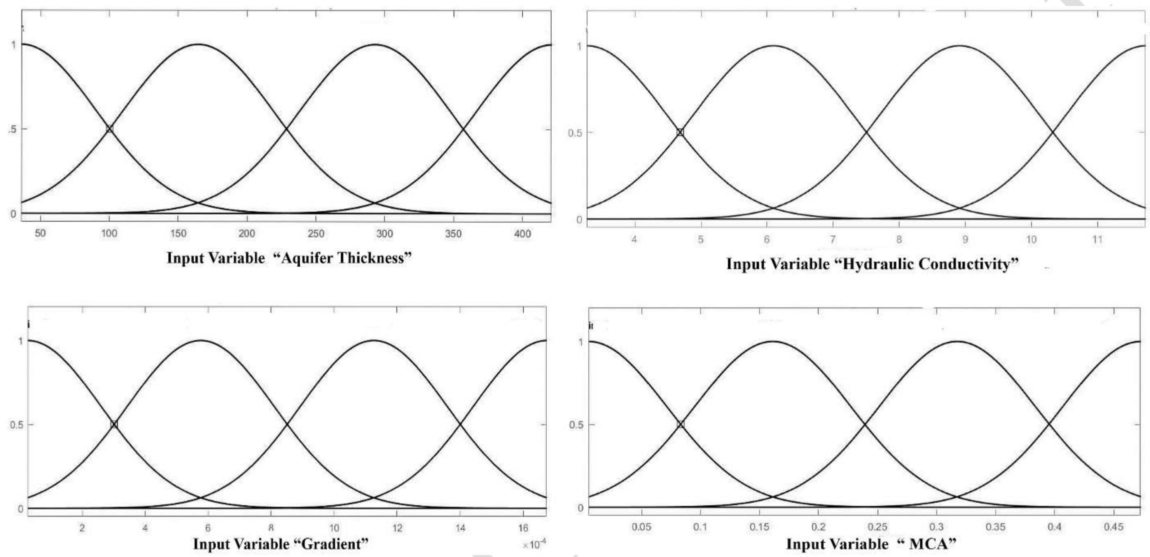

Figure 4. Membership Function Plot for Input Variable of calculating Capture zone area

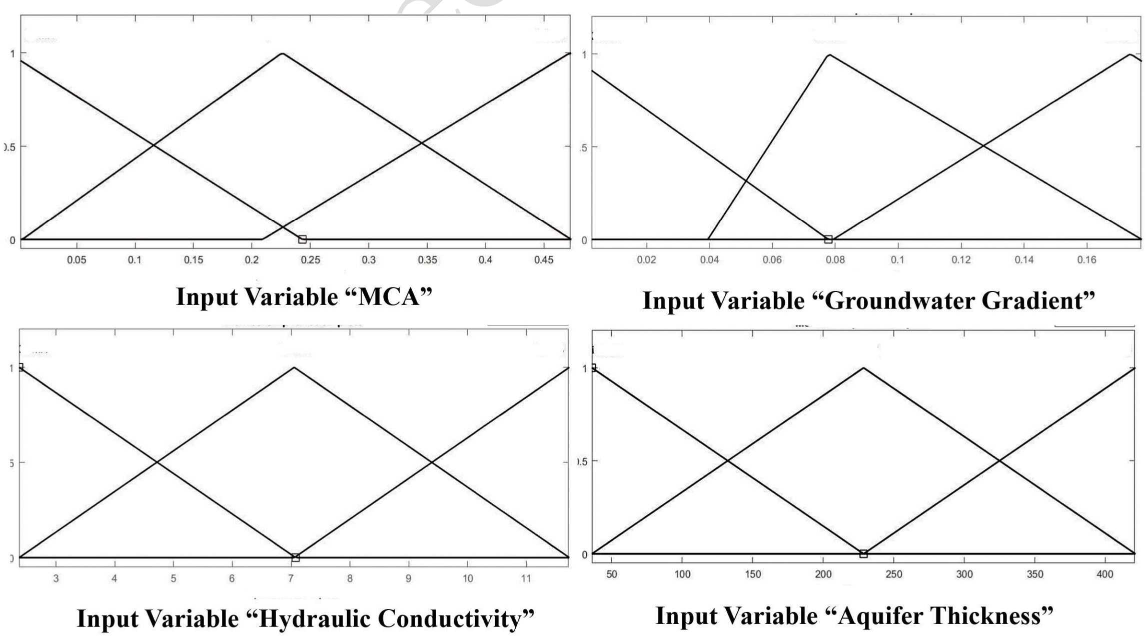

Figure 5. Membership Function Plot for Input Variable of calculating Elonation Coefficient

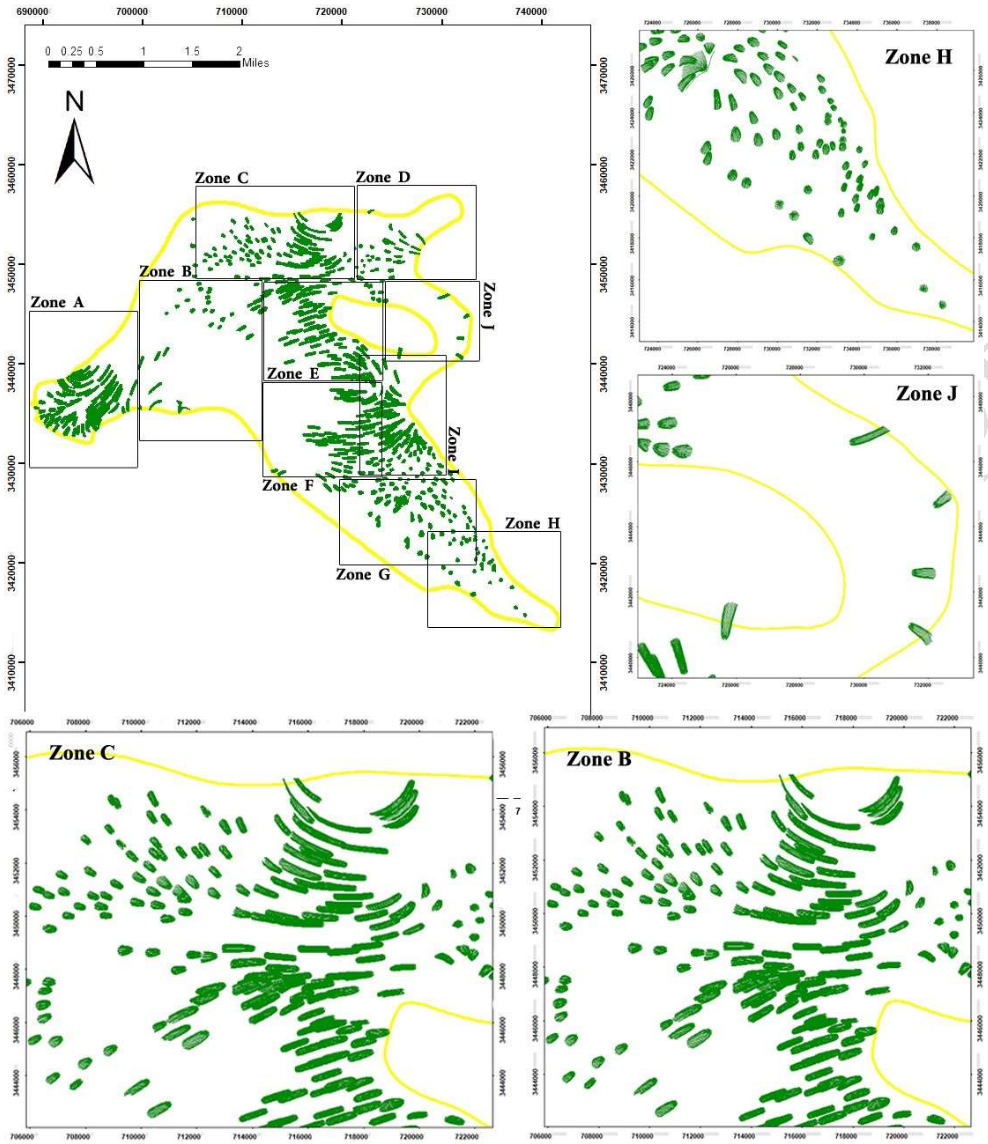

Figure 6. The capture zone of the wells, as determined by WhAEM software

Therefore, Different types of capture zones exist across various areas. Actually, These outcomes, which include million cubic meters (MCM) of water, hydraulic conductivity, groundwater gradient, and aquifer thickness, serve as the independent variables.

Figures 7 and 8 display the calculated capture zone area and elongation (WhAEM) versus the predicted values from the Fuzzy logic method. Therefore, There is an acceptable similarity between the calculated and predicted values. The B sections of the graphs clearly illustrate the characteristics of the 540 capture zones. Turning to the details of the graphs Fig 7B and 8B, the amplitudes of the predicted capture zone and elongation are remarkably similar to the calculated cases. Table 1 illustrates the descriptive statistics of input data for 540 wells in the Fuzzy Inference System (FIS). Overall, it can be observed that the range of the area calculated by WhAEM is between 7,991 m^2 and 4,173,535 m^2, with a mean of 21,620 m^2, while the elongation coefficient values range from a minimum of 1 to a maximum of 49.

For example, the mean capture zone area (0.216 km^2) and the mean elongation coefficient (3.46) are used to calculate the major and minor axes. Based on Equation 2, the calculated minor and major axes are 8.7 meters and 31.40 meters, respectively.

In the following equation, 'a' represents the length of the semi-major axis, and 'b' represents the length of the semi-minor axis.

$$
\begin{aligned}
&Area \quad of \quad Oval && = \pi \times a \times b \\
&1)\ \ 216 && = \pi(3.6b)b \\
&2)\ \ 216 && = 3.6\pi b^2 \\
&3)\ \ b^2 && = \frac{216}{3.6\pi} \\
&4)\ \ b && = \sqrt{\frac{216}{3.6\pi}} \\
&5)\ \ b && \approx 4.36\text{meters} \\
&6)\ \ a && = 3.6b \approx 15.70\text{meters} \\
&\text{Minoraxis} && = 2b \approx 8.72\text{meters} \\
&\text{Majoraxis} && = 2a \approx 31.40\text{meters}
\end{aligned}
\tag{2}
$$

A strong correlation exists between the target values calculated by WhAEM software and the predicted output areas. Regarding the predicted capture zone area, the correlation between target and output is notably high, with a correlation coefficient of approximately R=0.92. In contrast, the correlation for the elongation coefficient is lower, at around R=0.73.

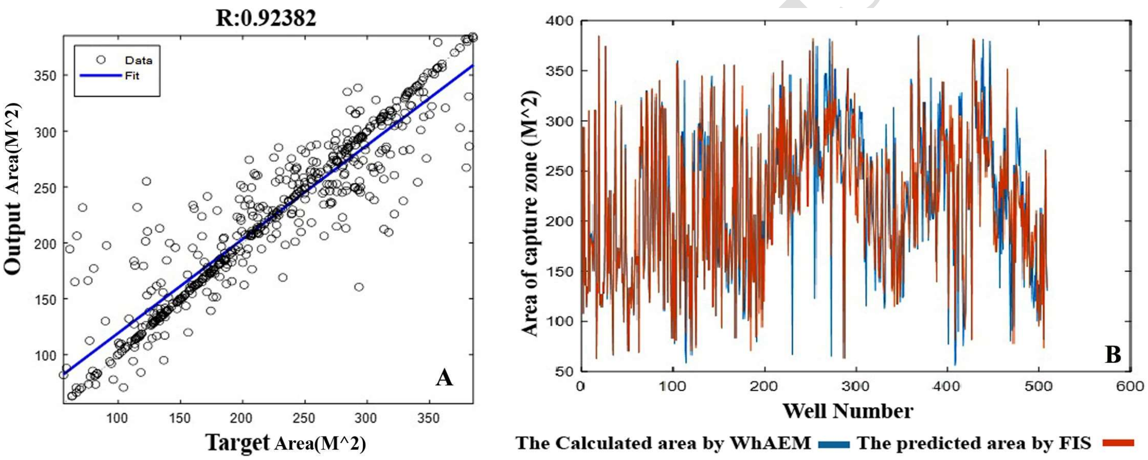

Figure 7. Results of the Fuzzy Inference System (FIS) for the capture zone's area)

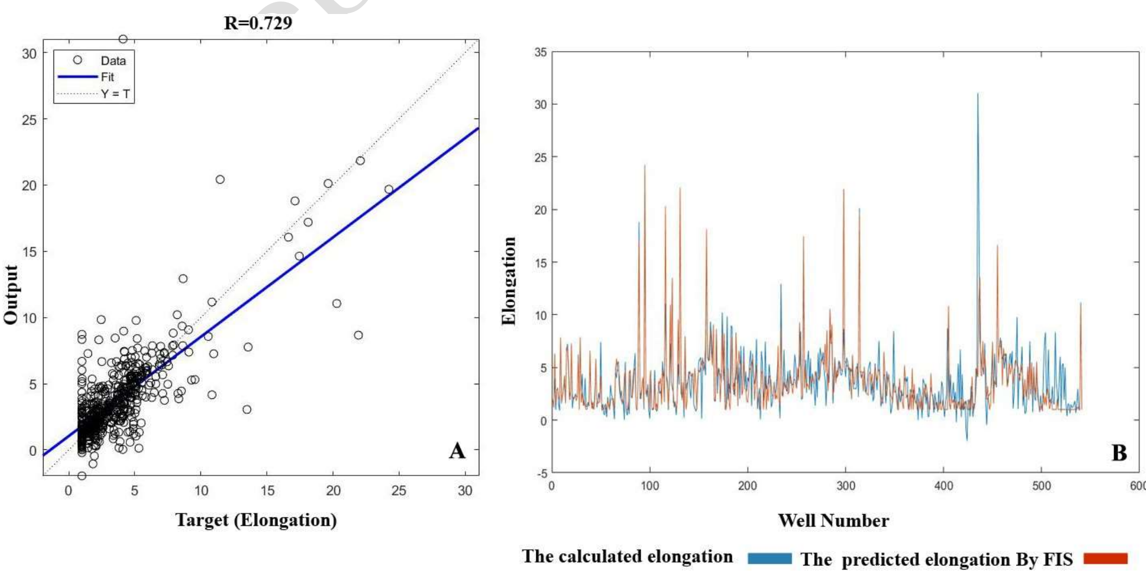

Figure 8. Results of the Fuzzy Inference System (FIS) for the elongation coefficient

Conclusion

One of the most important problems in hydrogeology is calculating the capture zone area, which can be obtained through various methods such as numerical modeling and analytical equations. However, a rapid and practical method is desirable. The aim of this research is to recalculate capture zones for 540 wells in the Abarkooh aquifer. To achieve this, it was used the results from the WhAEM software for capture area and elongation coefficient.

Input data included annual well discharge in million cubic meters (MCM), hydraulic conductivity, groundwater gradient, and aquifer thickness. A fuzzy inference system (FIS) was used to predict capture zones. The results show a strong correlation ($R = 0.93$) for the size of the capture zone. While the correlation for the elongation coefficient is lower, it still demonstrates a relatively strong correlation ($R = 0.73$).

These results indicate that FIS can be a useful and easier method to recalculate capture zones with a high degree of accuracy. With these findings, it is possible to recalculate capture zones using the shape of the elongation coefficient.

References

Altunkaynak, A., 2010. A predictive model for well loss using fuzzy logic approach. Hydrological processes, 24 (17): 2400-2404.

Chen, W., Panahi, M., Pourghasemi, H. R., 2017. Performance evaluation of gis-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (anfis) with genetic algorithm (ga), differential evolution (de), and particle swarm optimization (pso) for landslide spatial modelling. Catena, 157: 310-324.

Esbati, M., Ahmadieh Khanesar, M., Shahzadi, A., 2018. Modeling level change in lake urmia using hybrid artificial intelligence approaches. Theoretical and Applied Climatology, 133: 447-458.

Firat, M. and Gu¨ngo¨r, M., 2008. Hydrological time-series modelling using an adaptive neuro-fuzzy inference system. Hydrological Processes: An International Journal, 22(13): 2122-2132.

Fukuda, T., Shimojima, K., Arai, F., Matsuura, H., 1993. Multisensor integration system based on fuzzy inference and neural network. Information Sciences, 71(1-2): 27-41.

Goodarzi, M. and Eslamian, S. S., 2019. Evaluation of whaem and modflow models to determine the protection zone of drinking wells. Environmental Earth Sciences, 78(6):195.

Gupta, A. K., 2021. Fuzzy logic and their application in different areas of engineering science and research: A survey. International Journal of Scientific Research in Science and Technology, 8(2): 71-75.

Jafari, H., Moradi Nazarpoor, S., Niknam, M. S., Bagheri, R., Zarei Doudeji, S., 2023. Delineating capture zone of the production wells in abarkooh aquifer (central iran) using whaem model and statistical method of multivariate regression. Geopersia, 13(2): 357-363.

Keskin, M. E., Taylan, D., Terzi, O., 2006. Adaptive neural-based fuzzy inference system (anfis) approach for modelling hydrological time series. Hydrological sciences journal, 51 (4): 588-598.

Moradi Nazarpoor, S., Rezaei, M., and Mali, F., 2024. A new fuzzy method for investigating the effects of dam on aquifer: case study of rudbal dam, south of iran. Scientific Reports, 14(1):14503.

Nourani, V., Maleki, S., Najafi, H., Baghanam, A. H., 2024. A fuzzy logic-based approach for groundwater vulnerability assessment. Environmental Science and Pollution Research, 31(12):18010-18029.

Pham, Q. B., Mohammadi, B., Moazenzadeh, R., Heddam, S., Zola´, R. P., Sankaran, A., Gupta, V., Elkhrachy, I., Khedher, K. M., Anh, D. T., 2023. Prediction of lake water-level fluctuations using adaptive neuro-fuzzy inference system hybridized with metaheuristic optimization algorithms. Applied water science, 13(1):13.

Siarkos, I. and Latinopoulos, P., 2012. Delineation of wellhead protection zones for the control of point pollution sources in the aquifer of n. moudania, greece. Eur. Water, 40: 3-17.

Sugeno, M., 1985. An introductory survey of fuzzy control. Information sciences, 36 (1-2): 59-83.