A REVIEW ON PREDICTION AND ASSESSMENT OF GROUND WATER QUALITY BY GIS AND ANN TECHNIQUES

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ABSTRACT

This review article carefully examines the methods and implications of the most effective Geospatial Information Systems (GIS) and Artificial Intelligence (AI) approaches, particularly in the modelling and forecasting of groundwater quality for its acceptability in residential use.The most popular AI techniques, ANN and GIS approaches, are comprehensively reviewed in this study using a systematic approach.Despite certain limitations, in literature it is conferred that ANN fared better when dealing with a large number of data sets and produced precise predictions because of its capacity to represent complicated non-linear and complex connections. The conclusions of this research reveal that the effective adoption of AI models is determined by the suitability of input consideration, kinds of individual functions, the efficiency of performance measurements, etc. The findings from this study will help groundwater development plans and advance the use of AI in groundwater quality applications. In this study, suggestions are made to increase the growth of knowledge in the domain of modelling structure improvement.

Keywords : Artificial Intelligence, ANN, GIS, Efficiency

1.0 Introduction

Due to climate change, population increase, urbanisation, and intensive farming, water shortage has become a serious concern worldwide during the past century[1].In response to this problem, different behaviours, such as agricultural, industrial, and domestic ones, utilise groundwater resources in alternative ways. Yet, the over-exploitation of groundwater and decline in its quality are results of the expanding worldwide demand for water. Both anthropogenic (mining, industrial contamination, excessive use of fertilisers and pesticides, and domestic sewage) and natural (seawater intrusion, rock-water leaching interaction) factors have a significant impact on the degradation of groundwater quality. These factors also change the physical and chemical properties of groundwater [2-3].The availability and appropriateness of groundwater have been negatively impacted by groundwater pollution, which is bad for human health. Additionally, due to the complexity of groundwater systems and the hidden danger posed by groundwater contaminations, cleaning up contaminated groundwater is costly and time-consuming. Because of the possible risk of groundwater pollution and its impact on suitability for human consumption, groundwater quality evaluation and monitoring are very essential.

Accurate and trustworthy forecasts of groundwater resource information are key to effectively monitoring and improving groundwater quality, where a better knowledge of the hydrogeological process and behaviour is essential [4-5]. To produce such forecasts, however, specialised methods are needed due to the hydrogeological system's complex and mutable properties. In comparison to other methods, groundwater modelling has shown to be a useful tool for comprehending groundwater systems and recognising current groundwater hazards [6].To maintain utilisation and aid in consideration of the consequences for future groundwater supplies, it is essential to construct prediction modelling for both the short term and the long term. On the basis of a thorough understanding of the observed dynamic behaviour, the traditional methodologies, such as conceptual and numerical groundwater models, have typically been used to forecast the changing hydrogeological state and processes. To determine the model's forecast accuracy and dependability, the hydrological system must be calibrated and validated with sufficient and appropriate data [7].The enormous number of input factors required during the modelling process is only one of the approaches' many drawbacks. Many models, however, are currently unable to account for and quantify the non-linearity and hydrogeological forecast uncertainty. The inaccurate depiction of the actual system that might emerge from failing to recognise and analyse uncertainties and nonlinearity lowers the effectiveness of groundwater models and reduces forecasting accuracy[8]. Due to its capacity to handle the enormous quantity of data, artificial intelligence (AI) has been used by researchers as a replacement tool for complicated nonlinear hydrological modelling in order to overcome the aforementioned restrictions [9].

Artificial neural networks (ANN) and fuzzy logic, in particular, have been popular in recent years for modelling in the sciences and engineering. Artificial intelligence is evolving, and its uses for forecasting and tracking groundwater quality and quantity are expanding quickly [10-14]. AI has benefits over other traditional statistical approaches in that it can speed up data sampling and more reliably find nonlinear patterns in input and output [15]. As a result, many academics are interested in the great precision and stability of AI structures in modelling the complicated groundwater systems.

Several studies have demonstrated the value of WQI in assessing water quality in various global locations [16-18]. WQI, for instance, was created to research the appropriateness of groundwater in Malaysia for drinking and agricultural uses[19]. The collected results led to the conclusion that the designed WQI was successful in supplying data on the level of water purity and pollution in the area. An integrated water quality index (IWQI) was created in similar research to assess and map the quality of groundwater in Maharashtra, India [20]. It was discovered that IWQI delivered satisfactory outcomes for assessing groundwater quality and might be a useful tool.This review attempts to analyse the state of the art and determine the efficacy of AI and GIS technologies for assessing groundwater quality. In forecasting whether groundwater quality is suitable for household use, this research focuses on the most prevalent and current applications of AI, including ANN.

The objective of the present study is to identify the existing methods related to ground water modelling with reference to AI and ANN. The present study scope is limited to study and report the comprehensive review on prediction and Assessment of Ground Water Quality By GIS And ANN Techniques

2. Artificial intelligence methods for evaluating groundwater quality

2.1 ANN

ANN is a mathematical model that models human cognitive skills and is powered by a biological neural network[21]. The connection patterns or architecture of the nodes, the connection weight setting techniques, and the activation function were used to differentiate the neural network. The ANN is a computer model that excels in pattern recognition, machine learning, optimisation, and content addressable memory [22-23].

As illustrated in Fig. 1, ANN models have at least three layers of linked neurons, one or more hidden layers, an output layer, and an input layer. With a network topology of linked nodes, the parallel distributed processor of ANNs processes data from input to output. The output layer and the network response of the existing database or known input pattern are correlated with the input data generated in the input layer[24]. The hidden or intermediate layer is crucial for representing and calculating intricate relationships between patterns.

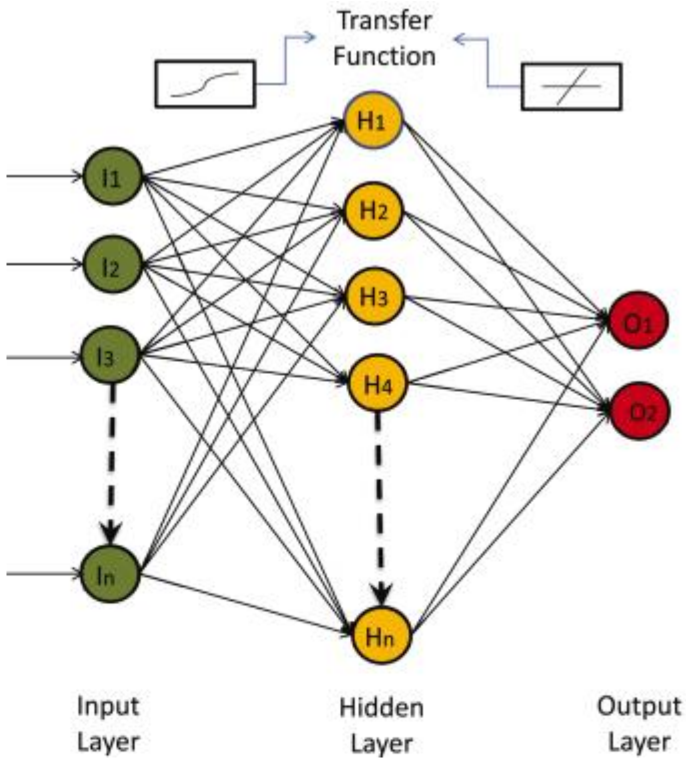

Fig.1 Typical ANN architecture with input, output, and hidden layer.

The most often used ANNs in groundwater modelling are the back-propagation neural network (BPNN), Levenberg-Marquardt back-propagation (LMBP), and multilayer perceptron (MLP) algorithms. This is because they are accurate. A straightforward technique known as a feed-forward neural network (FFNN) transfers information from input nodes via hidden nodes and finally to output nodes in a single direction.The BPNN is essential for training a neural network to locate global minima using a statistical approach. LMBP was developed by combining the sensitive back-propagation algorithm with the less sensitive Levenberg-Marquardt algorithm to achieve the best possible balance between the predictive model's training time and accuracy [26].MLP is renowned for its efficiency in the performance of prediction models employing feed-forward learning [27].When there is little or no training data, MLP can generalise non-linear mapping of input and output variables [28]. The simplest structure for a neural network is the radial basis function (RBF), which Broomhead and Lowe presented. It is made up of traditional approximation theory (1988). RBF is an alternative to MLP that has a single hidden layer and a quicker training rate.

In hydrology, hydraulics, and water resources management, researchers have been actively using ANN for forecasting water and groundwater level and quality, modelling sediment, estimating rainfall-runoff, and managing floods [29-38].Given how well ANN applications work at forecasting hydrochemical and hydrogeological variables, ANN is widely used in groundwater modelling [39-41]

In order to determine the geographical distribution and degree of variation of hydraulic conductivity in aquifer restoration, Ranjithan et al. (1993) [42] employed the three-layer FFNN. In contrast to traditional ANN, those authors discovered that pattern recognition in ANN is highly helpful to separate the uncertainty. By using back-propagation algorithms on a solute transport model, several pumping realisations were found [43]. In that work, a quasi-Newton approach for non-linear optimisation problems was suggested, leading to simulations that were more statistically significant and reliable.

In order to cognitively depict a logical network architecture of the output data through the dimension reduction process, the unsupervised neural network known as the self-organizing map (SOM) employs the FFNN technique [44]. The SOM approaches have been used by Sanchez-Martos et al. (2002)[45] to assess the quality of groundwater. In order to account for the hydrogeochemical processes that occurred in a semiarid region, temperature, Cl, SO42, HCO3, NO3, Na+, Mg2+, and Ca2+, as well as total dissolved solids (TDS), were chosen as input variables. To simulate the presence of saltwater in a constrained aquifer system, Cl and SO42 are utilised [46]. SOM offers a straightforward activation map interpretation of parameter data. The activation maps' parameter values were retrieved from each one using derived quadrat system.Since SOM can understand data from input and output relationships and store the knowledge in mathematical expressions, it may be used to hydrogeochemical systems [47]. But, the SOM application needs the precise and enough data to create a large cluster [48]. Particularly in nonlinear modelling, a lack of data leads to arbitrary categorization and inaccurate judgement.

In order to assess groundwater contamination in rural private wells, Ray and Klindworth (2000)[49] presented a generic BPNN coupled with a feed-forward neural network (FFBP). Nitrate contamination and pesticide contamination were divided amongst the models. The distance from farmland, well depth, and land surface to aquifer depth were input factors. By modifying and minimising the weight of error in the feed-forward neural network, BPNN implementation aims to achieve the desired output of prediction accuracy [50]. Finding significant input parameters was done by using the trial-and-error approach. As a result, the kind of wells had an effect on whether each parameter was present.

Using a BPNN, Kuo et al. (2004) [32] examined groundwater quality variance in the Taiwanese region affected by the blackfoot epidemic. The effects of seawater intrusion and arsenic contamination were assessed in relation to hidden neuron quantity and learning performance of various input variables. Electrical conductivity (EC), Cl, SO42, K+, and Mg2+ were utilised as the input variables for saltwater intrusion, whereas Alkalinity (Alk), Arsenic (As), and Total Organic Carbon were used as the input variables for Arsenic Pollution (TOC). Root mean square error (RMSE) was computed in this study to assess the effectiveness of the ANN model. Higher numbers of hidden neurons have little impact on ANN performance, but generalisation neurons still need to discover the right amount of hidden layers[51]. The most recent and earlier input data are crucial for an accurate and reliable forecast.

The conventional BPNN often has a slower convergence rate. As a result, training for big and complex datasets frequently becomes stuck around subpar local minima [52]. The second-order technique, which employs the Levenberg-Marquardt (LM) formula introduced by Hagan and Menhaj (1994)[53] and Sivanandam et al.,[54] is required to enhance the performance of BPNN (2005). Using the LMBP method, Yesilnacar et al. (2008)[55] created a computational model-based learning system for nitrate prediction in shallow aquifers. The simulations' four input variables were pH, temperature, EC, and groundwater level. In the hidden layer of the two-layer network, the tan-sigmoid transfer function was used, while the output layer used the linear transfer function.According to El-Din and Smith (2002)[56], a single hidden layer is sufficient for model simulation, but an extra hidden layer makes it possible to approximate complicated functions with the best connections weight [57].The number of neurons was set to 20 with a constant learning rate and momentum of 0.1 and 0.9, respectively, for choosing the best-fitting BPNN. Hagan et al. (1997)[53] claim that momentum enables the network to pass past a brief local minimum. The 'trainlm' BPNN had the best fit of the 12 BPNNs thanks to minimal training error and maximum R of the LM method.The use of LM reduced gradient descent convergence rate and the sum of squared error enhances the rate of efficiency of the BPNN algorithms in addressing a convex optimisation error in non-linear systems The most important input parameter was discovered to be EC, according to Yesilnacar et al. (2008).

Kumar (2010)[58] looked at how well BPNN performed in evaluating groundwater quality parameters in India. To map ion concentrations in groundwater, kriging was performed. The BPNN was trained using the 'trainlm' function. The creation of the BPNN model made use of the input variables Cl, SO42, and alkalinity, as well as the intended outputs pH, EC, Na+, Ca2+, Mg2+, and K. The dataset, which was sampled between 2006 and 2008, was analysed for pre- and post-monsoon.The number of hidden neurons and layers were adjusted to manage the non-linearity in the input data in order to get the ideal design for an ANN. 50 neurons were chosen as the configuration number for every pair of hidden layers. The requested data had a high uniform distribution mean error and a low value of correlation coefficient thanks to the 4-50-50-6 design. The safety of the groundwater from 79 sample wells was confirmed by the study of the cation and anion concentrations. According to the authors, EC was an important factor in model development.

RBF was shown to be successful in developing a multilayer feed-forward neural network of groundwater quality by Zhaoxian and Yuling (2011)[59]. Based on the quality of the water, ten input variables were selected. According on node activity rate and mutual information, the hidden nodes were either added or removed to produce the ideal RBF network layout. The outcomes show how accurate it is in predicting groundwater quality. The spatial distribution of the grading system was shown using GIS. Compared to BPNN, RBF offers fewer iterations because of faster convergence, better prediction accuracy, and more stability [60].

Poor model performance may result from an over- or under-fitting issue brought on by the random selection of the number of neurons. Typically, the trial-and-error method is used to assess the ideal structure, the pertinent learning rate parameter, and momentum [61]. In order to determine the ideal structure of BPNN and forecast the right number of hidden neurons, Kheradpisheh et al. (2015)[71] used a trial-and-error rule. Simple shells may be used to model and simulate complicated environmental systems in ANN [72,4]. Yet, the creation of data-driven models is highly influenced by the precise selection of input variables, particularly for non-linear hydrologic model analysis [73-75][. Kheradpisheh et al. (2015)[71]varied the number of epoch settings in the study in accordance with the acceptability of the various input parameter combinations. The five training algorithms with varying numbers of hidden nodes included gradient descent (traingd), gradient descent with adaptive learning rate (traingda), gradient descent with momentum and adaptive learning rate back-propagation (traingdx), Levenberg-Marquardt (trainlm), and scaled conjugate gradient back-propagation (trainscg). Although 'trainlm' was used to structure NO3, 'trainscg' was trained to provide the best structures for EC and Cl, yielding the lower values of RMSE, COREL, Nash-Sutcliffe coefficient, and R2. Cl, EC, and SO42 showed outstanding accuracy in the performance, however NO3 did not. In a paper published in 2016, Sakizadeh compared the results of three ANN methods for groundwater systems: ensemble ANN (EANN), ANN with Bayesian regularisation, and ANN with early stopping. These methods are frequently used with BPNN. Poor regularisation caused by a rising model complexity with too many parameters is the most frequent issue while training deep neural networks. Early stopping, when the iteration stops at a set number as the generalisation error grows, is a straightforward method to control the over-fitting problem [76]. Sharkey (1996)[77] found how to use the EANN technique to increase generalisation proficiency and stability. The output was created from a single, unified forecast, and the trained ANNs were divided into small groups with the same goals.

By regulating and penalising high model parameter weights, Bayesian regulation artificial neural networks (BRANN) and EANN are good in enhancing model network generalisation [78]. According to the study, both BRANN and EANN are successful in estimating WQI with reduced error validation (mean square error [MSE] = 7.71 and 9.25, respectively) as compared to the early stopping approach (MSE = 17.67). Due to the decreased error ratio of MSE, the sensitivity analysis identified SO42, EC, and NO3 as the groundwater quality metrics that were not significant [13].

A groundwater quality model was created using the MLP algorithm[79]. Deep neural network techniques such as MLP are frequently utilised to solve issues involving pattern categorization and regression [80-81]. Input variables were the GWQI factors, and the eight groundwater quality index (GWQI) parameters chosen as outputs were pH, TDS, K+, Na+, Ca2+, Cl, Mg2+, and SO42 (water table depth, distance from contamination, site elevation, aquifer formation, population and household activity). The GWQI value was divided into three categories: high (GWQI > 0.15), low (GWQI 0.04), and suitable (GWQI 0.04 – 0.15). Groundwater geographical data were gathered, analysed, and visualised using GIS.

The LM algorithm is the most suitable network structure to train groundwater quality, while the trial-and-error technique reveals the hyperbolic tangent to be the significant transfer function. Amazingly, hyperbolic tangent functions can distinguish between tiny input variables. When compared to sigmoid normalisation, the steep derivative was thought to be a more effective and potent method [82]. The ideal input factors that effectively explain the behaviour of the output variable in forecasting groundwater quality are the water table depth, distance from pollution, and aquifer transmissivity [83]. Although the combination of ANN and GIS was shown to be helpful in projecting groundwater quality, the prediction value of the ideal input variable was wrong owing to ANN's restriction in receiving the large input pixel.

Zio (1997) and Balkhair (2002)[84,85] used the multilayer perceptron with back-propagation approach to estimate aquifer parameter (MLPBP). MLPBP has also been used to simulate the quality of groundwater[86]. Since it is a more accurate and appropriate index for determining total water use, the Canadian Water Quality Index (CWQI) was used to evaluate 10 physicochemical factors than the conventional Water Quality Index (WQI). The effectiveness of MLPBP was then contrasted with that of a multilinear regression model (MLR). The investigation revealed that MLPBP's adaptive, data-driven, and effective computational tools make it stronger at complicated groundwater quality modelling.

The BPNN method has been used in the majority of the research we investigated, either for training or modelling [87-89]. The usage of BPNN does have several restrictions, though, including empirical risk minimization, a slow convergence rate, and a propensity to become trapped in local minima for large input data sets. Using LM increased convergence time and speed, reduced training error without becoming trapped at local minima, and improved prediction accuracy [90]. Yet, in modestly large samples, the LM method seems to be the quickest [91]. At the same time, it was found that the RBF performed better than BPNN in terms of recognition speed and efficiency rate. To evaluate performance effectiveness, several comparative studies between the RBF and MLP were carried out. RBF, according to Senthil Kumar et al. (2005) and Mutlu et al. (2008)[92-93], is quicker and more consistent in learning and training rate than MLP, but the huge number of neurons produced poor generalisation. When the proper input parameters were added, the MLP method demonstrated better prediction accuracy during both the training and validation processes [91], whereas the performance of RBF models degraded during the validation process when the introduction of input parameters compared to the better performance presented during the training process.

As shown, choosing the transfer function and input variables is essential for designing the best ANN functions. The features of groundwater should be taken into account while selecting prospective input factors to forecast groundwater quality. The correlation coefficient between the possible variables is used to assess the best input variables. In particular, total hardness (TH), Cl, SO42, Mg2+, EC, TDS, and groundwater level are often utilised input variables (GWL). The relationship between ANN modeling's non-linear input and linear output must be shaped by the transfer function. The most often used technique for determining the ideal ANN structure and the ideal number of neurons in the hidden layer is trial and error.

3.0 Assessment & Evaluation

This study has mostly discussed AI applications with reference to ANN for modelling groundwater quality. The analysis produced the following findings:

a. ANN and ANFIS are the AI tools that are most frequently used to evaluate the quality of groundwater among published state-of-the-art research and critical review of AI tools.
b. As of now, ANN has emerged as one of the most promising and well-liked technologies for simulating and modelling intricate hydrogeological systems.
c. The scientists are optimistic that more research or a combination of techniques may assist to increase the ANN's learning rates and performance accuracy despite certain downsides including local minima issues and a lengthy training period.
d. For lesser amounts of data, ANFIS, which combines the benefits of ANN and fuzzy inference systems, shows somewhat superior prediction. When evaluating the quality of groundwater, ANN and ANFIS both produce good findings.
e. Certain fundamental issues in AI approaches occur when creating an effective modelling structure, including the choice of the input parameters, the effects of initial uncertainty, and the model structure requirements.
f. Considerations including correlation analysis, statistical analysis, and the features of the research region must be taken into account while choosing the input parameters.

4.0 Conclusion

Without the help of computational tools, it is hard and challenging to comprehend the hydrologic functions and status of groundwater systems. An in-depth analysis of the different AI and GIS methodologies, approaches, and strategies are provided in this study.From the literature review, ANNs have shown to be accurate and effective instruments for assessing and controlling groundwater quality. But, as compared to standalone technologies, the hybridization of proper machine learning is far more potent. As a result, establishing and planning groundwater management and pollution control measures can benefit from using AI modelling approaches.

References

1. Kundzewicz, Z.W., 1997. Water resources for sustainable development. Hydrol. Sci. J. 42 (4), 467–480. https://doi.org/10.1080/02626669709492047.
2. Nourbakhsh, Z., Mehrdadi, N., Moharamnejad, N., Hassani, A.H., Yousefi, H., 2016. Evaluating the suitability of different parameters for qualitative analysis of groundwater based on analytical hierarchy process. Desalin. Water Treat. 57 (28), 13175–13182. https://doi.org/10.1080/19443994.2015.1056837
3. Tirkey, P., Bhattacharya, T., Chakraborty, S., Baraik, S., 2017. Assessment of groundwater quality and associated health risks: a case study of Ranchi city, Jharkhand, India. Groundwater Sustainable Dev 5, 85–100. https://doi.org/ 10.1016/j.gsd.2017.05.002.
4. Li, P., Wu, J., Qian, H., 2012a. Groundwater quality assessment based on rough sets attribute reduction and TOPSIS method in a semi-arid area, China. Environ. Monit. Assess. 184 (8), 4841–4854. https://doi.org/10.1007/s10661-011-2306-1.
5. Singh, K.P., Gupta, S., Rai, P., 2014. Investigating hydrochemistry of groundwater in Indo-Gangetic alluvial plain using multivariate chemometric approaches. Environ. Sci. Pollut. Res. 21 (9), 6001–6015. https://doi.org/10.1007/s11356-014-2517-4.
6. Bachmat, Y., Andrews, B., Holtz, D., Sebastian, S., 1978. Utilization of Numerical Groundwater Models for Water Resource Management U.S. Environmental Protection Agency Report EPA-600/8-78-012. https://nepis.epa.gov/Exe/ZyPDF. cgi/9101UCQJ.PDF?Dockey=9101UCQJ.PDF
7. Gao, L., Li, D., 2014. A review of hydrological/water-quality models. Front. Agric. Sci. Eng. 1, 267. https://doi.org/10.15302/J-FASE-2014041.
8. Guzman, J., Shirmohammadi, A., Sadeghi, A., Wang, X., Chu, M.L., Jha, M., Hernandez, J.E., 2015. Uncertainty considerations in calibration and validation of hydrologic and water quality models. Trans. ASABE (Am. Soc. Agric. Biol. Eng.) 58 (6), 1745–1762. https://doi.org/10.13031/trans.58.10710.
9. Remesan, R., Mathew, J., 2015. Machine learning and artificial intelligence-based approaches. In: Hydrological Data Driven Modelling: A Case Study Approach. Springer International Publishing, Cham, pp. 71–110. https://doi.org/10.1007/978- 3-319-09235-5_4.
10. Khaki, M., Yusoff, I., Islami, N., 2015. Application of the artificial neural network and neuro-fuzzy system for assessment of groundwater quality. Clean 43 (4), 551–560. https://doi.org/10.1002/clen.201400267.
11. Mirabbasi, R., 2015. Application of artificial intelligence methods for groundwater quality prediction. In: Nadir, A.A. (Ed.), Application of Artificial Intelligence Methods in Geosciences and Hydrology. OMICS Group, Foster City.
12. Barzegar, R., Adamowski, J., Moghaddam, A.A., 2016. Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay River, Iran. Stochastic Environ. Res. Risk Assess. 30 (7), 1797–1819. https://doi.org/ 10.1007/s00477-016-1213-y.
13. Sakizadeh, M., 2016. Artificial intelligence for the prediction of water quality index in groundwater systems. Model. Earth Syst. Environ. 2 (1), 8. https://doi.org/10.1007/ s40808-015-0063-9.
14. Bagheri, M., Bazvand, A., Ehteshami, M., 2017. Application of artificial intelligence for the management of landfill leachate penetration into groundwater, and assessment of its environmental impacts. J. Cleaner Prod. 149, 784–796. https://doi.org/ 10.1016/j.jclepro.2017.02.157.

15. Ay, M., Ozyildirim, S., 2018. Artificial Intelligence (AI) studies in water resources. Natural and Engineering Sciences 3 (2), 187–195. https://doi.org/10.28978/ nesciences.424674.

16. Brindha K, Paul R, Walter J et al (2020) Trace metals contamination in groundwater and implications on human health: comprehensive assessment using hydrogeochemical and geostatistical methods. Environ Geochem Health. https://doi.org/10.1007/s10653-020-00637-9

17. Farrag AEA, Megahed HA, Darwish MH (2019) Remote sensing, GIS and chemical analysis for assessment of environmental impacts on rising of groundwater around Kima Company, Aswan, Egypt. Bull Natl Res Centre 43:14. https://doi.org/10.1186/s42269-019-0056-3

18. Li, P., Wu, J., Qian, H., 2012a. Groundwater quality assessment based on rough sets attribute reduction and TOPSIS method in a semi-arid area, China. Environ. Monit. Assess. 184 (8), 4841–4854. https://doi.org/10.1007/s10661-011-2306-1.

19. Verma, P.; Singh, P.K.; Sinha, R.R.; Tiwari, A.K. Assessment of groundwater quality status by using water quality index (WQI) and geographic information system (GIS) approaches: A case study of the Bokaro district, India. *Appl. Water Sci.* **2020**, *10*, 27

20. Balakrishnan, P. Groundwater quality mapping using geographic information system (GIS): A case study of Gulbarga City, Karnataka, India. *Afr. J. Environ. Sci. Technol.* **2011**, *5*, 1069–1084.

21. Haykin, S., 2007. Neural Networks: A Comprehensive Foundation, third ed. PrenticeHall, Upper Saddle River, NJ, USA.

22. Jain, A.K., Mao, J., Mohiuddin, K.M., 1996. Artificial neural networks: a tutorial. Computer 29 (3), 31–44. https://doi.org/10.1109/2.485891.

23. Besaw, L.E., Rizzo, D.M., 2007. Counterpropagation neural network for stochastic conditional simulation: an application with Berea Sandstone. In: Seventh IEEE International Conference on Data Mining Workshops (ICDMW 2007). IEEE, New York.

24. Kheradpisheh, Z., Talebi, A., Rafati, L., Ghaneian, M.T., Ehrampoush, M.H., 2015. Groundwater quality assessment using artificial neural network: a case study of Bahabad plain, Yazd, Iran. Desert 20 (1), 65–71. https://doi.org/10.22059/ jdesert.2015.54084.

25. Wasserman, P.D., 1989. Neural Computing: Theory and Practice. Van Nostrand Reinhold Co., New York.

26. Ma, L., Xu, F., Wang, X., Tang, L., 2010. Earthquake prediction based on levenbergmarquardt algorithm constrained back-propagation neural network using DEMETER data. In: Bi, Y., Williams, M.A. (Eds.), Knowledge Science, Engineering and Management. Springer, Berlin, pp. 591–596.

27. Erdogan, A., Geckinli, M., 2003. A PWR reload optimisation code (XCore) using artificial neural networks and genetic algorithms. Ann. Nucl. Energy 30 (1), 35–53. https:// doi.org/10.1016/S0306-4549(02)00041-5.

28. Matignon, R., 2005. Neural Network Modeling Using SAS Enterprise Miner. Authorhouse, Bloomington.

29. Maier, H.R., Dandy, G.C., 2000. Application of artificial neural networks to forecasting of surface water quality variables: issues, applications and challenges. In: Govindaraju, R.S., Rao,

A.R. (Eds.), Artificial Neural Networks in Hydrology. Springer Netherlands, Dordrecht, pp. 287–309. https://doi.org/10.1007/978-94- 015-9341-0_15.

30. Dawson, C.W., Wilby, R., 1998. An artificial neural network approach to rainfall-runoff modelling. Hydrol. Sci. J. 43 (1), 47–66. https://doi.org/10.1080/ 02626669809492102.

31. Campolo, M., Soldati, A., Andreussi, P., 2003. Artificial neural network approach to flood forecasting in the River Arno. Hydrol. Sci. J. 48 (3), 381–398. https://doi.org/ 10.1623/hysj.48.3.381.45286.

32. Kuo, Y.-M., Liu, C.-W., Lin, K.-H., 2004. Evaluation of the ability of an artificial neural network model to assess the variation of groundwater quality in an area of Blackfoot disease in Taiwan. Water Res. 38 (1), 148–158. https://doi.org/10.1016/j. watres.2003.09.026.

33. Minns, A.W., Hall, M.J., 2009. Artificial neural networks as rainfall-runoff models. Hydrol. Sci. J. 41 (3), 399–417. https://doi.org/10.1080/02626669609491511.

34. Sreekanth, P.D., Geethanjali, N., Sreedevi, P.D., Ahmed, S., Kumar, N.R., Jayanthi, P.D. K., 2009. Forecasting groundwater level using artificial neural networks. Curr. Sci. 96 (7), 933–939.

35. Shuai, S., Xilai, Z., Fadong, L., 2010. Surface water quality forecasting based on ANN and GIS for the Chanzhi Reservoir, China. In: The 2nd International Conference on Information Science and Engineering (ICISE). IEEE, New York.

36. Ghuman, A.R., Ghazaw, Y.M., Sohail, A.R., Watanabe, K., 2011. Runoff forecasting by artificial neural network and conventional model. Alexandria Eng. J. 50 (4), 345–350. https://doi.org/10.1016/j.aej.2012.01.005.

37. Mustafa, M.R., Rezaur, R.B., Saiedi, S., Isa, M.H., 2012. River suspended sediment prediction using various multilayer perceptron neural network training algorithms: a case study in Malaysia. Water Resour. Manage. 26 (7), 1879–1897. https://doi.org/ 10.1007/s11269-012-9992-5.

38. Shiri, J., Kisi, O., Yoon, H., Lee, K.-K., Hossein Nazemi, A., 2013. Predicting groundwater level fluctuations with meteorological effect implications—a comparative study among soft computing techniques. Comput. Geosci. 56, 32–44. https://doi.org/ 10.1016/j.cageo.2013.01.007.

39. Singh, K.P., Basant, N., Gupta, S., 2011. Support vector machines in water quality management. Anal. Chim. Acta 703 (2), 152–162. https://doi.org/10.1016/j. aca.2011.07.027.

40. Trichakis, I.C., Nikolos, I.K., Karatzas, G.P., 2010. Artificial neural network (ANN) based modeling for karstic groundwater level simulation. Water Resour. Manage. 25 (4), 1143–1152. https://doi.org/10.1007/s11269-010-9628-6.

41. Yu, F.R., Liu, Z.P., 2012. The application of artifical neural network in the groundwater quality assessment in industrial Park Catchment. Adv. Mat. Res. 518–523, 1340–1343. https://dx.doi.org/10.4028/www.scientific.net/AMR.518-523.1340.

42. Ranjithan, S., Eheart, J.W., Garrett Jr., J.H., 1993. Neural network-based screening for groundwater reclamation under uncertainty. Water Resour. Res. 29 (3), 563–574. https://doi.org/10.1029/92WR02129.

43. Rogers, L.L., Dowla, F.U., 1994. Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling. Water Resour. Res. 30 (2), 457–481. https://doi.org/10.1029/93WR01494

44. Kohonen, T., 1982. Self-organized formation of topologically correct feature maps. Biol. Cybern. 43 (1), 59–69. https://doi.org/10.1007/BF00337288.

45. Sanchez-Martos, F., Aguilera, P.A., Garrido-Frenich, A., Torres, J.A., Pulido-Bosch, A., 2002. Assessment of groundwater quality by means of self-organizing maps: application in a semiarid area. Environ. Manage. 30 (5), 716–726. https://doi.org/ 10.1007/s00267-002-2746-z.

46. Yamanaka, M., Kumagai, Y., 2006. Sulfur isotope constraint on the provenance of salinity in a confined aquifer system of the southwestern Nobi Plain, central Japan. J. Hydrol. 325 (1), 35–55. https://doi.org/10.1016/j.jhydrol.2005.09.026.

47. Roussinov, D., Chen, H.-C., 1999. A scalable self-organizing map algorithm for textual classification: a neural network approach to thesaurus generation. Communication and Cognition in Artificial Intelligence Journal 15, 81–111.

48. Tjaden, B., Cohen, J., 2006. A survey of computational methods used in microarray data interpretation. In: Arora, D.K., Berka, R.M., Singh, G.B. (Eds.), Applied Mycology and Biotechnology, vol. 6. Elsevier, Amsterdam, pp. 161–178. http://www.sciencedirect. com/science/article/pii/S1874533406800109

49. Ray, C., Klindworth, K.K., 2000. Neural networks for agrichemical vulnerability assessment of rural private wells. J. Hydrol. Eng. 5 (2), 162–171. https://doi.org/ 10.1061/(ASCE)1084-0699(2000)5:2(162).

50. Kvaal, K., McEwan, J.A., 1996. Analysing complex sensory data by non-linear artificial neural networks. In: Naes, T., Risvik, E. (Eds.), Multivariate Analysis of Data in Sensory Science, vol. 16. Elsevier, Amsterdam, pp. 103–133. http://www.sciencedi rect.com/science/article/pii/S0922348796800281.

51. Mezard, M., Nadal, J.P., 1989. Learning in feedforward layered networks: the tiling algorithm. J. Phys. A: Math. Gen. 22 (12), 2191–2203. https://doi.org/10.1088/ 0305-4470/22/12/019.

52. Hamed, M.M., Khalafallah, M.G., Hassanien, E.A., 2004. Prediction of wastewater treatment plant performance using artificial neural networks. Environ. Modell. Software 19 (10), 919–928. https://doi.org/10.1016/j.envsoft.2003.10.005.

53. Hagan, M.T., Demuth, B.H., Beale, H.M., Jess, O.D., 1997. Neural Network Design, second ed. Oklahama State University, Stillwater, OK, USA.

54. Sivanandam, S.N., Sumathi, S., Deepa, S.N., 2005. Introduction to Neural Networks Using Matlab 6.0 Computer Engineering Series. Tata McGraw-Hill Education Pvt. Ltd., New Delhi.

55. Yesilnacar, M.I., Sahinkaya, E., Naz, M., Ozkaya, B., 2008. Neural network prediction of nitrate in groundwater of Harran Plain, Turkey. Environ. Geol. 56 (1), 19–25. https://doi.org/10.1007/s00254-007-1136-5.

56. El-Din, A.G., Smith, D.W., 2002. A neural network model to predict the wastewater inflow incorporating rainfall events. Water Res. 36 (5), 1115–1126. https://doi.org/ 10.1016/S0043-1354(01)00287-1.

57. Toth, E., Brath, A., Montanari, A., 2000. Comparison of short-term rainfall prediction models for real-time flood forecasting. J. Hydrol. 239 (1), 132–147. https://doi.org/ 10.1016/S0022-1694(00)00344-9.

58. Kumar, N., 2010. Analysis of groundwater for potability from Tiruchirappalli city using backpropagation ANN model and GIS. Indian J. Environ. Prot. Indian 1, 136–142. https://doi.org/10.4236/jep.2010.12018

59. Zhaoxian, Z., Yuling, Z., 2011. Application of RBF-ANN Model in Groundwater Quality Evaluation of Changchun Region. 2011 International Conference on Multimedia Technology. IEEE, New York.

60. Moradkhani, H., Hsu, K.-l., Gupta, H.V., Sorooshian, S., 2004. Improved streamflow forecasting using self-organizing radial basis function artificial neural networks. J. Hydrol. 295 (1), 246–262. https://doi.org/10.1016/j.jhydrol.2004.03.027.

61. Chang, H.H., Yen, J.Y., Lin, T.C., 2011. Parameter design for operating window problems: an example of paper feeder design. In: Zhou, M., Tan, H. (Eds.), Advances in Computer Science and Education Applications: International Conference, CSE 2011, Qingdao, China, July 9-10, 2011, Proceedings, Part II, vol. 202. Springer, Berlin

62. Khalil, A., Almasri, M.N., McKee, M., Kaluarachchi, J.J., 2005. Applicability of statistical learning algorithms in groundwater quality modeling. Water Resour. Res. 41 (5) https://doi.org/10.1029/2004WR003608

63. Seyam, M., Mogheir, Y., 2011. Application of artificial neural networks model as analytical tool for groundwater salinity. J. Environ. Prot. 2 https://doi.org/10.4236/ jep.2011.21006.

64. Galelli, S., Humphrey, G.B., Maier, H.R., Castelletti, A., Dandy, G.C., Gibbs, M.S., 2014. An evaluation framework for input variable selection algorithms for environmental data-driven models. Environ. Modell. Software 62, 33–51. https://doi.org/10.1016/ j.envsoft.2014.08.015

65. Ferreira, C., 2002. Gene expression programming in problem solving. In: Roy, R., Koppen, ¨ M., Ovaska, S., Furuhashi, T., Hoffmann, F. (Eds.), Soft Computing and Industry: Recent Applications. Springer, London, pp. 635–653. https://doi.org/ 10.1007/978-1-4471-0123-9_54

66. Galelli, S., Humphrey, G.B., Maier, H.R., Castelletti, A., Dandy, G.C., Gibbs, M.S., 2014. An evaluation framework for input variable selection algorithms for environmental data-driven models. Environ. Modell. Software 62, 33–51. https://doi.org/10.1016/ j.envsoft.2014.08.015.

67. Prechelt, L., 2012. Early stopping — but when? In: Montavon, G., Orr, G.B., Müller, K.-R. (Eds.), Neural Networks: Tricks of the Trade, second ed. Springer, Berlin, pp. 53–67. https://doi.org/10.1007/978-3-642-35289-8_5.

68. Sharkey, A., 1996. On combining artificial neural nets. Connect. Sci. 8, 299–314. https:// doi.org/10.1080/095400996116785

69. Krogh, A., Hertz, J.A., 1991. A Simple Weight Decay Can Improve Generalization. Morgan Kaufmann Publishers Inc., Denver, Colorado.

70. Gholami, V., Khaleghi, M.R., Sebghati, M., 2017. A method of groundwater quality assessment based on fuzzy network-CANFIS and geographic information system (GIS). Appl. Water Sci. 7 (7), 3633–3647. https://doi.org/10.1007/s13201-016- 0508-y

71. Anguita, D., Ridella, S., Rivieccio, F., 2005. K-fold generalization capability assessment for support vector classifiers. In: Proceedings 2005 IEEE International Joint Conference on Neural Networks. IEEE, New York

72. Chen, Lh., Zhang, Xy. (2009). Application of Artificial Neural Networks to Classify Water Quality of the Yellow River. In: Cao, By., Zhang, Cy., Li, Tf. (eds) Fuzzy Information and Engineering. Advances in Soft Computing, vol 54. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-88914-4_3

73. Baughman, D.R., Liu, Y.A., 1995. Fundamental and practical aspects of neural computing. In: Baughman, D.R., Liu, Y.A. (Eds.), Neural Networks in Bioprocessing and Chemical Engineering. Academic Press, Boston, pp. 21–109. http://www.sciencedirect.com/science/article/pii/B9780120830305500084.

74. Gholami, V., Sebghati, M., Yousefi, Z., 2016. Integration of artificial neural network and geographic information system applications in simulating groundwater quality. Environmental Health Engineering and Management Journal 3 (4), 10. https://doi. org/10.15171/EHEM.2016.17.

75.Zio, E., 1997. Approaching the inverse problem of parameter estimation in groundwater models by means of artificial neural networks. Prog. Nucl. Energy 31 (3), 303–315. https://doi.org/10.1016/S0149-1970(96)00013-3.

76. Balkhair, K.S., 2002. Aquifer parameters determination for large diameter wells using neural network approach. J. Hydrol. 265 (1), 118–128. https://doi.org/10.1016/ S0022-1694(02)00103-8

77. Nathan, N., Saravanane, R., Thirumalai, S., 2017. Application of ANN and MLR models on groundwater quality using CWQI at Lawspet, Puducherry in India. J. Geosci. Environ. Protect. 5, 99–124. https://doi.org/10.4236/gep.2017.53008.

78. Ray, C., Klindworth, K.K., 2000. Neural networks for agrichemical vulnerability assessment of rural private wells. J. Hydrol. Eng. 5 (2), 162–171. https://doi.org/ 10.1061/(ASCE)1084-0699(2000)5:2(162)

79. Kisi, O., Shiri, J., Karimi, S., Shamshirband, S., Motamedi, S., Petkovi´c, D., Hashim, R., 2015. A survey of water level fluctuation predicting in Urmia Lake using support vector machine with firefly algorithm. Appl. Math. Comput. 270, 731–743. https:// doi.org/10.1016/j.amc.2015.08.085.

80. Yoon, H., Jun, S.-C., Hyun, Y., Bae, G.-O., Lee, K.-K., 2011. A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. J. Hydrol. 396 (1), 128–138. https://doi.org/10.1016/j. jhydrol.2010.11.002.

81. Latifoglu, L., Kisi, O., Latifoglu, F., 2015. Importance of hybrid models for forecasting of hydrological variable. Neural Comput. Appl. 26 (7), 1669–1680. https://doi.org/ 10.1007/s00521-015-1831-1.

82. Kisi, O., Shiri, J., Karimi, S., Shamshirband, S., Motamedi, S., Petkovi´c, D., Hashim, R., 2015. A survey of water level fluctuation predicting in Urmia Lake using support vector machine with firefly algorithm. Appl. Math. Comput. 270, 731–743. https:// doi.org/10.1016/j.amc.2015.08.085.

83. Senthil Kumar, A.R., Sudheer, K.P., Jain, S.K., Agarwal, P.K., 2005. Rainfall-runoff modelling using artificial neural networks: comparison of network types. Hydrol. Processes 19 (6), 1277–1291. https://doi.org/10.1002/hyp.5581.

84. Mutlu, E., Chaubey, I., Hexmoor, H., Bajwa, S.G., 2008. Comparison of artificial neural network models for hydrologic predictions at multiple gauging stations in an agricultural watershed. Hydrol. Processes 22 (26), 5097–5106. https://doi.org/ 10.1002/hyp.7136.