Environ. Water Eng., 2025, 11(2), 144-154 https://doi.org/10.22034/ewe.2025.494616.1988

EWE

Environment and Water Engineering

Homepage: www.jewe.ir

ISSN: 2476-3683

Predicting saltwater concentration in coastal aquifers using hybrid models

Reza Karamd Sani[1], Reza Delirhasannia[1]✉, and Saeed Samadianfard[1]

[1]Department of Water Engineering, Faculty of Agriculture, University of Tabriz, Tabriz, Iran

ARTICLE INFO

Paper Type: Research Paper

Received: 22 December 2024
Revised: 12 April 2025
Accepted: 14 April 2025
Published: 06 May 2025

Keywords
Coastal Aquifers
Groundwater Modelling
Machine Learning
Optimization
Saltwater Intrusion

Corresponding author:
R. Delirhasannia
✉ delearhasannia@yahoo.com

ABSTRACT

This study presents an integrated approach that combines laboratory experiments, numerical modeling, and machine learning to enhance salinity prediction in coastal aquifers. A laboratory model simulated saltwater intrusion under controlled conditions, systematically varying water density (25, 35, 50 g/l), extraction rate (0.05, 0.12, 0.25 l/min), and extraction depth (12, 25, 36 cm) to examine hydrodynamic and geochemical interactions. Experimental data calibrated the SEAWAT numerical model, which generated additional scenarios for machine learning analysis. The study developed hybrid predictive models combining Support Vector Regression and Random Forest with Convolutional Neural Networks, optimized using the Golden Ball Optimization algorithm. Key input parameters, including relative water density, extraction rate, and well depth, were evaluated through a comprehensive statistical analysis. The evaluation results indicated that the RF-GBO-3 model, with a root mean square error (RMSE) of 0.039, exhibited the best performance among the models, while the SVR-GBO-3 model, with an RMSE of 0.056, also showed satisfactory performance. The Golden Ball Optimization algorithm enhanced model performance by effectively tuning critical parameters and capturing complex nonlinear relationships. These findings advance saltwater intrusion modeling by providing a robust framework that integrates physical experiments with data-driven techniques, offering improved tools for coastal water resource management.

Highlights

- Hybrid ML models predict salinity using lab data and SEAWAT simulations.
- RF-GBO-3 model achieved the best accuracy with RMSE of just 0.039.
- Golden Ball Optimization boosted model tuning and prediction accuracy.

How to cite this paper:
Karamd Sani, R., Delirhasannia, R., & Samadianfard, S. (2025). Predicting saltwater concentration in coastal aquifers using hybrid models. *Environment and Water Engineering*, *11*(2), 144-154. https://doi.org/10.22034/ewe.2025.494616.1988

1. Introduction

Coastal aquifers have long been recognized as important drinking water sources and key factors enabling the expansion of urban and agricultural areas near coastlines (Werner and Simmons 2009). This vital resource exists in dynamic equilibrium with the adjacent seas, where denser saltwater naturally forms beneath lighter freshwater, creating ongoing management challenges. Basack et al. (2012) highlighted the imperative need to conserve groundwater resources in densely populated coastal areas. Subsequent studies by Abd-Elhamid et al. (2016) documented how seawater intrusion degrades groundwater quality by raising salinity beyond acceptable standards. Klassen and Allen (2017) further identified seawater intrusion as the primary cause of groundwater quality deterioration in coastal aquifers. More recent research has expanded our understanding of these dynamics. Kolathayar et al. (2019) analyzed the hydrodynamic processes at the aquifer-sea interface, where saltwater intrusion occurs due to density and pressure differences. Abdolati et al. (2019) emphasized that managing seawater intrusion is a critical environmental challenge for the conservation of freshwater resources. Current perspectives from Banaduc et al. (2022) warned that coastal freshwater systems face a high risk of degradation without sustainable management practices. The most recent comprehensive analysis by Ravindiran et al. (2023) has shown that pollution from environmental, domestic, industrial, and agricultural sources exacerbates the problem of seawater intrusion and poses complex management challenges for modern coastal communities. These temporal advance highlights the growing understanding of coastal aquifer dynamics and the increasing recognition of seawater intrusion as both a natural process and a human challenge that requires innovative management solutions.

The scientific understanding of saltwater intrusion control methods has evolved significantly since Todd's (1974) foundational work, which first proposed comprehensive management strategies including pumping rate optimization, artificial recharge, and subsurface barriers. Early computational approaches emerged with Zhou et al. (2003), who pioneered three-dimensional modeling to optimize pumping rates in China's Leizhou Peninsula, demonstrating how spatial management could balance extraction and intrusion control. Subsequent advances in computational methods included Amaziane et al. (2004) integrating genetic algorithms with boundary element methods for well placement optimization, while Guo and Jiao (2007) provided early insights into how coastal land rehabilitation could influence the freshwater-saltwater interface. The development of sophisticated modeling tools continued with Gopinath et al. (2016) applying SEAWAT to simulate 50 years of variable-density flow in Nagapattinam's aquifers, quantifying the impacts of excessive groundwater withdrawal. Recent years have seen significant methodological innovations. Abd-Elaty et al. (2020) advanced physical barrier technology through slanted barrier simulations, identifying optimal 1/4 slope configurations. Ranjbar and Ehteshami (2019) achieved breakthroughs in predictive accuracy (R^2=0.91) by combining SEAWAT with genetic algorithms and variogram analysis for the Caspian Sea's coastal aquifers. Contemporary work by Abd-Elaty et al. (2021) has synthesized these approaches into comprehensive optimization frameworks, while their 2022 Florida case study demonstrated practical applications for sustainable management under climate change scenarios, predicting significant future recharge reductions (30%) and salinity increases (14.3%) (Abd-Elaty et al. 2022). Roy et al. (2024) used a machine learning approach based on automated model selection to predict seawater intrusion into coastal aquifers. The models showed an error range of 0.0003–1.4987 mg/l, which is considered to be a good prediction for any modeling approach. Wang and Ge (2025) predicted saltwater intrusion in the Changjiang Estuary by integrating machine learning methods with finite volume community ocean model (FVCOM). The results of this study showed that the ANN-FVCOM model showed high accuracy with root mean square error reductions of 53.8, 55.8, and 50.0% at Baozhen, Shidongkou, and Santiaogang stations, respectively. This progression reveals an evolution from basic management concepts to integrated numerical-experimental approaches, with each study building upon previous findings to address the growing complexity of coastal aquifer management challenges.

The sustainable management of coastal groundwater resources facing seawater intrusion challenges requires an integrated approach combining experimental and numerical methodologies, yet current research has predominantly investigated these approaches separately, creating a significant gap in comprehensive understanding and practical applications. Laboratory studies have proven essential for examining the fundamental physical and chemical interactions at the freshwater-saltwater interface under controlled conditions, enabling researchers to identify critical thresholds and evaluate mitigation strategies with precision. Meanwhile, numerical modeling techniques have advanced our capacity to simulate complex groundwater flow dynamics and solute transport processes across various spatial and temporal scales, providing valuable predictive capabilities for management scenarios. While both approaches offer distinct advantages, their integration remains underexplored in existing literature, representing a missed opportunity to develop more robust solutions to seawater intrusion.

This study develops a hybrid method combining lab experiments with advanced modeling. Experiments were conducted at the University of Tabriz to simulate saltwater intrusion. The SEAWAT model, enhanced with machine learning (SVR, RF, CNN) and Golden Ball Optimization, was used for simulation and prediction. A two-way validation process linked lab data with model calibration and refinement. This approach improves intrusion prediction accuracy and supports better water management. It offers practical tools for managing coastal aquifers under environmental and demand pressures.

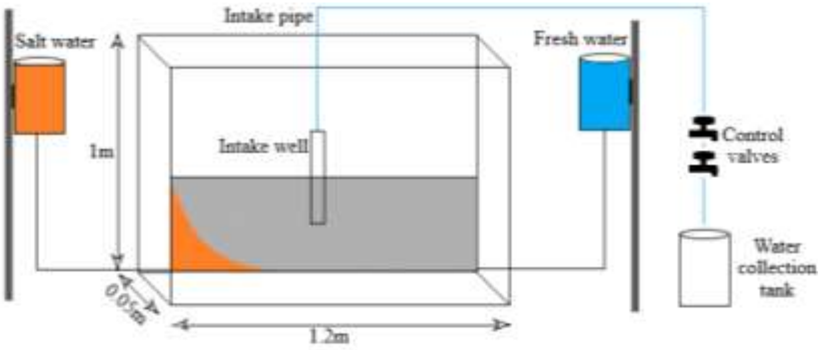
2. Materials and Methods

In the present study, three effective factors including changes in the density of the extracted water (25, 35, and 50 g/l), the flow rate of the extracted water from the well (0.05, 0.12, 0.25 l/min) and the depth of the water extraction point from the porous environment (12, 25, 36 cm) were simultaneously evaluated. Accordingly, 27 different scenarios were implemented using the experimental model. Then the results of these 27 scenarios were entered into the SEAWAT model, and the model was calibrated using these data. By changing the parameters of extracted water density, extraction flow rate, and water extraction depth in the SEAWAT model, more scenarios were executed, and finally, the total number of data generated from the execution of the scenarios reached 131. SEAWAT was chosen because of its ability to incorporate the effects of density, discharge, and extraction depth in a stable numerical framework. The model not only allowed for accurate calibration with laboratory data but also provided a comprehensive analysis of the system's behavior under different conditions by generating additional scenarios. These advantages make SEAWAT an ideal tool for studies of saltwater intrusion in coastal aquifers. Fig. 1 shows a schematic of the experimental setup. Also, two valves were used to adjust the flow rate of the extracted water, so that the first valve was used to open and close the flow of the extracted water, and the second valve was used to adjust the flow rate of the extracted water.

2.1 Support vector regression

Support Vector Regression (SVR) is a machine learning method derived from Support Vector Machines (SVM) and designed for regression tasks. The goal of Support Vector Regression is to approximate a continuous function based on training data (Basak et al., 2007). Unlike traditional regression models that directly minimize error for each data point, the goal of SVR is to fit the data within a tolerance margin, called the epsilon-insensitive region, which makes it less sensitive to outliers and more focused on overall generalization (Tanveer et al., 2024). This tolerance allows SVR to ignore small errors and focus on capturing the overall pattern of the data. The main optimization function in SVR is given in Eq. 1 (Drucker et al., 1996).

Fig. 1 Schematic of the experimental apparatus



$$OF = min_{w,b,\xi,\xi^*}\left(\frac{1}{2}\parallel w \parallel^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)\right) \quad (1)$$

$$\begin{cases} y_i - (w \cdot \phi(x_i) + b) \leq \epsilon + \xi_i \\ (w \cdot \phi(x_i) + b) - y_i \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \quad (2)$$

where w is the weight vector, b is the bias term, ξ and ξ^* are variables for controlling data points outside the ε-sensitive region, $\phi(x_i)$ is the mapping function, and C is a tuning parameter that controls the balance between maximizing the margin and minimizing the error (Basak et al., 2007). Additionally, Eq. 2 is the necessary condition for using Eq. 1. This equation enables the model to be used with high accuracy in various fields, including time series forecasting (Abuein et al., 2024) and complex engineering systems (Sharafi and Samadianfard 2024).

2.2 Random forest

Random Forest is an ensemble learning method that is commonly used for regression and classification, and is known for its accuracy, robustness to overfitting, and ability to handle large datasets and high-dimensional spaces (Breiman 2001). This model constructs multiple decision trees during training, each of which is based on a random subset of the data and features, creating a "forest" of trees that are collectively used for prediction (Fawagreh et al. 2014). RF randomly selects a subset of features for each split in the trees and ensures the decorrelation between trees, reducing the likelihood of overfitting (Breiman, 2001). The prediction of the random forest model for an input *x* is given in Eq. 3 (Breiman, 2001).

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x) \quad (3)$$

where *T* stands for the total number of trees in the forest, and $f_t(x)$ denotes the prediction of the t-th tree. This averaging of outputs among the trees makes the random forest robust to errors and capable of capturing complex patterns within the data, making it suitable for applications such as environmental modeling (Bakır et al., 2024).

2.3 Convolutional neural network

Convolutional Neural Network (CNN) are deep learning models specialized for processing structured data through automated feature extraction. These networks perform hierarchical learning using convolutional operations that systematically identify spatial and temporal patterns (Taye, 2023). Unlike traditional neural networks, CNNs preserve spatial relationships in input data through their unique filter-based architecture, making them ideal for grid-like data such as salinity distribution maps. The CNN architecture comprises interconnected layers including convolutional layers that apply learned filters to input data, pooling layers that condense feature information, and fully connected layers that generate final predictions (Abiodun et al., 2019). Each layer type serves a distinct purpose in transforming raw input data into increasingly abstract representations that capture essential patterns. The main operation in the convolutional layer of a CNN is given in Eq. 4 (LeCun and Bengio, 1995).

$$z_{i,j}^{(k)} = \sum_m \sum_n w_{m,n}^{(k)} \cdot x_{i+m,j+n} + b^{(k)} \quad (4)$$

In this equation, $z_{i,j}^{(k)}$ represents the output of the feature map at position *(i, j)* for filter k, $w_{m,n}^{(k)}$ denotes the weights of filter k, $x_{i+m,j+n}$ is the local input patch, and $b^{(k)}$ is the bias of the filter. This operation enables the network to learn spatial relationships by sliding filters across the input data. The filters act like feature detectors that become increasingly sensitive to complex patterns through the training process, allowing the network to automatically identify relevant characteristics in the data.

CNNs excel at learning directly from raw data with minimal preprocessing, making them effective for complex pattern recognition tasks. Their success has been demonstrated in diverse applications including advanced forecasting (Sharafi et al. 2024) and object detection (Naseer et al., 2024). For modeling seawater intrusion, CNNs are particularly valuable as they can automatically identify and learn the spatial patterns of salinity distribution and groundwater flow characteristics. The network's ability to capture both local and global patterns makes it well-suited for predicting how pumping activities or barrier installations might affect saltwater intrusion dynamics over time.

2.4 Golden ball optimization algorithm

The Golden Ball Optimization algorithm is a metaheuristic optimization technique inspired by the collective behavior and strategic coordination of football players during matches (Osaba et al., 2014). This swarm intelligence approach mimics how players with specialized roles collaborate to achieve optimal team performance, translating these dynamics into an effective search mechanism for complex optimization problems (Srilakshmi et al., 2024). The algorithm's effectiveness stems from its ability to balance individual player autonomy with coordinated team objectives, much like how a football team balances individual skills with team strategy. In the GBO framework, the solution space is conceptualized as a football field, where each potential solution corresponds to a player position, and the optimal solution represents the team's most advantageous configuration. This analogy allows the algorithm to efficiently explore complex, high-dimensional search spaces by leveraging both local player movements and global team coordination. The main equation of GBO used to update the position of a player is presented in Eq. 5 (Osaba et al., 2014).

$$x_i(t+1) = x_i(t) + r \times (G_{best} - x_i(t)) + s \times (x_{rand} - x_i(t)) \quad (5)$$

Where, $x_i(t)$ represents the position of player i at iteration t, G_{best} denotes the best group position, x_{rand} is a random position, and r and s are random coefficients that guide the search within the solution space. This update rule combines three key components: the current player position, attraction to the best-known team position, and exploration through random positions. The random coefficients r and s are dynamically adjusted during the optimization process, while preventing premature convergence to local optima, enabling efficient navigation of the solution space (Osaba et al., 2014). GBO has demonstrated particular effectiveness in solving complex, non-linear optimization challenges due to its inherent balance between intensive local search (exploitation) and broad global exploration(Suganya et al., 2022). The GBO-inspired mechanics, preserves population diversity, enables situational roles for specialized local searches, and ensures coordinated moves for efficient coverage of the solution space. These features make GBO particularly well-suited for optimizing the parameters of machine learning models in hydrological applications, where the non-convex and high-dimensional nature of seawater intrusion modeling requires robust optimization capabilities. The algorithm's ability to adaptively adjust its search strategy based on problem complexity makes it well-suited for handling the dynamic constraints and objectives inherent in coastal aquifer management.

2.5 Model development

The integration of Convolutional Neural Networks fundamentally transforms the predictive capability of standalone models by addressing their inherent limitations in feature extraction. Traditional machine learning approaches like Random Forest and Support Vector Regression rely on manually engineered features or raw input data, which often fail to capture the complex spatial patterns in salinity distribution. The CNN component overcomes this by automatically learning hierarchical representations through its layered architecture, where initial layers identify basic spatial features, and subsequent layers combine these into increasingly sophisticated patterns. This automated feature learning provides the base models with optimized input spaces that better represent the underlying physical processes of seawater intrusion, enabling more accurate predictions without requiring manual feature engineering.

The Golden Ball Optimization algorithm enhances model performance through intelligent parameter space exploration that surpasses conventional tuning methods. Where standard implementations use fixed parameters or basic grid searches, GBO employs its football-inspired search strategy to dynamically adjust hyperparameters during training. For Random Forest, this means optimally determining the number of trees, maximum depths, and feature selection thresholds in a way that adapts to the specific characteristics of the salinity prediction task. In Support Vector Regression, GBO precisely tunes kernel parameters and error tolerance margins by balancing global exploration of the parameter space with local refinement around promising regions. This results in model configurations specifically adapted to the unique challenges of seawater intrusion prediction. The combined effect of these enhancements creates models that surpass their standalone counterparts in both accuracy and robustness. The CNN processing enables the discovery of complex nonlinear relationships that traditional models might miss, while GBO optimization ensures the model architecture is perfectly tuned to exploit these discovered patterns. Where a standalone Random Forest might struggle with spatial autocorrelation in salinity measurements, the CNN-enhanced version explicitly accounts for these dependencies through its feature learning. Similarly, where a basic SVR could settle for suboptimal kernel parameters, the GBO-optimized version systematically identifies configurations that maximize prediction accuracy for the specific aquifer system being modeled.

Table 1 Hyperparameters used in hybrid models

Hyperparameter	Model			
	RF-CNN	RF-GBO	SVR-CNN	SVR-GBO
Number of convolutional layers	3	-	3	-
Number of filters per layer	64	-	64	-
Filter size	3x3	-	3x3	-
Learning rate	0.001	-	0.001	-
Number of trees	100	100	-	-
Number of players	-	30	-	30
Maximum number of iterations	100	100	100	100
C	-	-	10	10
Epsilon	-	-	0.1	0.1

This synergistic improvement is particularly valuable for seawater intrusion problems where the physical processes exhibit both strong spatial dependencies and complex nonlinear dynamics. The enhanced models demonstrate superior performance in capturing the interface between fresh and saltwater, predicting salinity gradients, and responding to management interventions like pumping adjustments or barrier installations. The automatic feature learning and parameter optimization also make the hybrid approaches more adaptable to different coastal aquifer systems without requiring extensive manual recalibration, representing a significant advancement over conventional modeling techniques. Additionally, Table 1 shows the hyperparameters used in the hybrid models. The values of these hyperparameters were obtained through trial and error for each hybrid model.

In this study, three different scenarios were used to evaluate the role of input parameters including relative water density ρ (ratio of changes in saline water density to freshwater density), relative abstraction flow rate Q (ratio of abstraction flow rate per unit aquifer width to hydraulic conductivity of the porous medium), relative abstraction depth d (ratio of depth of abstraction point to the height of saline water source), on the parameter of relative concentration of abstracted water C (ratio of final concentration of abstracted water to saline water concentration) as presented in Table 2. The order of the considered scenarios was based on the Pearson correlation coefficient, such that the first scenario had the lowest correlation, and the last scenario had the highest correlation with the relative concentration parameter. Also, 68% of the data were considered for the training phase and 32% were randomly selected for the testing phase. This combination was determined after trial and error and then used.

Table 2 Scenarios used to predict relative concentration

Scenario	Input Parameters			Output
	Parameter-1	Parameter-2	Parameter-3	
1	ρ			C
2	ρ	Q		C
3	ρ	Q	d	C

2.6 Evaluation criteria

In the present study, to predict the relative concentration parameter, the evaluation criteria of the coefficient of determination (R^2), root mean square error (RMSE), Nash-Sutcliffe coefficient (NS), and Wilmott agreement index (WI) were used, which are presented in Eqs. 6 to 9 (Karami Moghadam et al. 2020).

$$R^2 = \left(\frac{\sum_{i=1}^{N}(O_i-\overline{O_i})(P_i-\overline{P_i})}{\sqrt{\sum_{i=1}^{N}(O_i-\overline{O_i})^2 \sum_{i=1}^{N}(P_i-\overline{P_i})^2}} \right)^2 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \quad (7)$$

$$NS = 1 - \left[\frac{\sum_{i=1}^{N}(O_i-P_i)^2}{\sum_{i=1}^{N}(O_i-\overline{O_i})^2}\right] \quad (8)$$

$$WI = 1 - \left[\frac{\sum_{i=1}^{N}(O_i-P_i)^2}{\sum_{i=1}^{N}(|P_i-\overline{O_i}| + |O_i-\overline{O_i}|)^2}\right] \quad (9)$$

Where N represents the number of observations, P_i and O_i denote the predicted and observed values, respectively. $\overline{P_i}$ and $\overline{O_i}$ represent the average of the predicted and observed values, respectively.

3. Results and Discussion

In this research, the dimensionless parameters, including saline water density (ρ), extraction point depth (d), and extraction flow rate (Q) were considered using RF, RF-CNN, RF-GBO, SVR-CNN, SVR, and SVR-GBO models to predict the final extracted water concentration (C). Three different scenarios were used to evaluate the effect of input parameters on the output parameter, as shown in Table 2. The error between the measured and predicted data is reported in Table 3 in terms of coefficient of determination (R^2), root mean square error (RMSE), Nash-Sutcliffe coefficient (NS), and Willmott's agreement index (WI).

3.1 First scenario

In the first scenario, among the random forest-based models, the standalone RF model demonstrated the lowest performance, with R^2 = 0.714, RMSE = 0.065, NS = 0.634, and WI = 0.903. The RF-CNN model showed a slight improvement, achieving a higher coefficient of determination of 0.731 and a marginally reduced RMSE of 0.064. The RF-GBO model outperformed both by obtaining the highest NS of 0.664, the lowest RMSE of 0.062, and the best overall agreement with observed values. However, despite its superior error metrics, the RF-GBO-1 model did not exhibit a significant improvement in the coefficient of determination of 0.719 compared to RF-CNN with R^2=0.731, indicating a potential limitation in capturing the linear relationship between inputs and outputs when limited input parameters are used. This suggests that while GBO effectively optimized model parameters for better generalization, the restricted input scenario (only ρ) may have constrained the model's full predictive capacity. For the support vector regression models, the SVR-GBO model achieved the best performance, with the highest coefficient of determination of 0.637, the highest NS of 0.504, and the lowest RMSE of 0.076. The SVR-CNN and SVR models followed, with RMSE values of 0.079 and 0.085, respectively. These results highlight the importance of hybrid models and the effectiveness of combining machine learning algorithms with metaheuristic optimization techniques in enhancing predictive performance, particularly in modeling salinity concentration in coastal aquifers under data-limited conditions.

3.2 Second scenario

For the second scenario, the evaluation of different RF models shows that the hybrid RF-CNN model was able to increase the values of the WI, NS, and R^2 indices by 1.5%, 1%, and 1.5%, respectively. These moderate improvements suggest that while CNN-based feature extraction provides some benefits, the spatial patterns in salinity data may already be reasonably captured by the original RF features. Also, the RF-GBO model was able to increase the values of the WI, NS, and R^2 indices by 3%, 6.4%, and 3.1%, respectively, and decrease the value of RMSE by about 9.5%. The particularly large improvement in NS of 6.4% indicates GBO optimization significantly enhances the model's ability to capture the variance in salinity dynamics, which is crucial for reliable seawater intrusion forecasting. The greater increase in the WI, NS, and R^2 criteria in the RF-GBO model compared to the RF-CNN model indicates the superiority of the golden ball optimization over the convolutional neural network. This likely occurs because GBO directly optimizes the model's decision boundaries, while CNN's feature extraction may not align perfectly with the tree-based RF architecture. Similarly, the comparison of the hybrid support vector regression models shows that the SVR-CNN model was able to increase the values of the WI, NS, and R^2 indices by 1.3%, 1%, and 1.1%, respectively, with the relatively higher improvement in R^2 suggesting CNN features help better capture linear relationships in the data. The SVR-GBO model was able to increase the values of the WI, NS, and R^2 indices by 10.2%, 11.1%, and 1.9%, respectively, and decrease the value of RMSE by about 9.52%. The dramatic NS improvement of about 11.1% demonstrates GBO's exceptional ability to optimize SVR's kernel parameters for modeling the nonlinear saltwater-freshwater interface dynamics. Therefore, the GBO model performed better than the CNN and was able to increase the accuracy of the support vector regression model to a greater extent. This consistent outperformance across both RF and SVR hybrids suggests that for seawater intrusion modeling, parameter optimization may generally yield greater accuracy gains than feature enhancement alone.

3.3 Third scenario

In the third scenario, the comparison of different random forest models revealed that the RF-GBO model achieved the highest predictive performance, with a coefficient of determination of 0.885 and a root mean square error of 0.039. This model outperformed the baseline RF model by reducing the error by approximately 50% and improving the R^2 by 13.7%. Similarly, among the support vector regression models, SVR-GBO exhibited the best performance with $R^2 = 0.759$ and RMSE = 0.056, representing a 41.1% reduction in error and a 20.1% increase in R^2 compared to the standard SVR model.

The overall comparison across all three scenarios indicated that the third scenario consistently led to better model performance compared to the first and second scenarios. Notably, the RF-GBO-3 model achieved the highest accuracy among all models tested, with $R^2 = 0.885$, RMSE = 0.039, NS = 0.872, and WI = 0.963. Likewise, the SVR-GBO-3 model outperformed all other SVR variants with $R^2 = 0.759$, RMSE = 0.056, NS = 0.731, and WI = 0.926. Finally, the comparison of the performance of the utilized models using different scenarios showed that the third scenario had better performance compared to the second and first scenarios. Among the used models, the RF-GBO-3 model with $R^2 = 0.885$, RMSE = 0.039, NS = 0.872, and WI = 0.963 had the highest accuracy compared to all models. Also, the SVR-GBO-3 model with $R^2 = 0.759$, RMSE = 0.056, NS = 0.731, and WI = 0.926 had higher accuracy compared to different SVR models. An interesting finding from this study was the better performance of GBO in optimization in all scenarios compared to CNN. GBO proved to be a consistent algorithm that can effectively tune the model parameters to maximize the prediction accuracy. In contrast, while CNN offers valuable capabilities in pattern recognition, it does not reach the level of accuracy of GBO. This shows that GBO-based optimization is particularly effective in modeling environmental systems where various interacting factors affect the results.

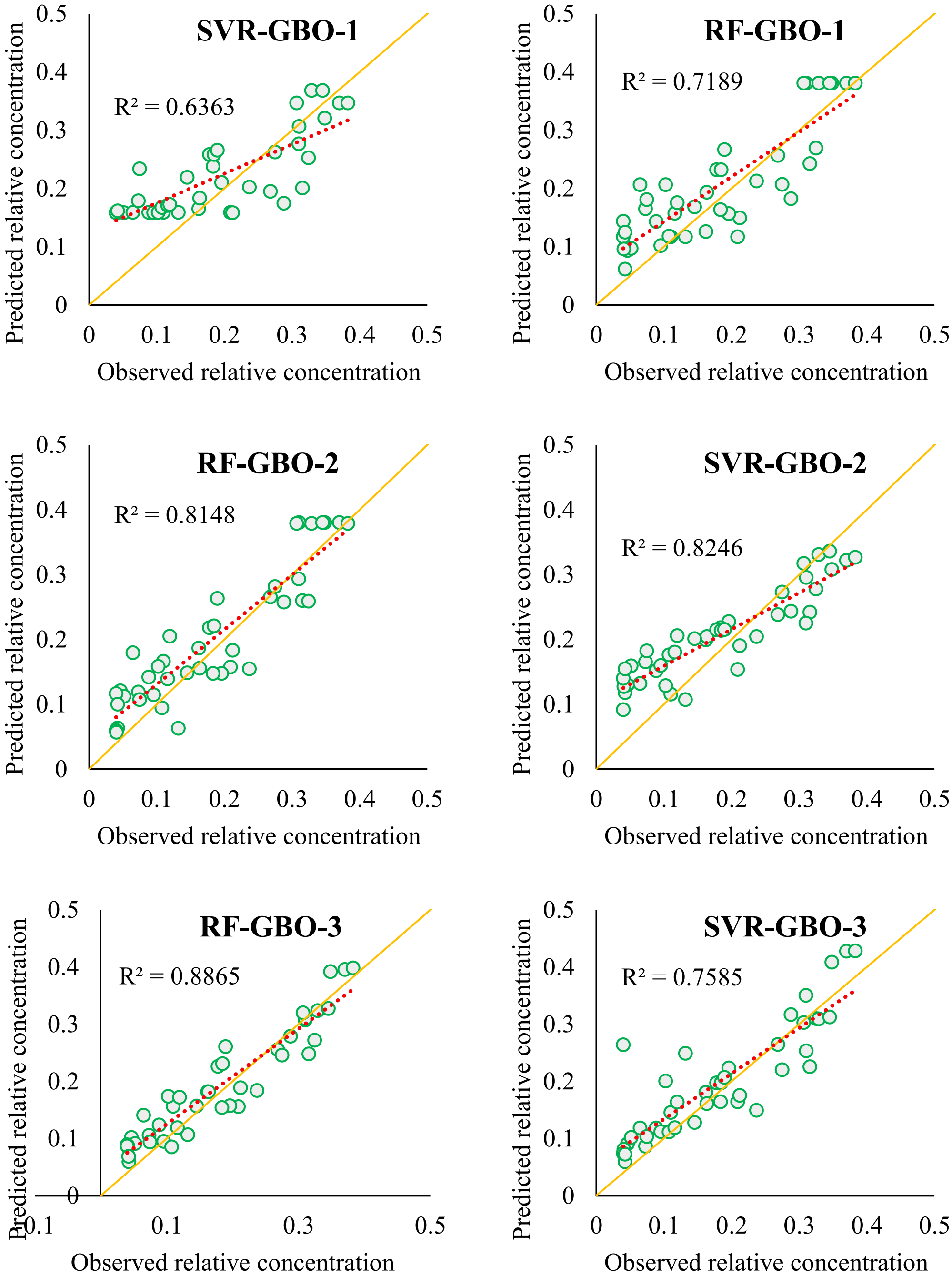
Table 3 Results of running the models

Scenario	Model	Evaluation criteria			
		R^2	RMSE	NS	WI
Scenario 1	RF-1	0.714	0.065	0.634	0.903
	RF-CNN-1	0.731	0.064	0.649	0.906
	RF-GBO-1	0.719	0.062	0.664	0.904
	SVR-1	0.613	0.085	0.376	0.843
	SVR-CNN-1	0.629	0.079	0.465	0.849
	SVR-GBO-1	0.637	0.076	0.504	0.808
Scenario 2	RF-2	0.767	0.055	0.737	0.931
	RF-CNN-2	0.790	0.054	0.743	0.934
	RF-GBO-2	0.815	0.05	0.786	0.941
	SVR-2	0.672	0.066	0.622	0.866
	SVR-CNN-2	0.691	0.065	0.628	0.897
	SVR-GBO-2	0.824	0.06	0.695	0.883
Scenario 3	RF-3	0.826	0.046	0.815	0.946
	RF-CNN-3	0.856	0.044	0.835	0.956
	RF-GBO-3	0.885	0.039	0.872	0.963
	SVR-3	0.707	0.065	0.632	0.889
	SVR-CNN-3	0.752	0.061	0.682	0.911
	SVR-GBO-3	0.759	0.056	0.731	0.926

3.4 Evaluation of results in the context of existing literature

The findings of this study align well with existing theories on saltwater intrusion, which emphasize the complexities and nonlinear interactions between freshwater and seawater in coastal aquifers. These interactions are governed by multiple factors such as tidal movements, groundwater extraction rates, aquifer heterogeneity, and recharge-discharge dynamics. Traditional numerical and analytical models, while rooted in hydrogeological principles, often face limitations in accurately capturing the dynamic behavior of these systems. This is particularly true in environments with limited data availability, high spatial variability, or complex boundary conditions. For example, Faal et al. (2020) utilized a polynomial Support Vector Regression model to predict saltwater intrusion, reporting a root mean square error (RMSE) of 0.23.

Fig. 2 Scatter plots for the best model in each scenario



Similarly, Tran et al. (2021) applied the CatBoost regression model in multilayered coastal aquifers in the Mekong Delta, Vietnam, and obtained an RMSE of 205.96. In contrast, the RF-GBO-3 model in this study achieved an RMSE of only 0.039, demonstrating a substantial improvement in predictive accuracy and confirming the superiority of combining ensemble learning with metaheuristic optimization. These findings further reinforce the value of integrating machine learning with optimization techniques, especially in environmental modeling, where system behavior is influenced by numerous interdependent variables. The lower RMSE achieved by the RF-GBO-3 model supports the idea that optimization algorithms can significantly enhance model performance by efficiently exploring the solution space and avoiding local minima during parameter calibration. Moreover, the improved performance of the RF-GBO-3 model, compared to both baseline models and other hybrid variants such as RF-CNN, highlights the effectiveness of GBO in tuning model parameters for structured tabular data. This aligns with recent trends in environmental data science that favor hybrid frameworks for their adaptability, scalability, and high accuracy. The combination of machine learning and optimization, as demonstrated in this study, offers a practical and powerful solution for saltwater intrusion forecasting, contributing valuable insights for groundwater management in coastal regions.

Fig. 2 shows the scatter plots for the two best models of random forest and support vector regression in each scenario. The yellow line is a 45-degree line, and the closer the data points are to it, the higher the accuracy of that model. Comparing the plots for the first scenario shows that the random forest model had a higher coefficient of determination compared to the support vector regression model. In the second scenario, the support vector regression model with a coefficient of determination of 0.8246 had higher accuracy compared to the random forest model (R^2=0.8148). Also, in the third scenario, the predicted data in the RF-GBO-3 model had better correspondence with the observed data, and therefore, this model performed better than SVR-GBO.

Fig. 3 shows the box plot diagrams of the models used in all three scenarios. Comparing the different random forest models, the RF-1 model has the weakest performance compared to the other models. This model has a higher median value than the observed values, and 25-75% of the data (the trimmed box) have underestimation. The RF-GBO-3 model has the most similar box to the observed values and has the closest median. Comparing the SVR models also shows that SVR-GBO-1 has the most distinct box compared to the other boxes, indicating the insufficient accuracy of the model using a single input parameter. The SVR-GBO-3 model, although overestimated from the top, has the most similar box to the observed values and the highest accuracy.

Fig. 3 Box plots of the models used

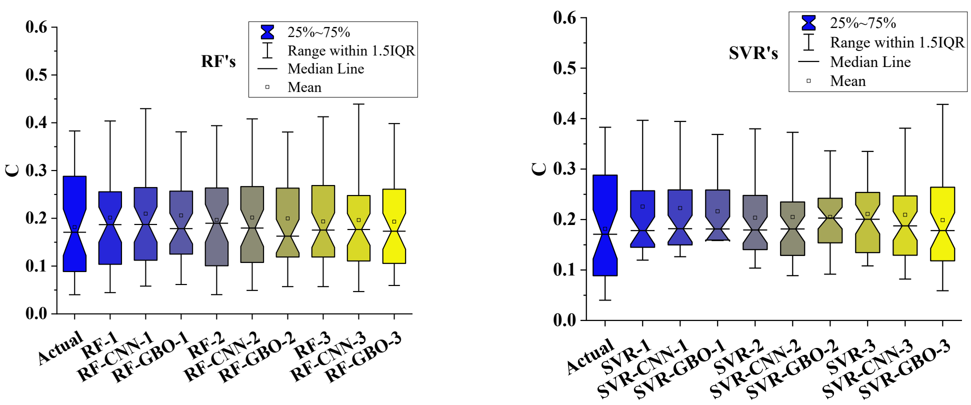


Fig. 4 Taylor diagrams of the utilized models

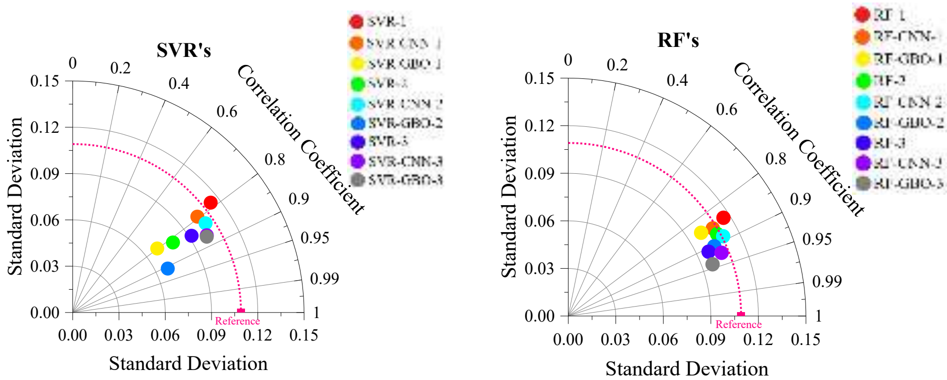


Fig. 4 shows the Taylor diagrams for the different models in all three scenarios. Comparing the different support vector regression models in the first scenario shows that the standalone model had a lower correlation coefficient than the hybrid models. Also, the standalone model had the closest standard deviation to the observed value. In the second scenario, the two hybrid models performed well, with SVR-CNN having the least distance from the observational standard deviation and SVR-GBO having the highest correlation coefficient. In the third scenario, SVR-GBO had a higher correlation coefficient than the other two models and therefore had higher accuracy.

Comparing the different random forest models in the first scenario shows that RF-CNN had the least distance from the observational line, and its correlation coefficient was slightly higher than the other two models. In the next scenario, RF-

GBO had a higher correlation coefficient than RF and RF-CNN and therefore had better performance. Finally, in the last scenario, RF-GBO had the highest correlation coefficient among all the models and the highest accuracy. Also, the overall comparison of the two diagrams shows that the different random forest models performed better than support vector regression.

4. Conclusion

Predicting salinity concentration in aquifers is crucial for safeguarding freshwater resources and ensuring sustainable water management in coastal regions. This study aimed to develop and evaluate advanced machine learning models for forecasting the relative salinity concentration in a laboratory-scale aquifer model. For this purpose, support vector regression (SVR) and random forest (RF) models were used individually and in hybrid form with Convolutional Neural Networks (CNN) and the Golden Ball Optimization (GBO) algorithm. The models were tested across three scenarios to assess their robustness and performance. The main findings of this research are as follows:

1. Among all models evaluated, the RF-GBO-3 model showed the highest predictive accuracy, achieving a coefficient of determination of 0.885, RMSE of 0.039, NS of 0.872, and WI of 0.963. This model outperformed all others, including its standalone counterpart, by a significant margin.

2. The SVR-GBO-3 model also demonstrated strong performance with $R^2 = 0.759$, RMSE = 0.056, NS = 0.731, and WI = 0.926. It consistently outperformed the base SVR model and SVR-CNN, proving the effectiveness of the GBO optimization approach in fine-tuning kernel parameters for nonlinear systems.

3. In all scenarios, hybrid models (RF-GBO and SVR-GBO) performed better than their standalone or CNN-based versions. The consistent improvement in correlation and error metrics highlights the potential of metaheuristic optimization over deep learning-based feature extraction in this specific environmental modeling context.

However, despite these advances, challenges remain, such as the limited availability of high-quality data, regional variations in aquifer characteristics, and the difficulty in fully integrating physical processes into data-driven models. These limitations highlight the need for further refinement in modeling techniques to improve generalizability across diverse regions. For future research, it is recommended to validate the proposed models using real-world field data from coastal aquifers to assess their practical applicability. Overall, the findings of this study contribute to and extend existing research, offering new insights into the optimization of models for saltwater intrusion forecasting while emphasizing the importance of overcoming these challenges in future research.

Statements and Declarations

Data Availability

The data used in this research are presented in the text of the article.

Conflicts of interest

The authors of this paper declared no conflict of interest regarding the authorship or publication of this article.

Author contribution

R. Karamad: Methodology, Investigation, Conceptualization, Writing Original Draft. R. Dalir Hasan Nia: Conceptualization, Supervision, Writing Original Draft. S. Samadianfard: Conceptualization, Methodology, Review-Editing.

AI Use Declaration

This study did not incorporate artificial intelligence techniques; instead, all analyses and optimizations were conducted using conventional and widely accepted analytical methods.

References

Abd-Elaty, I., Abd-Elhamid, H. F., & Qahman, K. (2020). Coastal aquifer protection from saltwater intrusion using abstraction of brackish water and recharge of treated wastewater: case study of the Gaza aquifer. *Journal of Hydrologic Engineering, 25*(7), 200-218. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001927.

Abd-Elaty, I., Sallam, G. A., Straface, S., & Scozzari, A. (2019). Effects of climate change on the design of subsurface drainage systems in coastal aquifers in arid/semi-arid regions: Case study of the Nile delta. *Science of the Total Environment, 672*(1), 283-295. https://doi.org/10.1016/j.scitotenv.2019.03.483.

Abd-Elaty, I., Straface, S., & Kuriqi, A. (2021). Sustainable saltwater intrusion management in coastal aquifers under climatic changes for humid and hyper-arid regions. *Ecological Engineering, 171*(14), 106-121. https://doi.org/10.1016/j.ecoleng.2021.106382.

Abd-Elhamid, H., Javadi, A., Abdelaty, I., & Sherif, M. (2016). Simulation of seawater intrusion in the Nile Delta aquifer under the conditions of climate change. *Hydrology Research*. 47 (6), 1198-1210. https://doi.org/10.2166/nh.2016.157.

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., Arshad, H., Kazaure, A. A., Gana, U. & Kiru, M. U. (2019). *Comprehensive review of artificial neural network applications to pattern recognition. IEEE* 7 (2), (pp.158820-158846). 10.1109/ACCESS.2019.2891234.

Abuein, Q. Q., Shatnawi, M. Q., Aljawarneh, E. Y. & Manasrah, A. (2024). Time Series Forecasting Model for the Stock Market using LSTM and SVR . *International Journal of Advances in Soft Computing and its Applications*. 16 (1), 17-28. 10.15849/IJASCA.240330.10.

Bakır, R., Orak, C. & Yüksel, A. (2024). Optimizing hydrogen evolution prediction: A unified approach using random forests, lightGBM, and Bagging Regressor ensemble model. *International Journal of Hydrogen Energy*. 67 (2), 101-110. https://doi.org/10.1016/j.ijhydene.2024.04.173.

Banaduc, D., Simić, V., Cianfaglione, K., Barinova, S., Afanasyev, S., Öktener, A., McCall, G., Simić, S. & Curtean-Bănăduc, A. (2022). Freshwater as a sustainable resource and generator of secondary resources in the 21st century: Stressors, threats, risks, management and protection strategies, and conservation approaches. *International Journal of Environmental Research and Public Health.* 19 (24), 16570-16584. https://doi.org/10.3390/ijerph192416570.

Basack, S., Bhattacharya, A. & Maity, P. (2012) Hydrogeological investigation on saline water intrusion into a coastal aquifer of West Bengal, India. *Proceedings of Indian Geotechnical Conference*.

Basak, D., Pal, S. & Patranabis, D. C. (2007). Support vector regression. *Neural Processing Letters*. 11 (10), 203-224. https://doi.org/10.4314/niplr.v11i10.37063.

Breiman, L. (2001). Random forests. *Machine Learning.* 45 (1), 5-32. https://doi.org/10.1023/A:1010933404324.

Drucker, H., Burges, C. J., Kaufman, L., Smola, A., & Vapnik, V. (1996). Support vector regression machines. *Advances in Neural Information Processing Systems*. 9 (1).

Faal, F., Ghafouri, H. R. & Ashrafi, S. M. (2020). Predicting Saltwater Intrusion into Coastal Aquifers Using Support Vector Regression Surrogate Models. *Water and Wastewater* 31 (126), 118-129. (In Persian with English abstract).https://doi.org/10.22093/wwj.2019.161020.2803.

Fawagreh, K., Gaber, M. M. & Elyan, E. (2014). Random forests: from early developments to recent advancements. *Systems Science & Control Engineering*. 2 (1), 602-609. https://doi.org/10.1080/21681163.2014.981123.

Gopinath, S., Srinivasamoorthy, K., Saravanan, K., Suma, C., Prakash, R., Senthilnathan, D., Chandrasekaran, N., Srinivas, Y. & Sarma, V. (2016). Modeling saline water intrusion in Nagapattinam coastal aquifers, Tamilnadu, India. *Modeling Earth Systems and Environment*. 2 (1), 1-10. https://doi.org/10.1007/s40808-015-0058-6.

Guo, H. & Jiao, J. J. (2007). Impact of coastal land reclamation on ground water level and the sea water interface. *Groundwater* 45 (3), 362-367. https://doi.org/10.1111/j.1745-6584.2006.00290.x.

Karami Moghadam, M., Amini, A., & Keshavarzi, A. (2020). Intake design attributes and submerged vanes effects on sedimentation and shear stress. *Water and Environment Journal,* *34*(4), 658–670. https://doi.org/10.1111/wej.12471.

Klassen, J. and Allen, D. (2017). Assessing the risk of saltwater intrusion in coastal aquifers. J. Hydrol. 551 (12), 730-745. https://doi.org/10.1016/j.jhydrol.2017.02.044.

Kolathayar, S., Sitharam, T. & Yang, S. (2019). Coastal reservoir strategy to enhance India's freshwater storage by impounding river flood waters: a detailed overview. *Water Supply* 19 (3), 703-717. https://doi.org/10.2166/ws.2018.140.

LeCun, Y., & Bengio, Y. (1995). Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361(10), (pp.191-200).

Naseer, A., Al Mudawi, N., Abdelhaq, M., Alonazi, M., Alazaib, A., Algarni, A. & Jalal, A. (2024). CNN-based Object Detection via Segmentation capabilities in Outdoor Natural Scenes. *IEEE* 17 (1), 25-32. https://doi.org/10.1109/ACCESS.2024.3413848.

Osaba, E., Diaz, F. & Onieva, E. (2014). Golden ball: a novel meta-heuristic to solve combinatorial optimization problems based on soccer concepts. *Applied Intelligence*. 41 (1), 145-166. https://doi.org/10.1007/s10489-013-051-۲y.

Ranjbar, A. & Ehteshami, M. (2019). Spatio-temporal mapping of salinity in the heterogeneous coastal aquifer. *Applied Water Science*. 9 (2), 32. https://doi.org/10.1007/s13201-019-0908-x.

Ravindiran, G., Rajamanickam, S., Sivarethinamohan, S., Karupaiya Sathaiah, B., Ravindran, G., Muniasamy, S. K. & Hayder, G. (2023). A Review of the Status, Effects, Prevention, and Remediation of Groundwater Contamination for Sustainable Environment. *Water* 15 (20), 3662-3674. https://doi.org/10.3390/w15203662.

Roy, D. K., Paul, C. R., Munmun, T. H., & Datta, B. (2024). An automatic model selection-based machine learning approach to predict seawater intrusion into coastal aquifers. *Environmental Earth Sciences*. 83(9), 287-301. https://doi.org/10.1007/s12665-024-11589-z

Sharafi ,M., Rezaverdinejad, V., Behmanesh, J. & Samadianfard, S. (2024). Development of long short-term memory along with differential optimization and neural networks for coagulant dosage prediction in water treatment plant. *Journal of Water Process Engineering*. 65 (14), 5784-5796. https://doi.org/10.1016/j.jwpe.2024.105784.

Sharafi, M. & Samadianfard, S. (2024). Prediction of daily evaporation values using support vector regression coupled with firefly algorithm in the coastal areas of Iran. *Water and Soil Science* 34 (1), 39-53. (In Persian with English abstract). https://doi.org/10.22034/ws.2023.54178.2500.

Srilakshmi, K., Sundaragiri, D., Gaddameedhi, S., Vangalapudi, R., Balachandran, P. K., Colak, I. & Selvarajan, S. (2024). Simulation of grid/standalone solar energy supplied reduced switch converter with optimal fuzzy logic controller using golden BallAlgorithm. *Frontiers in Energy Research*. 12 (2), 1370-1384. https://doi.org/10.3389/fenrg.2024.1370412.

Suganya, D., Thirunadana Sikamani, K. & Sasikala, J. (2022). Copy-move forgery detection of medical images using golden ball optimization. *International Journal of Computer Applications*. 44 (8), 729-737. https://doi.org/10.1080/1206212X.2021.1907905.

Tanveer, M., Rajani, T., Rastogi, R., Shao, Y.-H. & Ganaie, M. (2024). Comprehensive review on twin support vector machines. *Annals of Operations Research*. 339 (3), 1223-1268. https://doi.org/10.1007/s10479-022-04575-w.

Taye, M. M. (2023). Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions. *Computation*. 11 (3), 52-64. https://:doi.org/10.3390/computation11030052.

Todd, D. K. (1974). Salt-water intrusion and its control. *Journal - American Water Works Association*. 66 (3), 180-187. https://doi.org/10.1002/j.1551-8833.1974.tb01999.x.

Tran, D. A., Tsujimura, M., Ha, N. T., Van Binh, D., Dang, T . D., Doan, Q.-V., Bui, D. T., Ngoc, T. A., Thuc, P. T. B. & Pham, T. D. (2021). Evaluating the predictive power of different machine learning algorithms for groundwater salinity prediction of multi-layer coastal aquifers in the Mekong Delta, Vietnam. *Ecological Indicators*. 127(1), 107-128. https://doi.org/10.1016/j.ecolind.2021.107790.

Wang, N., and Ge, J. (2025). Predictions of saltwater intrusion in the Changjiang Estuary: Integrating Machine learning methods with FVCOM. *Journal of Hydrology*. 12(1), 132-145. https://doi.org/10.1016/j.jhydrol.2025.132739

Werner, A. D. & Simmons, C. T. (2009). Impact of sea-level rise on sea water intrusion in coastal aquifers. *Groundwater* 47 (2), 197-204. https://doi.org/10.1111/j.1745-6584.2008.005.۳۵x.