**A proposed IoT, Machine Learning, and Explainable (XAI) Deep Learning for Groundwater Salinization and Health Risk Assessment in Agricultural Land of Eastern Province Saudi Arabia**

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1.0 Introduction

Groundwater (GW) holds significant importance as a vital drinking water source, supplying approximately half of the global drinking water demand [1], [2]. Nevertheless, numerous coastal regions worldwide are grappling with freshwater shortages caused by the infiltration of seawater into surface water sources. Hence, GW in such areas serves as a substitute freshwater reservoir for household and industrial purposes [3], [4]. Additionally, GW serves a crucial function in sustaining agriculture, fulfilling nearly 40% of irrigation requirements, thereby aiding in food security and ensuring the sustainability of water resources [2]. Using groundwater for irrigation brings several advantages, such as reliability and consistency. Unlike surface water, which can be influenced by floods and droughts, GW typically remains stable, ensuring a steady provision of irrigation water [5]. Despite its crucial importance, the groundwater resource is susceptible to risks such as overexploitation, seawater intrusion, climate change, and rising sea levels [6].

In the context of middle east, particularly in nations like Saudi Arabia, the significance of groundwater is even more pronounced, as it becomes increasingly valuable due to the challenges presented by arid and semi-arid environments. According to the Saudi Arabian ministry of environment, water and agriculture (MEWA) annual report, GW constitutes about 34% of domestic consumption and over 90% of agricultural usage in the country [7]. The increased GW demand is primarily linked to a decrease in water levels and deterioration of GW quality. Similarly, the deterioration in GW quality can be attributed to either anthropogenic or natural/geogenic sources. This excessive utilization and deterioration of GW resources necessitate appropriate management strategies for adaptation and mitigation. This is crucial to ensure sustainable services that align with the long-term sustainability objectives of Saudi Arabian Vision 2030 [8].

One of the vital issues afflicting the groundwater reserves in coastal areas is salinization. Groundwater salinization refers to the gradual increase in salt content or salinity within groundwater [9]. It diminishes the accessibility of water and its appropriateness for various users. This phenomenon can arise naturally due to geological factors or triggered by human activities like irrigation, changes in land usage and the release of industrial or household waste [10], [11]. Specifically, salinization poses a significant threat to GW from coastal aquifers in numerous urban areas, primarily due to geological factors, anthropogenic activities [12], [13] climate change [14] and seawater intrusion [15], [16], [17]. Seawater intrusion occurred when the groundwater level fell below that of the sea, enabling saltwater to permeate the aquifer. Additionally, salty water could have a negative impact on human health. Saline GW might not be suitable for drinking, irrigation, or industrial purposes, and it could harm crops and natural ecosystems.

Rapid population growth, urbanization, and the expansion of industrial and agricultural activities have resulted in the overexploitation of GW in coastal aquifers across many regions all over the world. Consequently, the intrusion of seawater penetrated the coastal aquifer, leading to an increase in GW salinity to the point where the water turned salty and even saline. Recently, researchers around the world have extensively studied the groundwater salinity problem in coastal and sandstone aquifers, arising due to the various factors mentioned earlier [18], [19], [20], [21], [22], [23]. For instance, the authors of [18] employed two notable AI algorithms, namely artificial neural networks and support vector machine to predict the GW salinity of KhanYounis, Gaza coastal aquifer, in Palestine. Experimental results obtained demonstrate that both two models have the capability of predicting the GW salinity with outstanding accuracy. Similarly, results achieved indicate the developed models can effectively comprehend the intricate correlation between input variables and groundwater salinity levels within a highly intricate hydrogeological system.

Kloppmann et. al. [20] modeled the GW salinity in French aquifers. Their finding indicated that seawater intrusion predominantly governs GW salinization in coastal aquifers. Nosair et al. [21] employed 4 different ML techniques and long short-term memory (LSTM) to simulate the presence of seawater intrusion in the Nile Delta aquifer, Egypt. Result obtained revealed that the feed-forward backpropagation neural network demonstrated superior performance in predicting seawater intrusion indicators. Similarly, Ahmed et al. [22] investigated groundwater salinization in the volcanic sedimentary aquifer along the coastal region of Djibouti, Africa. Their findings indicated that seawater intrusion (SWI) and various geological processes contribute to groundwater salinity. Saudi Arabia is geographically classified as a semi-arid country largely due to its hot, dry climate and limited rainfall. Hence, efficient management of these crucial water resources is essential for achieving Saudi Arabia's sustainable goals by 2030 [8]. In Saudi Arabia, the increased extraction rates of the aquifers (i.e., shallow and deep) have led to the deterioration of groundwater quality, resulting in higher salinity levels, especially in the shallow aquifers along the coastlines [24], [25], [26], [27], [28].

For instance, Alshehri et al. [24] examined the groundwater quality of Al Qunfudhah coastal aquifer (i.e., shallow). Their findings highlighted seawater intrusion as the primary contributor to groundwater salinity, alongside agricultural activities and the dissolution of gypsum and halite silicate minerals. Abba et al [25] developed a GW salinization modelling scheme in sandstone aquifer using various standalone ML models integrated with non-linear ensemble ML methods. The outcome of the developed model showcases the excellent ability of ML techniques in handling complex GW salinization processes, thus serving as an effective AI-based tool for water process management. In particular, GRNN model achieved the highest accuracy in GW salinization modelling. Similarly, El Waheidi et al. [27] investigated the effects of seawater intrusion on the GW of the Aqaba Gulf region coastal aquifer in Saudi Arabia. Their experimental analysis demonstrates that GW exhibited elevated salinity due to seawater intrusion and other related factors.

The primary contributors to the rising salinity of GW resources in these regions are the excessive extraction of water from aquifers (overexploitation) and the intensive irrigation practices employed in crop production. GW salinization carries significant negative implications. It severely degrades water quality, rendering it unfit for human consumption, household activities, agricultural irrigation, and a variety of critical applications. It is essential to address and alleviate this challenge to protect the sustainability of our water sources and to promote a healthier environment for both humans and aquatic organisms [28]. Therefore, understanding the principles and processes regulating the groundwater system is essential for both reducing and avoiding global warming and salinization of coastal aquifers [29]. Similarly, unraveling the mechanisms that cause groundwater salinization is crucial for developing effective mitigation and prevention strategies. This knowledge is also essential for building long-term resilience of our water resources. Typically, addressing these challenges involves thorough field and laboratory investigations coupled with adoption of advanced modeling and simulation techniques to delineate the scope of groundwater salinization [24], [30].

Recently, there has been an increased focus on the utilization of artificial intelligence (AI) in applications related to mapping, forecasting and prediction of GW salinization, achieving outstanding performance. Researchers have utilized computational methods like ML, deep learning and other AI data-driven models, which are seen as efficient in terms of cost and time, for the purposes of modeling, simulating, and predicting GW salinity processes [31], [32], [33], [34], [35], [36]. For example,Tran et al [31] employed various ML algorithms to assess their capabilities in simulating the GW salinization of multi-layer Mekong Delta coastal aquifer in Vietnam. Several ML predictive models suchasrandom forest regression, extreme gradient boosting regression, CatBoost regression, and the light gradient boosting regression were employed to predict the GW salinization process. Their findings demonstrated that CatBoost regression (CBR) exhibited strong predictive capabilities for groundwater salinity. Additionally, this study highlights the progress of ML in regulating and managing environmental challenges. Abba et al. [32] developed an efficient GW salinity prediction model for a coastal aquifer in eastern Saudi Arabia based on hydro-chemical and physical properties using hybrid metaheuristic optimization algorithms. Their experimental analysis indicates that adaptive neuro-fuzzy inference system (ANFIS) integrated with particle swamp optimization algorithm (i.e., ANFIS-PSO) attained the highest performance in terms of MAE. Similarly, Mosavi et al. [33] present a GW salinity mapping based ondichotomous predictions using various ML models. The outcome of their experiments revealed that SVM outperformed the rest of the ML models by a wide margin.

The authors of [34] employed three different AI-based algorithms including Hammerstein–Wiener, back propagation neural network, and multi-variate regression, to simulate the total hardness (TH) and total dissolved solids (TDS) of GW in the Wajid aquifer (sandstone aquifer) in Saudi Arabia. Similarly, they utilized a geographical information system (GIS) to assess the spatial variability of various input parameters within the GW aquifer, encompassing both physical and hydro-chemical properties. Their experimental findings indicate that the Hammerstein–Wiener model (specifically, the HW-M1 combination) yielded the most favorable results in terms of mean bias error and mean squared error for both TDS and TH. Yassin et al. [35] proposed an efficient and sustainable ML-based models to predict the GW salinization (i.e., TDS) in eastern province of Saudi Arabia. Specifically, their approach employed three popular AI-based approaches including. Gaussian process regression, support vector regression, regression tree and robust linear regression. Result obtained from extensive experimental evaluations suggests that Gaussian process regression had the superior performance in both training and testing phase.

Additionally, Abba et al. [36] employed different data-driven ML techniques to model the groundwater salinization based on hydro-chemical and physical parameters of sandstone aquifer in southern Saudi Arabia. Specifically, the authors simulate electrical conductivity (EC) using various ML algorithms such as least square-boost, Gaussian process regression, support vector regression and stepwise linear regression. Among these four modeling schemes, the results obtained suggest that Gaussian process regression has the highest prediction capability of the GW salinization process in terms of MSE, MAE, and RMSE. While the utilization of ML has been well-documented in technical literature, the effectiveness of certain techniques has been hindered by various modeling challenges attributed to the complexity of groundwater salinity processes. Nevertheless, certain standalone ML models continue to face challenges such as complexity, reduced accuracy, and the need for fine-tuning.

Additionally, while ML models excel at GW salinity prediction, their “black-box” nature presents a challenge. We can’t easily understand how the model reaches its conclusions, making it difficult to interpret the results or grasp the relationships between the various factors (inputs) and the predicted GW salinization (output). Specifically, this tendency might restrict the interpretability of outcomes, posing challenges in comprehending the underlying connections between model inputs and predictions. Explainable Artificial Intelligence (XAI) is a field within AI dedicated to developing models that maintain transparency and interpretability while achieving high levels of accuracy [37] . Employing ML for prediction alongside XAI can notably enhance both the accuracy and interpretability of decision-making in GW salinity prediction processes. XAI offers a method to enhance the transparency and comprehensibility of deep learning models, enabling decision-makers to grasp the connections between hydrochemical/physical inputs and GW salinity predictions more effectively, thereby facilitating informed decision-making.

Similarly, none of the earlier reviewed studies adopting various AI-driven approaches to handle groundwater salinity processes have incorporated an explainable deep learning scheme to interpret exactly what the models are doing or to understand which specific features from the physiochemical data contribute the most to the GW prediction problem. To address this issue, this paper developed an intelligent GW salinity identification and mapping using explainable deep learning in agricultural land of eastern Province of Saudi Arabia. Three different ML models including artificial neural network, Hammerstein-wiener model, random forest were exploited to predict the GW salinity of coastal aquifer in eastern Saudi Arabia. To improve the transparency and interpretability of the ML models, we adopted the SHapley Additive exPlanations (SHAP) as a widely XAI technique to interpret and justify the predictions obtained from the GW salinization processes. SHAP works by assigning a value, called a SHAP value, to each piece of information (feature) fed into a ML model. This value represents how much that specific feature contributes to the final prediction the model makes. To the best of the authors’ knowledge, this is the first study that incorporates XAI to interpret the rationale behind the predictions obtained from groundwater salinization processes in the Saudi Arabian region. The rest of the paper is outline as follows.

**2. Methods**

**2.1 Hammerstein-Wiener (HW) model**

The Hammerstein-Wiener (HW) is a mathematical tool employed to understand and analyze systems with mixture of both linear and non-linear behavior[38], [39] . This model finds extensive application across engineering fields where nonlinear elements are prevalent, including the modeling of biological systems, electrical circuits, and mechanical systems. Recently its application has been extended to water process management domain such as water treatment prediction problem[40] and GW modelling [34] achieving remarkable performance. It majorly integrates the attributes of both Hammerstein and Wiener models, which are two distinct types of nonlinear systems.

The HW model offers a versatile way to parameterize nonlinear models. For instance, it allows for enhancing the quality of a linear model by incorporating input or output nonlinearities. Compared to other existing artificial neural networks (ANNs), the HW model provided a clearer and more accurate way to represent how linear and non-linear systems work together. Additionally, the HW model offers a flexible and straightforward method for determining parametric specifications for nonlinear models, effectively capturing the physical understanding of system characteristics [39]. The typical configuration of the Hammerstein-Wiener model consists of three components: a linear block situated between two nonlinear blocks, as shown in Figure 1(C) [38], [39].

**2.2 Random Forest (RF)**

RF is an ensemble learning technique developed by L. Breimen [41] that is employed to solve classification and regression problems. The algorithm works on the basis multitude or assemble decision tress during training and generates individual outputs of each of the decision tree. Each of the RF trees is grown based on either randomness or ensemble learning [42]. For classification task it generates the mode (i.e., majority voting among all the output of the individual trees), while for regression task it obtains the mean (i.e., the average of the predictions of the trees). Each of the ensemble trees is trained independently using a random subset of the data to generate its own prediction.

Random forest method is very popular because of its optimal performance with no feature scaling, minimal data cleaning, robustness to overfitting and its ability to handle complex datasets with higher dimensionality. As a result, it is widely employed across numerous applications such as image classification, GW quality prediction, disease prediction, fraud detection, medicine, remote sensing, etc. A simple structure of a basic RF is shown in Fig 1.

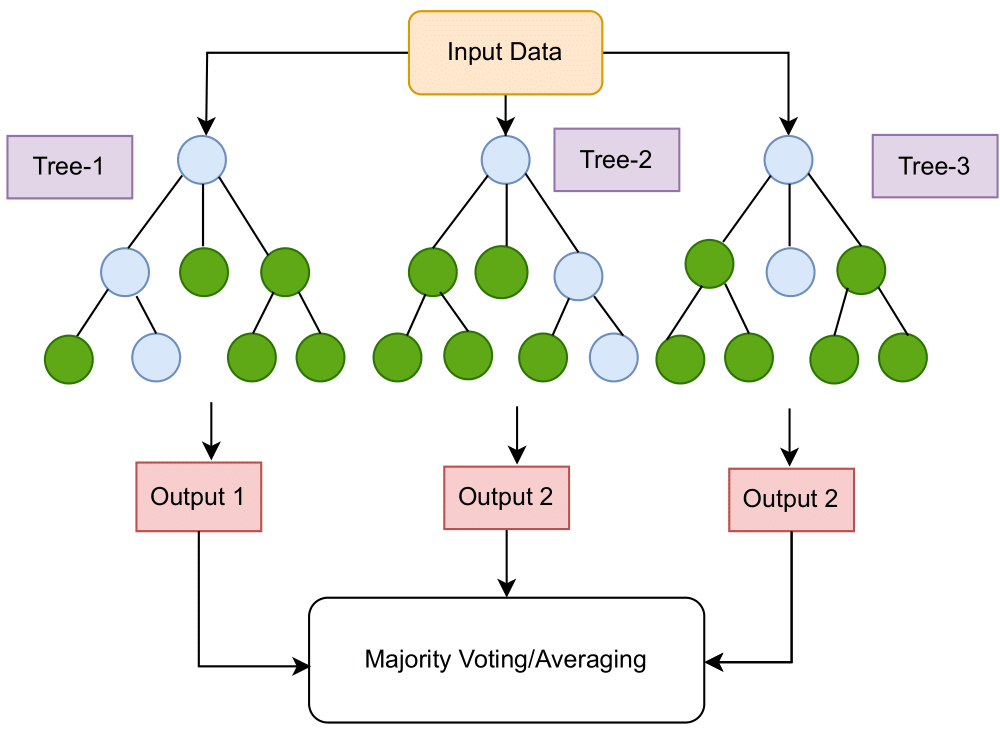


Fig 2; A simple structure of a basic RF

**2.3 Artificial Neural Networks (ANNs)**

ANNs are mathematical models developed to mimic the structure and function of the human brain [43]. They consist of multiple layers of interconnected processing units called neurons, processing information in parallel, enabling them to handle multiple calculations simultaneously, similar to the workings of biological neurons in the human brain [43]. A typical structure of a basic ANN constitutes the input layer, hidden layers, and output layer, interconnected via neurons, each characterized by its weight and bias. A neuron accepts input, aggregates it with coefficients like weights and bias, and then processes the outcome through a non-linear activation function to generate the neuron’s output. Neurons are structured in layers, allowing data to flow from the input to the output layers via one or more intermediary layers of neurons [44]. The network's performance is evaluated by comparing the predicted output to the expected output across various input data points. A cost function is employed to adjust the network's weights based on gradient descent and backpropagation algorithms, aiming to refine predictions and consequently minimize loss across successive iterations. In this study a feedforward multilayer perceptron (MLP) was considered to predict the GW salinization. A typical MLP is mathematically defined [45]:

were denotes the output of the neuron, is the input vector (for ), are the weights of a neuron , is the bias and is the activation function.

**2.4 Shapley Additive Explanations (SHAP)**

SHAP algorithm is a powerful technique introduced by Lundberg and Lee [46] to explain and interpret how complex ML models arrived at their predictions. It uses the concept of game theory developed by S. Llyod [47] to show how important each feature is to the final prediction outcome. For example, inputs (i.e. features) are considered as participants (i.e., players), while predictions are denoted as payouts (i.e., rewards or credits). SHAP aids in determining the individual contribution of each player in the game. It does this by assigning a Shapley value (score) to each piece of information or feature (covariate) used by the model. This score shows how much that specific piece of information affects the final prediction. It's like giving each factor a weight based on its influence, with a simple yes or no (binary) for whether it's even considered by the model.

In a nutshell the Shapley values indicate the equitable distribution of the “payout” (the prediction) among the features, determining how each feature value contributes fairly. Computationally, SHAP produces Shapley values, which depict model predictions as sums of weighted binary variables, signifying whether each covariate is included or excluded from the model The process of computing the Shapley value entails averaging the incremental impacts of each player (or feature) across all conceivable player arrangements. Mathematically, SHAP algorithm approximate every prediction based on , which is function of binary values with variable sets , defined by[[46]:

where denotes the number of explanations, and

where is the Shapley value for feature , denotes the SHAP model, represent the variable, indicates the selected variables, and is the number of features. While the term represents all the predictions.

**Study area and data (experimental method, mapping parameters, study location map)**

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