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MANAGEMENT OF AGRICULTURAL GROUNDWATER IN SUDAN: THE USE OF ARTIFICIAL INTELLIGENCE ALGORITHMS IN KHARTOUM STATE

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Abstract: This research aims to predict the irrigation indices of sodium adsorption ratio (SAR) and sodium percentage (Na%) using innovative machine learning (ML) techniques, including support vector regression (SVR) and Gaussian process regression (GPR). Thirty-seven groundwater samples were collected, and the primary investigation indicated that Ca-Mg-HCO_3 and Na-HCO_3 water types dominate the samples. The data is divided into two sets for training (70%) and validation (30%), and the models are tested with three statistical criteria, including mean square error (MSE), root mean square error (RMSE), and determination coefficient (R^2). The GPR algorithm showed better performance in predicting SAR and Na% than SVR since it provided the lowest errors. The implemented approach proved efficient for the sustainable management of agricultural water.

Keywords: *Groundwater quality, Irrigation indices, Machine learning, Nubian aquifer, Sudan.*

1. Introduction

Groundwater is one of the primary providers of irrigation water for agriculture in Sudan [1]. The utilization of groundwater for irrigation offers various benefits, including dependability and regularity. Unlike surface water, which can be impacted by floods and droughts, groundwater is generally consistent and can ensure a continuous supply of irrigation water [2]. This is crucial in areas with insufficient or unstable surface water supplies. Khartoum state is agricultural land with a high dependency on groundwater for irrigation. The high reliance on groundwater for irrigation is due to the absence of surface water transporting systems and the high cost of delivering Nile water to agricultural lands [3]. As a result, and due to the expanding agricultural lands and over-pumping of groundwater aquifers, the groundwater quality for domestic and agricultural purposes is declining. Therefore, this research attempts to evaluate the suitability of groundwater for irrigation using advanced computational artificial intelligence algorithms for sustainable crop production.

Irrigation indices are useful parameters to study the suitability of groundwater for agricultural purposes. However, the calculation of these indices is often lengthy and time-consuming [4]; therefore, Artificial Intelligence (AI) techniques are proposed to reduce the calculation time and avoid calculation errors. The use of AI models in irrigation water management has been growing in recent years due to their ability to analyze large amounts of data and make accurate predictions [5–7]. For instance, [8] used support vector regression (SVR) and random forest (RF) to model the irrigation water quality of potential salinity, sodium percentage and permeability index in Bahr El-Baqr, Egypt. They indicated the robustness of these algorithms to support the decision-making process for sustainable crop yield. [9] employed SVM and Gaussian process regression (GPR) for the simulation of SAR in three sub-watersheds in Iran. These studies demonstrated the potential of AI and ML as a tool for predicting various water quality indices in irrigation systems and highlighted the importance of such predictions in improving water management practices and ensuring sustainable agriculture.

This paper aims to examine the capability of support vector regression (SVR), and Gaussian process regression (GPR) to predict the spatial distribution of irrigational water quality indices of sodium adsorption ratio (SAR) and sodium percentage (Na %). The results of this research improve irrigation water management and the efficiency and sustainability of agricultural production.

2. Materials and methods

2.1. Study area

This study explores the suitability of groundwater for irrigation purposes in Khartoum state, Sudan (Figure 1). The area is characterized by a hot climate in summer, cold and dry in winter, and associated with an annual average precipitation of 115.7 mm/year in the fall season [10]. The main geomorphological features are the Nile River which bounds the study area from the west. Geologically, the area is located in the Blue Nile rift basin, where three geological units dominate. Figure 1 illustrates the primary geological units observed in the study area. The Pan African basement rocks of the Precambrian age form the bottom of the Blue Nile basin [11]. These rocks are dominated by biotite granite, gneiss, and schist, mainly observed near Khartoum's northern and eastern boundaries [12]. The Precambrian basement rocks are overlain by mudstone, sandy mudstone, conglomerates, and sandstone, which have been consolidated by limes, siliceous, and ferrous minerals. This rock accumulation is known as Cretaceous Nubian Formation [13]. This formation also comprises evaporite deposits formed in a braided environment and dispersed throughout the Nile and Blue Nile Rivers [14]. The recent deposit of Quaternary age is observed in the surroundings of the Blue Nile and Nile Rivers and the western part of the study area. This geological unit is also known as the Gezira formation and comprises unconsolidated sand, gravel, and silts. The Nubian sandstone, with an average thickness of 300 m, serves as a primary groundwater aquifer in the study area [15]. This aquifer is classified as highly productive, with an average transmissivity of 700 m^2/day [16]. Given that there is relatively minimal recharge from rainfall, the Nile River and ephemeral streams are the primary sources of groundwater recharge to the Nubian formation. As a result, groundwater levels range from 294 m in the southern parts to 366.6 m in the central part (Figure 2). Consequently, groundwater flows mainly from the western to the eastern and from northern to southern parts of the region [17].

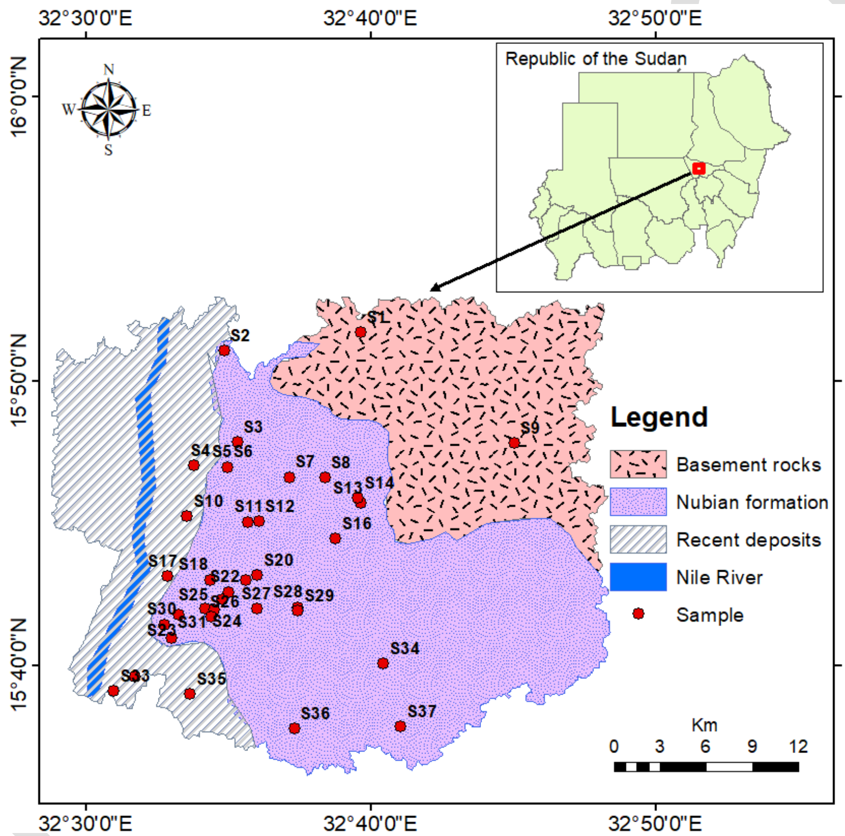

Figure 1

The geographical location and the main geological units in the study area modified after [10]

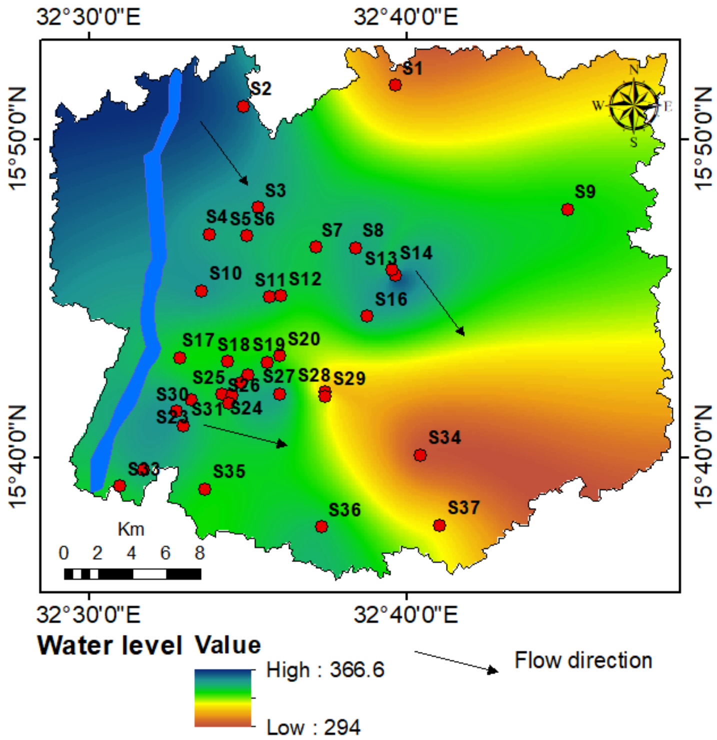

Figure 2

The water level map shows the main groundwater flow direction in the study area

2.2. Groundwater sampling

As part of the "zero thirsty" program administered by the Sudanese government, the Khartoum State Water Corporation collected 37 groundwater samples between October 2018 and December 2020. The groundwater samples were collected from public and privately owned groundwater wells with a depth ranging from 100 to 250 m [18]. The groundwater samples were analyzed in the labs of Groundwater and Wadies Directorate for ten physiochemical parameters. The parameters include total dissolved solids (TDS), hydrogen ion activity (pH), electrical conductivity (EC), calcium (Ca), magnesium (Mg), sodium (Na), bicarbonate (HCO_3), chloride (Cl), and sulfate (SO_4) concentration.

2.3. Irrigation indices

The quality of irrigation water and its suitability for various crops are assessed using irrigation water quality indices [19]. There are several different irrigation water indicators; however, in this research, two indices are used for the management of irrigation water, including Sodium Adsorption Ratio (SAR) and sodium percentage (Na%). SAR indicates the amount of sodium in water and how it could impact crops and soil [20]. Low SAR levels are often regarded as acceptable for irrigation, whereas high SAR values can cause soil dispersion and poor crop development. The overall amount of sodium in the water is also determined by the sodium percentage (Na%) in which the concentration of all ions is in meq/L. In general, SAR and Na% measures the concentrations of Na+ relative to the major cations including Ca, Mg, and K. However, in central Sudan hydrogeological system the concentration of K is low as a result, it is usually neglected in the hydrochemical analysis. The following formulas (Eqs. 1-2) are used to determine the irrigation indices.

$$SAR = \frac{Na^{+}}{\sqrt{\frac{Ca^{2+} + Mg^{2+}}{2}}}, \tag{1}$$

$$Na^{+}\% = \frac{Na^{+}}{Ca^{+2} + Mg^{2+} + Na^{+}} * 100, \tag{2}$$

2.4. Machine learning models

In this study, two machine learning models were utilized for predicting irrigation indices: Gaussian process regression (GPR) and support vector regression (SVR). The data set was divided into two parts, with 70% used for calibrating the machine learning models and the remaining 30% used for validating the models. The analysis of the machine learning algorithms was conducted using MATLAB software.

2.4.1. Gaussian Process Regression (GPR)

In this study, Gaussian Process Regression (GPR) was employed to predict the irrigation indices based on the concentration of the physiochemical parameters. Gaussian process regression aims to reconstruct the underlying signal by removing the contaminating noise. For a deeper understanding of the Gaussian Process Regression (GPR) method, one can refer to [21] and [22]. The Gaussian radial basis function (RBF) kernel is one of the most popular kernels used in Gaussian Process Regression, and it can model non-linear relationships between the input variables and the target variable. The parameter of the GPR models was optimized by using a repeated 10-fold cross-validation method to prevent overfitting.

2.4.2. Support Vector Regression (SVR)

Support Vector Regression (SVR) is a machine-learning technique that utilizes kernels to map the input space to a high-dimensional feature space, allowing for non-linear mapping [23]. The goal of SVR is to reduce both prediction errors and model complexity simultaneously. The optimization problem is solved using Lagrange multipliers and results in a set of support vectors that define the boundary. The prediction for a new data point is then made based on the support vectors and their weights. In this study, the Support Vector Regression (SVR) method was implemented using MATLAB and the model's parameters, including the choice of kernel function and the value of the parameter, were determined through a parameter tuning process using a random search method [24]. For a more detailed understanding of the SVR method, one can consult [25].

2.4.3. Models Performance

In this study, the accuracy of the predicted and observed data was evaluated using three widely used metrics: root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). To accurately reflect the overall accuracy of the machine learning models, only the evaluation metrics for the validation set are calculated. The performance metrics are measured using the following equations (Eqs. 3 - 5)

$$MAE = \frac{\sum_{i=1}^{n} |O_i - P_i|}{n} , \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - P_i)2}{n}} , \tag{4}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - O_{ave})(P_i - P_{ave})}{\sqrt{\sum_{i=1}^{n} (O_i - O_{ave})^2 (P_i - P_{ave})^2}} \right]^2 , \tag{5}$$

where O_i and P_i are, respectively, the observed and predicted values, with their average values represented by O_{ave} and P_{ave}, respectively, and n is the sample size in the validation set.

3. Results and discussion

3.1. Hydrochemical facies

The hydrochemical facies is studied with the aid of the Chadha [26] diagram (Figure 3). In this diagram, the difference between major cations (Ca + Mg) – (Na + K) and anions (HCO_3 – (SO_4 + Cl)) is used to detect the groundwater types (Fig. 3). Consequently, four groundwater facies are revealed as Na-Cl, Ca-Mg-SO_4/Cl, Na-HCO_3, and Ca-Mg-HCO_3. The majority of the groundwater samples (67.5%) fall in Ca-Mg-HCO_3 water type, which indicates the influence of groundwater recharge on groundwater chemistry. The locations of these samples are within the influence of the Nile River, which is 12 km [3]. The groundwater type gradually changes from the western to the eastern parts of the study area from Ca-Mg-HCO_3 to Na-HCO_3 water type. This change is likely due to ion exchange or the replacement of Ca and Mg with Na. As a result, 16.2% of groundwater samples are identified as Na-HCO_3 water type. 8.1% of the samples are classified as Ca-Mg-SO_4/Cl resulting from reverse anion exchange in which HCO_3 is replaced by Cl in groundwater. The continuation of cation and reverse anion exchange leads to the Na-Cl facies. In this study, 8.1% are classified as saline water. It can be concluded that the hydrochemical characteristics of groundwater in the eastern Nile River are mainly influenced by groundwater recharge and ion exchanges.

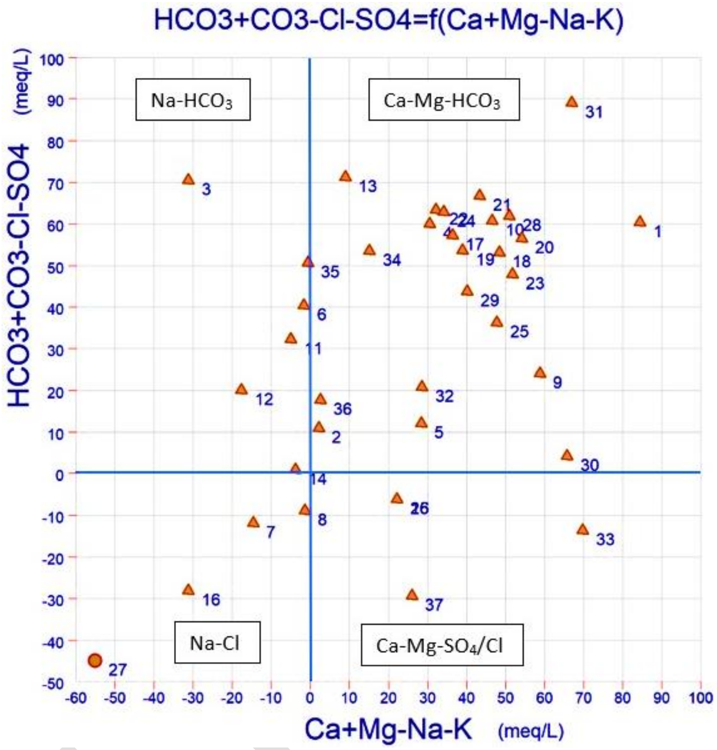

Figure 3

Chadha diagram showing the main groundwater facies of the collected samples

3.2. Irrigation indices

3.2.1. Sodium adsorption ratio (SAR)

The SAR ranged from 0.27 to 13.8. The classification of groundwater samples is represented in Figure 4 (USSL diagram). Groundwater is divided into four groups based on SAR: excellent with SAR < 10 (S1); good (SAR ranges from 10 to 18 (S2)); doubtful, in which SAR ranges from 18 to 26 (S3); and unsuitable with SAR > 26 (S4) [20]. In general, SAR is influenced by the concentration of Na relative to the other cations, such as Ca and Mg. In practice, groundwater is usually classified by conjugation of SAR with EC, since irrigation water with high salinity stimulates the ion exchange process and thus affects the adsorption of water by plants. Salinity. Based on EC, groundwater is classified as water with low (C1), medium (C2), high (C3), and very high (C4) salinity hazards. As a result, 59.4% of the groundwater samples are associated with low SAR (S1) and medium salinity hazard (C2). This class is considered excellent for irrigation purposes. 35% of the samples are projected in S1C3 class with low alkali and high salinity hazard. This class might not affect the soil permeability however, high salinity may influence the growth of salinity-sensitive plants and thus reduces the crops yield. One sample (S16) is plotted in S2C3 class with medium alkali and high salinity hazards. S27 is classified as unsuitable for irrigation since it is associated with high alkali and high salinity hazards (S4C4). This persistent use of this sample for irrigation will damage the soil permeability by incorporating Na within the soil particles and affect the growth of plants.

3.2.2. Sodium percentage (Na%)

The principle of Na% is almost similar to that of SAR in which the percentage of Na^+ relative to the cations of Ca and Mg is measured. Na is incorporated into the clay minerals sheets while the other cations are removed, which affects the infiltration of water to the plant's root. The exchange results in two types of soils, saline soils formed when Na reacted with Cl while the alkaline soil when Na reacted with HCO_3 in the irrigation water [27]. In this study, Na% varied between 7.8% to 77.3 %. On the basis of Na%, groundwater is classified as excellent for irrigation, good, acceptable, doubtful and unsuitable. The groundwater samples are plotted in Wilcox's (1948) diagram (Figure 5). Accordingly, 64.8% of the groundwater samples are projected in the excellent class zone. This class is associated with low salinity and alkali hazard. 21.6% of the samples are classified as good for irrigation with relatively high salinity and low alkali hazard. The permissible water class included 10.8% of the groundwater samples with high alkali hazard and relatively low salinity. The groundwater in this class is mostly influenced by the rock type. Only one sample is described as doubtful for irrigation purposes, and this sample is highly influenced by salinity.

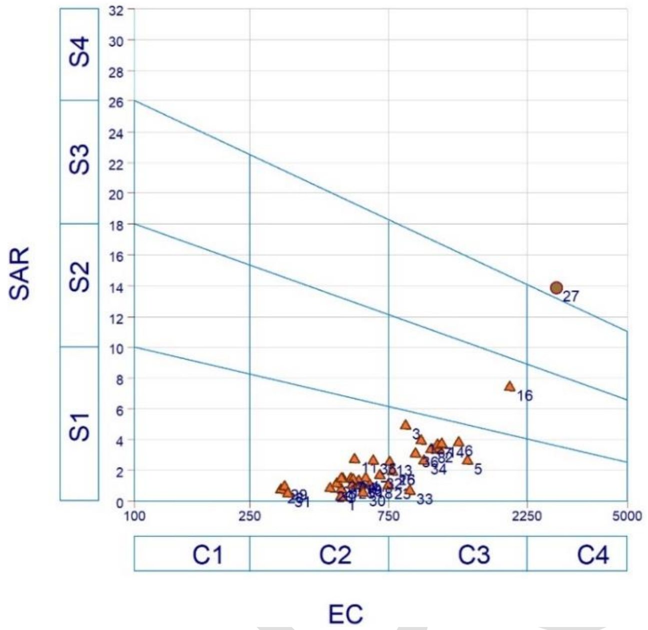

Figure 4
The USSL diagram shows the classification of groundwater based on SAR.

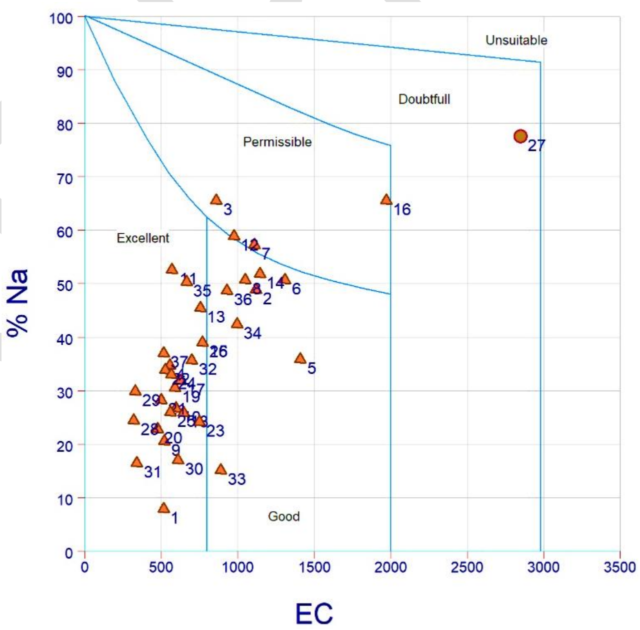

Figure 5
The Wilcox diagram shows the classification of groundwater based on Na %.

3.3. Modeling of irrigation indices

In this study, the SAR and Na values were estimated using the GPR and SVR models. These methods are applied to overcome the limitation of the conventional method for calculating irrigation groundwater quality indices. The analyzed parameters are considered the input, while the calculated irrigation indices using a statistical (conventional) approach are considered the output. Experimental data were categorized into training and testing, and the performance of each model was evaluated based on the R^2, MAE, and RMSE during the testing stages, as shown in Table 1. In general, the developed models provide adequate modeling of the SAR parameter in groundwater and produce satisfactory estimates based on the performance criteria. However, the results for SAR estimation showed that the GPR model was the best performer, with the highest R^2 value of 0.99 and the lowest error performance values, including MAE=0.0001 and RMSE=0.01, in the validation phase (Table 1). The error, as usual, in the training phase is higher than in the validation and testing phase. The prediction of SAR using SVR modeling showed a lower R^2 value of 0.99 and the lowest error performance values, including MAE=0.05 and RMSE=0.22.

As in SAR modeling, the GPR showed higher performance in the prediction of the Na% parameter in groundwater. The performance measures showed a reasonable estimate for the parameter. The modeling of Na% outcomes using GPR showed R^2 value of 0.99 and low error performance values, including MAE=0.003 and RMSE = 0.05 in the validation phase. In the training phase, a higher error is indicated by RMSE and MAE. The SVR model also showed a high performance with an R^2 value of 0.98 and error performance values of MAE = 5.14 and RMSE = 2.26 in the validation phase.

The scatter plot between the observed and predicted parameters (Figure 6) showed a reasonable correlation. The measured values of SAR and Na% are projected near the 1:1 line; as a result, the obtained values can be successfully used to evaluate the suitability of groundwater for irrigation purposes.

Table 1

Results of machine learning-based models in the training and testing phase.

Model-Index	Training Phase				Testing Phase			
	R^2	MAE	RMSE	R	R^2	MAE	RMSE	R
GPR-SAR	0.99	0.0001	0.01	0.99	0.99	0.0001	0.01	0.99
GPR-Na%	0.99	0.009	0.09	0.99	0.99	0.003	0.06	0.99
SVR-SAR	0.96	0.103	0.32	0.98	0.99	0.05	0.22	0.99
SVR-Na%	0.96	7.50	2.73	0.98	0.96	5.14	2.26	0.98

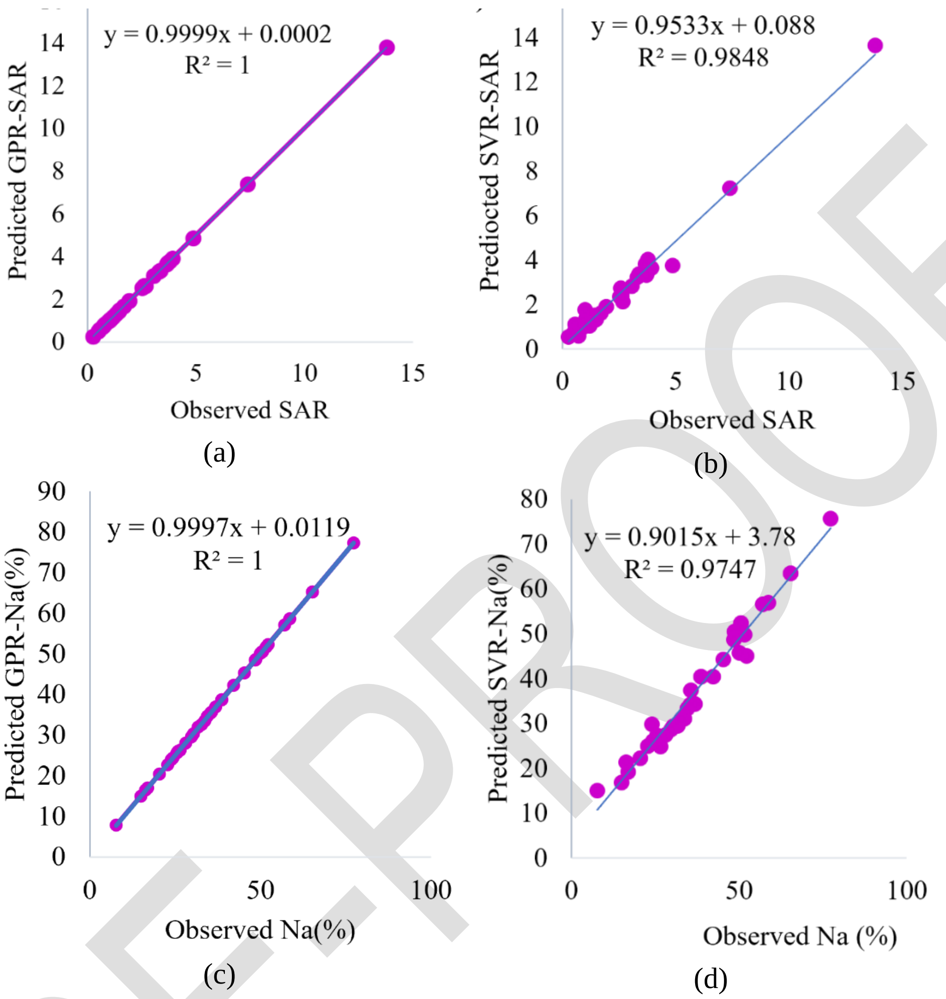

Figure 6

Scatter plot between the observed and predicted value of (a) SAR-GPR, (b) SAR-SVR, (c) Na %-GPR, and (d) Na %-SVR

The correlation between the irrigation indices of SAR and Na % and major physiochemical parameters is conducted to reveal the influence of each parameters on the predicted irrigation indices (Figure 7). SAR is highly correlated with Na^{+} with correlation coefficient (R) of 0.99, TDS (R = 0.86), and EC (r = 0.83). This reflect the high impact by of these parameters on SAR values. EC and TDS are the salinity parameters which is in general have great influence on SAR and thus, the suitability of groundwater for irrigation purposes. On the other hand, SAR has moderate with Mg^{2+} (R = 49), and low correlation with Ca^{2+} (R = 0.085). The low correlation indicate the leaset influence of these cations on SAR values. As in SAR, Na% has high correlation with Na^{+} (R =0.76) and TDS (R = 0.70). Moreevre, it has moderate correlation with EC (R = 0.67) and low correlation with Ca^{2+} and Mg^{2+}. The low correlation of SAR and Na % with Ca^{2+} and Mg^{2+} is likely due to the low concentration of these cations relative to Na^{+}. Additionally, the low correlation could be due to the effect of other dissolved ions on SAR value, such as HCO_3, SO_4, and Cl. These ions can interact with calcium and magnesium ions, altering their concentrations and ultimately affecting the SAR value [23].

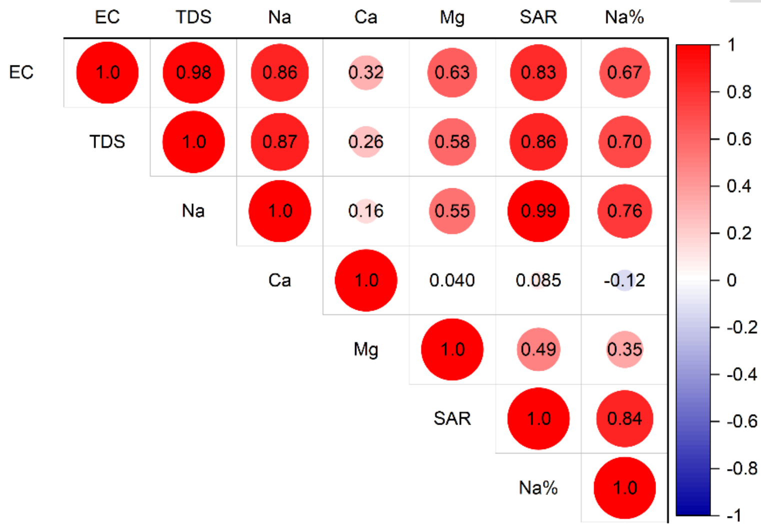

Figure 7

Correlation between irrigation indices and physiochemical parameters

Based on the predicted values of irrigation indices, GIS environment is used to map the spatial distribution of SAR and Na % concentrations in groundwater and the results are illustrated in Figure 8 and Figure 9, respectively. For SAR, the western parts of the study area are associated with low values of SAR, likely due to the influence of groundwater recharge on groundwater samples. The highest values in the southern and central parts are generally due to the high mineralization of groundwater samples due to the dissolution of halite minerals within the Nubian formations [28]. The variation of Na% shows a similar trend to that of SAR as the central and southern parts depict high concentrations relative to the rest of the study area. In general, evaluating groundwater use for agricultural purposes is comprehensively achieved by considering combined indices. It can also be said that the use of a certain type of water depends on the type of plant and its tolerance to salinity or its sensitivity to a certain parameter. The type of soil, whether it is acidic or alkaline, is also influencing plant growth. The quantity of water that a particular plant needs for growth may be related to one index rather than the other.

The results of irrigation indices modeling using machine learning techniques showed a resealable match with the conventional method. Consequently, the quality of groundwater for agricultural purposes in the north Khartoum area can be evaluated solely with ML techniques. It can be concluded that machine techniques such as GPR and SVR can effectively simulate irrigation indices and other hydrochemical parameters in a time and cost-effective way when large water quality data is recorded. In order to improve groundwater quality assessments and management, the application of artificial intelligence is recommended for sustainable groundwater resource management. The geospatial mapping of the predicted values of the irrigation indices allow examining the capabilities of the SVR and GPR to be used instead of the conventioal methods which area lengthy and prone to calculations error. Further, the produced models can be applied freely in systems with similar hydrogeological conditions. However, simultaneous use of GIS and ML algorithms is preferable to provide a continuous mapping of the indices and allow evaluation of the spatial uncertainty. For instance, pixels-based analysis can be conducted using the mean of the predicted values of the irrigation indices.

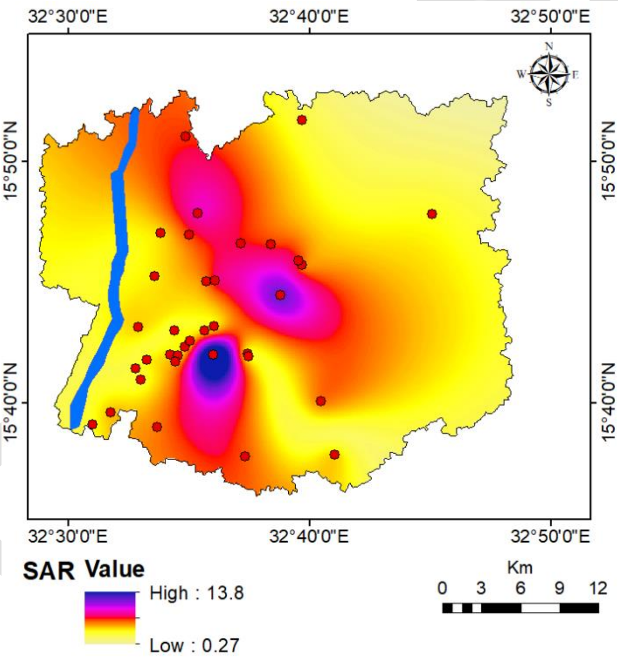

Figure 8
The spatial variation of SAR in the study area

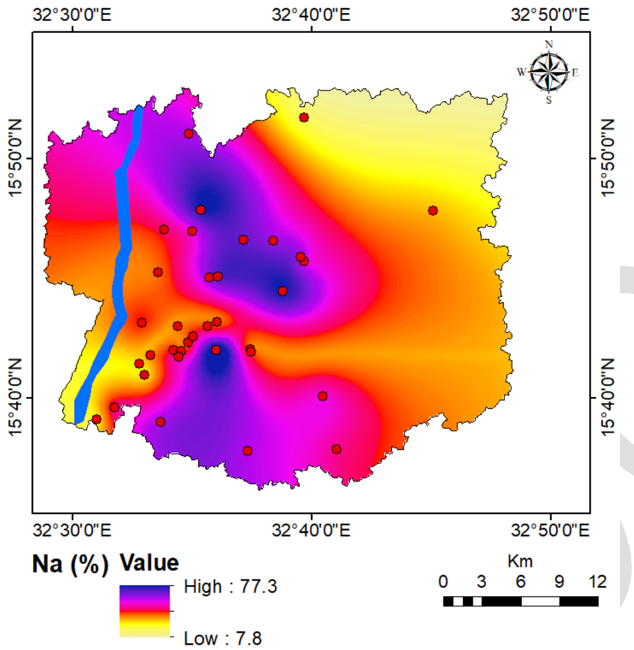

Figure 9
The spatial variation of Na% in the study area

4. Conclusions

In this research, two computational machine learning (ML) algorithms (GPR and SVR) integrated with GIS were used to evaluate the suitability of groundwater for irrigation purposes based on SAR and Na%. This approach is followed to overcome the limitations of the conventional assessment of the irrigation indices. Based on the modeling results, the conclusions can be summarized as follows:

- The initial analysis revealed that the groundwater samples are dominated by Ca-Mg-HCO_3 and Na-HCO_3 water types resulting from groundwater recharge and ion exchange processes.
- The observed irrigational indices indicated that the majority of the groundwater samples (60%) are for excellent agricultural purposes. The remaining samples are mostly influenced by high salinity resulting from rock-water interactions.
- GPR and SVR resulted in reasonable to good predictions of irrigation indices. However, the GPR algorithm showed the best performance, with the lowest error values.
- The GIS environment is successfully used to map the spatial distribution of the predicted groundwater irrigation indices. However, the integration of GIS and ML models is recommended for effective geospatial uncertainty analysis.

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