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Support Vector Machine: A Case Study in the Kert Aquifer for Predicting the Water Quality Index in Mediterranean Zone, Drouich Province, Oriental Region, Morocco

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ABSTRACT

The expansion of urbanization and the amplification of anthropic activities in the Rif region require the establishment of wells. However, the irrational exploitation of water and natural conditions have generated the rise of the water table and the increase in pollution. Thus, the assessment of water quality has emerged as a significant concern. This study's goal is to assess the adequacy of groundwater quality in two aquifers in the vicinity of the Mediterranean Zone - Drouich Province and Oriental Region, Morocco, for drinking water needs by taking 62 water samples of the Kert aquifer for 2019. The Water Quality Index (WQI) classifies water quality: as excellent, good, poor, very poor, etc. That is essential for conveying information about water quality to people and decision-makers in the affected area. The WQI in the Kert aquifer varies from 62.3 to 392.3. The calculation of the water quality index (WQI) of the Kert aquifer view is based that 45.16% of groundwater samples are of poor quality, making them acceptable for drinking. The study's analysis is established with a geographic information system (GIS) setting. The index map provides decision-makers with a complete and interpretable picture for better water resource planning and management. SVM models are shown to account for 87.71% of the varying water quality score. Different statistical and intelligence models may make the index more predictable. These forecasts assist us in better managing the aquifer's water quality.

INTRODUCTION

Public health issues involving the chemical contamination of groundwater must be addressed immediately. The availability of water for human use is a critical global and regional concern (Azizullah et al. 2011, El Yousfi et al. 2022, Schweitzer & Noblet 2018, Vesali Naseh et al. 2018). Water Quality Indices (WQIs) are an easy-to-understand tool that managers and decision-makers can use to evaluate a specific water body's quality and potential applications (Kumari & Sharma 2019, Rawat & Singh 2018). WQI is a mathematical technique for integrating detailed water quality data into a numerical score describing the general view of the water's quality (Gueddari et al. 2022, Mukate et al. 2019, Ponsadailakshmi et al. 2018, Singh et al. 2019) as a whole. In essence, the WQI aims to offer a system for presenting a cumulative score and an expression numerically describing a certain level of water quality (Deshpande et al. 2014, Tziritis et al. 2014). Horton's work led to the development of the first WQI in the US, which has been used in Europe since the 1970s, initially in the UK. Later, the United States National Sanitation Foundation refined this concept (Banda & Kumarasamy 2020, de Andrade Costa et al. 2020,

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Kachroud et al. 2019). As a result, the WQI principle has been the subject of extensive effort since then, using concepts that have been slightly modified (Brilli et al. 2013, Eden & Ackermann 2001, Von Zur Gathen & Gerhard 2013).

Prior research in this field has concentrated on groundwater quality (the source of salinity, the aquifer's geochemistry, and investigations of heavy metals). (Elgettafi et al. 2013, Hicham et al. 2021a, 2021b). This publication predicts the Water Quality Index in the unconfined Kert aquifer using a Support Vector Machine.

Water is required for the life of all organisms. As such, it is an irreplaceable resource (Butler 2017, Malekzadeh et al. 2019, Toolabi et al. 2021) We found that the WQI can be predicted using physical values and no sub-index computation of the input for physical and chemical parameters in this study.

MATERIALS AND METHODS

Study Area

North-eastern Morocco is home to the Kert Basin, which covers a space of around 250 square kilometers are shown in Fig. 1. The western Gareb chain forms its eastern boundary. The Kert basin's most important river, the seasonal Temsamane, flows around the massive Temsamane metamorphic mountain, which surrounds the plain to the north and northwest. The river's overall length is 90 km and its catchment area is 2710 sq. km (Zielhofer et al. 2008). According to some studies on the current regular fault system, Kert Basin was formed during the Messinian Paleocene. (Azdimousa 2007). Pump testing and electro-geophysical investigations were used to develop this model. The Kert plain is encircled by an open aquifer that flows through the Miocene Bluish Marls (bedrock aquifer). Numerous hydrogeological formations exist, and their stratification is visible in Fig. 2. Transgressed Miocene marls are overlain by an identical layer of limestone and conglomerate that serves as the aquifer's bedrock. The only other formation in the region, we think, is the Miocene, which contains gypsum. This sequence is completed with villafranchian gravel, silt, and clay. Two Miocene vertical faults created the Kert basin. As a result, the northern and southern bounds of the plain were extended. These faults may connect the aquifer to the Jurassic unit below

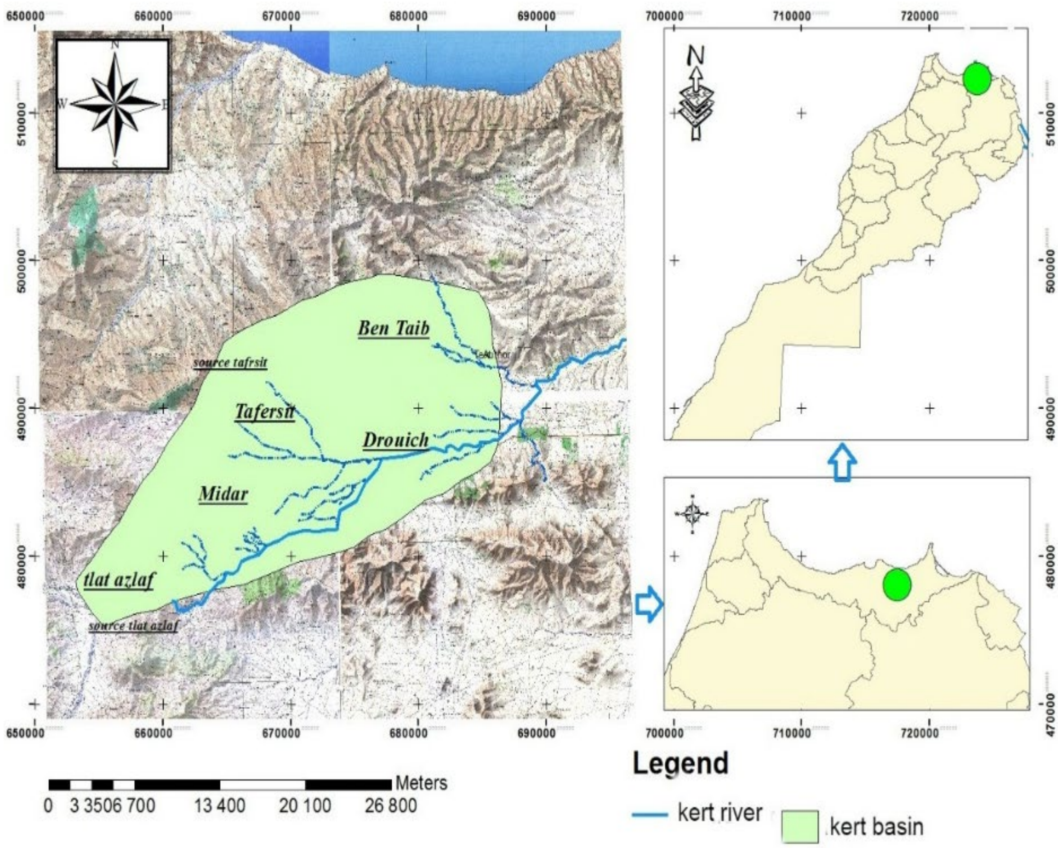

Fig. 1: The Kert basin's placement.

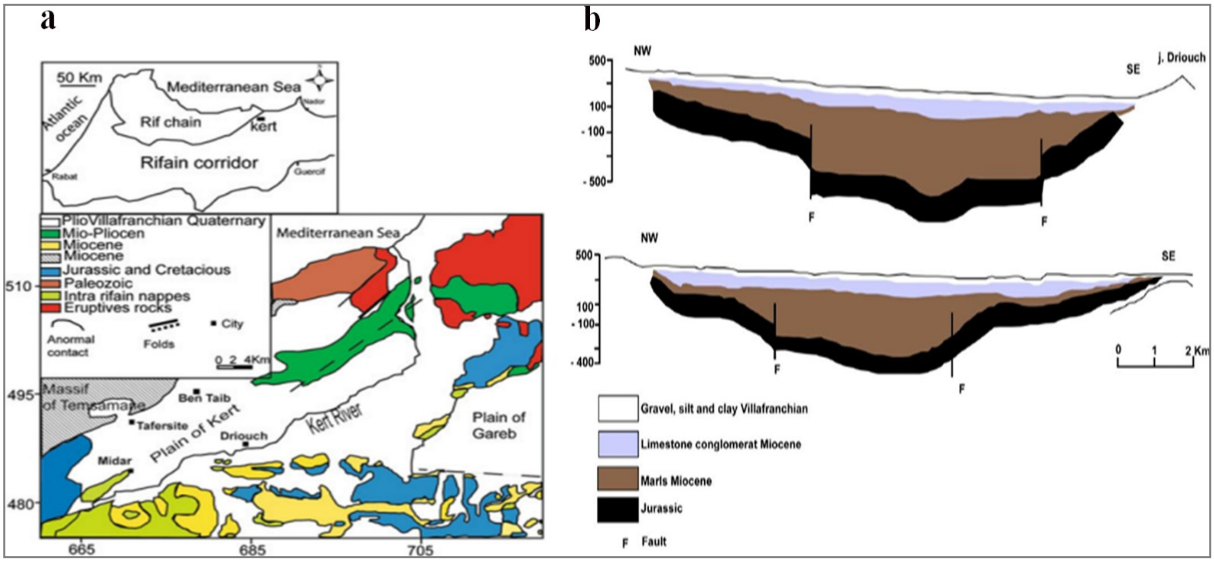

Fig. 2. a - The Kert Plain's base map and b - Hydrogeological section of the kert aquifer system (Carlier 1973).

(Carlier 1973). With an annual rainfall of just 276.9 mm, the area is semi-arid. Temperatures range from 10°C to 25°C annually. The Moulouya Hydraulic Basin Agency pegs the average annual evapotranspiration as 291.6 $mm.year^{-1}$.

Field Sampling

During the low water season of 2019, sixty wells and two springs are tested from the Kert groundwater. The groundwater samples are subjected to a physicochemical evaluation (Rodier et al. 2009), and a physico-chemical analytical procedure is used. Coolers were used to retain the models at 4^{o}Celsius right away. The ISO 5665 standard is used to collect the samples. The pieces were kept cool (2 to 4°C) in labeled plastic bottles to examine chemical parameters. EC, pH, main elements (Cl^-, Ca^{2+}, Mg^{2+}, K^+, Na^+, SO_4^{2-}, HCO_3^-, NO_3^-, and PO_4^{3-}) were investigated.

Data Processing

Physicochemical data is evaluated using Principal Component Analysis-based multivariate statistical methodologies (PCA). The statistical method is often used in water research to investigate water mineralization and pooling and determine the relationship between WQI and salinity phenomena. The statistical analysis was carried out using the R program. A comparison is made between the measured factors and the quality of drinking water requirements set by the WHO. Thematic maps employing Geographic Information Systems are used to display the results (GIS).

The water quality index (WQI) was developed to quantify the influence of human and natural activities on groundwater chemistry. While assigning weights for the WQI computation, the relative relevance of the physicochemical parameters in determining the overall quality of water for drinking water applications is evaluated. Between one and five, the weight is given. TDS, pH, EC, SO_4, nitrate, and

Table 1: Physicochemical parameters relative weight Parameters (WHO Edition 2011).

Chemical variables	WHO standards (Edition 2011)	Weight (wi)	Relative weight $Wi = wi / \Sigma^{n}_{i=1} wi$
pH (on the scale)	6.5-8.5	4	0.114
EC [$mS.cm^{-1}$]	250	4	0.114
TDS [$mg.L^{-1}$]	500	5	0.142
HCO_3^- [$mg.L^{-1}$]	500	3	0.086
Cl^- [$mg.L^{--1}$]	600	3	0.086
SO_4^{2-} [$mg.L^{-1}$]	400	4	0.114
NO_3^- [$mg.L^{-1}$]	50	5	0.142
Ca^{++} [$mg.L^{-1}$]	200	2	0.057
Mg^{++} [$mg.L^{-1}$]	150	1	0.029
Na^+ [$mg.L^{-1}$]	200	2	0.057
K^+ [$mg.L^{-1}$]	10	2	0.057

Table 2: WQI-based water quality rating ranges and kinds range water type (Bhargava 1983).

Range	Type of waters
≥ 50	Excellent water
50-100	Good water
100-200	Poor water
200-300	Very poor water
≤ 300	Water that is unfit for consumption

HCO_3 have been assigned a maximum weight of 5, 4 for pH, EC, SO_4^{2-}, 3 for HCO_3^-, and two for Ca^{++}, Na^+, and K^+ (Table 1). (Akhtar et al. 2021, Bhimanagouda et al. 2020, Gueddari et al. 2022, Karunanidhi et al. 2021, Selvam et al. 2014)). The comparative weight is calculated using the subsequent equation (eq.1).

$$\mathrm{Wi} = wi / \sum_{i=1}^{ni} wi \qquad \ldots(1)$$

Where:

Wi denotes the weight relative to another.

wi denotes the parameter's weight.

The argument count is n.

The level for evaluating the quality of each parameter is determined by dividing each water sample's concentration by the applicable standard (WHO Edition 2011) and multiplying the results by 100 (eq.2).

$$Qi = \left(\frac{ci}{si}\right) \times 100 \qquad \ldots(2)$$

Where,

Qi denotes the standard of quality.

ci denotes every chemical parameter's concentration in

The weight of each sample is determined, and the concentration is given in milligrams per liter. si is the recommended limit for every chemical parameter in milligrams per liter by the World Health Organization (WHO Edition 2011). Begin the last phase of WQI calculation by computing the SI for each parameter (Table.2). The water quality index is calculated by adding the SI values for each sample. (Abbasnia et al. 2019, Mukate et al. 2019) (eq.3 and 4).

$$Sli = Wi \times qi \qquad \ldots(3)$$

$$WQI = \Sigma Sli \qquad \ldots(4)$$

Where

Sli is the i^{th} parameter's sub-index.

qi is the score assigned to the ith parameter depending on its concentration.

The number n denotes the number of parameters.

Physical and Chemical Analysis

Because the parameters vary after sampling, and cannot be identified qualitatively, we took measurements of T (°C) and dissolved oxygen in situ, as well as pH, Cond (S.cm-1), and hydrogen potential (pH) (O2d). For these tests, we utilized a MULTI 350I multi-parameter meter that is easily portable.

Methods for analyzing various other variables were used in a laboratory, as per recommendations from Rodier et al. (2009):

- To identify and quantify (K^+, Na^+), we employed Flame Atomic Absorption Spectrophotometry (Varian Model 475-AA).
- According to the ISO17294-2:2016 standard, the measurements are made using spectrophotometry and colorimetric dose (SO_4^{2-}, NO_3^-, PO_4^{3-}).
- Complexometric measurements are used for calcium and magnesium. To measure the concentration of main anions, we used them as a technique.
- Chloride precipitation and bicarbonate titrimetry with 0.01 N HCl are two methods to determine precipitation. It is common practice to measure chemical levels in $mg.L^{-1}$ units.

Support Vector Machine (SVM)

Identifying the root causes of data is well-suited to the use of SVM-based supervised machine learning models. The statistical learning theory and the notion of structural risk reduction underlie these strategies (Bennett & Demiriz 1999, Evgeniou et al. 2002). The kernel approach in regression transforms non-linear correlations between inputs and outputs into a higher-dimensional regression analysis. (Üstün et al. 2007, Xu et al. 2006). D = x I,y I i = 1: n, where x is the contribution vector, y is the output variable, and n is the number of observations.

The SVR model aims to find the best function f defined (Kavousi-Fard & Kavousi-Fard 2013, Mohammadi & Mehdizadeh 2020) (eq.5):

$$f(x) = w^T \varphi(x) + b \qquad \ldots(5)$$

Where *a* is a nonlinear function that translates the data received into high dimensional space, w and b represent the weights and the bias that are determined by minimizing the regularized risk function (eq.6):

$$R = \frac{1}{2} w^T w + C \frac{1}{n} \sum_i^n L_\varepsilon(g(x_i), y_i) \qquad \ldots(6)$$

Where L_ε is the ε – I insensitive loss function; $C \frac{1}{n} \sum_i^n L_\varepsilon(g(x_i), y_i)$ is the empirical error and C is a positive Trade-off parameter between the observed error's magnitude and the model's flatness.

When attempting to forecast river water quality using an ungauged catchment in a dual scenario, this study turned to RBF (Model-Based Support Vector Machine Model for Predicting Water Quality) (eq.7).

$$K(x_i, x_j) = \exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2}\right) \qquad \ldots(7)$$

Where $\|x_i - x_j\|^2$ is the squared Euclidean distance between the two input vectors and, and is the band-

Table 3: Individual water quality index (WQI) categorization.

Wells	WQI	Water quality classification type	Wells	WQI	Water quality classification type
w1	219.4	Very poor water	w34	84.1	Good water
w2	334.98	Water that is unfit for consumption	w35	139.6	Poor water
w3	311.02	Water that is unfit for consumption	w36	190.7	Poor water
w4	264.48	Very poor water	w37	201.5	Very poor water
w5	138.29	Poor water	w38	175.1	Poor water
w6	202.1	Very poor water	w39	206.3	Very poor water
w7	197.5	Poor water	w40	216.2	Very poor water
w8	96	Good water	w41	224.1	Very poor water
w9	138.4	Poor water	w42	322.5	Water that is unfit for consumption
w10	282.8	Very poor water	w43	392.3	Water that is unfit for consumption
w11	179.7	Poor water	w44	301.1	Water that is unfit for consumption
w12	296.5	Very poor water	w45	320.1	Water that is unfit for consumption
w13	234.7	Very poor water	w46	186.7	Poor water
w14	228.6	Very poor water	w47	126.1	Poor water
w15	128.4	Poor water	w48	169.3	Poor water
w16	273.5	Very poor water	w49	74.6	Good water
w17	227.6	Very poor water	w50	138	Poor water
w18	197.7	Poor water	w51	89.6	Good water
w19	223.6	Very poor water	w52	74.9	Good water
w20	260.1	Very poor water	w53	99.5	Good water
w21	318.1	Water that is unfit for consumption	w54	110.2	Poor water
w22	245.2	Very poor water	w55	98.2	Good water
w23	222.6	Very poor water	w56	92	Good water
w24	179.3	Poor water	w57	96	Good water
w25	213.5	Very poor water	w58	152.5	Poor water
w26	116.6	Poor water	w59	158.8	Poor water
w27	109.3	Poor water	w60	185.3	Poor water
w28	139.3	Poor water	S1	95	Good water
w29	183.4	Poor water	S2	69.8	Good water
w30	153.2	Poor water			
w31	128.3	Poor water			
w32	163.2	Poor water			
w33	62.3	Good water			

width parameter of the RBF function (Sun & Fox 2014).

RESULTS AND DISCUSSIONS

Water Quality Index (WQI)

An assessment of water quality and the sustainability of drinking water can only be made using the Water Quality Index (WQI) (Bhimanagouda et al. 2020, Nong et al. 2020, Ponsadailakshmi et al. 2018). The Water Quality Index (WQI) is described as a technique of assessment that delivers the final impact of each water quality indicator (Adimalla 2019, Tripathi & Singal 2019).With an average of 110.16 28.55, 60 wells and two springs are evaluated for the Water Quality Index (WQI). Sixty percent of the water points have a WQI of more than 100, which indicates poor water quality. Because 88.89 percent of these boreholes had Nitrate levels over 50 $mg.L^{-1}$, it seems that high levels of nitrates influence

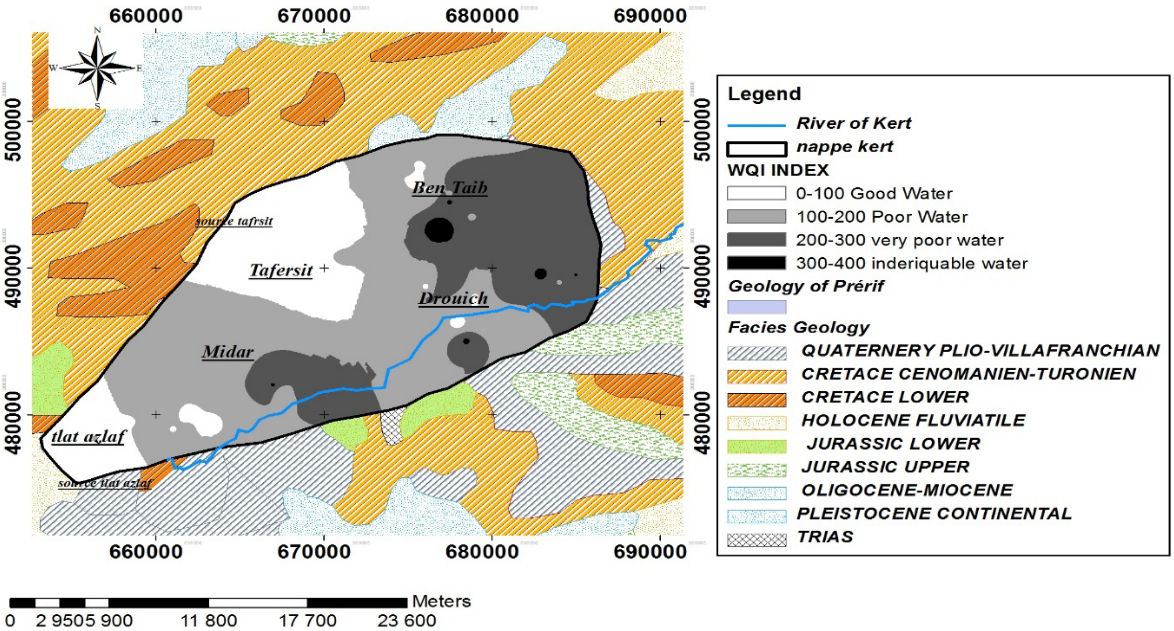

Fig. 3: Water quality classification ranges.

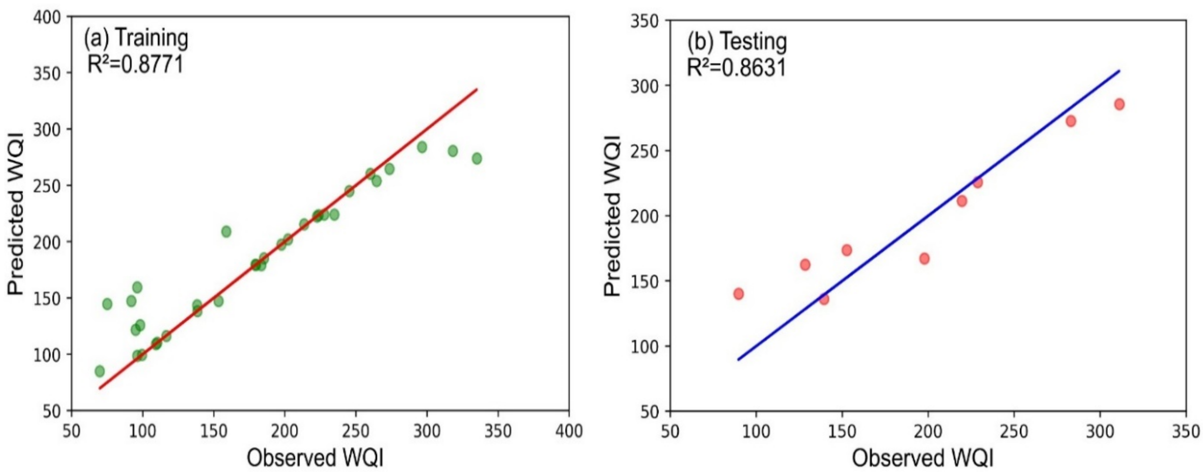

Fig. 4: Plot of prediction versus SVM-Model test data.

the WQI and the deterioration of water quality is shown in (Table.3). Fig. 3 illustrates how an examination of WQI and other metrics demonstrates that natural processes are crucial to the deteriorating water quality of the Kert Aquifer. Gypsum in rock formations may cause this phenomenon since rock salt dissolves readily in water (Gueddari et al. 2022, Liu et al. 2020, Lu et al. 2015, Zaier et al. 2021)). The elevated concentrations of EC, chloride, salt, and calcium demonstrate unequivocally that rock-water interactions are the dominant driver of water quality degradation in the studied region (Kawo & Karuppannan 2018, Mukate et al. 2019, Vaiphei et al. 2020).

All simulations were written with Python 3.8 using the sci-kit-learn library. Table 4 depicts the achieved results in

Table 4: Table predictive performances of the SVM model.

	R^2	RMSE
Training	0.8771	25.6819
Testing	0.8631	25.7497

Table 5: Correlation between variables and factors.

	pH	CE	TDS	Cl^-	Mg^{2+}	Ca^{2+}	K^+	NO_3^-	SO_4^{2-}	HCO_3^-	Na^+	WQI
pH	1.00											
CE	-0.61	1.00										
TDS	-0.55	0.89	1.00									
Cl^-	-0.56	0.95	0.82	1.00								
Mg^{2+}	-0.28	0.58	0.64	0.61	1.00							
Ca^{2+}	-0.37	0.51	0.72	0.37	0.45	1.00						
K^+	-0.19	0.14	0.24	0.05	0.17	0.25	1.00					
NO_3^-	0.11	-0.20	-0.15	-0.19	0.03	-0.14	-0.12	1.00				
SO_4^{2-}	-0.31	0.44	0.78	0.29	0.45	0.82	0.38	-0.12	1.00			
HCO_3^-	0.00	0.23	0.28	0.11	0.03	0.07	-0.14	0.14	0.18	1.00		
Na^+	-0.58	0.89	0.92	0.86	0.40	0.47	0.13	-0.18	0.57	0.31	1.00	
WQI	-0.58	0.86	0.93	0.80	0.57	0.56	0.19	-0.14	0.68	0.31	0.89	1.00

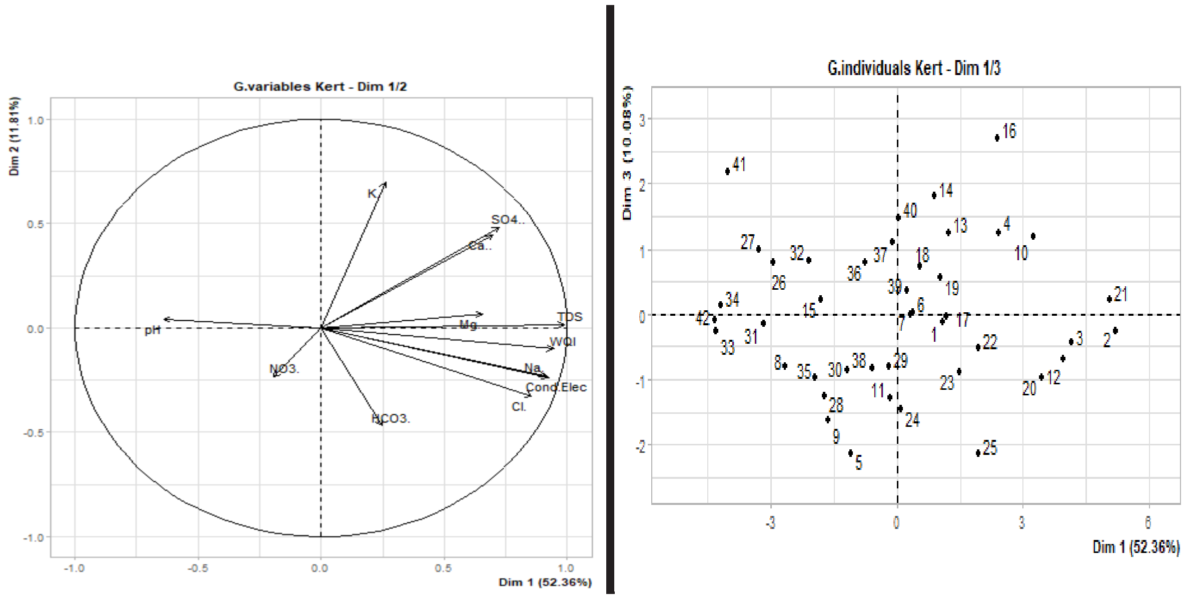

Fig. 5: Main components analysis circle.

both the training and testing stages. As this table indicates, the root means square error rose only by 0.26%, while R^2 decreased slightly by 1.6% during the testing phase. These results showed that the SVM model is stable (Table 4). Fig. 4 illustrates the SVM model's regression plots between the measured and predicted WQI values. As demonstrated by this figure, the SVM model showed a reasonable correlation between observed and estimated values with values of $R^2 = 0.8771$ and $R^2 = 0.8631$ in both the training and testing stages, correspondingly. These results reveal the SVM approach's resilience in predicting WQI.

Statistical Studies

Principal Component Analysis (PCA) is used to analyze the physicochemical data. A table of 15 variables (Ca^{2+}, Mg^{2+}, Na^+, K^+, HCO_3^-, SO_4^{2-}, Cl^-, NO_3^-, PO_4^{2-} Electrical conductivity (Cond), PH, O2d, and T) and 62 persons is used (wells and springs) (Table 5). The correlation matrix (Table 5) for the various parameters investigated revealed a strong link between Na+, SO_4^{2-}, Cl^-, and electrical conductivity. The correlation matrix, a square matrix characterized by a correlation coefficient, may determine the relationship between two variables. All water samples examined were put into a correlation matrix (Table 5).

After examining the correlation matrix, we discovered the following intriguing correlations between the variables:

- TDS (0.93) has the strongest correlation with the WQI, whereas Electric conductivity (0.86), Cl^- (0.8), Na^+ (0.89), SO_4^{2-}(0.68), and Mg^{2+} have modest correlations (0.57). CE and Cl^-(0.95) and CE and Na^+ have strong relationships (0.89). Only a little correlation exists between Calcium and WQI (0.56) and SO_4^{2-}(0.86), showing that the two are intertwined and affect the Kert alluvial aquifer's groundwater quality. The number of essential factors was calculated using the Kaiser criteria (1958). Based on these criteria, aquifer hydrogeochemistry variation can only be explained by components with eigenvalues larger than or equal to one.

A total of 64.83 percent of the variation may be attributed to the four primary kept components as shown in (Table 5). Na^+, Cl^-, WQI, CE and TDS positively influence Principal Component 1, accounting for 52.36 percent of the overall variance. Evaporitic rocks are responsible for this problem, as are residential and agricultural pollutants are shown in Fig. 5. Ca^{2+}, SO_4^{2-}, and K^+ contribute to Principal Component 2, accounting for 11.81 percent of the variation. The salinity of the water is consequently the determining element here. It results from surface salts being dissolved in water and then remineralized. Each of the four variables (components) represents one of the primary processes that explain how to understand how the Kert aquifer acquired and evolved its chemist; it is necessary to look at four variables (components): water-rock interaction, agricultural pollution, and the aquifer itself. As a result of these interactions between water and rock and pollution from home and industrial agriculture, the four variables (or components) reflect the primary processes that explain how the chemist of the Kert aquifer came to be. There are three families of water quality founded on the projection of persons shown in Fig. 5, the first and second of which are situated in the south and eastern regions of the research area, respectively. The third family characterizes Salinity-polluted environments.

CONCLUSIONS

Aquifer lithology and recharge areas, which favor geological dissolution, are connected to groundwater chemistry, associated with the Triassic marl-sulfate formations and the Quaternary evaporate formations. On the other hand, the Kert aquifer's groundwater is of low quality. According to a principal component analysis (PCA) chemical factors, such as sodium, calcium, magnesium, sulfates, and chlorides, have the most significant effect on the quality of Kert's quaternary water table. The Water Quality Index (WQI) reveals that 79% of the drillings had WQI values over 100. As salt levels rise, the Oust of Kert is particularly susceptible since it contains more than the WHO's recommended amount of salinity. Soil treatment is needed in light of this condition and conservative water management measures, such as establishing a strict residential discharge monitoring system.

REFERENCES

Abbasnia, A., Yousefi, N., Mahvi, A. H., Nabizadeh, R., Radfard, M., Yousefi, M. and Alimohammadi, M. 2019. Evaluation of groundwater quality using water quality index and its suitability for assessing water for drinking and irrigation purposes: A case study of Sistan and Baluchistan province (Iran). Human Ecol. Risk Assess. Int. J., 25(4): 988-1005.

Adimalla, N. 2019. Controlling factors and mechanism of groundwater quality variation in the semiarid region of South India: an approach of water quality index (WQI) and health risk assessment (HRA). Environ. Geochem. Health, 5: 1-28.

Akhtar, N., Ishak, M. I. S., Ahmad, M. I., Umar, K., Md Yusuff, M. S., Anees, M.T., Qadir, A. and Ali Almanasir, Y. K. 2021. Modification of the water quality index (WQI) Process for simple calculation using the multi-criteria decision-making (MCDM) method: A Review. Water, 13(7): 905.

Azdimousa, A. 2007. Lithostratigraphy and structure of the Temsamane Unit (Eastern External Rif, Morocco). Rev. Soc. Geol. España, 20(3): 187-200.

Azizullah, A., Khattak, M. N. K., Richter, P. and Häder, D.-P. 2011. Water pollution in Pakistan and its impact on public health; A review. Environ. Int., 37(2): 479-497.

Banda, T.D. and Kumarasamy, M.A. 2020. Review of the existing water quality indices (WQIs). J. Phys. Opt, 2: 1-19.

Bennett, K. and Demiriz, A. 1999. Semi-supervised support vector machines. Adv. Neural Inform. Process. Syst., 11: 368-374.

Bhargava, D.S. 1983. Use of water quality index for river classification and zoning of Ganga River. Environ. Pollut. Ser. B Chem Phys., 6(1): 51-67.

Bhimanagouda, B.P.V., Pinto, S.M., Thejashree, G., Shivakumar, H.V., Vignesh, B. and Nanjappa, K.L. 2020. Multivariate statistics and water quality index (WQI) approach for geochemical assessment of groundwater quality: A case study of Kanavi Halla Sub-Basin, Belagavi, India. Environ. Geochem. Health, 42(9: 2667-2684.

Brilli, R.J., McClead Jr, R.E., Crandall, W.V., Stoverock, L., Berry, J.C., Wheeler, T.A. and Davis, J.T. 2013. A comprehensive patient safety program can significantly reduce preventable harm, associated costs, and hospital mortality. J. Pediat., 163(6): 1638-1645.

Butler, D. 2017. Global challenges. Water, 1(1): 61.

Carlier, P. 1973. The hydrogeological map at 1:50,000 of the Moyen-Kerte plain: Province of Nador, north-eastern Morocco. Ed. Geol. Ser., 16: 1058.

de Andrade Costa, D., de Azevedo, J.P.S., Dos Santos, M.A. and Assumpção, R.S.F.V. 2020. Water quality assessment based on multivariate statistics and water quality index of a strategic river in the Brazilian Atlantic Forest. Sci. Rep., 10(1): 1-13.

Deshpande, A., Yadav, J., and Kharat, V. 2014. Zadeh-Deshpande's approach for the fuzzy description of air and water quality. BVICAM's Int. J. Inform. Technol., 6(1): 484.

Eden, C. and Ackermann, F. 2001. SODA: The principles. Ration. Anal. Prob. World Rev., 9: 21-41.

WHO Edition. 2011. Guidelines for drinking-water quality. WHO Chron., 38(4): 104-108.

Elgettafi, M., Elmandour, A., Himi, M. and Casas, A. 2013. The use of environmental markers to identify groundwater salinization sources in a Neogene basin, Kert aquifer case, NE Morocco. Int. J. Environ. Sci. Technol.,10(4): 719-728.

Evgeniou, T., Poggio, T., Pontil, M. and Verri, A. 2002. Regularization and statistical learning theory for data analysis. Comput Stat. Data Anal., 38(4): 421-432.

Hicham, G, Mustapha, A., Mourad, B., Abdelmajid, M., Ali, S., Yassine, E. Y., Mohamed, C., Ghizlane, A. and Zahid, M. 2021. Assessment of the physico-chemical and bacteriological quality of groundwater in the Kert Plain, northeastern Morocco. Int. J. Energy Water Resour., 7: 1-15.

Hicham, G., Mustapha, A., Mourad, B., Abdelmajid, M., Ali, S., Yassine, E. Y., Hanane, A. H., Mohamed, C., Ghizlane, A. andAbderahmane, R. 2021. Assessment of the metal contamination index in groundwater of the quaternary of the Middle Kert Basin, north‐eastern Morocco. Environ. Qual. Manag., 1: 26-34.

Kachroud, M., Trolard, F., Kefi, M., Jebari, S. and Bourrié, G. 2019. Water quality indices: Challenges and application limits in the literature. Water, 11(2): 361.

Kaiser, H.F. 1958. The varimax criterion for analytic rotation in factor analysis. Psychometrika, 23(3): 187-200.

Karunanidhi, D., Aravinthasamy, P., Subramani, T. and Muthusankar, G. 2021. Revealing drinking water quality issues and possible health risks based on the water quality index (WQI) method in the Shanmuganadhi River basin of South India. Environ. Geochem. Health, 43(2): 931-948.

Kavousi-Fard, A. and Kavousi-Fard, F. 2013. A new hybrid correction method for short-term load forecasting based on ARIMA, SVR, and CSA. J. Environ. Exp. Theoret. Artif. Intell., 25(4): 559-574.

Kawo, N.S. and Karuppannan, S. 2018. Groundwater quality assessment using water quality index and GIS technique in Modjo River Basin, Central Ethiopia. J. Afr. Earth Sci., 14: 300-311.

Kumari, R. and Sharma, R.C. 2019. Assessment of water quality index and multivariate analysis of high altitude sacred Lake Prashar, Himachal Pradesh, India. Int. J. Environ. Sci. Technol., 16(10): 6125-6134.

Liu, W., Zhang, X., Fan, J., Zuo, J., Zhang, Z. and Chen, J. 2020. Study on the mechanical properties of man-made salt rock samples with impurities. J. Nat. Gas Sci. Eng., 84: 103683.

Lu, Y., Song, S., Wang, R., Liu, Z., Meng, J., Sweetman, A. J., Jenkins, A., Ferrier, R.C., Li, H. and Luo, W. 2015. Impacts of soil and water pollution on food safety and health risks in China. Environ. Int., 77: 5-15.

Malekzadeh, M., Kardar, S. and Shabanlou, S. 2019. Groundwater for Sustainable Development Simulation of groundwater level using MODFLOW, extreme learning machine, and Wavelet-Extreme Learning Machine models. Groundwater Sustain. Dev., 9: 100279. https://doi.org/10.1016/j.gsd.2019.100279

Mohammadi, B. and Mehdizadeh, S. 2020. Modeling daily reference evapotranspiration via a novel approach based on support vector regression coupled with the whale optimization algorithm. Agric. Water Manag., 237: 106145.

Mukate, S., Wagh, V., Panaskar, D., Jacobs, J.A. and Sawant, A. 2019. Development of a new integrated water quality index (IWQI) model to evaluate the drinking suitability of water. Ecol. Indic., 101: 348-354.

Nong, X., Shao, D., Zhong, H. and Liang, J. 2020. Evaluation of water quality in the South-to-North Water Diversion Project of China using the water quality index (WQI) method. Water Res., 178: 115781.

Ponsadailakshmi, S., Sankari, S.G., Prasanna, S.M. and Madhurambal, G. 2018. Evaluation of water quality suitability for drinking using drinking water quality index in Nagapattinam district, Tamil Nadu in Southern India. Groundwater Sustain. Dev., 6: 43-49.

Rawat, K.S. andSingh, S.K. 2018. Water Quality Indices and GIS-based evaluation of decadal groundwater quality. Geol. Ecol. Landsc., 2(4): 240-255.

Rodier, J., Bernard, K. and Legube, N.M. 2009. Water Analysis. Ninth Edition. Dunod, UNOD (publisher), Paris, Fr. (p. 1600).

Schweitzer, L. and Noblet, J. 2018. Water Contamination and Pollution. Elsevier, The Netherlands. https://doi.org/https://doi.org/10.1016/B978-0-12-809270-5.00011-X

Selvam, S., Manimaran, G., Sivasubramanian, P., Balasubramanian, N. and Seshunarayana, T. 2014. GIS-based evaluation of water quality index of groundwater resources around Tuticorin coastal city, South India. Environ. Earth Sci., 71(6): 2847-2867.

Singh, A.P., Dhadse, K. and Ahalawat, J. 2019. Managing the water quality of a river using an integrated geographically weighted regression technique with a fuzzy decision-making model. Environ. Monit. Assess., 191(6): 1-17.

Sun, Z. and Fox, G. 2014. Traffic flow forecasting is based on the combination of multidimensional scaling and SVM. Int. J. Intell. Transport. Syst. Res., 12(1): 20-25.

Toolabi, A., Bonyadi, Z., Paydar, M., Asghar, A. and Ramavandi, B. 2021. Groundwater for Sustainable Development Spatial distribution, occurrence, and health risk assessment of nitrate, fluoride, and arsenic in Bam groundwater resource, Iran. Groundwater Sustain. Dev., 12: 100543. https://doi.org/10.1016/j.gsd.2020.100543

Tripathi, M. and Singal, S.K. 2019. Use of principal component analysis for parameter selection for development of a novel water quality index: A case study of river Ganga India. Ecol. Indic., 96: 430-436.

Tziritis, E., Panagopoulos, A. and Arampatzis, G. 2014. Development of an operational index of water quality (PoS) as a versatile tool to assist groundwater resources management and strategic planning. J. Hyrdol., 517: 339-350.

Üstün, B., Melssen, W.J. and Buydens, L.M. C. 2007. Visualisation and interpretation of support vector regression models. Anal. Chim. Acta, 595(1-2): 299-309.

Vaiphei, S.P., Kurakalva, R.M. andSahadevan, D.K. 2020. Water quality index and GIS-based technique for assessment of groundwater quality in Wanaparthy watershed, Telangana, India. Environ. Sci. Pollut. Res., 27(36): 45041-45062.

Vesali Naseh, M.R., Noori, R., Berndtsson, R., Adamowski, J. and Sadatipour, E. 2018. Groundwater pollution sources apportionment in the Ghana Plain, Iran. Int. J. Environmental Res. Pub. Health, 15(1): 172.

Von Zur Gathen, J. and Gerhard, J. 2013. Modern Computer Algebra. Cambridge University Press, Cambridge.

Xu, Y., Zomer, S. and Brereton, R. G. 2006. Support vector machines: a recent method for classification in chemometrics. Critic. Rev. Anal. Chem., 36(3-4): 177-188.

Zaier, I., Billiotte, J., Charmoille, A. and Laouafa, F. 2021. The dissolution kinetics of natural gypsum: A case study of Eocene facies in the north-eastern suburbs of Paris. Environ. Earth Sci., 80(1): 1-16.

Zielhofer, C., Faust, D. and Linstädter, J. 2008. Late Pleistocene and Holocene alluvial archives in the Southwestern Mediterranean: Changes in fluvial dynamics and past human response. Quat. Int., 181(1): 39-54.