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DISCRIMINANT ANALYSIS (DA) FOR SURFACE WATER QUALITY ASSESSMENT

Zainb Abd alelah Abd Alateef[1], Fatma Abd Alemam Jyad[2], Maha Atta Faroon[3] , Ahmed Naseh Ahmed Hamdan[4]

[1] Department of Civil Engineering, College of Engineering, University of Basrah, Basrah, Iraq, Email: Zainb.Abdallietef@uobasrah.edu.iq

[2] Department of Civil Engineering, College of Engineering, University of Basrah, Basrah, Iraq, Email: Fatima.Jiad@uobasrah.edu.iq

[3] Department of Civil Engineering, College of Engineering, University of Basrah, Basrah, Iraq, Email: Maha.Faroon@uobasrah.edu.iq

[4] Department of Civil Engineering, College of Engineering, University of Basrah, Basrah, Iraq, Email: Ahmed.Hamdan@uobasrah.edu.iq

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ABSTRACT

This study evaluated the quality of surface drinking water using ten hydro-chemical variables at three stations on the shatt al arab river. A water quality index (wqi) was established, with values ranging from poor to unsuitable for the three stations. Statistical data revealed that all parameters at st1 and st3 were outside the standard limits. Furthermore, na+ > ca+2 > mg+2 > k+ were found for all three stations. Pumping specific amounts of water from the al-badaa canal for specific periods of time improved water quality, but it remained unfit for human consumption. The variables primarily responsible for spatial variation were identified using a discriminant analysis (da) approach. Sulfate, magnesium, calcium, and alkalinity were found to be the most significant characteristics that characterized different locations and contributed to spatial variations in surface water quality. The results of this study provide decision makers with useful information to address the important issue of water quality management and protection.

KEYWORDS

Discriminant analysis (da), hydro-chemical variables, pollutants.

1. INTRODUCTION

Surface water is the main source for various aspects of life on Earth, and preserving it in its pristine state has become almost impossible today(Jian et al., 2011, Al-Bahrani et al., 2020). Surface water continuously absorbs pollutants from factories, farms, sewage, etc. runoff is greatly affected by climate, especially rainfall in winter, which has the greatest impact on surface runoff and increase the pollutant concentration in river(Singh et al., 2004, Al-Sulaiman et al., 2025). These intricacies, decision-makers and experts in water quality frequently encounter formidable obstacles when attempting to manage water contamination (Elhatip et al., 2008, Kadhim et al., 2025). It is necessary to assess the quality of water before it is used by humans (Tahraoui et al., 2023, Tahraoui et al., 2021). Goodness of Water can be evaluated by monitoring certain hydro-chemical variables that enter the calculation of water quality index intended for human consumption (Maghrebi et al., 2020, Adimalla and Taloor, 2020).

It is quite difficult to pinpoint the source of any pollutant along the rivers due to the abundance of pollution sources. Spatial variation data is made available by routine monitoring but it can be difficult to analyze the vast volume of data; one must apply accurate data interpretation techniques (Dixon and Chiswell, 1996). Environmetric analysis is the most effective method for preventing misinterpretation of complicated environmental monitoring data (Simeonov et al., 2002). The most popular environmental clustering approaches are hierarchical-agglomerative cluster- analysis HAC-A and principal components- analysis (PC-A) with factor-analysis (F-A) (Kannel et al., 2007). Analyzing and studying a complex phenomenon such as the spatial differentiation of water using ancient verbs gives excessive and imperfect results (Noori et al., 2010, Noori et al., 2012). Through the identification of linear combinations of discriminant variables that will best discriminate between the groups, discriminant analysis (DA) seeks to determine associations between two or more groups of pre-specified sample items (Lee et al., 2001). According to studies investigating seasonal and regional variability in water quality, land use patterns and the effects of watershed runoff significantly influence water quality problems, such as eutrophication (Zhang et al., 2011, Yang et al., 2010). Surface water quality is closely related to urbanization, according to studies conducted in Shanghai, China, and other large cities around the world (Wang et al., 2008, Duh et al., 2008). Furthermore, a large body of research has identified pollution sources and the potential effects of natural and anthropogenic processes on spatial and temporal variability in water quality (Fan et al., 2010, Huang et al., 2010).

This study aims to Study the differences or similarities between surface water monitoring sites in order to develop and improve the monitoring plan, Identify the factors causing spatial change of surface water and provide modern strategies for water quality assessment and to find the hidden factors elucidating the database's structure, and to measure the effect of manmade and natural resources on the water parameters.

2. THE METHODOLOGY

2.1. Area of Study and Gathering Data

The Tigris and Euphrates rivers travel through Iraq and meet at Al-Qurna, a city north of Basra. The Tigris and Euphrates meet in Al-Qurna to form the Shatt Al Arab River. The river is 200 km long, its width in Basra is about 400 meters and reaches 2 km at its mouth in the Arabian Gulf. The region is very hot during summer, and temperatures may reach half the boiling point, while in winter cold and rainy. Shatt Al Arab is considered the only source for drinking in Basra Provence in southern Iraq. As a result of the river branching into several branches within the Provence and extending to the Provence center, sewage water flows into it in addition to many pollutants (Faroon et al., 2023).

(Al Saad and Hamdan, 2020) using factor and cluster analysis of 17 factors and 9 stations during 2017, they concluded that the Muhajiran station is the most polluted, while the Al-Abbas station is the least polluted among all stations. Depending on the difference in the amount of pollution, and due to the continuous increase in pollution resulting from surface water absorbing pollutants from factories, farms and sewage, and the significant impact of surface runoff on climate, especially rainfall in the winter, in addition to population growth, the stations of Muhajiran, Al-Abbas and Al-Hussein were taken as areas for this study in order to study the variables most responsible for spatial discrimination.

Over three years from 2019 to 2021, three stations Muhajiran ST1, Al-Abbas ST2, and Al-Hussein ST3) in the Shatt Al Arab River were subject to monthly monitoring of water quality indicators, which were maintained by the Basrah Environment Directorate. These indicators are potassium K+, calcium Ca+2, magnesium Mg+2, sodium Na+, sulphate SO4-2, chloride Cl-, total hardness T.H, alkalinity Alk., electrical conductivity E.C, and total dissolved solids T.D.S. Location of the three stations on Shatt Al Arab are depicted in Fig. 1.

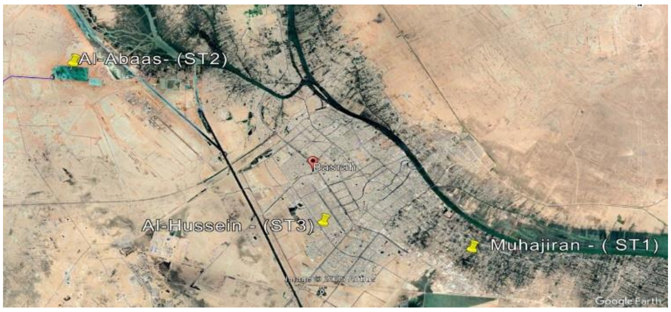


Fig. 1. Location of the three stations on Shatt Al Arab

2.2. Computing the Water Quality Index (WQI)

The WQI calculation technique required three steps. First, a weight was assigned to each hydro-chemical parameter according to how relevant it was to the quality of drinking water Eq.1. Since the criteria Ca+2 and T.H. have the major effect on goodness of water, they were given highest weight five, on the other hand gave the parameter K lowest weight of two, which is thought to be harmless. WQI which is divided to 5 appropriateness classes as Table 1, follow the guidelines that the World Health Organization WHO has suggested Table 2. The second step is to use Eq.1 to get relative weight Wi for each hydro-chemical variable. Third step involves computing the quality grade Qi for each hydro-chemical variable from Eq.2.

$$Wi = wi \Big/ \sum_{i=1}^{n} wi \qquad (1)$$

Where, n is the number of variables, wi is their respective weights, and Wi signifies the relative weight.

$$Qi = 100 * ki/Si \qquad (2)$$

Where, ki is the concentration of every hydro-chemical characteristic. Si is represented by Standard hydro-chemical parameter concentration. Qi is the grade of quality (Steduto et al., 2012, WHO, 2018). Lastly, Eq.3 is utilized to find Water Quality Index (WQI):

$$WQI = \sum_{i=1}^{n} Wi * Qi \qquad (3)$$

Seven hydro- chemical parameters were used in the current study to determine the WQI: Na^{+}, K^{+}, Ca^{+2}, Cl^{-}, SO_4^{-2}, Mg^{+2}, and T.H.

Table1. WQI classification for potable water

Values of WQI	**< 25**	**26-50**	**51-75**	**76-100**	**More than 100**
Quality of water	Excellent	Good	Poor	Very poor	Unsuitable

Table 2. Water quality parameters, related standards, and relative weight

Parameters	**K^{+} (mg/l)**	**Na^{+} (mg/l)**	**Ca^{+2} (mg/l)**	**Mg^{+2} (mg/l)**	**$SO4^{-2}$ (mg/l)**	**Cl^{-} (mg/l)**	**T.H (mg/l)**
ISS (2009) (IQS 417/2009, 2009)	12	200	150	100	500	350	500
WHO (2017) (WHO, 2017)	10	200	75	50	250	250	300
Weight (wi)	2	4	5	3	4	3	5
Relative weight (Wi)	0.0769	0.1538	0.1923	0.1154	.1538	0.1154	0.1923

Notes: ISS: Iraqi standard specification; WHO: World Health Organization.

2.3. Discriminant Analyze (DA)

Discriminant Analyze DA is typically employed for sort samples or forecast the dependent variance categories. The output data must always be categorical, while the input data must always be of a continuous form. Eq.4 is utilized to find discriminant function:

$$F(Di) = Ci + \sum_{j=1}^{n} Gij * Pij \qquad (4)$$

Where, i is groups number D. The present investigation chose three groups, the constant Ci denotes the intrinsic value of every group, n is the variables total number utilized in classify set of data into a certain category, Gj is coefficient weight that DA specify to a specified parameter Pj, and Pj is analytical value for specified variable. Hydro-chemical characteristics at each of the three sites served as the study's independent variables.

SPSS version 24 was used for statistical and data analyze techniques, and R version 4.4.1 for data imagination.

3. RESULTS AND DISCUSSION

3.1. Statistical Details and Correlation Analyzes

An approximation of a region's hydro-chemical characteristics may be provided by the descriptive statistics of surface water hydro-chemical parameters. The surface water hydro-chemical parameters of each station are presented statistically in Table 3 and Fig. 2. All hydro-chemical parameters in ST1 and ST3 outside the standard limits, and the water quality is indicated that the water is not accepted to drink in all stations Fig. 3. The ST1 site is the most polluted site, followed by the ST3 site, because the first site is an agricultural area and contains many animals, while the second site contains a large population density, and thus the increase in human activities in all agricultural and industrial fields, in addition to the increase in sewage leakage into the river, are factors that cause an increase in pollution. ST2 site is less polluted because the site is connected to the waters of the Al-Badaa Canal, which have good specifications. However, the water passes through an unlined part of the canal, which causes an increase in suspended and dissolved materials, and thus an increase in pollution. All values of the coefficient of variation at the ST3 are high compared to ST1 and ST2, except for the alkalinity indicating that the temporal variability of parameters was very high at ST3 compared to the other stations. $Na^{+} > Ca^{+2} > Mg^{+2} > K^{+}$ for all of the three stations. Sodium is the dominant cation, followed by calcium. $Cl^{-} > SO_4^{-2}$, Chloride concentration at ST1 and ST3 is higher than sulfate but for ST2, vice versa. when comparing the rates of the values of the variables included in the calculation of water quality for the year 2017 (Al Saad and Hamdan, 2020) with the rates of the same coefficients for the years 2019-2021, we note a slight decrease in these values, but the water is still unfit for human use. This improvement and decrease is the result of the local government in Basra pumping part of the water from the Al- Badaa Canal for limited periods of time to all areas of the governorate after many cases of poisoning occurred in the governorate resulting from the increase in the percentage of salts coming from the rise of the salt tongue to the sea due to the decrease in the water level in the Shatt al-Arab Table 3.

Apart from pinpointing the source of the hydro-chemical formation process and determining the level of significance among the elements (Jehan et al., 2019), many kinds of correlations among the hydro-chemical variables assessed in examined area. By utilizing Pearson's correlation analysis and the corrplot tool in R, the correlation matrix was generated for every parameter, Fig. 4 displays the correlation matrix between the hydro-chemical parameters and WQI.

From Fig. 4, we notice that there are no strong negative correlations between water quality and the various parameters in the three stations. We also notice that water quality has a strong positive correlation with chlorine, sodium, electrical conductivity, and total dissolved solids in the first site ST1. While in the second site ST2, the water quality index is positively correlated with sulfates, magnesium, total hardness, calcium, total dissolved solids, and electrical conductivity. As for the third site ST3, the quality index is positively correlated with all parameters except alkalinity. Precipitation, ion exchange, human activities, and utilizing fertilizers which contaminate waterways through seepage from fields have all been implicated in significant links (Belkhiri et al., 2017, Tiri et al., 2017).

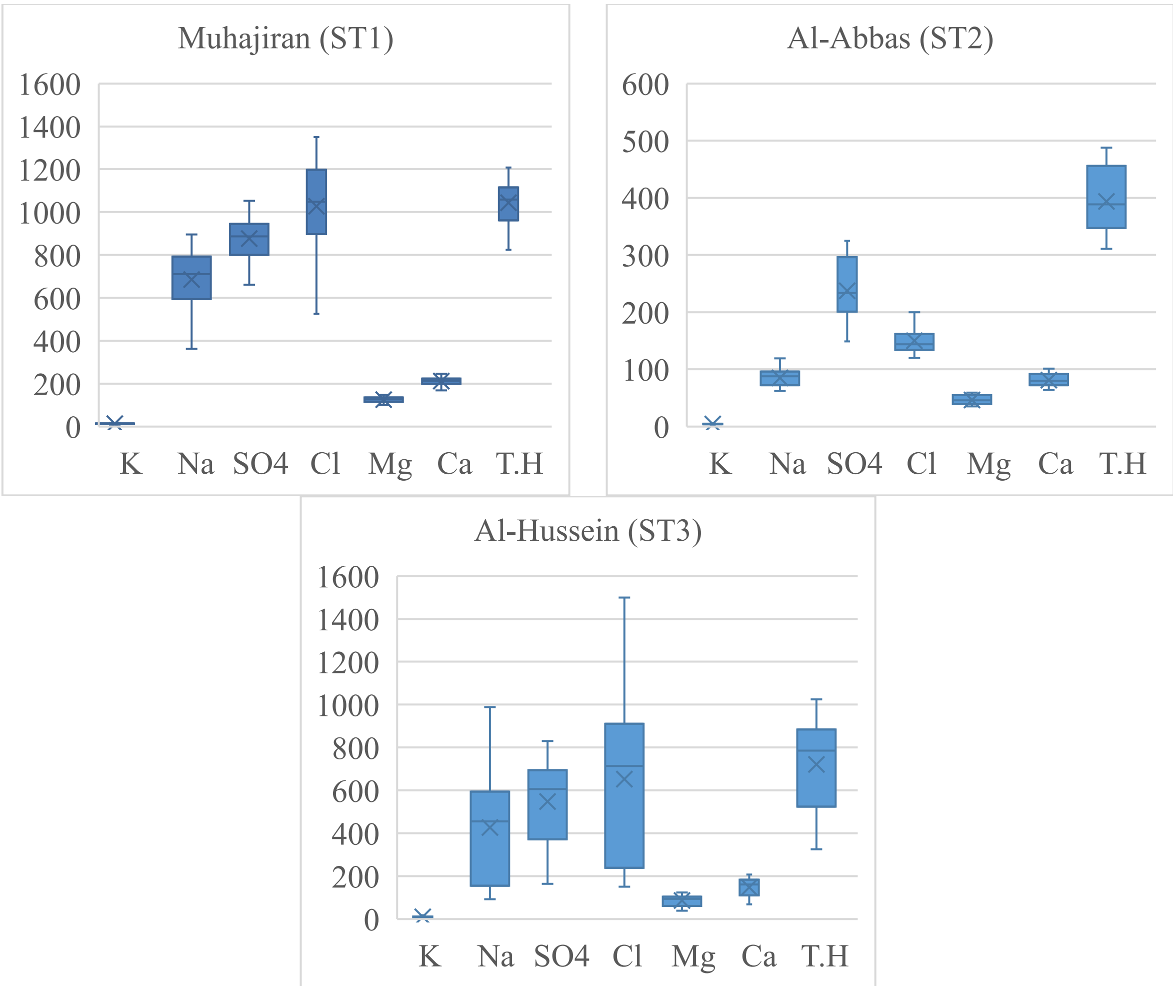


Fig. 2. Boxplot showing the surface water's hydro-chemical characteristics

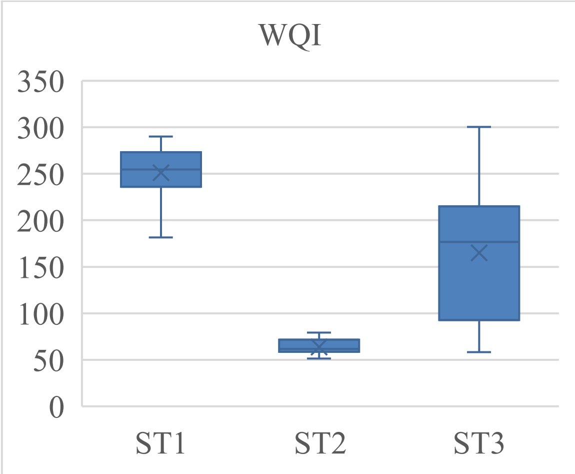


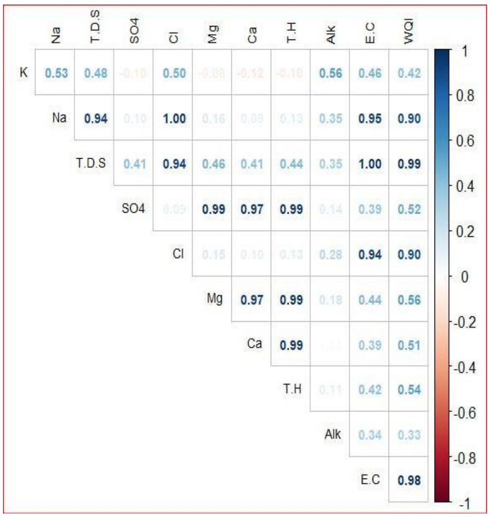
Fig. 3. Boxplot showing the WQI for surface water of three stations

Table 3. Provides a summary of the hydro-chemical properties of the samples of surface water

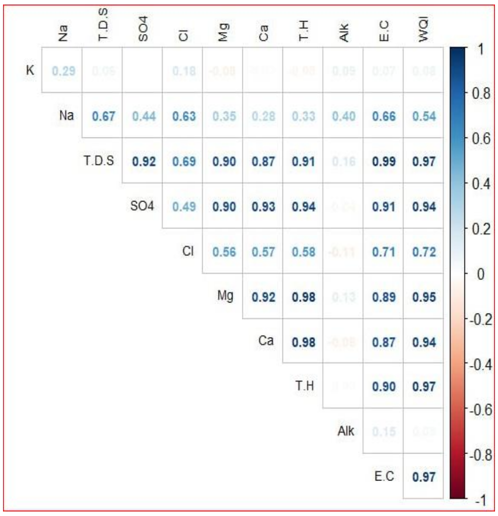
	K^+	Na^+	T.D.S.	SO_4^{-2}	Cl^-	Mg^{+2}	Ca^{+2}	T.H	Alk	E.C	WQI
Muhajiran (ST1)											
Min.	9	362	2102	661	525	99	168	824	120	3378	181.7
Max.	18	896	3596	1053	1350	147	246	1208	200	5682	290.0
Mean	13	684.8	3072.4	876.2	1027.8	125.3	211.9	1043.2	168.9	4891.7	251.1
SD	2.1	135.3	388.1	94.5	206.8	12.8	19.4	100.0	19.6	601.8	28.1
CV%	16.2	19.7	12.6	10.8	20.1	10.2	9.2	9.6	11.6	12.3	11.2
Mean 2017	14.1	919.6	3812.9	969.5	1376.1	136.6	230.9	1137.4	183.6	5975.4	303.2
Al-Abbas (ST2)											
Min.	4	62	538	149	120	35	64	311	80	883	51.2
Max.	6	119	880	325	200	59	101	488	160	1442	79.3
Mean	4.4	84.8	690.9	237.3	150.2	46.6	81.1	393.6	116.5	1138.5	63.9
SD	.60	14.3	93.0	53.1	20.1	7.7	11.1	58.0	19.0	153.7	8.4
CV%	13.6	16.8	13.5	22.4	13.4	16.5	13.7	14.7	16.3	13.5	13.1
Mean 2017	4.4	85.6	731.4	260.6	161.3	50.1	87.4	423.4	108.6	1201.5	68.1
Al-Hussein (ST3)											
Min.	5	93	684	164	150	38	68	326	128	1137	58.2
Max.	18	988	3770	830	1500	123	208	1024	188	5830	300.2
Mean	9.5	426.2	2007.5	547.8	652.9	85.9	147.5	720.8	155.3	3213.7	165.1
SD	3.6	242.6	894.0	195.0	366.8	24.8	41.3	204.2	16.5	1396.3	67.6
CV%	37.9	56.9	44.5	35.6	56.1	28.8	28	28.3	10.6	43.4	40.9
Mean 2017	10.9	658.7	2817.2	719	994.3	106.1	181.4	888	165.4	4450.5	226.1

3.2. Differentiations of Water goodness by Site

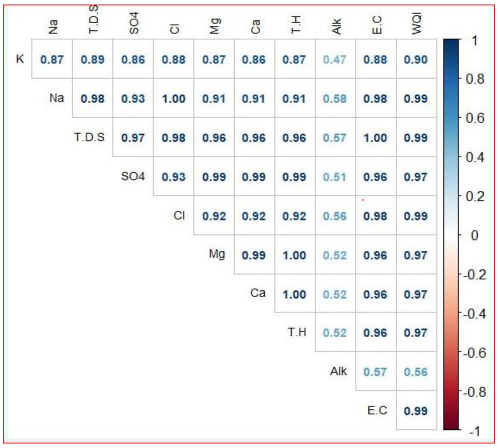
Discriminant analyze DA on raw data group, which comprised ten variables (T.D.S, EC, Cl, Ca, Na, Mg, K, SO4, T.H, Alk., and WQI) divided into three stations (ST1, ST2, ST3) was utilized to test water goodness with the variation of sites. Stepwise method of DA was utilized, in this method a variable which reduced of total Wilks' Lambda was taken or subtracted in each stage. It was intended to determine which factors were most important in explaining the variations between the different stations. The dependent variable was made up of four stations, whereas the independent variables were the primary hydro-chemical characteristics that were assessed.



ST1 for p-value < 0.01



ST2 for p-value < 0.01



ST3 for p-value < 0.01

Fig. 4. Shows the hydro-chemical parameter correlation analysis

The group mean equality Wilks' Lambda statistic is important when p-values < 0.01. Elements that significantly influenced station distinction were found using Wilks' Lambda Test F. Table4 presents the results of the ANOVA. The findings demonstrate that, at the p-level < 0.05, the Test F is significant for all variables.

Canonical discriminant functions are summarized in Table 5. Two eigenvalues in a discriminant analysis were obtained by utilizing two discriminant functions (DFs) to examine three stations. With the largest eigenvalue between the two discriminant functions, the first one appears to have the most discriminating power. Table 5 shows that, in contrast to the other function that unifies the parameters under study and indicates a dispersion of less than 10%, Function (1) demonstrate 96% of difference among sites. Nevertheless, only 83.5%, or (0.914)2, of difference was demonstrated with canonical coefficient, suggesting differences. Canonical coefficient is the discriminating factor coordinates divided by the grouping variable.

Table 4. Tests the quality for group mean for DA

Parameter	Wilks' lambda	F	df1	df2	sig.
K	.316	113.855	2	105	.000
Na	.293	126.385	2	105	.000
T.D.S.	.247	160.357	2	105	.000
SO4	.192	221.517	2	105	.000
Cl	.308	117.909	2	105	.000
Mg	.209	199.122	2	105	.000
Ca	.200	209.817	2	105	.000
T.H	.202	206.878	2	105	.000
Alk	.401	78.319	2	105	.000
E.C	.243	163.455	2	105	.000
WQI	.231	174.970	2	105	.000

Table 5. Eigenvalues for DA

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
(1)	5.081[a]	96.0	96.0	.914
(2)	.214*	4.0	100.0	.420

Note: * First two discriminant canonical functions were utilized.

Wilks' lambda and chi-square sites for every discriminant function DF are shown in Table 6. Table 6 shows that for each discriminant function (DF), the Wilks' Lambda and Chi-square ranged from 0.135 to 0.824 and 20.050 to 206.883, respectively. Given that the values of all two functions (sig.) were less than 0.01 according to Wilk's Lambda statistic, the spatial discriminant analysis was both significant and successful.

Table 6. Wilks' lambda and chi-square for DA

Test of functions	Wilks' lambda	Chi-square	Df	Sig.
1 through 2	.135	206.883	8	.000
2	.824	20.050	3	.000

Various measuring units are used to express factors that are thought to be discriminating (Jaba et al., 2007). Discriminant score for every case is constructed using coefficients of discriminant function. Analyzing the output of the first function should be the primary focus, as it possesses the greatest discriminating capacity. Magnesium (Mg) was a significant hydro-chemical variable for differentiating the spatial variance in water goodness among three sites, as shown by the results of the first discriminant function. The discriminant function coefficients are shown in Table 7.

Table 7. Standardized canonical discriminant function coefficients

Parameter	Function	
	1	2
SO4	1.697	-3.617-
Mg	-1.855-	-.578-
Ca	.944	3.770
Alk	.418	.847

The association among every predictor variable and discriminant function is represented by the coefficient of the structure matrix. Magnesium, sulfate and calcium correlation coefficients, that confess the greater value, is severely associated with the first discriminant function. Table8 displays derived structural coefficient values.

Table 8. Matrix structural coefficient values for DA

Parameter	Function	
	1	2
SO4	.910*	-.264-
Ca	.886*	-.150-
T.H[b]	.880*	-.168-
Mg	.863*	-.183-
WQI[b]	.849*	-.097-
T.D.S[b]	.836*	-.061-
E.C[b]	.831*	-.061-
Na[b]	.747*	-.038-
Cl[b]	.724*	-.037-
K[b]	.671*	.093
Alk	.528	.595*

Notes: Pooled within groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function. * Largest absolute correlation between each variable and any discriminant function. [b] This variable not used in the analysis.

Table 9 demonstrates how first discriminant function distinctly depicts spatial variance among the three sites. The classification functions (CFs) and matrices that were produced as a result of the DA are displayed in Tables 10 and 11. According to the results, 87% of the instances that were first grouped were correctly classified by the DA. 85.2% of the cases that were grouped in the beginning in classification matrix were successfully classified by the DA. Discriminant analysis revealed that the primary factors responsible for most predicted changes of water goodness across the three stations were sulfate, magnesium, calcium and alkalinity Table 10.

Table 9. Canonical Discriminant Function Coefficients

	Function	
	1	2
SO4	.013	-.028-
Mg	-.111-	-.035-
Ca	.035	.139
Alk	.023	.046
(Constant)	-6.216-	-8.677-

Note: Unstandardized coefficients.

Table 10. Classification function coefficients

	Station		
	ST1	ST2	ST3
SO4	-.222-	-.295-	-.283-
Mg	-.410-	.192	-.165-
Ca	1.492	1.309	1.542
Alk	.509	.388	.498
(Constant)	-79.345-	-46.308-	-68.942-

Note: Fisher's linear DF.

Table 11. classification results [a, c]

		Station	Predicted group membership			Total
			1	2	3	
Original	Count	1	35	0	1	36
		2	0	36	0	36
		3	6	7	23	36
	%	1	97.2	.0	2.8	100.0
		2	.0	100.0	.0	100.0
		3	16.7	19.4	63.9	100.0
Cross-validated[b]	Count	1	34	0	2	36
		2	0	36	0	36
		3	6	8	22	36
	%	1	94.4	.0	5.6	100.0
		2	.0	100.0	.0	100.0
		3	16.7	22.2	61.1	100.0

Notes: [a] 87.0% of original grouped cases correctly classified. [b] Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case. [c] 85.2% of cross-validated grouped cases correctly classified.

4. CONCLUSIONS

The discriminant analysis DA was successfully applied in this study to assess spatial variation in Shatt Al Arab River water quality and identify potential anthropogenic sources of water quality patterns at monitoring sites. The results are useful for river water quality management. The statistical analysis of three sites with different pollution rates based on similar water quality characteristics provides a useful classification of surface waterways that can be used to improve a future spatial monitoring network in the river at lower costs. Furthermore, the pollution of Sites 1 and 3 is relatively serious and should be controlled. Pollution in the river likely originates from four sources:

- Excessive industrial discharge of various types (food processing, cement production, and manufacturing);
- Increased pollution from large-scale livestock farms, possibly pesticides and chemical fertilizers used on agricultural land;
- Municipal and domestic wastewater resulting from increasing population density;
- Weather factors such as rain, dust storms, and others.

Hydro-chemical parameters (Na, K, T.D.S., SO4, Mg, T.H, Cl, Alk., Ca, and E.C) were utilized in this work to compute the surface water quality indices for potability (WQI). from 2019 to 2021, samples were taken every month at three different locations. The statistical information showed that all the hydro-chemical parameters of surface water for ST1 and ST3 outside the standard limits. The water quality index indicated that water samples from ST1 were classified as unfit for drinking. The water quality of ST2 was classified as poor to very poor while that of ST3 station ranged from poor to unfit. $Na^+ > Ca^{+2} > Mg^{+2} > K^+$ for all of the three stations. Sodium is the dominant cation, followed by calcium. $Cl^- > SO_4^{-2}$, Chloride concentration at ST1 and ST3 is higher than sulfate but for ST2, vice versa. Pumping specific quantities of water from the Al-Badaa Canal for specific periods of time has improved the quality of the water, but it is still unfit for human use. The ST1 site is the most polluted site, followed by the ST3 site, may be because the first site is an agricultural area and contains many animals, while the second site contains a large population density, and thus the increase in human activities in all agricultural and industrial fields, in addition to the increase in sewage leakage into the river, are factors that cause an increase in pollution. ST2 site is less polluted because the site is connected to the waters of the Al-Badaa Canal, which have good specifications. However, the water passes through an unlined part of the canal, which causes an increase in suspended and dissolved materials, and thus an increase in pollution An essential method for providing a comprehensive understanding of the collected data and enabling managers to apply it to better manage surface water contamination of water resources is discriminant analysis (DA). Using discriminant analysis (DA), we examined the spatial differences in surface water quality between the three sites. We discovered that the most significant changes in surface water quality at each site are attributed to the discriminating criteria of sulfate, magnesium, calcium, and alkalinity.

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