**Application of Multivariate Statistical Techniques in the surface water quality Assessment of Tigris River at Baghdad stretch, Iraq**

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Abstract

Multivariate statistical techniques namely factor analysis and cluster analysis were applied to evaluate spatial variations, and to interpret measured water quality data set in Tigris river at Baghdad. The water quality was monitored at seven different sites, along the water line, over a period of one year (2011) using 14 water quality parameters. When factor analysis was applied, three factors were identified, which were responsible from the 86.750% of the total variance of the water quality in the Tigris river. The first factor called the anthropogenic factor explained 49.829% of the total variance and the second factor called the erosion and rainfall factor explained 24.967% of the total variance. While, the third factor called the pH factor explained 11.954% of the total variance. Hierarchical cluster analysis was used to classify seven stations with similar properties and results distinguished three groups of stations. Results revealed that, water quality in Tigris river was strongly affected from anthropologic influences. Thus, these methods are believed to be valuable to help water resources managers understand complex nature of water quality issues and determine the priorities to improve water quality.

**Keywords:** Multivariate statistical techniques, water quality assessment, Tigris River, Factor analysis, Cluster analysis.

**الخلاصة**

في هذه الدراسة تم أستخدام التحليل المتعدد المتغيرات عن طريق تطبيق التحليل العاملي (طريقة المركبات الأساسية) والتحليل العنقودي لمعرفة التغيرات المكانية وأعطاء تفسير لبيانات نوعية المياه المقاسة على نهر دجلة في بغداد. تم رصد نوعية المياه عن طريق سبعة مواقع مختلفة على طول النهر لفترة سنة واحدة (2011) بأستخدام 14 عنصرا من متغيرات نوعية المياه. عند تطبيق التحليل العاملي، حددت ثلاثة عوامل، وهي مسؤولة عن 86.75% من التباين الكلي لنوعية المياه لنهر دجلة. وقد سمي العامل الاول (بشري المصدر) والذي يفسر 49.829% من التباين الكلي والعامل الثاني يسمى عامل التعرية وهطول الامطار حيث يفسر 24.967% من التباين الكلي، اما العامل الثالث وهو عامل الاس الهيدروجيني يفسر 11.954% من التباين الكلي. كما تم استخدام التحليل العنقودي الهرمي لتصنيف السبع محطات مع خصائصها المماثلة وأظهرت النتائج ثلاث مجموعات من المحطات. كشفت نتائج الدراسة ان نوعية مياه نهر دجلة تتأثر بشدة بالعوامل البشرية. وبالتالي ممكن ان تكون هذه الطرق/الاساليب ذات قيمة لمساعدة العاملين في الموارد المائية في فهم الطبيعة المعقدة للقضايا وتحديد الأولويات لتحسين نوعية المياه.

**الكلمات المفتاحية:** الأساليب الإحصائية متعدد المتغيرات، وتقييم نوعية المياه، ونهر دجلة، التحليل العاملي، وتحليل الكتلة

Introduction

The quality of water is identified in terms of its physical, chemical and biological parameters (Sargaonkar & Deshpande, 2003). The anthropological influences (i.e., urban, industrial and agricultural activities) as well as the natural processes (i.e., changes in precipitation amounts, erosion and weathering of crustal materials) degrade surface water quality and impair its use for drinking, industrial, agricultural, recreational and other purposes (Carpenter et al. 1998). Increasing exploitation of water resources in catchment is responsible for much of the pollution load (Singh et al. 2005). On the other hand, rivers and streams play a major role in assimilation or carrying off the municipal and industrial wastewater and run-off from agricultural land. The municipal and industrial wastewater discharge constitutes the constant polluting source, whereas the surface run-off is a seasonal phenomenon, largely affected by climate in the basin. (Vega et al. 1998; Singh et al. 2004).

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The particular problem in the case of water quality monitoring is the complexity associated with analyzing the large number of measured variables and high variability due to anthropogenic and natural influences (Saffran, 2001; Simeonov et al. 2002).

The application of different multivariate statistical techniques, such as cluster analysis (CA) and factor analysis (FA), helps in the interpretation of complex data matrices to better understand the water quality and ecological status of the studied systems, allows the identification of possible factors/sources that influence water systems, and offers a valuable tool for reliable management of water resources as well as rapid solution to pollution problems (Wunderlin et al. 2001; Reghunath et al. 2002; Simeonova et al. 2003; Shrestha and Kazama 2007).

Factor and cluster analyses have been used successfully in hydrochemistry for many years. Surface water quality assessment and environmental research employing these techniques are well described in the literature. (Sojka et al. 2008) have assessed different physico-chemical parameters of the Mała Wełna waters in Western Poland by using Factor, cluster and discriminant analyses, they identified different water quality indicators suitable for characterizing its temporal and spatial variability. (Arzu, et al. 2009) presented the necessity and usefulness of multivariate statistical assessment of large and complex databases in order to get better information about the quality of surface water. (Zhang et al. 2009) were applied different Multivariate statistical techniques to assessing the water quality in Xiangjiang watershed, china for twelve parameters at 34 different profiles. They stated that these methods are valuable to understand complex nature of water quality issues. (Palma, et al. 2010) were applied Multivariate statistical techniques to evaluate spatial/temporal variations, and to interpret water quality data set obtained at Alqueva reservoir, their results emphasized the need for the implementation of some remediation processes in order to improve the water quality at the Alqueva reservoir, by reducing pollutant inputs to the reservoir, such as pesticides, and by the implementation of wastewater treatment processes.

All of them allow deriving hidden information from the data set about the possible influences of the environment on water quality and offer greater possibilities to managers in terms of aiding the decision-making process.

Factor analysis attempts to explain the correlations between the observations in terms of the underlying factors, which are not directly observable (Yu et al. 2003). Observations that are highly correlated (either positively or negatively) are likely influenced by the same factors, while those that are relatively uncorrelated are likely influenced by different factors.

There are three stages in factor analysis (Gupta et al. 2005):

1. For all the variables a correlation matrix is generated.
2. Initial set of factors are extracted. The factors are extracted based on the fundamental theorem of factor analysis, which says, that every observed value can be written as a linear combination of hypothetical factors. There are a number of different extraction methods, including centroid, maximum likelihood, principal component, and principal axis extraction.
3. To maximize the relationship between some of the factors and variables, the factors are rotated. By rotating it is attempted to find a factor solution that is equal to that obtained in the initial extraction but which has the simplest interpretation. The best rotation method is widely believed to be Varimax. After a Varimax rotation, each original variable tends to be associated with one (or a small number) of factors, and each factor represents only a small number of variables.

The term cluster analysis encompasses a number of different algorithms and methods for grouping objects of similar kind into respective categories. In other words cluster analysis is a group of multivariate techniques whose primary purpose is to assemble objects based on the characteristics they possess. Cluster analysis classifies objects so that each object can be similar to the others in the cluster with respect to a predetermined selection criterion. Hierarchical agglomerative clustering is the most common approach, which provides intuitive similarity relationships between any one sample and the entire data set, and is typically illustrated by a dendrogram (tree diagram) (Singh et al. 2004; Shrestha and Kazama 2007). Euclidean distance method was used for determining distance. This is probably the most commonly chosen type of distance. It simply is the geometric distance in the multidimensional space and is computed as (Singh et al. 2008):

Distance

In this study, the data sets observed during 2011 in Tigris River for the Baghdad stretch in Iraq, are analyzed with FA and CA analyses. Statistical calculations were performed using the “Statistical Package for the Social Sciences Software - SPSS 17 for Windows”. This study aimed at extract information about: (1) identify the main components of the water quality and the most important variables causing difference in the water quality of Tigris River for the Baghdad stretch in Iraq, (2) the similarities or dissimilarities between the monitoring sites, (3) the influence of the possible sources (natural or/and anthropogenic) on the water quality parameters. The results of these analyses may provide a crude guideline for officials to identify and prevent the pollution sources in the Tigris River, Baghdad stretch, especially, there are few scientific studies on this river.

Materials and methods

Study area

The Tigris River is one of the largest rivers of the Middle East stretching for over 1,900 km, of which 1415 km are within Iraq, with a catchment area of 235000 km2, sharing with Euphrates River as the main sources for man use, especially for drinking water since they pass the major cities in the country (Rzoska 1980).

The Tigris River originates in the Toros mountains of southeastern Turkey; it passes through Turkey, Syria, and Iraq. There are many tributaries flow into the river; these include Botmanse, Kessora, A1-Khabur, the Greater and Lesser Zabs, and A1-Adhaim and Diyala Rivers (Mutlak et al. 1980) Tigris River is the main source of drinking water for Baghdad, the capital of Iraq. Baghdad stretch of the Tigris River extends from Al-Tarmiyahm in the north to Al-Zafaraniah in the south and is located in the Mesopotamian alluvial plain between latitudes 33°14'-33°25' N and longitudes 44°31'- 44°17' E, 30.5 to 34.85 m.a.s.l (Fig. 1). The River divides the city into a right (Karkh) and left (Risafa) sections with a flow direction from north to south. The area is characterized by arid to semi-arid climate with dry hot summers and cold winters; the mean annual rainfall is about 151.8 mm (Al-Adili 1998).

Baghdad, with its six million people, is considered to be the most populated and industrialized city in Iraq. The majority of its municipal and industrial wastes are discharged directly into the river without adequate treatment.

Sampling and analyses

Seven sampling stations were selected on Tigris River namely Al-Tarmiyahm (S1), Al-Muthana bridge (S2), Al-Adhamiyah bridge (S3), Midecal City bridge (S4), Al-Jadriyah Bridge (S5), Al-Rashed (S6) and Al-Zafarania (S7). Figure 1 shows the sampling stations along the Tigris river. The data for seven water quality monitoring stations, consisting of 14 water quality parameters, were monitored over 1 year.

Water samples were collected in polypropylene bottles at monthly intervals from sampling sites between January 2011 and December 2011. Grab sampling procedure was adopted for the analysis of various water quality parameters as recommended by standard methods (APHA, 1998). The polypropylene bottles were used for water quality parameter analysis. Water samples for BOD estimation were collected in BOD bottles (non-reactive borosilicate glass bottles of 300 ml capacity). Analysis of water samples was started as soon as possible after collection to avoid unpredictable changes. Microbiological samples were taken in sterile dark glass bottles. The bottles were kept at +4°C and analyzed within approximately 24 h. The analysis of the samples was done at chemical laboratory of water resource techniques department, institute of technology. Certain analyses were carried out in the Research Directorate for Environment and Water Technology, Ministry of Science and Technology. Table 1 shows the water quality parameters, alongside some of the abbreviations and units used in this study.

The selected parameters included water pH, electrical conductivity (EC), total hardness (TH), biochemical oxygen demand (BOD), fecal coliform (FC) total alkalinity (TA), turbidity (TBR), nitrate nitrogen (NO3-N), chloride (Cl ̄), sulfate (SO4), magnesium (Mg), calcium (Ca), total dissolved solids (TDS), and iron (Fe).

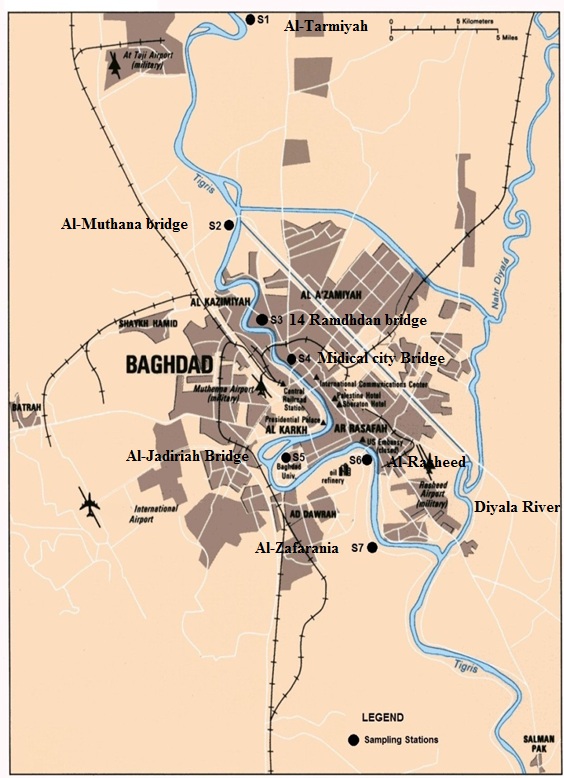


Figure 1 study area and monitoring sites (modified from <http://iraqmap.org/>)

Table 1: Analytical method, Abbreviation, units for water quality parameters

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** | **Abbreviation** | **Units** | **Instruments / technique used** |
| pH | pH | - | Digital pH meter |
| nitrate nitrogen NO3-N, | NO3̄ | mg/L | MAS\*\* |
| Total Hardness | TH | mg/L | EDTA Titrimetric method |
| Turbidity | TBR | NTU | Digital Turbidity Meter |
| Fecal coliform | FC | CFU/100 ml | Membrane filtration technique |
| Biochemical oxygen demand | BOD | mg/L | Winkler’s method, incubation for 5 days at 20°C |
| Calcium | Ca | mg/L | Titrimetric method |
| Magnesium | Mg | mg/L | Titrimetric method |
| Total dissolved solids | TDS | mg/L | Temperature controlled oven |
| Total Alkalinity | TA | mg/L | Titration method |
| Electrical conductivity | EC | µs/cm | Measured by conductivity meter |
| Chloride | Cl‾ | mg/L | Silver nitrate method |
| Sulphate | SO42− | mg/L | UV. visible spectrophotometer |
| Fe | - | mg/L | Detection by FAAS\* |

\*FAAS: Flame atomic absorption spectrophotometr

\*\* MAS: Molecular absorption spectrometry

Results and discussion

Water quality monitoring was conducted at 7 stations in the study area along one year (Jan2011 to Dec 2011). Monitoring stations are seen at Figure 1. The selected parameters for the estimation of surface water quality characteristics were: pH, electrical conductivity (EC), total hardness (TH), biochemical oxygen demand (BOD5), fecal coliform (FC) total alkalinity (TA), turbidity (TBR), nitrate nitrogen (NO3-N), chloride (Cl ̄), sulfate (SO4), magnesium (Mg), calcium (Ca), total dissolved solids (TDS), and iron (Fe). The measured water quality results of Tigris River for one year are summarized in Table 2.

Factor analysis

Factor analysis was applied to fourteen water quality parameters from the 7 surface water quality monitoring stations situated in the Tigris river within Baghdad stretch during one year 2011 using SPSS 17 (Panda et al. 2006; Shrestha & Kazama 2007). The correlation matrix of variables was generated and factors extracted by the Centroid method, rotated by Varimax rotation (Ahmed et al. 2005).

An Eigenvalue gives a measure of the significance for the factor, which with highest Eigenvalue is the most significant. Eigenvalues of 1.0 or greater are considered significant (Kim and Mueller 1978). Therefore, from the results of the FA, the first three eigenvalues were found to be bigger than 1 and the fourth eigenvalue was found to be slightly less than 1. The screen plot of the factor analysis is shown in Fig. 2.

Table 2: The summary of the observed water quality of Tigris river over one year. (n=12)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Parameters** | | **Sampling locations** | | | | | | | |
| *Al-Tarmiyah* | | *Al-Muthana bridge* | *14 Ramdhdan bridge* | *Midical city Bridge* | *Al-Jadiriah*  *Bridge* | *Al-Rasheed* | *Al-Zafarania* |
| pH | | Min  Max  Mean | 6.7  8.1  7.3 | 7.3  8.1  7.8 | 6.9  8.0  7.4 | 6.6  7.9  7.7 | 6.6  7.9  7.5 | 6.7  7.8  7.2 | 6.9  8.0  7.6 |
| TBR | | Min  Max  Mean | 17  114  39 | 22  118  43 | 20  82  29 | 23  132  52 | 23  110  53 | 35  140  60 | 25  110  83 |
| T.A | | Min  Max  Mean | 118  144  139 | 118  147  140 | 111  145  132 | 131  170  161 | 109  141  132 | 120  169  155 | 130  136  154 |
| T.H | | Min  Max  Mean | 182  372  234 | 220  356  254 | 200  340  267 | 244  395  291 | 230  352  302 | 220  300  257 | 250  330  297 |
| EC | | Min  Max  Mean | 393  546  447 | 416  840  520 | 402  747  512 | 666  1132  894 | 720  1112  869 | 594  890  684 | 610  1019  842 |
| TDS | | Min  Max  Mean | 190  372  278 | 256  540  360 | 243  516  362 | 351  1012  766 | 349  955  733 | 395  520  432 | 410  575  505 |
| Cl | Min  Max  Mean | 26  56  38 | 32  67  43 | 30  61  40.5 | 77  158  102 | 68  160  123 | 42  80  74 | 90  213  185 |
| Ca | Min  Max  Mean | 47  72  54 | 60  74  64 | 67  103  83 | 67  111  77 | 72  105  93 | 69  109  82 | 87  116  94 |
| Mg | Min  Max  Mean | 19  54  27 | 20  62  29 | 20  50  26 | 23  73  35 | 33  70  43 | 52  64  58 | 36  68  51 |
| SO4 | Min  Max  Mean | 51  102  69 | 70  202  94 | 105  249  168 | 144  275  174 | 120  222  182 | 168  253  193 | 185  220  190 |
| Fe | Min  Max  Mean | 0.093  0.49  0.12 | 0.13  1.73  0.82 | 0.07  1.10  0.81 | 0.15  3.8  0.9 | 0.11  2.9  1.33 | 0.9  2.3  1.05 | 0.65  1.72  1.13 |
| NO3 | Min  Max  Mean | 0.15  3.2  1.7 | 0.3  3.7  1.5 | 0.54  3.3  1.9 | 0.81  3.5  2.9 | 0.91  3.9  2.9 | 1.1  3.3  2.2 | 1.3  2.6  2.05 |
| BOD | Min  Max  Mean | 0.8  2.5  1.5 | 1  1.5  1.3 | 0.9  2.1  1.4 | 2.3  7.4  4.2 | 2.1  6.5  4.6 | 1.9  5.1  3.4 | 2.0  6.3  4.2 |
| FC | Min  Max  Mean | 200  1000  421 | 200  1400  590 | 210  1500  620 | 260  1400  730 | 263  1320  1020 | 200  1350  920 | 210  1400  663 |

\* All values in mg/l except pH, EC (µs/cm), FC (CFU/100 ml) and TBR (NTU)

According to the Fig. 2 and a subsequent interpretation of the factor loadings, the first three components were extracted and the other components have been eliminated. This means that majority of the total variance of the original data has been explained by the first three factors. Then, it was used factor rotation (Varimax) to obtain readily interpretable factor loadings (Johnson and Wichern 2002). Table 3 shows the proportion of total variance explained by the first three factors for both rotated and non-rotated factor loadings.

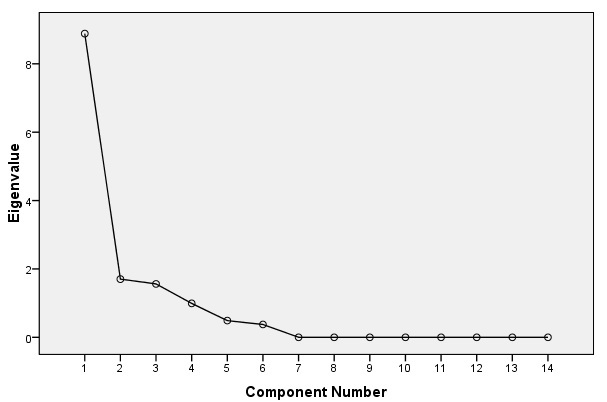


Figure 2 Scree plot of eigenvalues versus components for the observed water quality

It is clear that 49.829%, 24.967% and 11.954% of the total variance of the observed water quality data are explained by the first, second and the third components, respectively. While the first three components explain about 86.75% of the total variance, the remaining 11 components only explain 13.25%. The factor loadings for the first three components from the factor analysis of the observed water quality data are given in Table 4. And the factor loadings were classified as ‘strong’, ‘moderate’ and ‘weak’, corresponding to absolute loading values of >0.75, 0.75–0.50 and 0.50–0.30, respectively (Liu et al. 2003).

Table 3 Total variance explained before and after Varimax rotation

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 8.882 | 63.445 | 63.445 | 8.882 | 63.445 | 63.445 | 6.976 | 49.829 | 49.829 |
| 2 | 1.702 | 12.154 | 75.599 | 1.702 | 12.154 | 75.599 | 3.495 | 24.967 | 74.796 |
| 3 | 1.561 | 11.151 | 86.750 | 1.561 | 11.151 | 86.750 | 1.674 | 11.954 | 86.750 |
| 4 | 0.992 | 7.086 | 93.836 |  |  |  |  |  |  |
| 5 | 0.488 | 3.484 | 97.320 |  |  |  |  |  |  |
| 6 | 0.375 | 2.680 | 100.000 |  |  |  |  |  |  |
| 7 | 6.308E-16 | 4.506E-15 | 100.000 |  |  |  |  |  |  |
| 8 | 2.785E-16 | 1.989E-15 | 100.000 |  |  |  |  |  |  |
| 9 | 2.045E-16 | 1.461E-15 | 100.000 |  |  |  |  |  |  |
| 10 | 6.190E-17 | 4.422E-16 | 100.000 |  |  |  |  |  |  |
| 11 | -7.033E-17 | -5.024E-16 | 100.000 |  |  |  |  |  |  |
| 12 | -1.197E-16 | -8.548E-16 | 100.000 |  |  |  |  |  |  |
| 13 | -2.089E-16 | -1.492E-15 | 100.000 |  |  |  |  |  |  |
| 14 | -3.859E-16 | -2.756E-15 | 100.000 |  |  |  |  |  |  |
| Extraction Method: Principal Component Analysis. | | | | | | | | | |

The first factor (F1) explained 49.829% of the total variance and was strong positive loading EC, TDS, Ca, SO4, TH, Fe, FC, NO3 and BOD; moderate positive loading Mg and Cl. The contribution to different sources can be from the anthropogenic stresses like urban, industrial activities which carry domestic and industrial wastewater of the city. Based on the presence of different constituents in the

factors extracted, the latter can be associated with different sources. The first factor (F1) has contribution from sources which can be linked to point source pollution from domestic and industrial waste and nonpoint source pollution from agricultural activities. The domestic and industrial wastes contain heavy metals and their signature is evident from the higher loadings of Fe in the Factor 1. This factor also invariably indicated that the TDS in the river was mostly contributed by the TH. The association of EC was known for obvious reasons. F1 has strong positive loading with FC (0.885), which represents microorganisms, F1 may involve an urban origin, where waste disposal from populated areas increases fecal contents in the affected waters (Arzu et al. 2008). The contribution to Factor 1 is from anthropogenic influences. This factor assigned as the anthropogenic factor.

Table 4 Factor loadings (Varimax rotation) rotated component matrix

|  | Component | | |
| --- | --- | --- | --- |
| Parameters | F1 | F2 | F3 |
| pH | 0.070 | 0.089 | 0.895 |
| TRB | 0.306 | 0.919 | -0.011 |
| TA | 0.022 | 0.820 | 0.138 |
| TH | 0.856 | 0.283 | 0.349 |
| EC | 0.802 | 0.504 | 0.282 |
| TDS | 0.837 | 0.167 | 0.425 |
| Cl | 0.560 | 0.708 | 0.186 |
| Ca | 0.846 | 0.293 | -0.159 |
| Mg | 0.459 | 0.718 | -0.477 |
| SO4 | 0.818 | 0.361 | -0.240 |
| Fe | 0.862 | 0.260 | -0.034 |
| NO3 | 0.859 | 0.090 | 0.184 |
| BOD | 0.791 | 0.539 | 0.100 |
| FC | 0.885 | 0.088 | -0.285 |

Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser Normalization, a Rotation converged in four iterations

The second factor F2 explained 24.967% of the total variance and was strong positive loading TBR and TA; moderate positive loading Mg, Cl and BOD. This factor is linked with the agricultural activities, municipal wastewater, erosion effect which occurs during cultivation of soil and heavy rainfall from upland areas (Mutlak et al. 1980). The third factor (F3), explaining the lowest variance (11.954%), has strong positive loadings on pH.

From the factor analysis results it can be concluded that, three factors representing three different processes are: anthropogenic factor, erosion and rainfall factor and pH factor.

Cluster analysis

In this study sampling site classification was performed by the use of cluster analysis (z-transformation of the input data, squared Euclidean distance as similarity measure and Ward’s method of linkage). The results of cluster analysis CA are presented in a dendrogram (Fig. 3). Dendograms in cluster analysis provides a useful graphical tool determining the number of clusters which describe underlying process that lead to spatial variation (Boyacioglu, & Boyacioglu 2007).

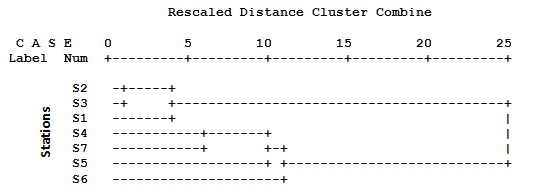


Figure 3 Dendogram showing clustering of monitoring sites of Tigris River (The axis shown at the top indicates the relative similarity of different cluster groups. Lesser distance corresponds to greater similarity between samples)

Since we used hierarchical agglomerative cluster analysis, the number of clusters was decided by water environment quality, which is mainly effected by types of land use and industrial structure. Based on the results of cluster analysis and locations of the monitoring sites, it can be concluded that three major groups were formed by treating all data by clustering:

*Cluster 1 (Stations 1 – 2 – 3)*

Sites mainly located at the entrance of the river to Baghdad city. Cluster I showing reach that has least concentrations of almost all the variables including the total dissolved solids. S1, S2 and S3 are located upstream of sewage and domestic wastes mixing zones and so no contamination was observed.

*Cluster 1I (Stations 4 – 5 – 7)*

In this cluster, stations (4 and 5) mainly located at the middle of the river and were grouped under Cluster II. These stations located downstream of sewage mixing zones from medical city. In addition, Station 7 which located in south of Baghdad city, showed the similar water environment quality characteristics with these stations.

*Cluster 1II (Station 6)*

This cluster consists one station mainly located near Al-Rasheed water treatment plant. Most of the city's factories (Al-Dora oil refinery, oil vegetables factory,tanning factory and cement factory) and agricultural areas located downstream of this station. Therefore, this station received pollutants mostly from non-point source pollution and industrial effluents.

Obviously, the station 7 (cluster II) is much less polluted than station 6 (cluster III), the inclusion of the sampling location suggests the self-purification and assimilative capacity of the river are strong.

Conclusions

In this study, different multivariable statistical methods were successfully applied to assess the quality of Tigris river at Baghdad stretch. The results are useful for river water quality management. The conclusion drawn of this study as follows:

1. Factor analysis results revealed that 14 quality variables can be grouped under three factors namely: anthropogenic factor, erosion and rainfall factor and pH factor.
2. Hierarchical cluster analysis grouped 7 sampling sites into three clusters of similar water quality characteristics. Based on obtained information, it is possible to design an optimal sampling strategy, which could reduce the number of sampling stations and associate costs. It is concluded that stations can be grouped under three clusters.
   * Cluster I included sites (Al-Tarmiyahm, Al-Muthana Bridge and Al-Adhamiyah Bridge) which showing least concentrations of all the variables including and are located upstream of sewage and domestic wastes mixing zones. Cluster I represent less polluted sites.
   * Cluster II represents sites (Midecal City bridge, Al-Jadriyah Bridge and Al-Zafarania). This cluster considered as moderately polluted zone.
   * While the cluster III represents one station (Al-Rashed) located downstream of Baghdad factories and agricultural areas which is corresponded to highly polluted site.
3. With serious situation of Tigris river water pollution at populated city like Baghdad, the management of water quality of the different zones is becoming more important. According to the sources of pollution, different measures should be adopted, in order to control the total quantity of the pollutants and achieve the water quality standard of Tigris river. It could be helpful to managers and government agencies in water quality management.
4. As a result, multivariate statistical methods including factor and cluster analyses can be used to understand complex nature of water quality issues and determine priorities to improve water quality. These methods are believed to assist decision makers assessing water quality and determining priorities in pollution prevention efforts.

**Acknowledgement** The authors are thankful to (the late Eng. Anas Faleh Abed) for providing necessary facilities. God bless his soul.

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