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Identification of Groundwater Quality by Statistical Methods and a Mathematical Method in the Khemisset–Tiflet Region

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ABSTRACT

Groundwater is one of the most important natural resources that is overexploited and extensively polluted by human activity. Furthermore, drinking this dirty water might have major consequences for human health. Before using groundwater, it is consequently required to conduct a precise and regular assessment of its quality. Furthermore, for five monitoring stations in the Khemisset-Tiflet region, cluster analysis (CA), principal component analysis (PCA), and a fuzzy logic technique were utilized to analyze water quality. The CA classified the sample sites into three categories. The PCA identified temporal characteristics of water quality status. Group I include stations characterized by high temperature and low DO, COD, and BOD5 values. Group II includes stations characterized by high values of pH and low concentrations of NO_3^-, Cl^-, SO_4^{2-} and turbidity. Group III includes stations characterized by high concentrations of NO_3^-, Cl^-, SO_4^{2-} and turbidity and low concentrations of pH. In addition, fuzzy logic to reveal more information about groundwater quality. In effect, water quality in spring and winter was the best; the parameters responsible for the deterioration of water quality are NO_3^-, Cl^-, SO_4^{2-} and turbidity.

Keywords: principal component analysis, cluster analysis, fuzzy logic approach, groundwater quality, Khemisset-Tiflet region.

INTRODUCTION

Groundwater is one of the most valuable natural resources and its use in many sectors has made it a part of the daily lives of millions of people. In addition, the steady and rapid growth in demand for groundwater has placed enormous pressure on groundwater supply and adequacy, raising serious concerns about groundwater sustainability and ecosystem behavior (Benhamiche et al, 2014). According to the literature (Santanu Mallikune et al, (2021) and (Tomas et al, 2017), human activities and many chemical reactions that occur in the aquifer, soil interaction with accumulated water, aquifer rocks and other processes are among the most important sources of groundwater pollution. In addition, pollutants may be released as waste products into waterways or the atmosphere, which can accumulate over time in the aquifer due to infiltration and increase the risks associated with groundwater contamination. Controlling and mitigating groundwater pollution, as well as establishing regular monitoring programs that help us understand temporal and spatial changes in groundwater quality and diagnose current groundwater quality, are therefore essential. Traditional water quality laws, on the other hand, include quality classes based on brittle groupings, and class boundaries are fundamentally wrong. In other words, the concentration of the parameter is determined equally by its proximity to or distance from the boundary. Each quality measure can be classified into one of several categories (Shwetank et al, 2020). To put it another way, a class cannot have all parameters. Furthermore, different quality classes at the same sampling site might lead to confusion (ambiguity) when determining the quality of a sampling site. As a result, the use of multivariate statistical approaches such as cluster analysis (CA), principal component analysis (PCA) (Jayaraman et al, 2003), and fuzzy logic aids in the interpretation of complicated data matrices in order to better comprehend groundwater quality. The systems investigated also identify sources and factors impacting groundwater and provide a vital tool for dependable water resource management as well as speedy remedies to pollution problems. In this work, statistical analytic methods (CA, PCA, and fuzzy logic approach) were used to analyze the water quality in the study area. Principal component analysis was utilized to identify probable factors/sources affecting water quality, and a fuzzy logic technique was employed to evaluate/classify groundwater from five wells based on the Moroccan standard.

MATERIAL AND METHOD

Study zone

The Khemisset-Tiflet region is part of the Sebou watershed, one of Morocco's most important watersheds. The Khemisset-Tiflet area is around 40 square kilometers and is located northwest of Morocco between the parallels 33° and 35° north latitude and 4° 15′ and 6° 35′ west longitude. It is bounded to the north by the Rif mountain range, to the south by the Middle Atlas mountains, to the east by the Fez-Taza corridor, and to the west by the Atlantic Ocean. The research area includes various municipalities located within the province of Khemisset (Figure 1). This location is situated in a hydrogeological context widely renowned for its substantial water resource potential. Indeed, the Maâmora and Rharb aquifers form its western limit, and the Fez-Meknes aquifer constitutes its eastern limit.

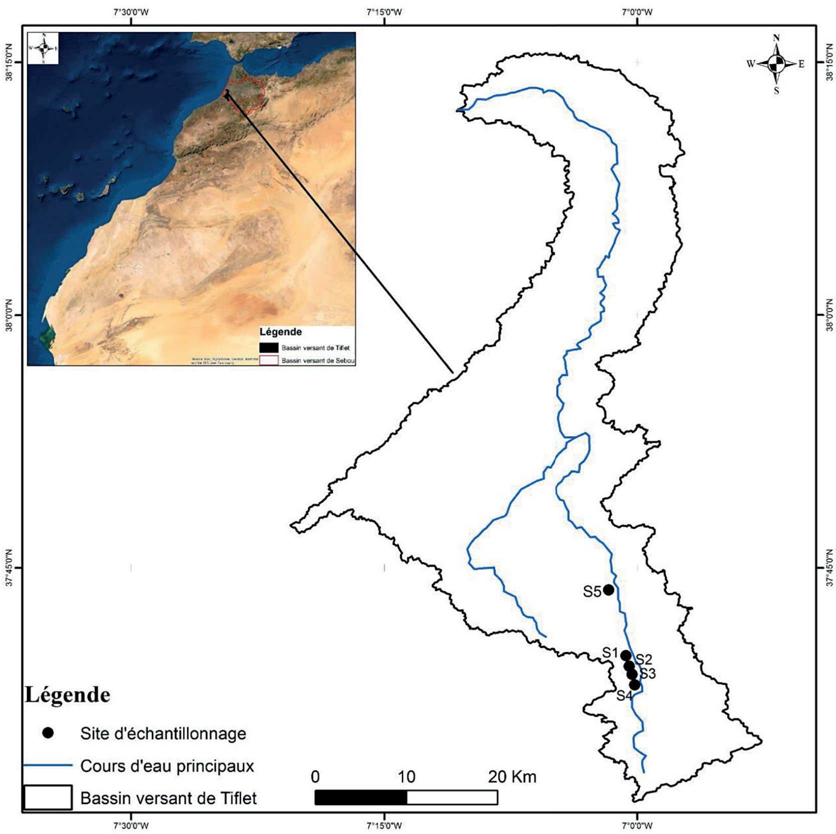

Figure 1. Monitoring stations in the Khemisset-Tiflet region

Methods of sampling and analysis

During the 2018–2019 year, surface water samples were collected seasonally (fall, winter and spring). Samples were collected (Repeated twice) between 7 a.m. and 2 p.m and stored in polyethylene bottles. They were then placed in a freezer and transported to the laboratory the same day, where they were kept at 4°C until processing and analysis. The selection of these stations was based on environmental heterogeneity, in particular the location of potentially polluting resources. In addition, five wells in the study area were selected for this monitoring. Four physico-chemical parameters (temperature, dissolved oxygen, conductivity and pH) are measured in situ after the removal of the sample using an appropriate portable multiparameter instrument of the HACH type, model HQ40d. A complete analysis of the chemical elements was carried out for this study: the BOD_5 was determined on the same day of the sampling by the so-called "Respiratory" method to avoid time-induced changes in the bacterial concentration. The chemical oxygen demand (COD) is determined by oxidation in an acid medium with an excess of potassium dichromate. The TKN was measured after mineralization of the water with selenium. Nitrites were measured by a method based on the reaction of NO_2^- with amino-4-benzensulfonamide and N-(naphthyl-1)-ethylene-dia-mine dihydrochloride. Nitrates were measured by a photometric method with 2,6dimethylphenol. Ammonium was measured by a photometric method. The concentration of SO_4^{2-} was determined spectrophotometrically by the barium sulphate turbidity method and chloride by titration of silver nitrate (AgNO3) using potassium chromate solution (K_2CrO_4) as an indicator. PT-P and PO_4-P were measured by the phosphomolybdic complex photometric method. The determination of the suspended solids content (SS) was carried out by filtration at 0.45 µm. All water quality analyzes are carried out within the national laboratory for water studies and monitoring and by standard methods for water analysis.

Cluster analysis

Cluster analysis (CA) is a collection of multivariate methodologies with the primary goal of grouping things based on their shared characteristics. Cluster analysis arranges items so that they are comparable to others in the cluster based on a predetermined criterion. The most often used technique, hierarchical agglomerative clustering (HAC), creates intuitive similarity correlations between each individual sample and the data set and is frequently displayed as a dendrogram (Araoye, 2009., May, 2009). The dendrogram visualizes clustering procedures by depicting groupings and their proximity. To compute the distances between clusters, the analysis of variance technique is utilized.

Principal component analysis

Principal component analysis (PCA) is a pattern recognition method that turns a big collection of intercorrelated variables into a smaller set of independent variables in order to evaluate variance (Lu et al, 2019). It gives information on the most essential factors used to describe the entire data set, data reduction, and a summary of the statistical correlation between water components with the least loss of original data (Jayaraman et al, 2003). PCA was used to generate a correlation matrix of the rearranged data in order to explain the structure of the underlying data set and uncover latent and unobservable sources of pollution.

The fuzzy logic approach

Zadeh invented fuzzy logic in 1965 (Shwetank et al, 2020), which is a new technique of describing imprecision in ordinary life. This assessment method uses fuzzy mathematics to transform questionable boundary factors into certain ones. In fuzzy logic, processes include fuzzification, applying the rule base to fuzzy inputs, inferring fuzzy results, and defuzzification. The main idea behind the fuzzy logic assessment approach for assessing water quality consists of four operations:

- Fuzzification is a procedure that converts real observed data into fuzzy data using membership functions defined for the problem features (Shwetank et al, 2020). The degree of membership of each evaluation parameter to the evaluation criteria at each level can be quantified using the membership function equations;
- The application of the rule base to fuzzy data;
- Inference of fuzzy results;
- Defuzzification.

The Table 1 represents the classification of water quality into five categories according to the Moroccan standard. These categories are class I-excellent, class II-good, class III-moderate, class IV-poor, and class V-very poor. In addition, to normalize the natural measurement scales of the quality parameter

Table 1. Surface water quality classification based on Moroccan standards

Category	Unity	Class I	Class II	Class III	Class IV	Class V
		Excellente	Bonne	Moyenne	Mauvaise	T. Mauvaise
Temperature	°C	0–20	20–25	25 –30	30 –35	+ de 30
pH	–	6.5–8.5	6.5–8.5	6.5–9.2	<6.5 ou +9.2	<6.5 ou +9.2
Conductivity	Us/cm	<300	400–1300	1300–2700	2700–3000	+ de 3000
Dissolved oxygen	mg/l	>7	7–5	5–3	3–1	<1
Sulfate (SO_4^{2-})	mg/l	<100	100–200	200–250	250–400	+ de 400
Chloride (Cl^-)	mg/l	< 200	200–300	300–750	750–1000	+ de 1000
Turbidity	NTU	< 15	15–35	35–70	70–100	>100
BOD_5	mg/l	<3	3–5	5–10	10–25	+ de 25
COD	mg/l	<30	30–35	35–40	40–80	+ de 80
NO_3–N	mg/l	<5	5–25	25–50	50–100	>100
NO_2–N	mg/l	<0.1	0.1–0.5	0.5–2	2–8	>8
NH_4–N	mg/l	≤0.1	0.1–0.5	0.5–2	2–8	>8
TKN	mg/l	<1	1–2	2–3	+ de 3	

into a measure of the degree of quality (degree of membership) a membership function was used.

In this work, we used five membership functions of the triangular (Figure 2) and trapezoidal (Figure 3) shape because of these simple structures. The mathematical representation of the triangular and trapezium membership function for water quality parameters takes into account classes I, II, III, IV and V is as follows:

$$\mu(X) = \begin{pmatrix} \dfrac{x-a}{b-a} \; if \; a \le x \le b \\ \dfrac{c-x}{c-b} \; if \; b \le x \le c \\ 0 \; otherwise \end{pmatrix} \quad (1)$$

$$\mu(X) = \begin{pmatrix} \dfrac{x-a}{b-a} \; if \; a \le x \le b \\ 1 \; if \; b < x < c \\ \dfrac{d-x}{d-c} \; if \; c \le x \le d \\ 0 \; otherwise \end{pmatrix} \quad (2)$$

where: µA (X) is the membership function, x the observed value; a, b, c and d are the limits of the membership functions (Table 2).

Furthermore, a set of rules are applied based on the previously realized categories, and the “or” operations are used to obtain maximum values (Shwetank et al, 2020):

$$\begin{array}{c} \text{If QP1} = \text{ I or QP2} = \text{I or } .... \\ ... \text{ or QPN} = \text{I then QP} = \text{I} \\ \text{If QP1} = \text{ II or QP2} = \text{II or } .... \\ ... \text{ or QPN} = \text{II then QP} = \text{II} \\ \text{If QP1} = \text{ III or QP2} = \text{III or } .... \\ ... \text{ or QPN} = \text{III then QP} = \text{III} \\ \text{If QP1} = \text{ IV or QP2} = \text{IV or } .... \\ ... \text{ or QPN} = \text{IV then QP} = \text{IV} \\ \text{If QP1} = \text{ V or QP2} = \text{V or } .... \\ ... \text{ or QPN} = \text{V then QP} = \text{V} \end{array} \quad (3)$$

QPi ($I = 1, 2, 3, 4, 5$) represents the quality parameter, I, II, III, IV and V are the quality classes and N is the number of quality parameters.

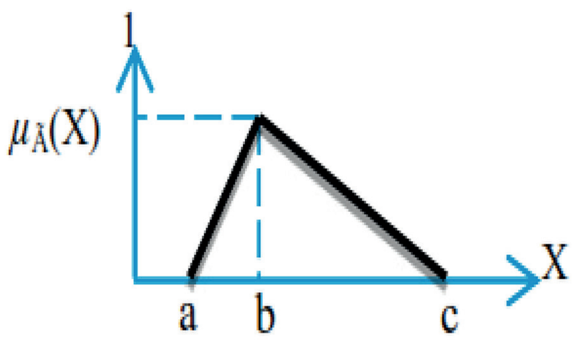

Figure 2. Graphical representation of Equation 1

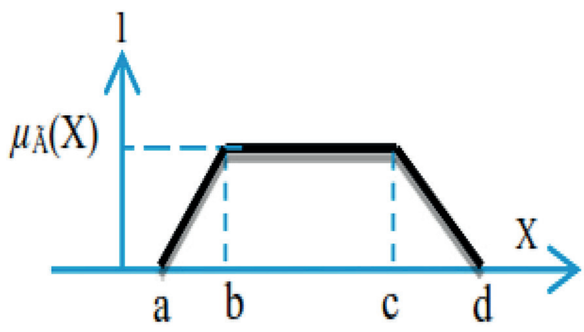

Figure 3. Graphical representation of Equation 2

Table 2. Limits of membership functions

Parameters	Unity	Interval		Excellent (E)	Good (B)	Medium (M)	Poot (MV)	V.poor (TM)
Temperature	°C	0–40	a b c	–5 10 15	10 20 25	20 25 30	25 30 35	30 35 40
pH	–	0–10	a b c d	0 2.5 5 8.5	2.5 5.5 8.5	5.5 8.5 8.75	8.5 8.75 9.5	8.75 9.5 10
Conductivité		200–3500	a b c	0 300 500	300 800 1300	800 1225 2125 2700	1300 2700 3000	2700 3000 3500
Sulfate	mg/l	10–2000	a b c	0 10 100	10 100 200	100 200 250	200 250 400	250 400 1500 2000
Turbidity	NTU	0–280	a b c d	0 0 15	5 15 35	15 35 70	35 70 110	70 110 280 280
Dissolved oxygen	mg/l	0.5–8	a b c	8 7.5 6	7.5 6 5	6 5 3	5 3 1	3 1 0.5
NO_3–N	mg/l	0–110	a b c d	0 2 4	2 10 15 25	10 20 25 50	20 35 50 100	35 80 110 110
NO_2–N	mg/l	0–8.5	a b c	0 0.01 0.1	0.01 0.1 0.5	0.1 0.5 2	0.5 2 5 8	2 6.5 8.5 8.5
NH_4–N	mg/l	–0.25–8.5	a b c	–0.25 0 0.1	0.01 0.1 0.5	0.1 0.5 2	0.5 2 5 8	2 8 8.5 8.5
TKN		0.25–5	a c c	0.25 0.5 0.75	0.5 0.75 2	0.75 2 3	2 3 4	3 4 5 5
BOD_5	mg/l	1–30	a b c	1 2 3	2 3 5	3 5 10	5 15 20 25	10 25 30 30
COD	mg/l	4–85	a b c	4 20 30	20 30 35	30 35 40	35 40 80	40 80 85
Chloride	mg/l	20–1100	a b c	20 80 200	80 200 300	200 300 500 750	400 700 800 1000	750 900 1100 1100
Output1	–	0–100	a b c d	60 80 100 100	40 60 80	20 40 60	0 20 40	0 0 20

RESULTS AND DISCUSSION

Cluster analysis

Cluster analysis (CA) was applied to detect similar clusters in the sampling sites of three seasons (autumn, winter and spring) (Figure 4). Therefore, a dendrogram was generated grouping the sampling sites into three clusters, and the difference between the clusters was significant. However, group 1 includes stations S3w, S3a, S2a, S2sp and S2w (two sampling stations S2 and

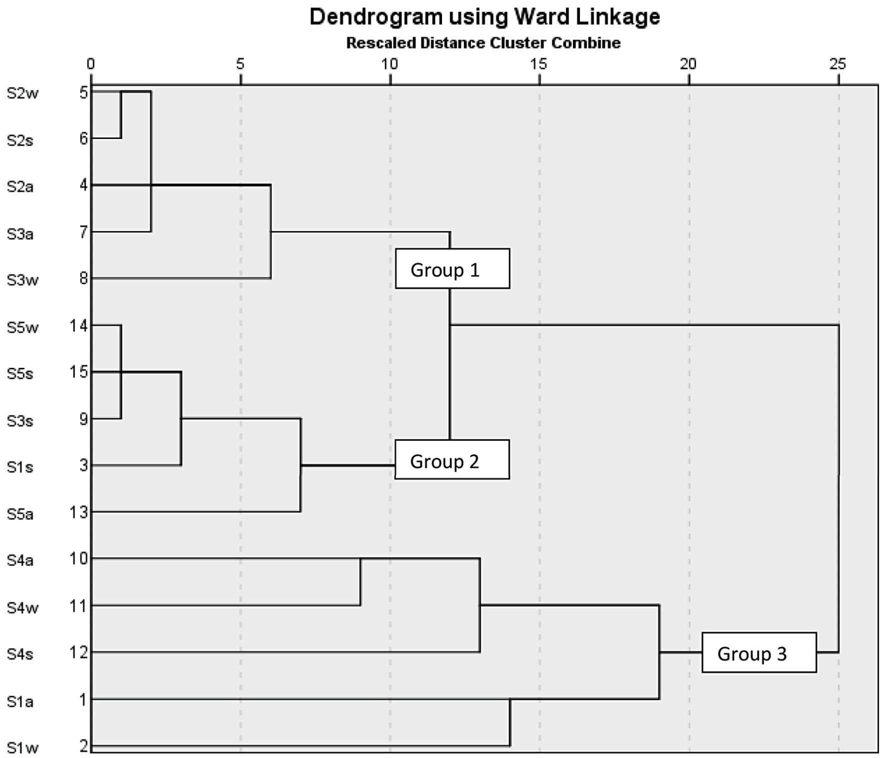

Figure 4. Dendrogram based on Ward's method for three seasonal surveys in Tiflet river

S3), group 2 includes stations S5a, S5sp, S5w, S1sp and S3sp (most stations in spring), group 3 includes stations S4a, S4sp, S4w, S1a and S1w (two sampling stations S1 and S4).

Principal component analysis

Before applying PCA, a correlation analysis (Table 3) was performed to identify the sources of pollutants. The correlation matrix of 13 parameters shows links between the different physico-chemical parameters. Indeed, pH values correlate negatively with conductivity (-0.539), ammonium (-0.489) and chloride (-0.509) concentrations. In fact, pH is a parameter affected by atmospheric deposition of acidifying materials, as well as the discharge of certain effluents. A positive correlation is observed between the concentration of conductivity and chloride (0.450). These two parameters evolve in parallel. There is also a negative correlation between dissolved oxygen and sulfate levels (-0.422). Turbidity concentrations

Table 3. Correlation matrix

Parameter	pH	T	Conductivty	Dissolved oxygen	Turbidité	NO_3–N	NO_2–N	NH_4–N	TKN	Cl	BOD_5	COD	Sulfate
pH	1 .000												
T	.145	1.000											
Conductivity	–.539	.145	1.000										
Dissolved oxygen	.313	.123	.215	1.000									
Turbidity	–.294	–.373	–.060	–.019	1.000								
NO_3–N	–.371	–.236	.203	–.123	.561	1.000							
NO_2–N	.238	.227	–.115	.101	.204	–.020	1.000						
NH_4–N	–.489	–.001	.168	–.275	–.108	–.040	–.087	1.000					
TKN	–.143	.042	.001	–.370	.317	.367	.002	–.273	1.000				
Cl	–.509	.310	.450	–.205	.306	.662	.201	.143	.219	1.000			
BOD_5	–.087	–.397	.168	.350	.551	.345	–.234	–.052	–.190	.043	1.000		
COD	.053	–.345	.031	.192	.614	.406	–.097	–.250	.464	–.055	.709	1.000	
Sulfate	–.205	.078	.165	–.422	.104	.619	.026	.104	.062	.779	.138	–.030	1.000

correlate positively with NO_3 (0.561), BOD_5 (0.551) and COD (0.614). NO_3 values correlate positively with COD (0.406) and sulfate (0.619) while NTK values correlate positively with COD (0.464). Chloride levels correlated positively with sulfate (0.779) and BOD_5 values correlated positively with COD (0.709).

Furthermore, because of the complexities of the linkages, it was difficult to make more obvious conclusions. However, principal component analysis may extract latent information and describe the data structure in depth. In fact, a Kaiser-Meyer-Olkin (KMO) measure was utilized to assess the data quality for principal component analysis. The KMO index in this study is 0.7, indicating that the PCA could allow for a reduction in the dimensionality of the data set.

Three components (Table 4) of the multivariate analysis showed 60.42% of the variance of the data set. Five variables are involved in the constitution of component 1, which represents 26.736% of the total variance of all the data, namely pH, turbidity, NO_3^-, Cl^- and sulfate (Figure 5). In addition, this axis corresponds to a concentration gradient of the evaluated elements, increasing from the negative to the positive side of the mentioned axis, for NO_3^-, Cl^-, $SO_4^{2-}$and turbidity and decreasing for pH. Therefore, the stations (S4a, S4sp, S4w, S1a and S1w) located in the right part of this axis have high concentrations of NO_3^-, Cl^-, SO_4^{2-} and turbidity and low concentrations of pH, while the stations (S5a, S5sp, S5w, S1sp and S3sp) located in the left part of this axis have high concentrations of pH and low concentrations of NO_3^-, Cl^-, SO_4^{2-} and turbidity. The strong positive load of NO_3_N and SO_4^{2-} indicates nutrient pollution, the origins of which are probably related to the fertilizers used in the region (Zhang, D et

Table 4. Eigenvalues on the correlation matrices of the concentration of physico-chemical parameters in %

Parameter	Composante		
	1	2	3
NO_3–N	.877	.013	.147
Cl	.726	–.549	.159
Turbidity	.700	.448	.146
Sulfate	.618	–.450	.170
pH	–.593	.407	.447
COD	.517	.742	.075
BOD_5	.499	.621	–.416
NH_4–N	.086	–.482	–.539
NO_2–N	–.061	–.089	.527
Conductivity	.372	–.298	–.461
O– dissous	–.233	.466	–.260
T	–.254	–.509	.294
TKN	.414	.064	.593
Eigen values	3.476	2.617	1.762
Total variance %	26.736	20.127	13.554
Cumulative variance %	26.736	46.863	60.417

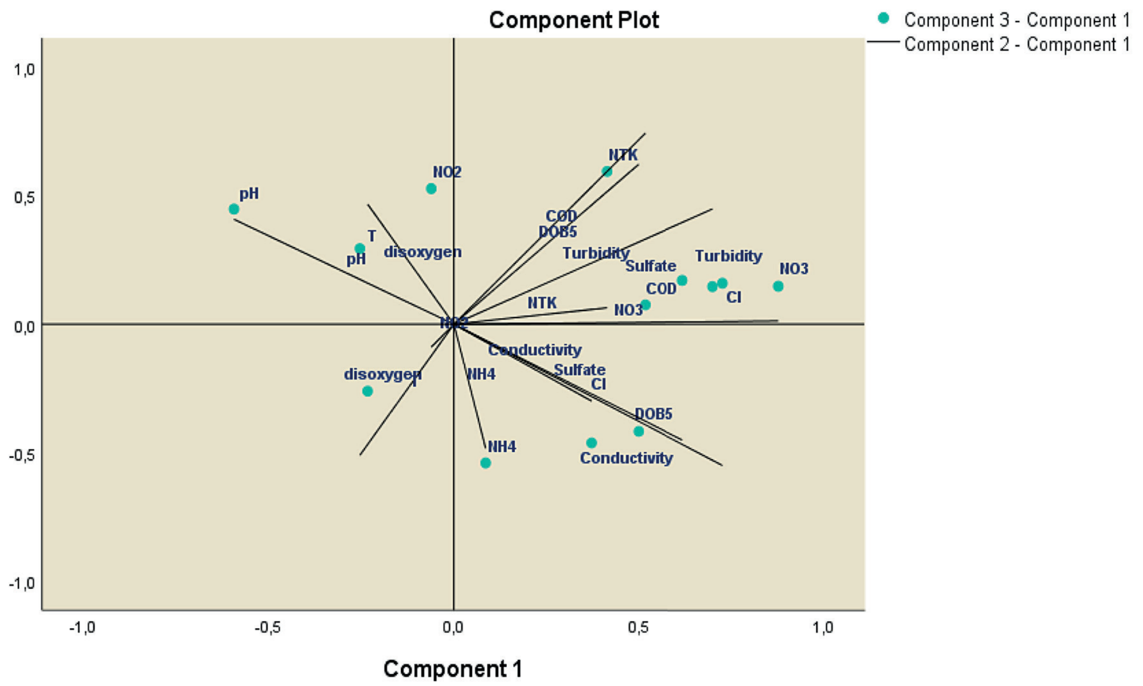

Figure 5. Graphic representation of the factor loads of the principal components

al, 2016). The strong chloride and sulfate load is explained by high mineralization of the groundwater (Benhamiche et al, 2014). The high concentration of mineral salts in water may be due to leaching of sedimentary rocks; dissolution of rocks may result in high concentrations of chlorides in water (Combe M. 1975). In addition, the contamination of water can also be of anthropogenic origin; the use of chemical fertilizers and manures in agriculture will increase the level of mineral salts in drainage water from agricultural land. the positive strong turbidity load may be due to the presence of undissolved matter in the water, the high turbidity levels is also due to natural geological factors (Santanu Mallikune et al, 2021). In our study, the second hypothesis is highly probable since the high concentration is always accompanied by a high concentration of suspended matter (Tomas et al, 2017). In addition, four physico-chemical parameters intervene in the constitution of component 2, which represents 20.127% of the total variance of the data set, namely T, DO, BOD_5 and COD. In addition, this axis corresponds to a gradient of concentration of the elements evaluated, increasing from the negative to the positive side of the axis concerned, for the elements DO, COD and BOD_5 and decreasing for T. Moreover, the stations (S3w, S3a, S2a, S2sp and S2w) located on the negative side of this axis have high values of temperature and low values of DO, COD and BOD_5. In addition, the high load of BOD_5 and COD is explained by the organic load due to the location of the wells in relation to the source likely to be the origin of the organic matter and microorganisms responsible for its degradation; the infiltration of wastewater brings an additional organic load to the water table (Oufline, R et al, 2012). Thus, the high DO load may be due to photosynthetic activity. The negative T loading is attributed to seasonal change (Derradji, F et al, 2007). The third component accounted for 13.554% of the total variance in the data set and included conductivity, NO_2-N, NH_4-N and TKN. The high positive loading of NO_2-N and TKN is attributed to anthropogenic pollution from seepage wastewater discharge.

The analysis results show that the principal component, C1 and C2, provided an overview of the temporal and spatial variations of the water quality parameters and accounted for 46.863% of the variance.

The fuzzy logic approach

The groundwater quality of five wells, used for human consumption, was assessed by the fuzzy logic approach. The results of the classification of the different wells during three seasons are summarized in Table 5.

The fuzzy logic results show differences between the three seasons. Indeed, the scores of different stations during the autumn season vary from 56.8 to 65.8. Moreover, during this period the groundwater belongs to the class good in the

Table 5. Classification of different wells for three seasons

Season	Stations	Score	Water quality class					Class
			I	II	III	IV	V	
Autumn	S1	56.8		+				Good
	S2	65.8		+				Good
	S3	61.4		+				Good
	S4	57.3		+				Good
	S5	60		+				Good
Winter	S1	55		+				Good
	S2	73.4	+					Excellent
	S3	75.9	+					Excellent
	S4	64.9		+				Good
	S5	75.7	+					Excellent
Spring	S1	76.3	+					Excellent
	S2	66		+				Good
	S3	75.4	+					Excellent
	S4	64.4		+				Good
	S5	75.5	+					Excellent

Moroccan standard of groundwater classification. The degrees of belonging of the sampling stations are close to 0; these stations are characterized by high contents of NO_3^-, Cl^-, SO_4^{2-} and turbidity. Water quality at S1 and S4 was the worst compared to the other monitoring sites. In general, groundwater quality in winter and spring was the best compared to the fall season; these waters belong to the excellent class during these periods, and some stations could reach class II (good). In fact, stations S2w, S3w and S5w, belonging to the excellent class, are characterized by low concentration of DO, COD and BOD_5. On the other hand, stations S1sp, S3sp and S5sp are characterized by low concentrations of NO_3^-, Cl^-, SO_4^{2-} and turbidity; the scores of these stations are higher than 70 and their degrees of belonging are close to 1. consequently, seasonality has an influence on the quality of groundwater; the values of physico-chemical parameters depend not only on the anthropic activities but also on the sampling time. Besides, NO_3^-, Cl^-, SO_4^{2-} and turbidity can play an important role in determining groundwater quality and can also be a determining factor for water quality deterioration. Furthermore, in fuzzy logic each sampling site has a degree of cluster membership. Thus, points on the cluster center have a higher degree of membership than points on the cluster edge. In addition, it can provide major determinants of water quality deterioration.

Classification according to projection planes 1 and 2

The CA and PCA analysis allowed to define a typology determined by the presence of three groups (clusters) of stations GI, GII and GIII (Figure 6).

The fuzzy logic approach was applied to determine the factors responsible in the deterioration of water quality. Group I include stations S3w, S3a, S2a, S2sp and S2w which are characterized by high temperature and low DO, COD and BOD_5 values. The fuzzy logic shows scores above 60; the waters of stations S3w and S2w belong to the excellent class and the waters of stations S3a, S2a and S2sp belong to the class good. Group II includes stations S5a, S5sp, S5w, S1sp and S3sp, characterized by high values pH and low concentrations of NO_3^-, Cl^-, SO_4^{2-} and turbidity. The scores of the mentioned stations, according to the fuzzy logic, show waters belonging to the excellent class for all the stations S5sp, S5w, S1sp and S3sp of this group except the water of the station S5a which belongs to the class good. Group III includes stations S4a, S4sp, S4w, S1a and S1w, which are characterized by high concentrations of NO_3^-, Cl^- SO_4^{2-} and turbidity and low concentrations of pH; the scores of all the stations of this group according to the fuzzy logic belong to the class good with the degrees of membership different. Therefore,

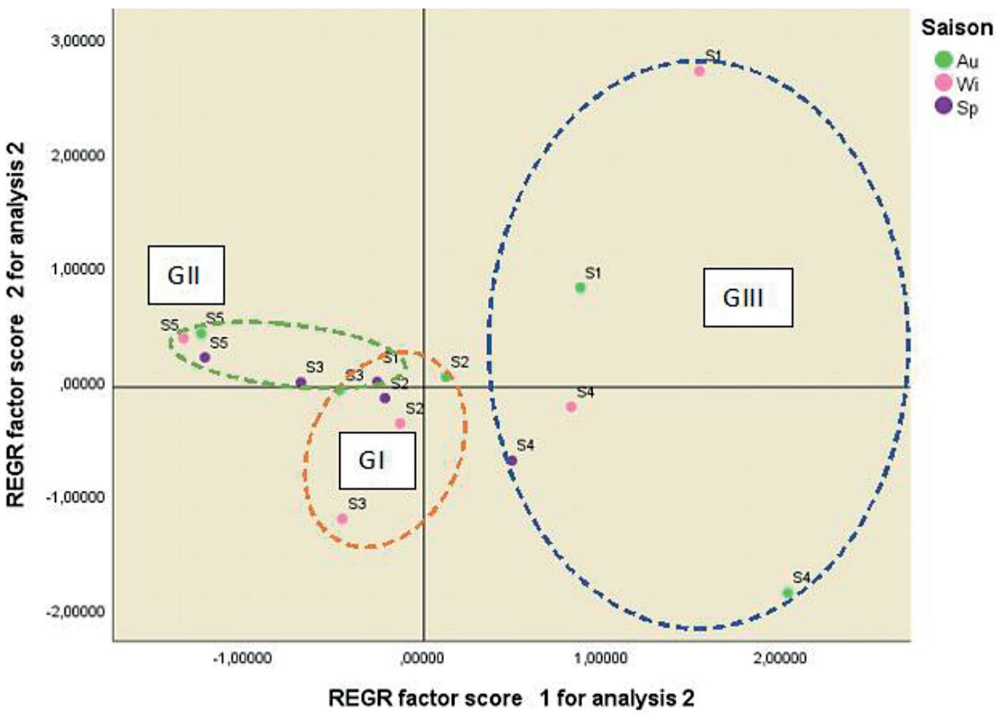

Figure 6. The scores of the five sampling sites monitored seasonally for the two axes PC1 and PC2. Au: Autumn; Wi: Winter; Sp: Spring

the water quality in spring and winter was the best; the parameters responsible for the deterioration of the water quality are NO_3^-, Cl^-, SO_4^{2-} and turbidity. Moreover, the enrichment of water in mineral salts is related to the leaching of rocks and plantations by rainwater, as well as the contributions of domestic wastewater and runoff.

CONCLUSIONS

CA, PCA, and the fuzzy logic technique were used in this work to identify groundwater quality in the Khemisset-Tiflet area. Indeed, the CA results can be used to determine the similarities between sampling sites, with each cluster containing similar sampling sites. Principal component analysis (ACP), on the other hand, provides for the interpretation of traits by grouping the sampling sites and can also define their properties. Furthermore, the presence of three groups enabled us to create a typology using principal component analysis (GI, GII and GIII). The first group of stations is distinguished by high temperature values and low DO, COD, and BOD_5 levels. The second category contains stations with high pH values and low NO_3^-, Cl^-, SO_4^{2-}, and turbidity concentrations. The third group includes stations with high NO_3^-, Cl^-, SO_4^{2-}, and turbidity concentrations but low pH values. Furthermore, the fuzzy logic approach provided information about the status of groundwater quality and enables for the identification of the causes responsible for water quality decline. The results showed the presence of two water classes, the excellent class (class I) and the class good (class II). In fact, all the results show that NO_3^-, Cl^-, SO_4^{2-} and turbidity are the main parameters responsible for the deterioration of water quality in the majority of the stations receiving or neighboring the discharges of anthropic origin and natural. Thus, the results of this study can help policy makers and other stakeholders to find the necessary actions to take.

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