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Study of the Physico-Chemical Parameters of Surface Water Resources in the Oued Ansegmir Watershed Area (Morocco)

Hassan Rahoui[1*], Hind Ait Kessou[1], Zohra Bejjaji[1], Said Chakiri[1]

[1] Laboratory of Natural Resources Geosciences, Department of Geology, Faculty of Sciences, Ibn Tofail University, B.P.133, 14000 Kenitra, Morocco

* Corresponding author's e-mail: hassan.rahoui@uit.ac.ma

ABSTRACT

This study aims to analyze the physico-chemical parameters of 11 water samples to establish a qualitative description of water resources and assess their suitability for agricultural irrigation in the Oued Ansegmir (OAW) catchment area (1060 km²). The study involved the collection and analysis of water samples, focusing on cations and anions. Hydrogeochemical classification diagrams, including trilinear Piper and Scholler-Berkaloff diagrams, were modeled using Diagrammes software. A multivariate statistical method, principal component analysis (PCA), was employed to evaluate the physico-chemical parameters. The water quality index (WQI) was calculated for all samples to provide a comprehensive assessment of water quality. The Schöeller Berkaloff diagram indicated the presence of a sodium chloride facies (S1, S4) and a calcium bicarbonate facies for the remaining samples. The Piper diagram revealed a potassium sulphate-chloride facies and a calcium and magnesium bicarbonate facies. PCA identified two main factors: salinity and ion concentration (PC1), and the distinction between geochemical influences and potential human impacts (PC2). The WQI results showed that 36.4% of the water samples were of good quality, while 63.6% were of poor quality. To the best of our knowledge, this is the first study that examined water quality of OAW for agricultural purposes. Our results clearly indicate the suitability of OAW water resources for agricultural irrigation, while providing essential and relevant information for agricultural practices along Oued Ansegmir.

Keywords: physico-chemical parameters, hydrogeochemistry, principal component analysis, water quality index, Oued Ansegmir watershed.

INTRODUCTION

Water is an essential and irreplaceable element for sustaining life. It is the foundational component of living organisms, and its quality is considered a key factor in controlling health and disease in living beings [El-Fadeli et al., 2015]. Surface waters, including springs, streams, and rivers, are generally considered potable for various uses but are more susceptible to contamination [Egbueri et al., 2019].

Indeed, previous study has shown that only 4.9% of surface waters are fresh and suitable for human consumption [Annapoorna et al., 2015] and other uses. This situation is primarily due to overexploitation and contamination [Chen et al., 2018; Avci et al., 2018]. The water quality of rivers can be severely impacted by changes related to snowmelt, agriculture, and human activities along the banks. Water quality is determined by physicochemical parameters such as pH, electrical conductivity (EC), major cations (Na^+, K^+, Mg^{2+}, Ca^{2+}, etc.), and major anions (F^-, Cl^-, SO^{4-}, NO^{3-}, PO_4^{2-}, etc.) [Prabodha et al., 2015]. These factors vary significantly from one location to another due to discharges from human activities [El Moustaine et al., 2013].

Several conventional scientific approaches, such as hydrogeochemistry, multivariate statistics, and numerical models, can be successfully applied to assess water quality. Hydrogeochemistry analysis revealed the main chemical ions present in water, while multivariate statistical tools, such as correlations and principal component analysis, are invaluable for identifying pollution sources and distinguishing between natural and anthropogenic inputs affecting water quality. WQIs are widely accepted mathematical evaluations that describe the overall quality of water [Egbueri et al., 2019].

Over the past decade, and as part of the Green Morocco Plan, hundreds of new farms have been established along the banks of the Oued Ansegmir [Rahoui et al., 2024]. Indeed, the inhabitants of the OAW (1060 km²) in Midelt Province, Morocco, use multiple water sources, including hand-dug wells, springs, and streams, for irrigation purposes. Consequently, human activities and pesticide use are increasingly raising concerns about the sustainability of these water resources. However, no previous research has assessed the quality and suitability of these water sources for various uses, particularly agricultural irrigation, within the study area. Therefore, it is crucial to study the hydrogeochemistry and water quality of these sources within the watershed.

This study aims to conduct a comprehensive evaluation of water quality in the OAW through:
- hydrogeochemical analysis;
- multivariate statistical analyses, including correlation matrix, principal component analysis, and cluster analysis;
- numerical modeling of the water quality index (WQI);
- mapping of the quality index across the watershed using the universal kriging method.

The research findings are expected to help determine the water quality in the OAW and its suitability for agricultural irrigation.

MATERIALS AND METHODS

Study area

The watershed of River of Ansegmir (1060 km²), in the Province of Midelt (Figure 1), in Morocco, is limited to the west by the watershed of River of Moulouya in its upstream part, and to the east by River of Bel Lahcen, a tributary of River of Outat. It is part of the basin of the Upper Moulouya which constitutes the western end of the Oranese Meseta. This basin stretches from West to East between the High Atlas in the South and the Middle Atlas in the North and North-East [Rahoui et al., 2024].

The primary network is highly developed, throughout the basin, this promotes a fairly rapid downstream transmission capacity of runoff (flash flow) and therefore a high runoff coefficient, especially in areas uncovered by vegetation. This density of primary drainage could be explained by the low permeable natures of the substrates, steep slopes, and low vegetation cover [Rahoui et al., 2024] (Figure 2).

These water sources have being used by the population in plant cultivation, for animal breeding and for human consumption.

The rainfall regime in the study area is Mediterranean. The average annual hydric contributions of precipitation are relatively low in the northern (downstream) part of the basin (210 mm/year at Ansegmir) and high upstream (south) (320 mm/year at Tounfite). This precipitation is characterized by very high intra-annual and inter-annual variations (Figure 3).

Temperature data shows that July is the hottest month in the region. Maximum temperatures

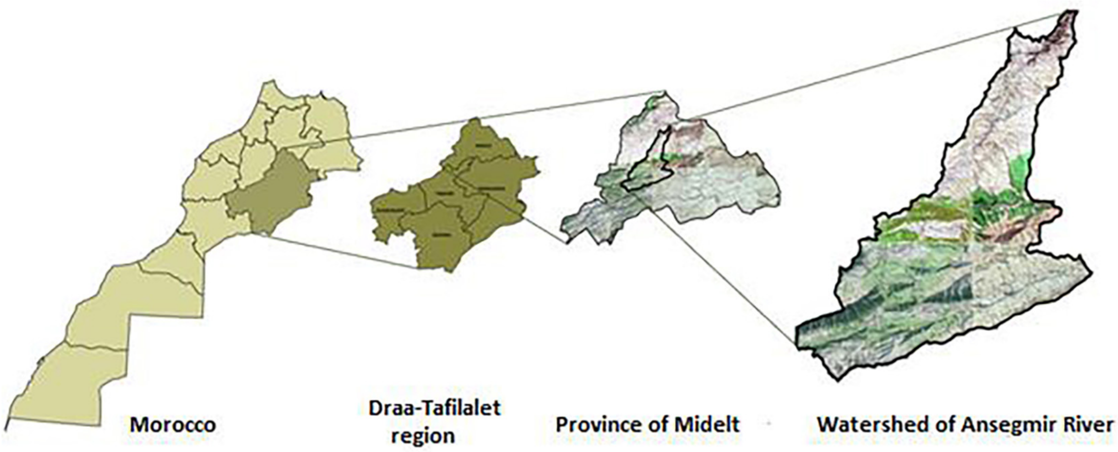

Figure 1. Geographic location of watershed Ansegmir river

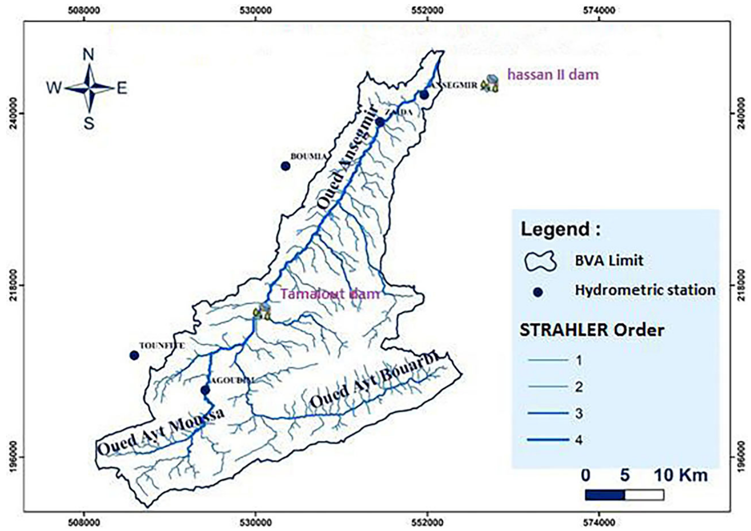

Figure 2. Map of hydrographic network of the Oued Ansegmir watershed

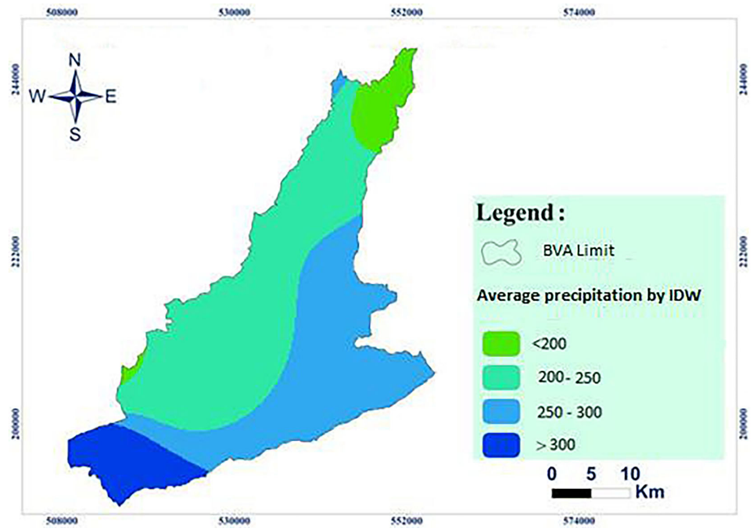

Figure 3. Map of average annual precipitation by IDW of the watershed of Oued Ansegmir (1970–2018)

exceed 32 °C. The coldest month is January with minimum temperatures that can be negative.

The study area is recognized for its intense agricultural activity (apple tree and market garden cultivation). This agriculture represents 25.7% of useful agricultural surface of which 8800 ha are irrigated agriculture.

Samples of study

Considering the possibility of rainy periods, three collection campaigns were carried out in 11 sampling points, from stream (7), and hand–dug wells (3) and dam (1) were randomly collected across the study area (Table 1).

The eleven sampling sites were selected taking into account the presence of agricultural activities, the presence of water resources, the proximity of habitats and the ease of access to waterways likely to receive runoff and its effluents (Figure 4).

The parameters commonly measured in the field are: pH and electrical conductivity (EC). In the laboratory, we were able to determine the major elements: carbonates and bicarbonates (HCO), chloride (Cl), sulphates (SO), nitrates (NO), sodium (Na), potassium (K), calcium (Ca) and magnesium (Mg).

Methodological approach

After analysing the physico-chemical parameters of the collected samples, the cations and anions obtained were used to model hydrogeochemical classification diagrams such as trilinear

Table 1. Information of 11 water sample collection points at the BV of River of Ansegmir

Samples	X	Y	Z	Provenance	Commune
S1	548 881	241 392	1449	Stream	Ait Ayach
S2	544 759	236 986	1464	Stream	Ait Ayach
S3	542 126	232 183	1517	Hand–dug wells	Ait Ayach
S4	538 669	228 063	1569	Hand–dug wells	Ait Ayach
S5	538 490	227 851	1570	Hand–dug wells	Ait Ayach
S6	532 495	213 762	1781	Stream	Tounfite
S7	530 340	215 232	1682	Stream	Tounfite
S8	522 976	212 910	1909	Stream	Tounfite
S9	524 080	209 414	1781	Stream	Tounfite
S10	522 408	200 334	1959	Stream	Agoudim
S11	558 586	243 438	1320	Dam	Zaida

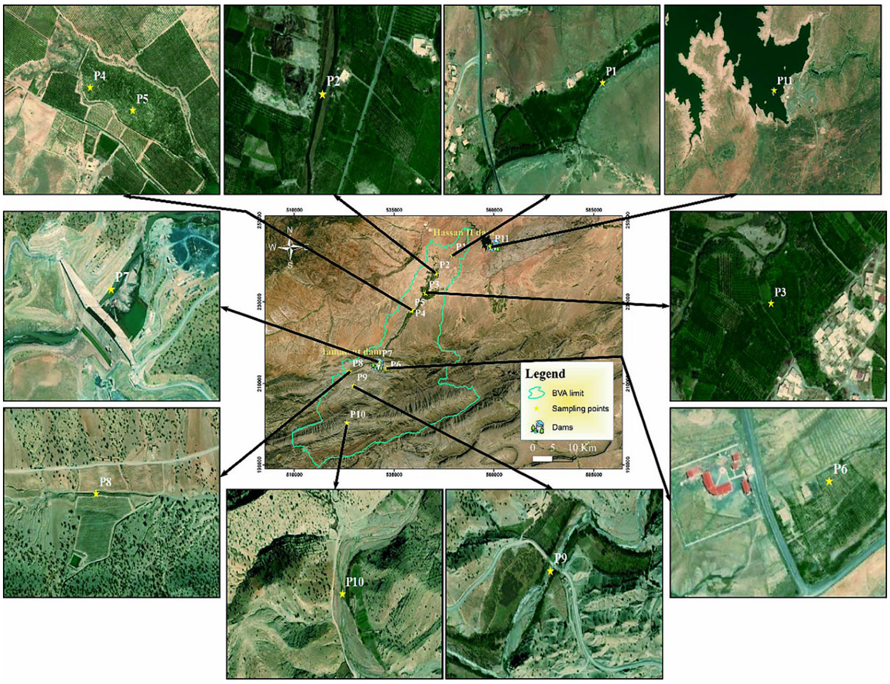

Figure 4. Location map of an aerial view of the 11 water sample collection points

Piper and Scholler-berkaloff diagrams using DIAGRAMMES software (Version 8.44, Roland SIMLER, France).

In order to evaluate the various physico-chemical parameters obtained, we performed a multivariate statistical method using principal component analysis (PCA). This method is an exploratory data analysis technique that is often used to reduce high-dimensional data into lower-dimensional data. The original dataset, which contains many correlated variables, can often be interpreted in terms of a few uncorrelated variables (axes), known as principal components (PCs). These variables are linearly independent (orthogonal) and are the product of the original correlated variables with the eigenvectors, which are lists of coefficients (called weights). The representation of the PCs in a sequential array of elements whose contribution to the overall variability decreases, i.e. the first PC describes the highest fraction of variance in the dataset, and successive PCs describe the remaining fraction of variance.

In order to obtain a complete summary of the quality status of the water samples, we calculated the WQI for all the samples. In fact, we assigned specific weights (from 1 to 5) to the physico-chemical parameters obtained at the top according to their importance for overall water quality (Wr). The relative weight is calculated using the following formula:

$$Wr = Wai / \sum Wai \text{ (i = 1 to n)} \quad (1)$$

where: *Wr* – relative weight, *Wai* – specific weight attributed to each parameter, n - number of parameters taken into account for the WQI.

Next, we calculated the quality index (*Qi*) for each parameter. In fact, we measured the ratio of the concentration of these parameters and the existing standards of the World Health Organisation [WHO 2011–2017] (Table 2) and then multiplied it by 100 as follows:

$$Qi = (Ci/Si) \times 100 \quad (2)$$

where: *Qi* – quality scale, *Ci* – measured concentration of each parameter, *Si* – measured concentration of each parameter according to WHO.

We then calculated sub-indices (SI) to calculate the WQI as follows:

$$Sii = Wr \times Qi \quad (3)$$

$$WQI = \sum SIi \quad (4)$$

Finally, the *WQI* values obtained were classified according to the reference system proposed by [Mgbenu and Egbueri, 2019] (Table 5).

To get an idea of the overall water quality in the OAW, we produced a water quality index map using the universal "kriging" method.

RESULTS AND DISCUSSION

Hydrogeo-chemical characteristics and processes

The descriptive statistics of the data for all the 10 physicochemical parameters water considered for the samples are presented in Table 2. The results were compared with the World Health Organization [WHO 2011–2017] guidelines for water.

The identification of the different types of reactions and processes that take place in water systems is carried out using the chemistry of the main ions in water. In order to determine the hydrogeochemical characteristics of the water samples in the BVA area of action, various diagrams are used.

Schoëller-Berkalloff logarithmic diagram

This diagram is used to determine the chemical facies of the water. Each major element has a vertical line with a logarithmic scale on which its content in mg/l is plotted (Figure 5).

Plotting the results of the chemical analyses on this diagram enabled us to determine two main facies, namely a sodium chloride facies (S1, S4) and a calcium bicarbonate facies for the other samples. The sodium chloride facies could be a result of irrigation water runoff. As for the other facies (calcium bicarbonate) they are often associated with the reaction of water with rocks containing calcium carbonate, such as limestone. It is important to note that the study area is replete with limestone formations (lower Lias limestone, Domerian and Pliensbachian marly limestone and lacustrine limestone of Oligo-Miocene age) [Rahoui et al., 2024].

PIPER diagram

The Piper diagram is used to represent the chemical facies of a set of water samples. It is made up of two triangles representing the cationic and anionic facies and a rhombus summarising the overall facies.

Table 2. Physico-chemical parameters of water in the BV of river of Ansegmir

Statistic	pH	CE* (mS/cm)	Ca^{2+}	Mg^{2+}	Na^{+}	K^{+}	HCO^{3-}	Cl^{-}	SO^{4-}	NO^{3-}
Nbr. of observations	11	11	11	11	11	11	11	11	11	11
Minimum	7.45	0.45	8.30	16.20	16.00	1.40	175.00	15.80	53.00	5.10
Maximum	9.98	1.08	124.00	32.00	183.00	6.40	338.00	79.00	114.00	43.00
1st Quartile	7.85	0.60	53.50	19.80	18.40	1.55	219.50	26.00	62.50	8.85
Median	8.10	0.79	81.00	25.00	19.30	2.50	320.00	28.00	87.00	15.10
3rd Quartile	8.23	0.81	119.50	30.00	23.40	3.30	331.50	36.00	92.00	17.75
Mean	8.16	0.72	82.03	24.85	35.77	2.87	273.73	36.29	82.36	17.05
Variance (n-1)	0.44	0.03	1583.77	34.25	2416.87	2.99	4609.22	410.47	419.45	135.73
Standard deviation (n-1)	0.66	0.19	39.80	5.85	49.16	1.73	67.89	20.26	20.48	11.65
WHO (2011, 2017)	6.5–8.5	1	75	50	200	12	250	250	250	50

Note: *Unit of the parameters is (mg/l) but the unit of CE parameter is (mS/cm).

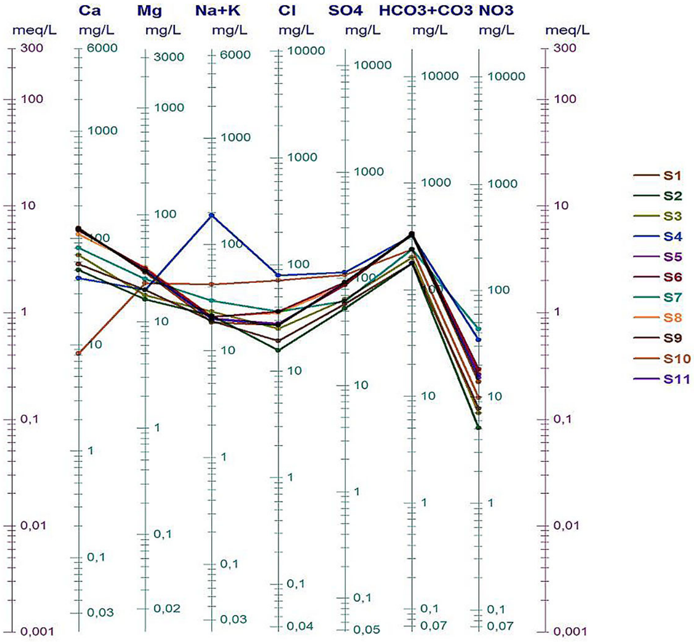

Figure 5. Schöeller Berkaloff logarithmic diagram of water samples in the Oued Ansegmir watershed

In order to clearly identify the hydrogeo-chemical facies and to have an indication of the qualitative hydric aspect, it is necessary to graphically represent the analysis results on a Piper diagram (Figure 6).

By projecting the results of the chemical analysis of the samples onto the Piper diagram, it is possible to distinguish two groups of water, the first comprising samples S4 and S10, which have a potassium sulphate-chloride facies. This facies may be the result of the alteration of certain minerals such as potassium feldspath (in Carboniferous granite) which can release potassium and combine with chlorides or sulfates under certain conditions, we can also add certain soil fertilizers which may contain potassium salts in different forms (KCl and K_2SO_4).

The second group, comprising the rest of the water samples, has a calcic-magnesian bicarbonate facies and this facies typically occurs in environments where water remains in extended contact

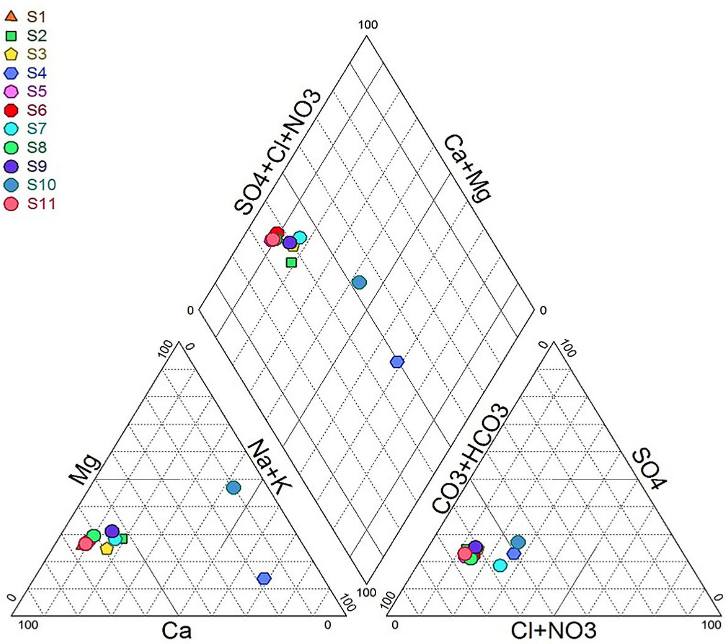

Figure 6. Piper diagram of water samples in the Oued Ansegmir watershed.

with rocks containing carbonates, such as limestone ($CaCO_3$) and dolomite ($CaMg(CO_3)_2$), which release these ions into the water through dissolution.

Quality of water resources

Water quality and suitability for agricultural use were assessed using the WQI model. The WQI calculated for all 11 water samples taken from the OAW revealed the quality status of each of these samples. Relative weights were assigned to the parameters selected for calculating the WQI (Table 3). The WQI results indicate that 36.4% of the water samples were of good quality and 63.6% were of poor quality (Table 4 and Table 5). However, although most samples are poor, they can be used for agricultural irrigation.

Geostatistical analysis

The WQI variability thematic map was prepared for the study area using the universal kriging technique (Figure 7).

The spatial map of WQI values represents the level of water quality by distinct color codes (dark blue to light blue). Low WQI scores (25–50) representing good water quality are observed in the northern and southern parts of the basin, poor quality values (51–75) are observed in a large part of the central west, central and at the outflow which is at the extreme north-east of the basin. Our watershed's poor water quality may be the result of the influx of domestic waste from the population and leaching from agricultural land near the Oued. Moderate values, of good to poor quality, between 42 and 52 are widespread and are not limited to a particular part of the OAW.

Multivariate statistical analysis of physicochemical characteristics

Correlation

The correlation matrix provided offers insights into the relationships between various

Table 4. Results of determination of WQI of surface water resources in the OAW

Samples	Water source	WQI	Water type
S1	stream	52.67	Poor
S2	stream	32.54	Good
S3	Hand-dug wells	33.36	Good
S4	Hand-dug wells	65.26	Poor
S5	Hand-dug wells	55.02	Poor
S6	stream	53.04	Poor
S7	stream	52.09	Poor
S8	stream	51.94	Poor
S9	stream	37.53	Good
S10	stream	36.37	Good
S11	dam	71.38	Poor

Table 5. Classifcation of WQI range and category of water [Mgbenu and Egbueri 2019]

Water quality index	Water quality	Samples in category (%)
0–25	Excellent	–
26–50	Good	4 (36.4%)
51–75	Poor	7 (63.6%)
76–100	Very poor	–
Above 100	Unsuitable	–

Table 3. Relative weight of physicochemical parameters.

Parameter	WHO (2011, 2017)	Weight assigned (wai)	Relative weight (Wr) Wr = wai/∑wai (i = 1 to n = 10)
pH	6.5-8.5	4	0.1481
CE (mS/cm)	1	1	0.0370
Ca^{2+}	75	2	0.0741
Mg^{2+}	50	2	0.0741
Na^{+}	200	2	0.0741
K^{+}	12	2	0.0741
HCO^{3-}	250	2	0.0741
Cl^{-}	250	4	0.1481
SO^{4-}	250	3	0.1111
NO^{3-}	50	5	0.1852
		∑wai=27	∑Wr=1.0000

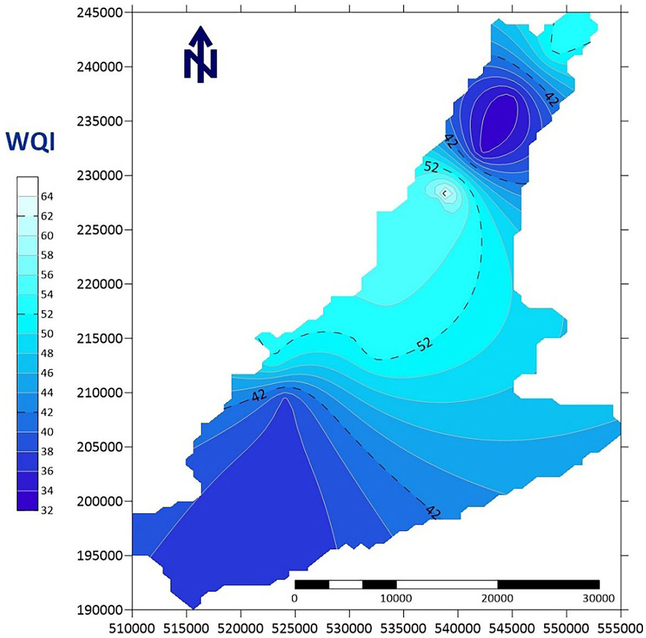

Figure 7. Spatial distribution of WQI in River Ansegmir Watershed

physicochemical variables in water samples from 11 stations (Table 6).

The pH shows moderate positive correlations with Ca^{2+} (0.430) and HCO_3^- (0.344), suggesting that these ions may influence the pH levels. However, pH has weak correlations with most other variables, indicating that it is relatively independent of them. Electrical Conductivity (EC) is strongly positively correlated with HCO_3^- (0.863), SO_4^{2-} (0.867), and Cl^- (0.667), reflecting that EC is influenced by the concentration of dissolved ions. It also has moderate correlations with Mg^{2+} (0.523) and Na^+ (0.650), further supporting that these ions contribute significantly to the conductivity. Ca^{2+} has a strong positive correlation with Mg^{2+} (0.789) and HCO_3^- (0.662), indicating a common geologic source, possibly from carbonate minerals. The strong negative correlation with K^+ (-0.901) suggests a competitive relationship, where the presence of K^+ might inhibit Ca^{2+} concentration in water. Mg^{2+} shows strong correlations with Ca^{2+} (0.789) and HCO_3^- (0.845), pointing to a shared geologic origin. It also has a moderate correlation with SO_4^{2-} (0.421), potentially indicating the influence of sulfate minerals.

Na^+ correlates positively with Cl^- (0.769) and SO_4^{2-} (0.546), typical of water affected by saline intrusion or evaporation. Its negative correlations with Ca^{2+} (-0.402) and Mg^{2+} (-0.292) suggest possible ion exchange processes at play. K^+ shows positive correlations with Na^+ (0.616) and Cl^- (0.787), indicating a similar source, possibly related to human or agricultural activities. Its strong negative correlations with Ca^{2+} (-0.901) and Mg^{2+}

Table 6. Correlation coefficient matrix

Variables	pH	CE (mS/cm)	Ca^{2+}	Mg^{2+}	Na^+	K^+	HCO^{3-}	Cl-	SO^{4-}	NO^{3-}
pH	1									
CE (mS/cm)	0.181	1								
Ca^{2+}	0.430	0.255	1							
Mg^{2+}	0.294	0.523	0.789	1						
Na^+	-0.021	0.650	-0.402	-0.292	1					
K^+	-0.395	0.112	-0.901	-0.597	0.616	1				
HCO^{3-}	0.344	0.863	0.662	0.845	0.205	-0.336	1			
Cl^-	-0.256	0.667	-0.517	-0.058	0.769	0.787	0.268	1		
SO^{4-}	0.109	0.867	0.002	0.421	0.546	0.369	0.722	0.786	1	
NO^{3-}	-0.046	0.564	0.081	0.205	0.505	0.070	0.341	0.439	0.220	1

(-0.597) suggest antagonistic interactions between these ions. HCO_3^- is strongly correlated with EC (0.863), Mg^{2+} (0.845), Ca^{2+} (0.662), and SO_4^{2-} (0.722), signifying that bicarbonate is a major component influencing water chemistry, likely linked to carbonate rocks. Its moderate negative correlation with K^+ (-0.336) suggests complex ion interactions. Cl^- has strong positive correlations with Na^+ (0.769) and K^+ (0.787), hinting at a common origin, often associated with saline water intrusion or contamination. It also shows a moderate correlation with SO_4^{2-} (0.786), which could relate to evaporation processes. SO_4^{2-} is strongly correlated with EC (0.867) and Cl^- (0.786), indicating that sulfate contributes significantly to conductivity. Moderate correlations with Na^+ (0.546) and Mg^{2+} (0.421) may reflect geological or anthropogenic inputs. NO_3^- shows moderate positive correlations with Cl^- (0.439) and Na^+ (0.505), suggesting possible anthropogenic influences, such as agricultural pollution. It has weak correlations with other variables, indicating it is driven by different sources, primarily human activities.

Principal component analysis (PCA)

Table 7 presents the rotated factor loadings for two principal components (PC1 and PC2) from a principal component analysis (PCA) of various water quality variables. The eigenvalues, proportions of variance explained by each component, and cumulative variance are also provided. The first principal component (PC) explains 41.36% of the total variance, while PC2 explains 37.41% of the total variance. Together, PC1 and PC2 account for 78.77% of the total variance, indicating that these two components capture the majority of the variability in the dataset (Figure 8).

PC1 is strongly associated with high negative loadings for electrical conductivity (EC), sulfate (SO_4^{2-}), chloride (Cl^-), bicarbonate (HCO_3^-), and sodium (Na^+). This indicates that PC1 primarily captures the variability related to water salinity and mineral content. The strong correlations suggest that these variables are key contributors to the water's conductivity and overall salinity, which could be influenced by the concentration of dissolved salts. On the other hand, PC2 shows high negative loadings for calcium (Ca^{2+}) and magnesium (Mg^{2+}), and high positive loadings for potassium (K^+) and sodium (Na^+). This component appears to differentiate between water sources rich in alkaline earth metals, like Ca^{2+} and Mg^{2+}, which likely originate from geological sources such as carbonate rocks, and those influenced by alkali metals like K^+ and Na^+. The positive loadings for K^+ and Na^+ suggest an anthropogenic influence, possibly from agricultural activities or urban runoff, indicating a mix of natural and human-related factors affecting water quality.

Regarding the factorial map, we plot the variables on a 2D plane where the *x*-axis represents PC1 and the *y*-axis represents PC2. Each variable's position is determined by its loadings on these components.

Table 7. Rotated factor loadings of principal components

Variables	PC1	PC2
pH	-0.096	-0.521
CE (mS/cm)	-0.974	-0.190
Ca^{2+}	-0.053	-0.971
Mg^{2+}	-0.406	-0.832
Na^+	-0.719	0.504
K^+	-0.315	0.917
HCO^{3-}	-0.754	-0.635
Cl^-	-0.812	0.548
SO^{4-}	-0.908	0.005
NO^{3-}	-0.584	0.005
Eigen values	4.136	3.741
Proportion of variance	41.36%	37.41%
Cumulative proportion of variance	41.36%	78.77%

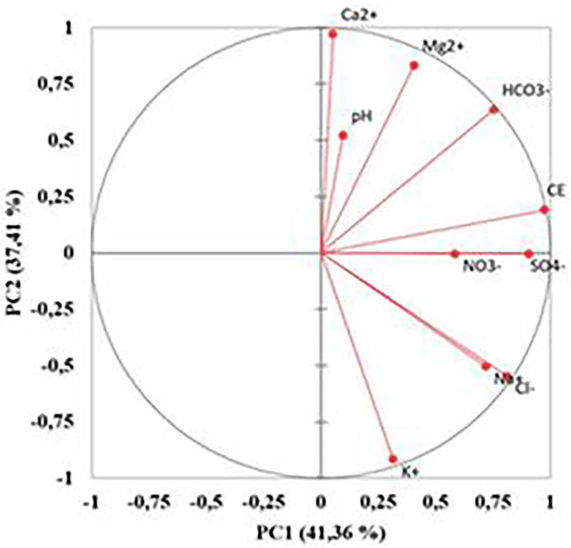

Figure 8. Component plot in rotated space of physico-chemical water factors

Factor scores

Factor scores were listed in Table 8 According to the results of the Table 8, the monitoring points were divided into four groups, as shown in (Fig. 9).

The analysis of Figure 9 allows identification of groups that have taken similar values for certain analysis parameters. We defined four groups that contributed to correlations between analysis parameters.

Group 1 (S1, S11, S5, S6, S8) showed High PC1 scores (high salinity and ion concentration) and high PC2 scores (strong geochemical influence from calcium and magnesium). Indeed, stations in this groupe have high levels of both salinity and geochemical influence. Despite high ion concentrations, the high WQI values suggest that the water quality is generally poor. This implies that the positive effects of the geological factors (calcium and magnesium) may be contributing to better overall water quality, offsetting the impacts of high salinity.

Group 2 (S2, S3, S9, S10) showed low PC1 scores (low salinity and ion concentration) and low PC2 scores (minimal geochemical influence). These results indicated that stations in this group experience low salinity and minimal geochemical benefits, along with poor water quality as indicated by the low WQI values. The combination of low ion concentrations and lack of significant geochemical influence likely contributes to the good water quality.

Group 3 (S7) has relatively low salinity and minimal geochemical influence. The slightly negative scores for both PC1 and PC2 suggest that the water is low in both ions and geochemical factors. WQI value and low salinity associated with a lack of the geochemical factors may explain the low water quality.

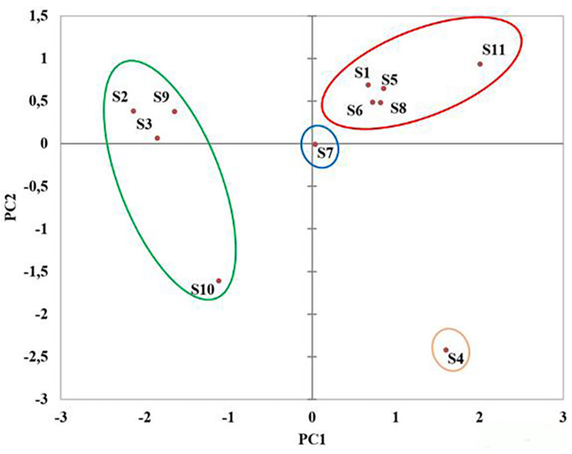

Figure 9. Perceptual map using principal component analysis interactions of factors 1 and 2.

Group 4 (S4) showed high PC1 scores (high salinity and ion concentration) and low PC2 scores (low geochemical influence). This station has high salinity but low geochemical influence, which is contributing to lower water quality.

CONCLUSIONS

In the present study, hydrogeochemical, WQI and PCA analysis were used to evaluate water quality in the OAW. The following conclusions were drawn after studying the assessment of water quality in the OAW:

1. The Schöeller Berkaloff analysis has identified two main facies, specifically a sodium chloride facies (S1 and S4) and a calcium bicarbonate facies (the rest of the samples). The Piper diagram has distinguished two main groups, a potassium sulphate-chloride facies (S4 and S10) and a calcium-magnesium bicarbonate facies (the rest of the samples);
2. The results of the water quality index show that 36.4% of water samples are of good quality and 63.6% of poor quality;
3. The PCA reveals that most of the variability in water quality is driven by two main factors: the first component (PC1) related to salinity and ion concentration, and the second component (PC2) distinguishing between geochemical influences and potential human impacts. These two components provide a comprehensive understanding of the factors influencing water quality across the sampled stations.

To our knowledge, this is the first study to examine the water quality of OAW for agricultural purposes. By combining multiple approaches, our results demonstrate that the water quality in the OAW is adequate for agricultural irrigation. Future research should include the integration of piezometric data to better understand the quantitative water situation in the OAW. This will help clarify the spatio-temporal evolution of water resources, particularly following the installation of agricultural farms under the Green Morocco Plan.

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