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Human health risk assessment (carcinogenic and non-carcinogenic) for heavy metals in groundwater: Case study of the Soummam Basin, Algeria

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ABSTRACT

The contamination of groundwater by heavy metals poses a significant threat to public health, particularly in developing regions. This study evaluates the presence, sources, and health risks associated with six heavy metals (Pb, Cd, Cr, Ni, Zn, Fe) in 135 groundwater samples from the Soummam watershed, located in northeastern Algeria. A combination of multivariate analyses, pollution indices, and quantitative health risk assessment methods was used to identify contamination profiles and their implications. Principal component analysis revealed two major factors explaining 59.80% of the total variance. The first factor, dominated by Pb, Cd, Cr, Zn, and Fe, reflects a strong anthropogenic influence related to industrial discharges and urban pressures. The second factor, characterized by electrical conductivity, pH, and Ni, reflects geogenic processes, particularly the alteration or erosion of nickel-rich geological formations, as well as localized contributions of agricultural origin (use of fertilizers containing nickel). Cluster analysis allowed the samples to be classified into two distinct groups: group 1 (66.67% of the samples), heavily contaminated with Pb and Cd, and group 2 (33.33% of the samples), showing moderate pollution dominated by Ni. The pollution indices (HEI and C_{deg}) confirmed this spatial heterogeneity in groundwater quality. The assessment of non-carcinogenic risks, based on HQ and HI indices for five age groups and three exposure pathways (ingestion, skin contact, inhalation), showed that ingestion is the most concerning pathway, while the other two present negligible risks. The assessment of carcinogenic risks revealed values exceeding the tolerable thresholds for all population groups. Finally, Monte Carlo simulations have reinforced these results, highlighting the persistence of significant health risks related to groundwater contamination in the studied region. These results highlight the need to implement appropriate management measures to ensure the protection of water resources and the health of exposed populations.

Keywords: groundwater, heavy metals, multivariate analysis, pollution indices, health risk assessment, Monte Carlo simulation.

INTRODUCTION

Groundwater is an essential element in the supply of drinking water worldwide, particularly in regions where surface resources are limited. However, the quality of this water is increasingly threatened by multiple sources of pollution, both anthropogenic and natural. Human activities, such as industrial discharges, intensive agricultural practices, and domestic effluents, significantly contribute to the degradation of aquifers by introducing contaminants such as heavy metals, nitrates, and persistent organic compounds (Aspros Santé, 2022). Moreover, natural geochemical processes, such as the dissolution of minerals and the alteration of rocks, can also lead to the release of toxic elements into groundwater (Belkhiri et al., 2017).

Among the most worrying contaminants, heavy metals occupy a central position due to their toxicity, persistence in the environment and propensity for bioaccumulation. Some metals, such as iron (Fe), zinc (Zn) and copper (Cu), are necessary for human metabolism in low doses. On the other hand, others such as lead (Pb), cadmium (Cd), arsenic (As) and mercury (Hg) are highly toxic, even at low concentrations (Marshall et al., 2021; Saha et al., 2022). Their toxicity depends not only on their concentration but also on their chemical form (speciation), their mobility, their bioavailability, and the duration of exposure (Ali et al., 2019; Chowdhury et al., 2023). Indeed, chemical speciation influences the solubility and reactivity of metals, thus affecting their mobility in the environment and uptake by living organisms (Du et al., 2017; Qu et al., 2019). Bioavailability, meanwhile, is modulated by factors such as pH, organic matter and interactions with other ions, determining the fraction of metal actually accessible for biological uptake (Caporale and Violante, 2016). In addition, the duration of exposure plays a crucial role, as chronic exposure, even at low doses, can lead to progressive accumulation in biological tissues, increasing the risk of long-term toxic effects (Chowdhury et al., 2016).

Once released into the environment, these elements can infiltrate aquifers and be absorbed by living organisms. They accumulate in biological tissues and progressively concentrate through the food chain, causing chronic harmful effects such as neurological, hepatic, and renal disorders, as well as cancer diseases (Zhao et al., 2022; Singh et al., 2021). This reality necessitates a rigorous assessment of the health risks associated with prolonged exposure to these contaminants, both in terms of non-carcinogenic and carcinogenic effects (Barkat et al., 2023).

In this context, the present study aims to analyze the spatial distribution of heavy metals in the groundwater of the Soummam watershed, located in the northeast of Algeria, using multivariate statistical methods, particularly principal component analysis (PCA). This approach allows for the identification of the main factors influencing water quality and the determination of potential sources of pollution, whether natural or resulting from human activities (Sanad et al., 2024). The data were interpreted by considering eigenvalues greater than 1 with Varimax rotation to reduce the dimensionality of the factors (Singh et al., 2017).

The level of groundwater contamination was assessed using widely recognized indices, including the degree of contamination (Cdeg) and the heavy metal evaluation index (HEI), to quantify the overall pollutant load (Sbai et al., 2024). Moreover, a quantitative health risk assessment was conducted for each metal, in accordance with the methodology established by the USEPA (2016). This approach was based on the calculation of hazard quotients (HQ) and the hazard index (HI), taking into account three main exposure pathways (ingestion, dermal absorption, and inhalation), as well as different age groups. In order to distinguish between potentially non-carcinogenic effects (related to systemic toxicity) and carcinogenic effects (related to the probability of developing cancer) (Khan et al., 2023). This analysis was strengthened by the use of Monte Carlo probabilistic simulations, in order to incorporate the uncertainty and variability of exposure parameters and to enhance the robustness of the obtained results. This methodology provides a comprehensive framework for understanding the severity and probability of adverse health effects associated with groundwater contamination by heavy metals.

The results of this study aim to support informed decision-making by local water management authorities, in order to implement targeted mitigation strategies and ensure the long-term sustainability of groundwater resources.

The ultimate aim is to help prevent the health risks associated with metal pollution and preserve groundwater quality for future generations. This study proposes a novel and comprehensive approach by combining multivariate statistical analysis, pollution indices and deterministic and probabilistic human health risk assessment (including multiple exposure pathways and populations of different age groups to obtain an accurate assessment) in a region that has been insufficiently studied to date: the Soummam watershed in northeastern Algeria.

MATERIALS AND METHODS

Study area and sampling locations

This study was conducted in the Soummam watershed, a large hydrological basin located in northeastern Algeria (Figure 1). It spans three administrative provinces (wilayas): Bejaia, Setif, and Bouira. This basin covers an area of approximately 9,200 km², with a perimeter of 554 km, between latitudes 36°15′ and 36°45′ N and longitudes 4°30′ and 5°30′ E (Ould Fah, 2016; Turki et al., 2016). It stretches from the highlands of the Tellian Atlas Mountains in the south, where altitudes exceed 2,000 meters (Djurdjura Mountains), to the coastal

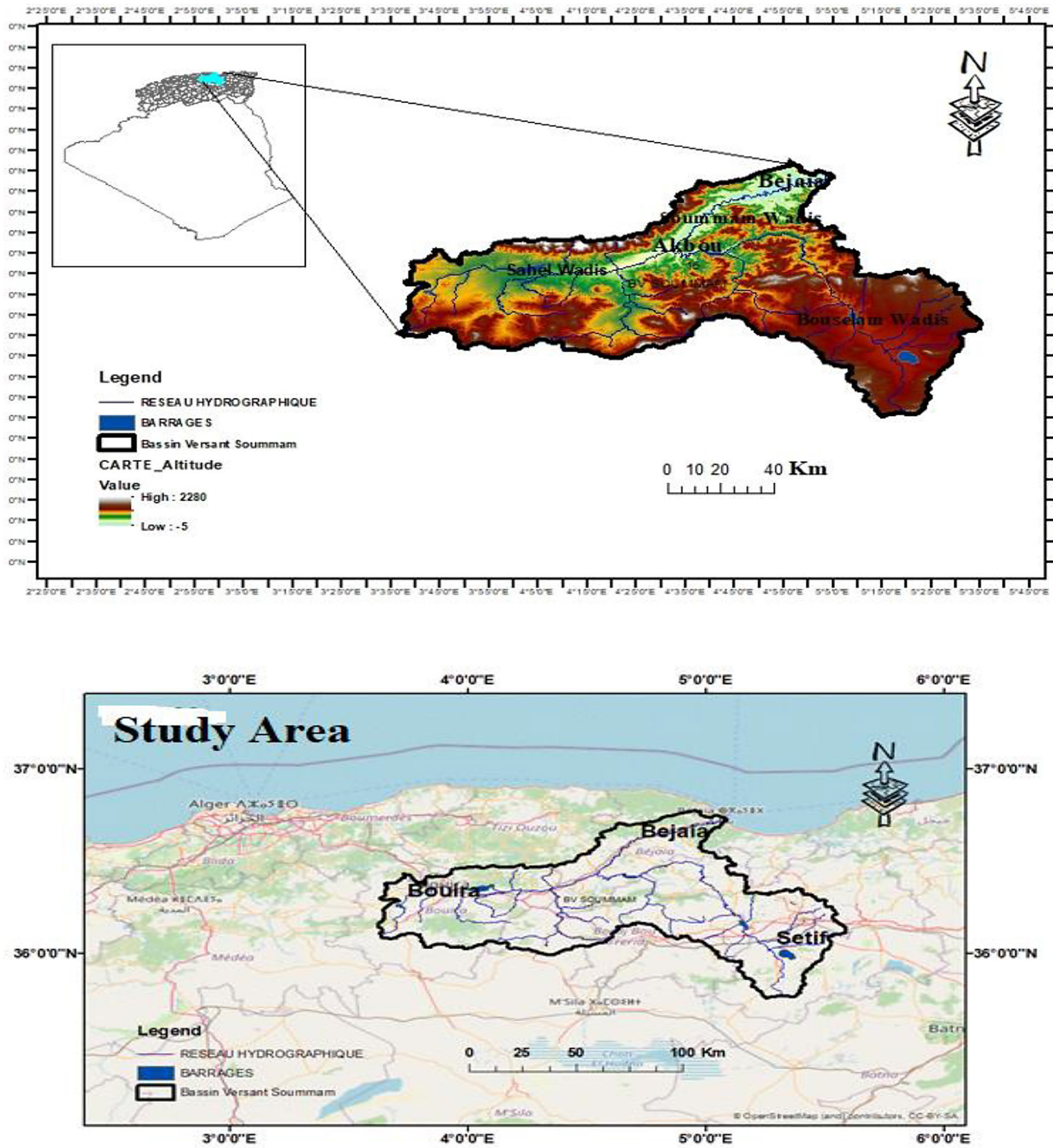

Figure 1. Geographical location of the study area

plains of Bejaia, where the Soummam River flows into the Mediterranean Sea. The region has a wide variety of topography and climate, with a humid Mediterranean climate on the coast, becoming semi-arid to continental in the highlands. Annual rainfall varies from over 1.200 mm on the coast to around 400 mm inland, contributing significantly to the recharge of underground aquifers (Turki et al., 2016). Hydrologically, it has a dense and hierarchical hydrographic network, dominated by three main watercourses: the Boussellam, Sahel, and Soummam wadis. The Boussellam River, which drains the high plains of Setif, joins the Sahel River in the Akbou region to form the Soummam River, which crosses the valley to the northeast before flowing into the Mediterranean Sea at Bejaia (ANRH, 2009; Ould Fah, 2016).

This region is subject to significant anthropogenic pressure, particularly in densely populated areas such as Bejaia, where urban, agricultural, and industrial development is constantly increasing. Intensive agricultural practices (fertilizers, pesticides), domestic and industrial waste, and overexploitation of groundwater resources are potential sources of contamination, particularly by heavy metals (Hamhoum and Aoudia, 2015).

In this context, the Soummam watershed is a critical area for assessing groundwater quality and health risks associated with contamination by trace metals.

The methodology used is based on the application of multivariate statistical methods, such as ascending hierarchical classification (AHC) and standardized PCA, as well as pollution indices and health risk assessment approaches to better understand the extent of contamination and its potential impacts on human health.

To this end, 135 groundwater samples were collected throughout the Soummam watershed during the dry season of July and August 2023. The locations of each sampling point are shown in Figure 2. The physicochemical parameters measured were temperature (T), pH, and electrical conductivity (EC), using a portable multiparameter HANNA Instruments model HI991300N, specifically designed for in situ water quality monitoring. The concentrations of heavy metals such as Pb, Cd, Cr, Ni, Zn, and Fe were determined by graphite furnace atomic absorption spectrometry, in accordance with standard analytical protocols.

The reference sample from the World Health Organization (WHO, 2022) and the Official Journal of the Algerian Republic (JORADP, 2011), as well as the statistical summary of the water samples, are compared in Table 1.

Various software programs were used to process, analyze, and visualize the data. Descriptive statistical analysis (minimum, maximum, and average values, standard deviations), comparison of parameter averages, and verification of their compliance with potability standards were performed using Microsoft Excel.

Mapping of the study area, including location maps, elevation maps, hydrographic network maps, and sampling point maps, was performed using ArcGIS 10.8.2 software.

Multivariate statistical analyses, including PCA and AHC, were performed using IBM SPSS Statistics 26.0, which also enabled the production of the graphs required for the multivariate statistical study. Finally, the Monte Carlo simulation was coded in Python and executed via the PyCharm Community Edition 2023.1.1 development environment (Table 2).

Multivariate statistical methods

Factor analysis

Factor analysis was applied with the aim of identifying and modeling the underlying structure of the data by reducing it to a limited set of orthogonal variables (which are not correlated), called principal components (PCs), ranked according to their decreasing contribution to the total variance. This method not only allows for a significant reduction in dimensionality but also ensures optimal preservation of the initial information contained in the multidimensional data. In order to improve

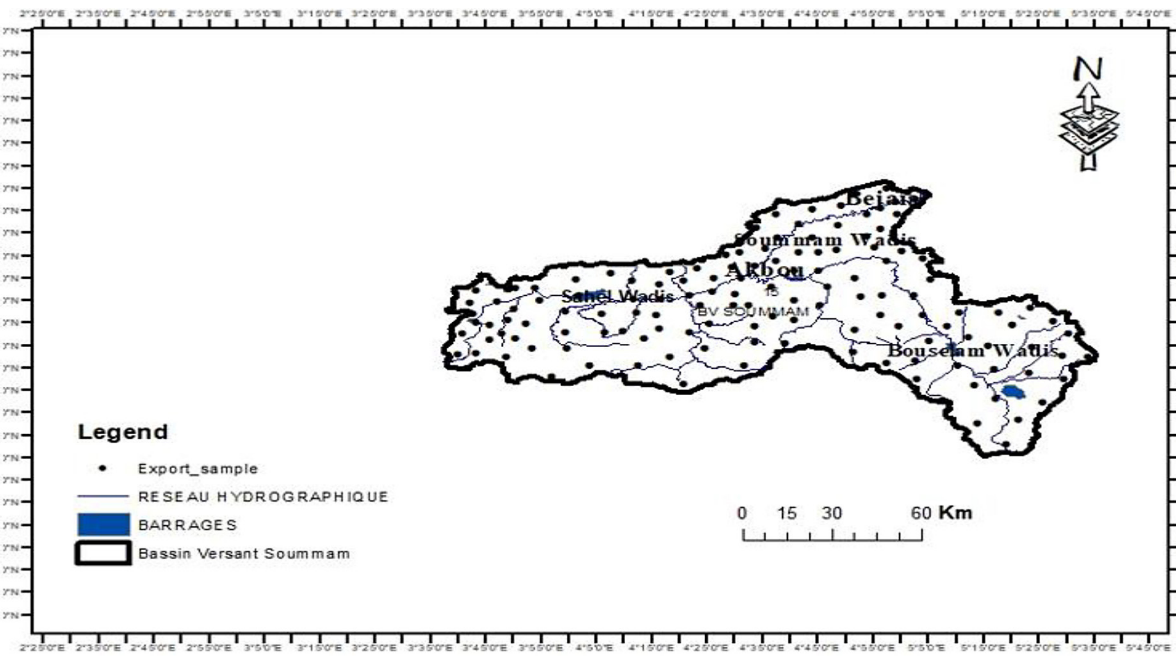

Figure 2. Spatial distribution of groundwater sampling points

Table 1. Descriptive statistics for the parameters studied

Parameters	Units	Min	Max	Mean	SD	Algerian standard (2011)	WHO standard (2022)
T°C	°C	12.2	18.6	14.66	1.31	25	25
pH		6.1	8.3	7.41	0.36	6.5–8.5	6.5–8.5
EC	µS/cm	368	1567	966.29	277.13	2800	1000
Pb	mg/L	0.0008	0.683	0.129	0.154	0.01	0.01
Cd	mg/L	0.0006	0.258	0.027	0.041	0.003	0.003
Cr	mg/L	0.0007	0.163	0.028	0.039	0.05	0.05
Ni	mg/L	0.0005	0.361	0.019	0.051	0.07	0.07
Zn	mg/L	0.0009	0.256	0.041	0.057	3	3
Fe	mg/L	0.0011	0.68	0.091	0.119	0.3	0.3

Table 2. Pearson correlation matrix

Parameters	T°	EC	pH	Pb	Cd	Cr	Ni	Zn	Fe
T°	1								
EC	0.04	1							
pH	-0.24	0.24	1						
Pb	0.45	0.01	-0.41	1					
Cd	0.30	0.06	-0.38	0.50	1				
Cr	0.31	-0.07	-0.38	0.70	0.57	1			
Ni	0.17	-0.25	-0.10	0.28	0.31	0.29	1		
Zn	0.49	0.01	-0.44	0.72	0.51	0.71	-0.002	1	
Fe	0.46	-0.10	-0.33	0.70	0.47	0.58	0.31	0.62	1

the interpretability of the results, an orthogonal Varimax rotation was applied to the standardized factor loadings. The selection of the retained components was based on the Kaiser criterion, which considers only the components with an eigenvalue greater than 1 as significant (Goretzko et al., 2021). Moreover, the quality of the sampling was verified using the Kaiser-Meyer-Olkin (KMO) index, whose value exceeding 0.7 indicates a satisfactory adequacy, and Bartlett's test of sphericity, whose significant result ($p < 0.05$) confirms the sufficient correlation between the variables to justify the analysis. This factorial approach thus helps to extract latent structures while ensuring the independence of the factors, making it a powerful tool for the analysis of complex environmental data (Rohe and Zeng, 2023).

Cluster analysis

Cluster analysis (CA) was applied to group objects (cases) into categories or clusters on the basis of similarities within a group and dissimilarities between different groups as a function of distance between objects. Agglomerative hierarchical analysis of all standardized data was performed using Euclidean distances as similarity and Ward's method to formulate the dendrograms.

Pollution assessment indices

Assessment of groundwater quality in terms of metal pollution is based on indices such as the degree of contamination (C_{deg}) and the heavy metal assessment index (HEI).

The contamination index (C_{deg}) is based on the recognition of pollution diffusion, and quantifies the degree of contamination as a function of measured concentrations in relation to permissible standards. Generally, C_{deg} is classified into three levels: low ($C_{deg} < 1$), medium ($1 \le C_{deg} < 3$) and high ($C_{deg} > 3$) (Backman et al., 1998). It was calculated from the following equations:

$$C_{deg} = \sum_{i=1}^{n} C_{fi} \tag{1}$$

$$C_{fi} = \frac{C_{Ai}}{C_{Ni}} - 1 \tag{2}$$

where: C_{fi} is the contamination factor for the ith component, C_{Ai} is the analytical value for the ith component, et C_{Ni} is the maximum permissible concentration of the ith component (N is the normative value).

Furthermore, the HEI provides a comprehensive assessment of the metal load in groundwater, thereby facilitating the classification of pollution levels. According to the established criteria, HEI values are generally interpreted as follows: HEI < 10 indicates low pollution (Good quality water), 10 ≤ HEI < 20: Moderately contaminated water, and HEI ≥ 20: Highly contaminated water (Edet and Offiong, 2002). The index was determined based on the following relationship:

$$HEI = \sum_{i=1}^{n} \frac{H_c}{H_{MAC}} \tag{3}$$

where: H_c and H_{MAC} are the measured value and the maximum allowable concentration (MAC) of the ith parameter, respectively.

Recent studies have confirmed the effectiveness of these indices in various regions, particularly in assessing heavy metal contamination of groundwater (Rajkumar et al., 2020; Verma et al., 2021).

Human health risk assessment

In the context of the present study, the assessment of health risks associated with heavy metals in the groundwater of the Soummam watershed was conducted in accordance with the methodological recommendations of the United States Environmental Protection Agency (USEPA, 1989, 2004). This approach distinguishes non-carcinogenic effects, assessed using the hazard quotient (HQ) and the hazard index (HI), and carcinogenic effects, estimated by the individual risk (CR).

The HQ and HI values were calculated by comparing the estimated daily exposure (via ingestion, skin contact, or inhalation) to the reference doses (RfD) considered as having no observable adverse effect for humans (Table 3). For carcinogenic substances, the risk is determined based on slope factors (SF) that translate the probability of cancer occurrence as a function of the cumulative dose (Table 4). All calculation equations are derived from the framework established in the Risk Assessment Guidance for Superfund (USEPA, 1989), supplemented by the updated guidelines of the Human Health Risk Assessment Framework (USEPA, 2004; USEPA, 2016).

This integrated method allows for a differentiated quantification of health risks by taking into account multiple exposure pathways, the variability of population groups, and the inherent uncertainty of exposure parameters, particularly through the application of Monte Carlo probabilistic simulations. It proves particularly relevant in a complex hydrogeochemical context and under strong anthropogenic pressure, such as that of the studied region.

Assessment of non-carcinogenic risks

The assessment of non-carcinogenic risks associated with exposure to heavy metals in groundwater is based on three main exposure routes: ingestion, inhalation and dermal absorption. Of these, ingestion and dermal absorption are the most common in the context of contaminated water (USEPA, 2016). The numerical formulas used to estimate exposure doses were derived from U.S. Environmental Protection Agency's Risk Assessment Guidance for Superfund (RAGS) method (USEPA, 2016).

$$Exp_{ingestion} = \frac{C_{Water} \times IR \times EF \times ED}{BW \times AT} \tag{4}$$

$$Exp_{dermal} = \frac{C_{Water} \times SA \times K_p \times ET \times EF \times ED \times CF}{BW \times AT} \tag{5}$$

$$Exp_{inhalation} = \frac{C_{Water} \times InhR \times ET \times EF \times ED}{PEF \times BW \times AT} \tag{6}$$

where: $Exp_{ingestion}$ – water ingestion exposure dose (kg/day), Exp_{dermal} – exposure dose by skin absorption, $Exp_{inhalation}$ – inhalation exposure dose, C_{water} estimated concentration of metals in groundwater (μg/l), IR – ingestion rate (2.2 l/day), EF – exposure frequency (365 days/year), ED – exposure time (30 years), BW – average body weight (kg), AT – average length of exposure (25,550 days), SA – exposed skin surface (18 cm^2), ET – exposure time (0.58 h/day), CF – unit conversion factor

Table 3. Reference dose factor (USEPA, 2016)

Chemical elements	RfD $_{Ingestion}$	RfD $_{Dermal}$	RfD $_{Inhalation}$
Pb	1.4	0.42	14
Cd	0.5	0.2	0.5
Cr	0.5	0.3	3
Ni	0.02	0.02	0.025
Zn	0.3	0.3	0.35
Fe	0.7	0.7	0.8

Table 4. Carcinogenic slope factor of selected heavy metals

Heavy metal	Cancer slope factor (CSF;kg/day/mg)
Pb	0.085
Cd	6.1 (CALEPA)
Cr	0.5 (CALEPA)
Ni	1.7 (CALEPA)
Zn	Not considered toxic by USEPA
Fe	Not considered toxic by USEPA

(0.0001 l/cm^3), K_p – skin permeability coefficient (0.35), *InhR* – inhalation rate, *PEF* – particle emission factor.

Parameters used for non-carcinogenic risk assessment, such as HQ and HI, are established in accordance with USEPA guidelines (USEPA, 2016).

$$HQ_{Ing/\,derm/\,inh} = \frac{Exp_{ing/\,derm/\,inh}}{RfD_{ing/derm/\,inh}} \tag{7}$$

$$HI_{\frac{ing}{\frac{derm}{inh}}} = \sum_{i=1}^{n} HQ_{ing/derm/inh} \tag{8}$$

where: $HQ_{ing/derm/inh}$ – ingestion/dermal/inhalation hazard quotient (unitless), $HI_{ing/derm/inh}$ – ingestion/dermal/inhalation hazard index (without unit), $RfD_{ing/derm/inh}$ – ingestion/dermal/inhalation reference dose (µg/kg/day).

It is generally considered that an HI less than 1 indicates the absence of significant risk of non-carcinogenic effects, and if HI > 1 Possibility of adverse effects.

Assessment of carcinogenic risk

The ingestion route was used to characterize the carcinogenic risk in the present study, since it is identified as the main route of exposure for heavy metals present in the groundwater of our basin. Exposure doses show that ingestion leads to higher levels of contamination than inhalation and dermal exposure. Carcinogenic risk assessment enables us to effectively guide, manage and protect populations at risk.

The carcinogenic risk (CR) can be determined by multiplying CDIing by the carcinogenic slope factor (CSFing), measured in mg/kg/day (Equation 9).

$$CRing = CDIing \times CSFing \tag{9}$$

According to the USEPA: CRing < 10^{-6}: Negligible risk; $10^{-6} \leq$ CRing $\leq 10^{-4}$: Acceptable risk according to certain regulations; CRing > 10^{-4}: Risk of concern, requiring management measures.

CSFing values for all the heavy metals studied are listed in Table 4, while CRing values describing the carcinogenic risk are recorded in Table 10.

Monte Carlo simulation techniques

The deterministic approach is not capable of examining risk accurately, due to natural variabilities and measurement uncertainties. Monte Carlo simulation is used as a solution for this problem, as it generates a large number of possible scenarios and serves to model data variability.

This method makes it possible to evaluate the probable distribution of HI and CR (for modeling non-carcinogenic/carcinogenic risk assessments), calculate the probability of exceeding the critical threshold and visualize the uncertainty of the results, thus providing a decision-support tool for environmental risk management.

In addition, in order to obtain a reliable simulation of the non-carcinogenic and probable carcinogenic risk distribution estimate, we generated 10.000 iterations using Python code (PyCharm Community Edition 2023.1.1). We chose a lognormal distribution because environmental risk indices often have skewed distributions.

Taking into account oral, dermal and inhalation exposure modes in five communities of various age groups. The 95th and 5th percentile risk exposures were indicative of best-case and worst-case scenarios, respectively. Consistency between actual and simulated values was used to calibrate model performance.

By integrating this simulation with the USEPA's health risk assessment framework, we can assess the adverse effects of heavy metal exposure, estimating probability distributions of non-carcinogenic risk using the HI risk index (Figure 5), and probability distributions of carcinogenic risk using the CR carcinogenic risk index (Figure 6).

RESULTS AND DISCUSSION

The descriptive statistics for the study area, presented in Table 1, indicate that the quality of groundwater in the Soummam watershed varies significantly, reflecting the complexity of local hydrogeochemical conditions. The EC of the samples varies between 368 and 1567 µS/cm, with an average of 966.29 µS/cm, reflecting a degree of mineralization ranging from low to high. This wide range reflects marked heterogeneity in hydrochemical conditions within the basin, suggesting the combined influence of several processes affecting the chemical composition of groundwater. Among natural factors, the dissolution of carbonate formations (calcite, dolomite) and evaporite minerals (gypsum, halite) plays a major role in the ionic enrichment of water. However, the highest values could also reflect anthropogenic inputs, particularly in densely populated areas or areas of intensive agricultural use, where domestic discharges, industrial effluents, and fertilizer use can increase salinization. Thus, the relatively high average EC highlights a complex interaction between geogenic and anthropogenic sources, illustrating the duality of the mechanisms responsible for the mineralization observed in the basin's groundwater. The water temperature ranges from 12.2 °C to 18.6 °C, with an average of 14.66 °C, which is consistent with a shallow aquifer influenced by seasonal variations. The pH varies between 6.1 and 8.3, with an average of 7.41, indicating a slightly alkaline character, typical of groundwater flowing through carbonate terrain.

Heavy metal analysis reveals worrying average concentrations of lead (0.129 mg/L) and cadmium (0.027 mg/L), which are significantly higher than WHO standards (2022) and Algerian standards (JORADP, 2011). These pose serious health risks, particularly for vulnerable populations such as children and pregnant women. These metals are toxic even at low concentrations and are known to affect the nervous system, kidneys, and bone metabolism. The other metals analyzed (Cr, Ni, Zn, Fe) have average concentrations below regulatory thresholds, although Fe and Zn, while not toxic at these levels, can cause organoleptic discomfort (metallic taste, discoloration, deposits). The descending order of average heavy metal content in groundwater was as follows: Pb > Fe > Zn > Cr > Cd > Ni.

Analysis of Pearson's correlation matrix (Table 2) revealed a negative correlation between pH and heavy metals, suggesting that slightly acidic conditions promote the solubility and mobility of metals, resulting in higher concentrations in groundwater. This relationship confirms that pH variations play a key role in the distribution of metals in the aquifer studied. Furthermore, the strong positive correlations between several heavy metals, notably Pb, Cd, Cr, Zn, and Fe, indicate a possible common origin or similar mobilization mechanisms. Given the hydrochemical context and human land use, this association reinforces the hypothesis of a predominantly anthropogenic origin, particularly industrial or urban.

The high presence of Pb and Cd above regulatory thresholds, combined with their significant correlations with other metals, suggests a worrying environmental and health risk. These results underscore the need to implement urgent mitigation measures, including the identification of contamination sources, regular monitoring of water quality, and targeted corrective actions.

In order to further this analysis and better understand the mechanisms of distribution and association of heavy metals in the groundwater of the Soummam watershed, a PCA was performed. This multivariate statistical approach makes it possible to identify the dominant factors responsible for the observed chemical variability, highlighting groups of metals influenced by common geogenic or anthropogenic processes. Principal component analysis (PCA) made it possible to synthesize the variability of the data into two main factors, accounting for 59.80% of the total variance. The principal components selected are those with eigenvalues greater than 1, in accordance with Kaiser's criterion, in order to ensure a meaningful explanation of the variance in the data (Table 5). The first principal component (PC1), explaining 45.65% of the total variance, is strongly correlated with heavy metals (Zn, Pb, Cr, Fe, Cd) and temperature (Table 6). The associated factor loadings are as follows: Zn (0.88), Pb (0.87), Cr (0.81), Fe (0.78), Cd (0.70) and temperature (0.62). This configuration suggests a predominantly anthropogenic origin, potentially linked to industrial activities, road traffic and urban discharges. The presence of temperature as a correlated variable can be explained by its catalytic effect on the solubility of metals and their mobility in the aquifer. It could also accentuate their dispersion by promoting their diffusion through hydrogeologically permeable areas. The second principal component (PC2), representing 14.15% of the total variance, is dominated by high factor loadings for electrical conductivity (-0.83), nickel (-0.70), and pH (0.51). This component reflects the predominant influence of natural geochemical processes, particularly groundwater mineralization linked to the dissolution of source rocks and the mineralogical composition of the basin. The strong negative correlation with EC suggests chemical variability structured by geogenic factors. Ni, which is also highly loaded, could come from natural sources, including erosion or weathering of Ni-rich rocks. However, an anthropogenic contribution cannot be ruled out, particularly through the use of phosphate fertilizers or other agricultural inputs. This factor thus illustrates the interaction between natural (geogenic) sources and localized anthropogenic inputs linked to agricultural practices.

The relationships between the variables based on the first two factors are illustrated in Figure 3.

The projection of variables on the factorial plane confirms a clear separation between them: heavy metals (Zn, Pb, Cr, Fe, and Cd) and temperature are grouped together on PC1, confirming that they have a common source (anthropogenic pollution), while CE and Ni are clearly separated on PC2. pH appears isolated because it does not strongly load a single factor; it acts directly on several parameters, reflecting its cross-cutting and modulating role in chemical processes, notably influencing the solubility, mobility, and speciation of heavy metals.

Hierarchical classification analysis grouped the 135 samples into two distinct clusters (Figure 4), with significant differences in chemical composition, thus verifying and complementing the PCA results. The first group (Cluster 1) comprised 66.67% of the samples, had a high average electrical conductivity (1125.26 µS/cm) and maximum concentrations of Cd (0.26 mg/l), Cr (0.16 mg/l) and Fe (0.68 mg/l). This group includes water samples that share similarities in their heavy metal content, influenced by sources of intense anthropogenic pollution. The second group (Cluster 2) occupied 33.33% of the samples, with moderate average electrical conductivity (648.36

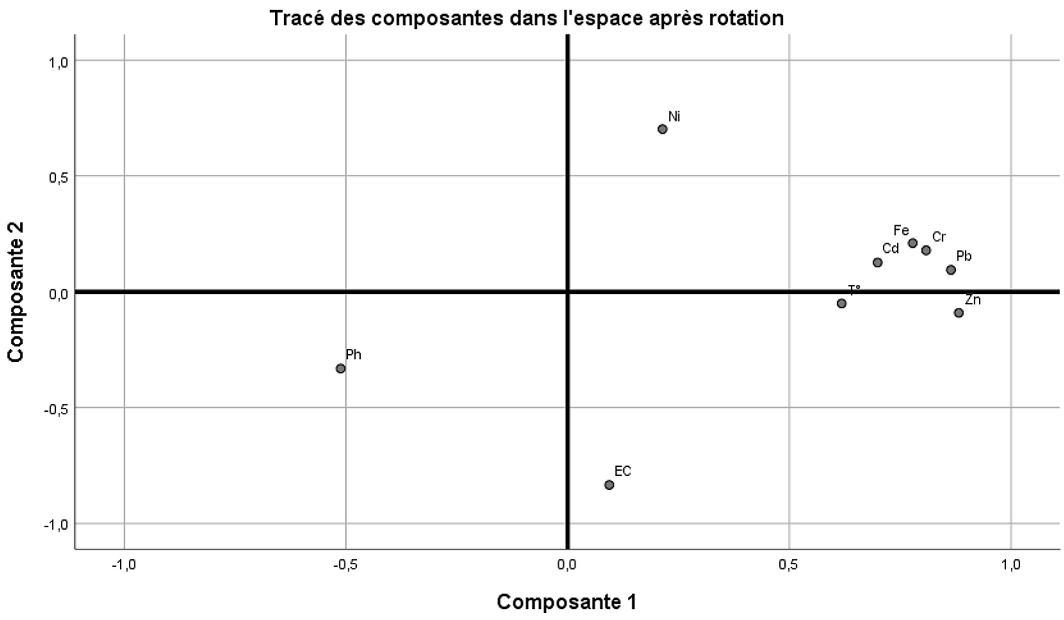

Figure 3. PCA results showing chemical variables in the factorial plane

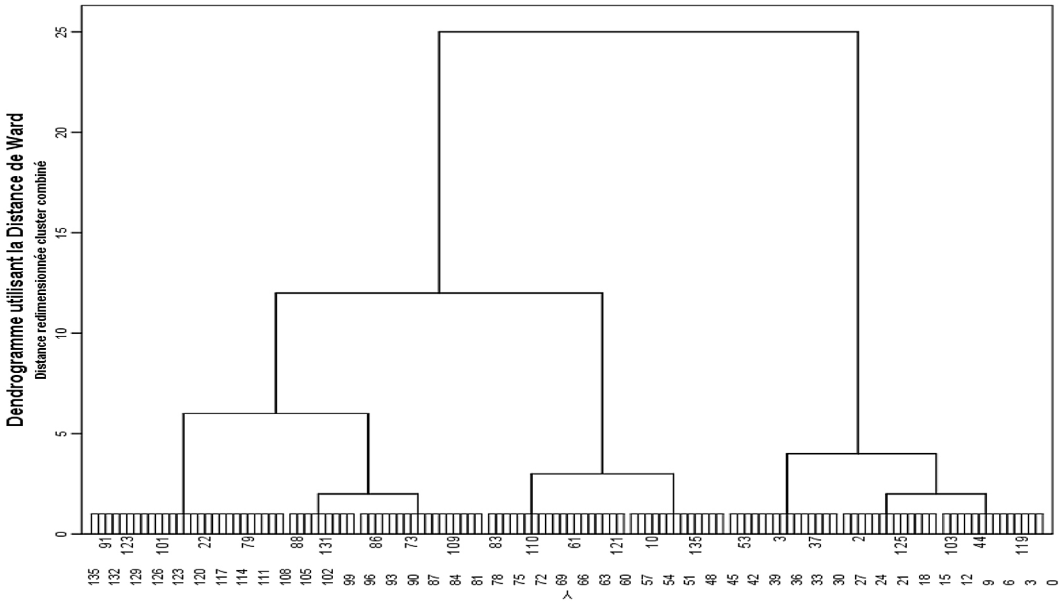

Figure 4. Hierarchical clustering results for groundwater samples

Table 5. Factor analysis of groundwater data. Significant factors (> 1) are shown in bold

Component	Eigenvalues	% of variance	Cumulative %
1	**4.11**	**45.65**	**45.65**
2	**1.27**	**14.15**	**59.80**
3	0.96	10.62	70.41
4	0.79	8.78	79.19
5	0.64	7.09	86.28
6	0.44	4.86	91.14
7	0.38	4.25	95.39
8	0.24	2.65	98.035
10	0.18	1.97	100

µS/cm). This group of samples recorded the highest Ni concentrations (0.36 mg/l), which could be the result of the alteration of Ni-rich rocks. It may also be influenced by physicochemical parameters such as pH and conductivity. This indicates that mineralization, associated with acid-base conditions, plays an important role in the dispersion of nickel in groundwater. This group may reflect groundwater with a different chemical signature, whose quality is mainly controlled by specific natural or anthropogenic geochemical processes. These intergroup differences validate the observations from the PCA.

Analysis of the results of the C_{deg} and HEI groundwater pollution indices (Table 7) has made it possible to clearly differentiate between the two clusters identified in the Soummam watershed. Cluster 1 has particularly high values, with a C_{deg} of 1391.3 and an HEI of 1931.3, reflecting a critical groundwater contamination situation. This pollution is dominated by excessive concentrations of Pb, Cd, and other heavy metals, probably resulting from anthropogenic activities such as industrial discharges, mining, or intensive use of fertilizers and pesticides in agriculture. In contrast, Cluster 2, although still affected, shows moderate pollution with C_{deg} and HEI values of 539.83 and 1199.14, respectively. This situation suggests the presence of more diffuse or less concentrated sources of pollution, and potentially moderate dispersion of contaminants by natural processes. These results highlight the need for differentiated interventions. Cluster 1 requires immediate corrective measures, including the identification and control of point sources of pollution, as well as improved water quality monitoring. At the same time, preventive measures and

Table 6. Rotation of the component matrix

Variables	Component 1	Component 2	Communalities
T°	0.62	-0.05	0.39
EC	0.09	-0.83	0.70
pH	-0.51	-0.33	0.37
Pb	0.87	0.09	0.76
Cd	0.70	0.13	0.51
Cr	0.81	0.18	0.69
Ni	0.21	0.70	0.54
Zn	0.88	-0.91	0.79
Fe	0.78	0.21	0.65

Table 7. Description of pollution assessment indices for selected heavy metals (mg/l) in groundwater samples

Parameter	MAC			Cluster 1		Cluster 2	
		Mean	HEI	C_{deg}	Mean	HEI	C_{deg}
Pb	0.01	0.12	1045.54	955.54	0.15	693.79	648.79
Cd	0.003	0.03	804.6	714.6	0.03	432.57	-1.74
Cr	0.05	0.03	44.71	-45.29	0.03	30.52	-14.48
Ni	0.07	0.01	12.36	-77.64	0.04	23.74	-21.26
Zn	3	0.04	1.14	-88.86	0.05	0.70	-44.30
Fe	0.3	0.08	22.95	-67.05	0.12	17.82	-27.18
$\sum HEIet\ C_{deg}$			1931.3	1391.3		1199.14	539.83

continuous monitoring should be considered in areas corresponding to Cluster 2 in order to limit the worsening of contamination and preserve the quality of groundwater resources in the long term.

In order to better understand the potential effects of heavy metals in groundwater on human health, a health risk assessment was conducted. We determined the daily exposure doses (Table 8), taking into account three main routes (ingestion, skin contact, and inhalation), thus covering all possible modes of transfer of contaminants to the body. In addition, the study was conducted on five distinct age groups, representing different physiological sensitivities: (0–6 years), (7–15 years), (16–25 years), (26–50 years), and (> 50 years). This stratification makes it possible to identify the most vulnerable groups and to adapt risk management measures according to the exposure profile specific to each population category.

The results obtained reveal significant variability in heavy metal exposure levels depending on age group and route of exposure. Young children aged 0 to 6 appear to be the most vulnerable group, with the highest exposure levels, particularly through oral exposure. The estimated daily doses for this group reach 2.73 mg/kg/day for Pb and 1.92 mg/kg/day for Fe, values that are considered concerning in terms of toxicity thresholds. This increased exposure is explained by their low body weight, their relatively high water consumption in relation to their mass, and their still-developing metabolic system. A gradual decrease in exposure doses is observed with advancing age, with adults and the elderly showing significantly lower levels. For all groups studied, the estimated average exposure doses through ingestion (Exp_{ing}), skin contact (Exp_{derm}), and inhalation (Exp_{inh}) were in the following order: Pb > Fe > Zn > Cr > Cd > Ni. The results highlight the predominance of lead and iron in overall contributions to risk through ingestion, while cadmium, chromium, and nickel, although present in lower concentrations, pose potential long-term threats due to their cumulative toxicity. The analysis thus highlights a clear hierarchy of risks, both in terms of age and type of metal, and fully justifies the choice of a multi-pathway and multi-group assessment to comprehensively understand the health impacts associated with groundwater contamination.

Table 8. Daily exposure by ingestion, dermal and inhalation routes in five populations

Heavy metal	(0–6)			(7–15)			(16–25)			(26–50)			> 50		
	Exp_{ing}	Exp_{derm}	Exp_{inh}	Exp_{ing}	Exp_{derm}	Exp_{inh}	Exp_{ing}	Exp_{derm}	Exp_{inh}	Exp_{ing}	Exp_{derm}	Exp_{inh}	Exp_{ing}	Exp_{derm}	Exp_{inh}
Pb	2.73	4.99E-4	6.36E-10	1.03	1.89E-4	2.41E-10	0.66	1.21E-4	2E-10	0.56	1.03E-4	1.7E-10	0.55	9.99E-5	1.65E-10
Cd	0.58	1.07E-4	1.36 E-10	0.22	4.03E-5	5.13 E-11	0.14	2.57 E-5	4.26 E-11	0.12	2.19 E-5	3.63 E-11	2.34E-12	2.13 E-5	3.53 E-11
Cr	0.59	1.08E-4	1.37E-10	0.22	4.09E-5	5.2E-11	0.14	2.61E-5	4.31E-11	0.12	2.22E-5	3.68E-11	0.12	2.16E-5	3.58E-11
Ni	0.4	7.26E-5	9.24E-11	0.15	2.75 E-5	3.5E-11	0.1	1.75 E-5	2.9E-11	0.08	1.49E-5	2.47E-11	0.08	1.45E-5	2.4E-11
Zn	0.87	1.58E-4	2.02E-10	0.33	5.99E-5	7.63E-11	0.21	3.82E-5	6.33E-11	0.18	3.26E-5	5.4E-11	0.17	3.17E-5	5.24E-11
Fe	1.92	3.51E-4	4.47E-10	0.73	1.33E-4	1.69E-10	0.46	8.48E-5	1.4E-10	0.4	7.23E-5	1.2E-10	0.38	7.02E-5	1.16E-10

The non-carcinogenic risk assessment parameters associated with heavy metals detected in groundwater in the Soummam watershed were estimated for the three exposure routes and for the five defined age groups. Table 9 presents detailed calculations of the hazard quotient (HQ) and the non-carcinogenic risk index (HI). The results highlight that ingestion is the main route of exposure for all population groups, with HI_{ing} values significantly higher than those for dermal (HI_{derm}) and inhalation (HI_{inh}) routes. Among children aged 0 to 6, the risk is particularly worrying, with an HIing index reaching 29.8, well above the safety threshold of 1, indicating an extremely high health risk. Although this trend remains observable in other age groups, the intensity of the risk decreases gradually with age. All heavy metals assessed contributed, to varying degrees, to the total risk through ingestion. The descending order of contribution to HIing is as follows: Ni > Zn > Fe > Pb > Cr > Cd. Nickel (Ni) stands out as the main contributor to chronic non-carcinogenic risk, due to its high cumulative toxicity and significant presence. Skin exposure, although secondary, is not negligible, particularly in children (HIderm = 6.72×10^{-3}), while inhalation exposure remains marginal, with HIinh values ranging from 10^{-4} to 10^{-9}, suggesting a negligible health impact.

Furthermore, the assessment of the carcinogenic risk associated with heavy metals (Table 10) shows that all populations studied have a risk level above the critical threshold of 10^{-4}, suggesting significant exposure to potentially carcinogenic substances. The risk is particularly high in young children (0–6 years old), with a cumulative value reaching 4.75, reflecting high biological vulnerability. Cd appears to be the main carcinogen, followed by Ni, while Pb and Cr present more moderate risks. The gradual decrease in risk observed with age could be explained by a relative decrease in exposure and a high capacity for toxin elimination.

As these values exceed the safety thresholds set by health agencies, it is crucial to implement preventive measures to reduce exposure to sources of contamination, particularly among the most vulnerable populations. In order to strengthen the robustness of this assessment, a Monte Carlo simulation was performed to estimate non-carcinogenic risks using a probabilistic approach. The results (Figure 5) confirm that ingestion of contaminated water remains the main route of risk, with HI values significantly above 1 in all

Table 9. Results for hazard quotient HQ and hazard index HI (non-cancer risk)

Parameter	(0–6)			(7–15)			(16–25)			(26–50)			> 50		
	HQ_{ing}	HQ_{derm}	HQ_{inh}	HQ_{ing}	HQ_{derm}	HQ_{inh}	HQ_{ing}	HQ_{derm}	HQ_{inh}	HQ_{ing}	HQ_{derm}	HQ_{inh}	HQ_{ing}	HQ_{derm}	HQ_{inh}
Pb	1.95	1.19E-3	4.54E-11	7.4E-1	4.5E-4	1.72E-11	5.3E-1	2.87E-4	1.43E-11	4E-1	2.45E-4	1.22E-11	3.9E-1	2.38E-4	1.18E-11
Cd	1.17	5.33E-4	2.71E-10	4.4E-1	2.02E-4	1.03E-10	2.8E-1	1.29E-4	8.51E-11	2.4E-1	1.1E-4	7.26E-11	2.3E-1	1.07E--4	7.05E-11
Cr	1.18	3.36E-4	2.4E-5	4.47E-1	1.36E-4	1.73E-11	2.85E-1	8.69E-5	1.44E-11	2.43E-1	7.41E-5	1.23E-11	2.36E-1	7.2E-5	1.19E-11
Ni	19.86	3.63E-3	3.7E-9	7.51	1.37E-3	1.4E-9	4.79	8.76E-4	1.16E-9	4.09	7.47E-4	9.89E-10	3.97	7.26E-4	9.61E-10
Zn	2.89	5.28E-4	5.76E-10	1.09	1.1E-4	2.18E-10	6.68E-1	6.66E-4	1.81E-10	5.95E-1	1.09E-4	1.54E-10	5.78E-1	1.06E-4	1.5E-10
Fe	2.75	5.02E-4	1.25E-4	1.04	1.9E-4	2.11E-10	6.63E-1	1.21E-4	1.75E-10	5.65E-1	1.03E-4	1.49E-10	5.49E-1	1E-4	1.45E-10
$\sum$ HI	29.8	6.72E-3	1.49E-4	11.27	2.46E-3	1.97E-9	7.22	2.17E-3	1.63E-9	6.13	1.39E-3	1.39E-9	5.95	1.35E-3	1.35E-9

Table 10. Carcinogenic risk (CR) of heavy metals by the oral route

Populations	(0–6)	(7–15)	(16–25)	(26–50)	> 50
Pb	0.23	0.09	0.06	0.05	0.05
Cd	3.54	1.34	0.85	0.73	1.43E-11
Cr	0.30	0.11	0.07	0.06	0.06
Ni	0.68	0.26	0.17	0.14	0.14
$\sum CR$	4.75	1.8	1.15	0.98	0.25

age groups, particularly during childhood. On the other hand, the dermal and inhalation routes generate very low indices, well below the threshold value, confirming their negligible contribution to overall exposure. These results call for preventive efforts to focus on reducing the risks associated with ingestion, in particular by controlling sources of pollution and improving groundwater treatment systems used for domestic purposes.

In parallel with the assessment of non-carcinogenic risks, a Monte Carlo simulation was also used to estimate the CR associated with exposure to heavy metals present in groundwater (Figure 6). The results obtained reveal that all age groups studied present a risk level above the critical threshold of 10^{-4}, which reflects a worrying situation in terms of health. Once again, children aged 0 to 6 appear to be the population most likely to be affected, with their risk distribution curve (CR) clearly differing from those of other groups due to significantly higher values, linked to their physiological immaturity, relatively high water consumption, and reduced detoxification capacity. The estimated risk decreases gradually with age, with individuals over 50 showing the lowest levels, reflecting lower exposure or more effective metabolic defense mechanisms. The marked separation between the distributions of the different age groups highlights significant variations in exposure profiles, underscoring the need for in-depth investigation of potential sources of contamination. These results reinforce the call for the implementation of targeted prevention strategies, particularly measures to reduce exposure to carcinogens in children. Particular efforts should be focused on limiting risks through ingestion, identified as the main route of contamination, by improving control of drinking water sources, optimizing treatment, and raising awareness among at-risk populations.

The results obtained in this study are fully in line with the research conducted at the national and international levels on groundwater contamination by heavy metals. At the local level, several previous studies in the sub-basins of the Soummam watershed corroborate our observations. Bouguerra et al. (2023) reported high concentrations of lead in the Soummam plain, attributed to anthropogenic

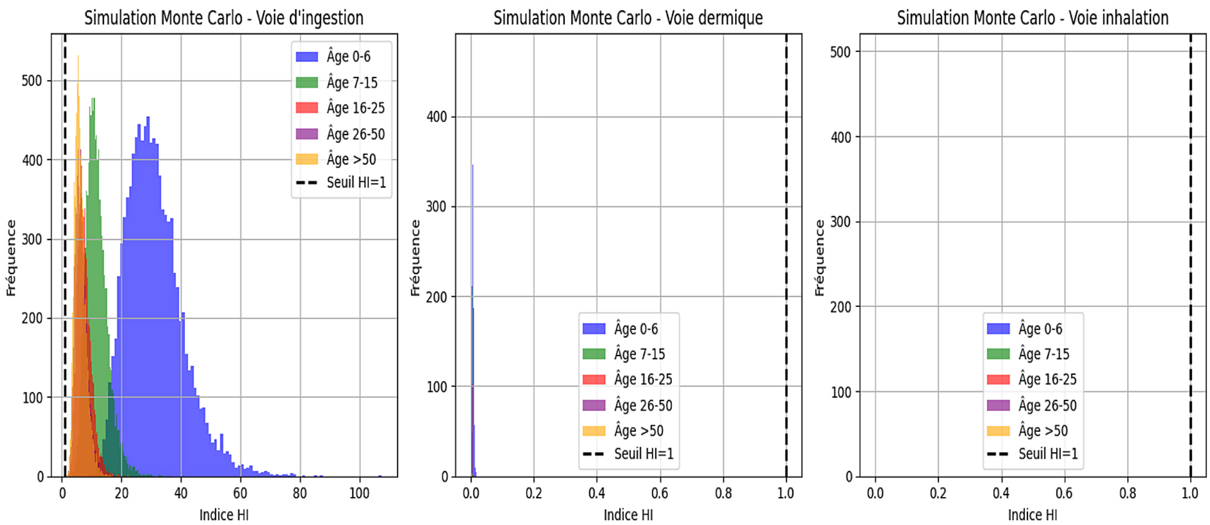

Figure 5. Monte Carlo simulation of non-carcinogenic risks

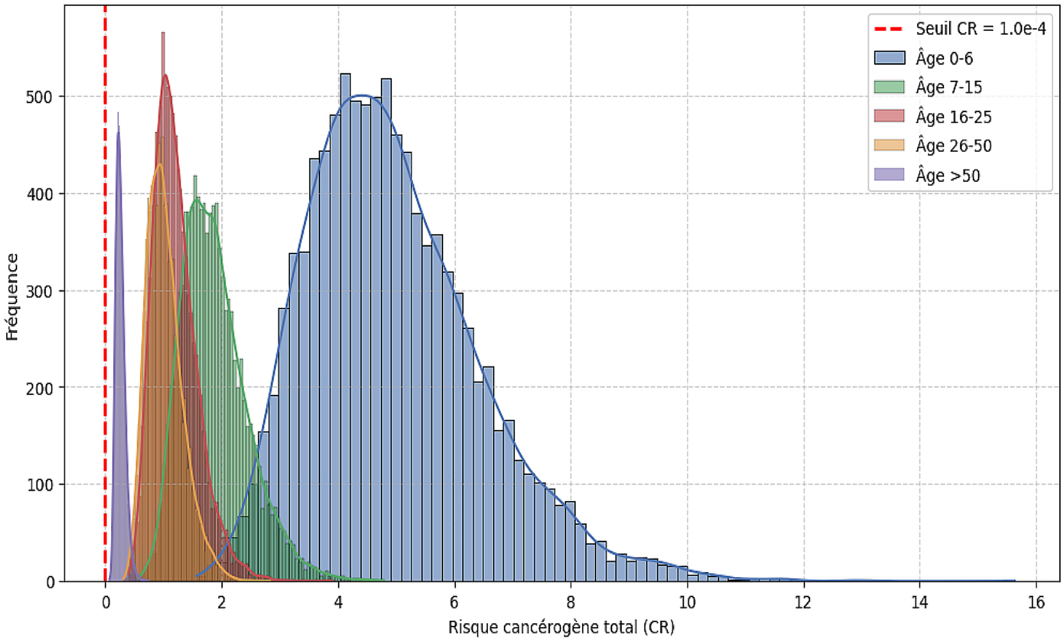

Figure 6. Monte Carlo simulation of carcinogenic risks

sources, while Nasiruddin et al. (2023) identified cadmium contamination in the Bousselam sub-basin, reflecting similar conditions to those observed in our study. Khoudja et al. (2022) and Bekhti et al. (2020) also highlighted a dominant influence of human activities and geogenic inputs on the distribution of heavy metals in the Sahel and lower Soummam sub-basins through the application of multivariate methods. Moreover, Ouahrani et al. (2022) observed particularly high pollution indices (Cdeg and HEI) in the intensely exploited areas of the lower Soummam, which reinforces the validity of the critical levels noted here. Moreover, the levels of non-carcinogenic risk detected in children are consistent with those reported by Lammari and Daghi (2021) in the lower Soummam, although our results reveal an increased severity of carcinogenic risks, with values exceeding the critical threshold in all age groups.

These findings also resonate on an international scale. Jahan et al. (2025), in the Ganges basin in India, applied a combination of PCA, MLR, and Monte Carlo simulation, highlighting multiple contributions from anthropogenic sources and high health risks among young populations. Shi et al. (2022), in China, demonstrated that heavy metals present in Hainan aquifers, notably Cr, Cd, and Pb, also pose significant carcinogenic risks, while Kumar and Maurya (2025) observed concerning exposure to aluminum, iron, nickel, and lead in the State of Bihar.

In summary, this study stands out for its integrated approach combining comprehensive spatial coverage of the Soummam watershed, a detailed multi-path and multi-age group assessment, the use of a complete and multidisciplinary methodology, combining hydrochemical analysis, multivariate statistics, pollution indices, health risk assessment, and probabilistic modeling.

It thus offers a complete and unprecedented vision of the dynamics of contamination and its health implications, making it a reproducible model for other regions facing similar environmental pressures, while enriching the international scientific corpus in the field of sustainable management of groundwater resources.

CONCLUSIONS

This study provides a thorough and integrated assessment of groundwater quality in the Soummam watershed, emphasizing heavy metal contamination, its potential sources, and associated health risks. The results reveal alarming average concentrations of Pb and Cd, which exceed both national and international drinking water standards. These exceedances underscore the growing environmental and public health challenges posed by rapid urbanization, industrial activities, and agricultural practices in the region. Through to the application of multivariate statistical methods (PCA and CAH), the combined influence of anthropogenic and geogenic sources, such as the natural weathering of geological formations, has been clearly identified. This approach not only highlights the dominant sources of contamination but also confirms the value of statistical tools in hydrogeochemical investigations. The pollution indices (HEI and Cdeg) further indicate the presence of critical contamination hotspots, particularly in urbanized and industrialized areas. The health risk assessment, which considered three exposure pathways (ingestion, dermal, inhalation) and five age groups of the population, demonstrated that children aged 0 to 6 years are the most susceptible to both carcinogenic and non-carcinogenic effects, largely due to their higher water consumption relative to their body weight and their physiological sensitivity. The application of Monte Carlo simulations has enhanced the reliability of these risk estimates by accounting for uncertainties in exposure parameters, providing a robust probabilistic assessment of health risks. The originality and scientific value of this study lie in its holistic approach, which integrates full spatial coverage of the Soummam basin with advanced statistical tools, exhaustive pollution indices, quantitative assessment of health risks, and the use of the probabilistic Monte Carlo method. This methodology ensures a precise and multidimensional understanding of groundwater quality, making it an effective model for regions facing similar environmental pressures and public health risks. The results not only provide a diagnosis of current contamination levels but also offer strategic perspectives for groundwater management and risk reduction. Looking forward, several research and management strategies should be prioritized to build on these results. Long-term spatiotemporal monitoring of groundwater quality is necessary to detect seasonal or interannual variations and better understand the dynamics of contamination. Expanding the scope of the analysis to include microbiological contaminants and emerging pollutants, such as pharmaceuticals and pesticides, would lead to a more comprehensive health risks assessment. The application of geospatial modeling techniques, such as GIS and remote sensing, could further refine the identification of pollution sources, track their dispersion patterns, and support predictive modeling of contamination trends. Additionally, evaluating the effectiveness of local water treatment technologies would help develop tailored solutions to reduce heavy metal concentrations and improve water safety. Finally, this research highlights the importance of a participatory approach involving local authorities, decision-makers, public health agencies, and economic actors. Collaborative efforts are essential to transform scientific findings into practical management strategies and policies, ensuring sustainable water resources governance and the protection of vulnerable populations. The results of this study thus serve both as a scientific foundation and a call to action for integrated water management and environmental protection in the Soummam watershed and beyond.

REFERENCES

1. Ali, H., Khan, E., Ilahi, I. (2019). Environmental chemistry and ecotoxicology of hazardous heavy metals: Environmental persistence, toxicity, and bioaccumulation. *Journal of Chemistry.* https://doi.org/10.1155/2019/6730305
2. Aspros Santé. (2022). *Groundwater pollution*. https://www.aspros-sante.fr/pollution-de-leau-souterraine/
3. Backman, B., Bodis, D., Lahermo, P., Rapant, S., Tarvainen, T. (1998). Application of a groundwater contamination index in Finland and Slovakia. *Environmental Geology, 36*(1–2), 55–64. https://doi.org/10.1007/s002540050320
4. Barkat, A., Bouaicha, F., Ziad, S., Mester, T., Sajtos, Z., Balla, D., Makhloufi, I., Szabo, G. (2023). The integrated use of heavy-metal pollution indices and the assessment of metallic health risks in phreatic groundwater aquifers: the case of the Oued Souf valley in Algeria. *Hydrology, 10*(10), 201. https://doi.org/10.3390/hydrology10100201
5. Bekhti, Y., Daghi, K. (2020). Assessment of health risks associated with the presence of heavy metals (Pb, Cr, Cd) in groundwater in the Lower Soummam watershed (Master's thesis). Abderrahmane Mira University, Bejaia.
6. Belkhiri, L., Mouni, L., Tiri, A. (2017). Assessment of groundwater quality and health risk in the region of El Elma, Algeria. *Environmental Earth Sciences, 76*(2), 1–13.
7. Bouguerra, R., Sahraoui, O., Bousnoubra, H. (2023). Heavy metal contamination in urban and peri-urban groundwater of Northern Algeria: Levels, sources, and human health risk assessment. *Environmental Monitoring and Assessment*, *195*, 215.
8. Caporale, A. G., Violante, A. (2016). Chemical processes affecting the mobility of heavy metals and

metalloids in soil environments. *Current Pollution Reports, 2*(1), 15–27.

9. Chowdhury, M. A. Z., Karim, M. A., Fakhruddin, A. N. M. (2016). Toxicity and risk assessment of heavy metals in foodstuffs from a local market in Bangladesh. *International Journal of Environmental Research and Public Health, 13*(7), 762.
10. Chowdhury, S., Mazumder, M. A. J., Husain, T. (2023). Fate and transport of heavy metals in groundwater: Recent developments. *Environmental Advances, 11*, 100336.
11. Djafer Khodja, H., Aichour, A., Rezig, A., Baloul, D., Ferhati, A. (2022). Application of multivariate statistical methods to the hydrochemical study of groundwater quality in the Sahel Watershed, Algeria. *Journal of Ecological Engineering, 23*(8), 341–349. https://doi.org/10.12911/22998993/151147
12. Du, L., Sun, T., Liu, Y., Wang, F., Wang, C. (2017). Speciation and bioavailability of heavy metals in sediments in a contaminated river, China. *Environmental Science and Pollution Research, 24*(21), 17467–17479.
13. Edet, A. E., Offiong, O. E. (2002). Evaluation of water quality pollution indices for heavy metal contamination monitoring: A case study from Curtin Lake, Miri City, East Malaysia. *Environmental Geology, 43*(3), 282–291.
14. Goretzko, D., Pham, T. T. H., Bühner, M. (2021). Exploratory factor analysis: Current use, methodological developments and recommendations for good practice. *Current Psychology, 40*, 3510–3521. https://doi.org/10.1007/s12144-019-00300-2
15. Hamhoum, A., Aoudia, L. (2015). Instrumental analysis of the physicochemical variability of the waters at the mouth of the waters at the mouth of the Soummam wadi (using the TROLL 9500 probe) (Master's thesis). Abderrahmane Mira University, Bejaia.
16. Jahan, A., Rai, N., Khan, M.U 2025). Groundwater contamination characterization and source apportionment of heavy metals and associated sources-specific health Risque appraisal using Monte Carlo simulation coupled with PCA-MLR and PMF models in the middle Gangetic Basin, India.*Exposure and Health, 17*(3), 755–806.
17. Khan, J., Shrivastava, R., Gupta, G., Singh, N. K. (2023). Heavy metal contamination in groundwater: Environmental concerns and mitigation measures. *Heavy metal toxicity: Environmental concerns, remediation and opportunities* 139–165. Springer. https://doi.org/10.1007/978-981-99-0397-9_7
18. Kumar, S., Maurya, N.S. (2025). Analysis of heavy metal contamination in groundwater and associated probabilistic human health risk assessment using Monte Carlo simulation: A case study in Gaya, Bihar, India. *Journal of Water and Health, 23*(5), 630–647. https://doi.org/10.2166/wh.2025.348
19. Lammari, Y., Daghi, K. (2021). Assessment of health risks associated with the presence of heavy metals (Pb, Cr, Cd) in groundwater in the Lower Soummam watershed (Master's thesis). Abderrahmane Mira University – Bejaia.
20. Marshall, F. M., Holdgate, M., Anjum, F. (2021). *Heavy metals in the environment: Impact on human health.* WHO/UNEP Report.
21. Nasiruddin, A., Slimani, R., Bouzidi, A., Kamel, K., Fares, M. (2023). Groundwater chemistry origin and quality assessment of the Sahel–Soummam Wadi plain aquifer. *Groundwater for Sustainable Development, 23*, 100845.
22. National Water Resources Agency (ANRH). (2009). *Ramsar description sheet for the Soummam River Valley*. Ramsar Sites Information Service. https://rsis.ramsar.org/RISapp/files/RISrep/DZ1898RISformer_161020.pdf
23. Ouahrani, M., Takarli, M., Bouzidi, A. (2022). Groundwater pollution assessment using water quality index and multivariate statistical analysis in the Lower Soummam Valley, Algeria. *Environmental Earth Sciences, 81*, 273.
24. Ould Fah, M. M. (2016). *Hydrological study of the Soummam watershed* [Master's thesis, Mohamed Boudiaf University of M'Sila]. Theses Algeria. https://bucket.theses-algerie.com/files/repositories-dz/1395110317754249.pdf
25. People's Democratic Republic of Algeria. (2011). Executive Decree No. 11-219 of 20 June 2011 establishing the specifications of water intended for human consumption. *Official Journal of the People's Democratic Republic of Algeria, 37*, 12–23.
26. Qu, C. S., Ma, Z. W., Yang, J., Liu, Y., Bi, J., Huang, L. (2019). Human exposure pathways of heavy metals in a lead–zinc mining area, Jiangsu Province, China. *PLOS ONE, 14*(2), e0211830.
27. Rajkumar, H., Naik, P. K., Rishi, M. S. (2020). A new indexing approach for evaluating heavy metal contamination in groundwater. *Chemosphere, 245*, 125598. https://doi.org/10.1016/j.chemosphere.2019.125598
28. Rohe, K., Zeng, M. (2023). Vintage factor analysis with Varimax performs statistical inference. *Journal of the Royal Statistical Society: Series B (Statistical Methodology), 85*(4), 1037–1060. https://doi.org/10.1093/jrsssb/qkad029
29. Saha, N., Rahman, M. S., Ahmed, M. B. (2022). Assessment of groundwater contamination by heavy metals and associated health risk in Bangladesh. *Environmental Research, 204*, 112055.
30. Sanad, H., Moussadek, R., Dakak, H., Zouahri, A., Oueld Lhaj, M., Mouhir, L. (2024). Ecological and health risk assessment of heavy metals in groundwater within an agricultural ecosystem using GIS and

multivariate statistical analysis (MSA): A case study of the Mnasra Region, Gharb Plain, Morocco. *Water, 16*(17), 2417. https://doi.org/10.3390/w16172417

31. Sbai, K., Tahri, L., Hafiane, F. Z., Iben Halima, O., Fekhaoui, M. (2024). Assessment of heavy metal pollution in groundwater using a multivariate analysis approach. *Journal of Water and Land Development, 2024*(2), 21–30.
32. Shi, H., Li, H., Zeng, M., Peng, H., Huang, Ch., Sun, H., Hou, Q., Pi, P. (2022). Health risque assesment of heavy metals in groundwater of Hainan Island using the Monte Carlo simulation coupled with the APCS/MLR model. *International Journal of Environmental Research and Public Health, 19*(13), 7827. https://doi.org/10.3390/ijerph19137827
33. Singh, C. K., Kumar, A., Shashtri, S., Kumar, A., Kumar, P., Mallick, J. (2017). Multivariate statistical analysis and geochemical modeling for geochemical assessment of groundwater of Delhi, India. *Journal of Geochemical Exploration, 175*, 59–71. https://doi.org/10.1016/j.gexplo.2017.01.001
34. Singh, S., Kumar, V., Sharma, J. (2021). Health risk assessment of groundwater contaminated with heavy metals in an industrial area. *Environmental Geochemistry and Health, 43*(5), 1731–1744.
35. Turki, I., Laignel, B., Massei, N., Nouaceur, Z., Benhamiche, N., Madani, K. (2016). Hydrological variability of the Soummam watershed (Northeastern Algeria) and the possible links to climate fluctuations. *Arabian Journal of Geosciences, 9*(6), 1–13. https://doi.org/10.1007/s12517-016-2448-0
36. U.S. Environmental Protection Agency. (1989). *Risk assessment guidance for Superfund. Volume I: Human health evaluation manual (Part A)* (EPA/540/1-89/002). https://www.epa.gov/sites/default/files/2015-09/documents/rags_a.pdf
37. U.S. Environmental Protection Agency. (2004). *Risk assessment guidance for Superfund. Volume I: Human health evaluation manual (Part E, Supplemental guidance for dermal risk assessment)* (EPA/540/R/99/005). https://www.epa.gov/sites/default/files/2015-09/documents/ragse.pdf
38. U.S. Environmental Protection Agency (U.S. EPA). (2016). *Risk assessment guidance for Superfund (RAGS), Part A: Human health evaluation manual* (EPA/540/1-89/002). https://www.epa.gov/risk/risk-assessment-guidance-superfund-rags-part
39. Verma, C., Hussain, A., Madan, S., Kumar, V. (2021). Assessment of heavy metal pollution in groundwater with respect to distance from ash pond by using heavy metal evaluation index. *Applied Water Science, 11*(58). https://doi.org/10.1007/s13201-021-01390-9
40. World Health Organization. (2022). *Guidelines for drinking-water quality: Fourth edition incorporating the first and second addenda.* Geneva, Switzerland: World Health Organization. https://www.who.int/publications/i/item/9789240045064
41. Zhao, Y., Liu, C., Zhang, T. (2022). Bioaccumulation and biomagnification of trace metals in aquatic food webs: A review. *Environmental Pollution, 292,* 118279.