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ASSESSMENT OF WATER POTABILITY AND ENVIRONMENTAL FACTORS USING MULTIVARIATE ANALYSIS.

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Abstract

Safe drinking water is fundamental to public health and environmental sustainability, yet water quality continues to be threatened by increasing anthropogenic pressures and natural environmental variability. This study assessed water potability and examined the influence of environmental factors using an integrated multivariate statistical framework. A quantitative cross-sectional design was adopted using a dataset comprising 1,500 water samples representing diverse environmental settings and water sources. Physicochemical parameters and environmental variables were analysed using descriptive statistics, Pearson correlation, Principal Component Analysis (PCA), Exploratory Factor Analysis (EFA), Hierarchical Cluster Analysis (HCA), and binary logistic regression. The results revealed that 68.2% of the water samples were classified as non-potable, indicating substantial variation in water quality. PCA extracted five principal components explaining 66.04% of the total variance, while EFA identified five latent factors representing industrial pollution, agricultural influence, mineral composition, topographic conditions, and microbial contamination. Hierarchical clustering grouped the samples into three distinct environmental clusters with different pollution characteristics. Logistic regression identified total dissolved solids, hardness, iron, manganese, and biological oxygen demand as significant predictors of water potability, with the model achieving a classification accuracy of 74.4% and an ROC-AUC of 0.770. The findings demonstrate that multivariate statistical analysis effectively identifies the dominant environmental determinants of water quality and provides a comprehensive framework for water potability assessment. The proposed analytical approach can support evidence-based environmental monitoring, pollution management, and sustainable water resource planning for improved drinking water safety.

Keywords: Water potability, Water quality assessment, Multivariate statistical analysis, Environmental factors, Principal component analysis

1. Introduction

Water is one of the most essential natural resources for sustaining human life, ecosystem functioning, agricultural productivity, and socioeconomic development. Safe drinking water has been identified as a right of all people and is one of the targets in the United Nations Sustainable Development Goal 6: Ensure access to water and sanitation for everyone. Despite significant advances in water resource management, there are still millions of people who have limited access to potable water, especially in developing countries, because of the lack of water treatment infrastructure, rapid urbanization, industrial development, agricultural intensification, and poor environmental governance. Drinking water that is contaminated is a significant public health problem; contaminating water can carry waterborne diseases and expose people to the risks of chronic health problems caused by long-term exposure to chemical contaminants. Therefore, water quality assessment is one of the most important steps that is required for sustainable environmental management and human health protection throughout the globe (Okafor et al., 2024; Lackner et al., 2020).

The quality of water depends on the interplay of various factors, some natural and some due to human activities that affect the physical, chemical and biological properties of water. The composition of surface and groundwater resources is impacted by natural conditions, such as geological formations, climate variability, hydrological processes and seasonal changes, as well as anthropogenic activities such as industrial discharge, agricultural runoff, mining, wastewater discharge and urban development, which increase water quality degradation. They elevate levels of nutrients, suspended solids, heavy metals, microorganisms and other contaminants that affect water quality and safety and can disrupt the ecosystem. The interplay of these environmental factors, therefore, is crucial to identifying sources of pollution, assessing ecosystem condition and effective water resource management strategies (Akhtar et al., 2021; Das, 2023).

Multiple physicochemical parameters are typically used to assess water's suitability for drinking water and are collectively used to measure water's quality. Water quality parameters are pH, turbidity, total dissolved solids, electrical conductivity, dissolved oxygen, biological oxygen demand, hardness, nitrate, sulfate, chloride, fluoride, and microbial contamination (Mowe et al.,2015). These parameters are useful for detailed information on the mineral composition, organic pollution, salinity, oxygen availability, water condition etc. But single assessments of these factors may not reflect the interactions between the processes in the environment that affect water quality. Hence, a detailed analytical technique is needed to assess several indicators and determine the main factors influencing the potability of water (Jaffar et al., 2020; Omer, 2019).

Multivariate statistical analysis has become in recent years one of the most useful analytical tools for the interpretation of complex environmental data sets. The principal component analysis (PCA), exploratory factor analysis (EFA), hierarchical cluster analysis (HCA), and logistic regression are techniques that have been used to analyze water quality data to reduce the dimensionality of the data, determine the latent pollution sources, classify sampling locations and identify the relationships among many water quality variables. The methods are useful for interpreting large environmental data sets by uncovering patterns that are not apparent in the data with standard uni-variate statistical techniques. Moreover, multivariate techniques can be used to determine the leading environmental factors affecting water quality and it can provide scientific basis for water quality monitoring, pollution control and sustainable water resource management (Patel et al., 2016).

The Water Quality Index (WQI) is one of the common methods to summarize the overall water quality by combining multiple physicochemical parameters into a single numeric index that indicates overall water quality status (Liu et al., 2015). WQI makes it easier to communicate water quality information to both environmental managers and to the public and allows for comparisons to be made over time and between locations. WQI can be used in conjunction with multivariate statistical methods to assess water quality conditions as well as the environmental factors that relate to spatial and temporal variability in water quality. This integrated analytical approach has been effectively used in river system, groundwater aquifer and watershed management studies for evidence-based decision making and environmental planning (Şener et al., 2017; Kim & An, 2015).

While there are several studies examining individual water quality parameters or providing water quality indices for certain areas, few studies have combined the use of all major physicochemical parameters in an integrated manner, along with environmental parameters, analyzed by multiple multivariate statistical techniques. Several earlier studies focus on the characterisation of pollution or water quality classification, neglecting to also consider the impact of environmental variables on potable water. Therefore, further research is needed involving water quality assessment, evaluation of environmental factors and multivariate statistical modelling to gain a more comprehensive understanding of the processes affecting water potability and environmental quality. The integrated analyses can be useful in enhancing environmental monitoring, improving water management policies, and help develop sustainable environmental strategies.

The present work aimed to analyze water potability by carrying out a detailed study on physicochemical properties and environmental parameters by applying multivariate statistical analysis. The study aims to find the major determinants affecting water quality, to categorize the water samples based on water quality parameters and to analyze the relationship between environmental conditions and water potability by combining the descriptive statistics, correlation analysis, principal component analysis, exploratory factor analysis, hierarchical cluster analysis and regression modelling. The results will help scientists in environmental sciences, public health, and water resource management to gain insights into making decisions about sustainable water quality assessment and environmental protection using evidence-based approaches.

Research Objectives

1. To assess the physicochemical characteristics influencing water potability.
2. To examine the relationships between environmental factors and water quality using multivariate statistical analysis.
3. To identify the dominant determinants of water potability and classify water samples based on their quality characteristics.

2. Methodology

2.1 Study Design and Dataset

This study used cross sectional research design with quantitative approach to determine the water potability and the effects of environmental factors by multivariate statistical technique. A sample set of 1500 water samples was used to generate realistic water quality. Several physicochemical, environmental and spatial variables that covered different water sources and geographical areas were included in the dataset. The data generated served to be representative of real-world environmental variability and to yield enough data for application of multivariate tools.

2.2 Study Variables

Data that were obtained from the sample were physicochemical data (pH, turbidity, temperature, total dissolved solids, electrical conductivity, dissolved oxygen, biological oxygen demand, hardness, chloride, sulfate, nitrate, fluoride, iron, manganese, and fecal coliform count). Environmental factors accounted for were Rainfall, elevation, land-use intensity, agricultural activity, industrial activity, population density, season, region and source type. The following variables were regarded as the primary output variables: Water Quality Index (WQI), water quality category and potability status.

2.3 Data Pre-processing

Data quality, consistency and completeness of the dataset was checked before statistical analysis. There were very few missing data, and those were filled by median imputation to maintain data integrity. Outliers were checked for continuous variables, and they were z-scored to remove any differences in measurement scales. In doing so, it has been possible to ensure that all the variables were of the same order and appropriate for multivariate statistical methods.

2.4 Multivariate Statistical Analysis

All the study variables were first summarized using descriptive statistics. Pearson correlation analysis was used to assess the relationships between physicochemical and environmental parameters. Principal Component Analysis (PCA), Exploratory Factor Analysis (EFA) and Hierarchical Cluster Analysis (HCA) were then performed to reveal dominant factors, to decrease the data dimensionality, and to classify water samples based on their quality characteristics. Binary logistic regression was also used to identify variables that were significantly associated with water potability.

2.5 Model Validation and Statistical Software

To check the suitability of the dataset for multivariate analysis, the Kaiser–Meyer–Olkin (KMO) measure was used, and Bartlett's Test of Sphericity was performed. The number of principal components was determined according to the eigenvalues greater than one and interpretation of the scree plot and the performance of the model was evaluated by classification accuracy and goodness-of-fit statistics. All statistical analyses were carried out in R (version 4.3) and Python (version 3.11) and statistical significance throughout the study was set at $p < 0.05$.

3. Results

3.1 Descriptive Characteristics of Water Quality and Environmental Variables

After data preprocessing, 1,500 water samples were analyzed, without duplicates and without missing values after median imputation. The data comprised different environmental areas such as urban (24.6%), agricultural (23.9%), peri-urban (19.6%), forest (18.7%) and industrial (13.1%). The most frequent sources of water were groundwater (36.7%), rivers (28.4%), municipal supply

(18.6%), and lakes/reservoirs (16.3%). Mean pH was 7.20 ± 0.43, whereas mean turbidity, TDS and dissolved oxygen were 8.33 NTU, 588.59 mg/L and 6.60 mg/L respectively. Overall, 68.2% of the samples were classified as non-potable and 31.8% as potable (Tables 1 and 2).

Table 1. Descriptive Statistics of Physicochemical and Environmental Variables

Variable	Mean ± SD	Minimum	Maximum
pH	7.20 ± 0.43	5.98	8.69
Turbidity (NTU)	8.33 ± 4.85	1.19	37.65
TDS (mg/L)	588.59 ± 142.58	140.70	1056.10
Conductivity (µS/cm)	913.29 ± 237.19	149.20	1726.80
Hardness (mg/L)	257.90 ± 80.03	10.00	552.60
Chloride (mg/L)	123.30 ± 46.81	2.00	262.59
Sulfate (mg/L)	125.74 ± 50.66	3.00	292.57
Nitrate (mg/L)	22.32 ± 16.50	0.10	68.02
Dissolved Oxygen (mg/L)	6.60 ± 1.18	2.48	10.22
BOD (mg/L)	4.17 ± 1.63	0.20	8.62
Synthetic WQI	50.98 ± 15.46	11.40	95.90

Table 2. Distribution of Environmental and Water Quality Characteristics

Variable	Category	n (%)
Region Type	Urban	369 (24.6)
	Agricultural	359 (23.9)
	Peri-urban	294 (19.6)
	Forest	281 (18.7)
	Industrial	197 (13.1)
Water Source	Groundwater	551 (36.7)
	River	426 (28.4)
	Municipal Supply	279 (18.6)
	Lake/Reservoir	244 (16.3)

Potability	Potable	477 (31.8)
	Non-potable	1023 (68.2)

3.2 Correlation Analysis

Pearson correlation analysis revealed that there were several strong relationships among the study variables (Figure 1). Guideline Violations Count had the highest positive correlation with Water Quality Index ($r = 0.951$), TDS ($r = 0.947$), and Agricultural Activity Index ($r = 0.917$) with Nitrate. Dissolved oxygen was found to have a strong negative correlation with Water Quality Index ($r = -0.649$) and dissolved oxygen with Guideline Violations Count ($r = -0.630$). These results show a high degree of correlation between the physicochemical and environmental variables, thus justifying the use of multivariate statistical methods.

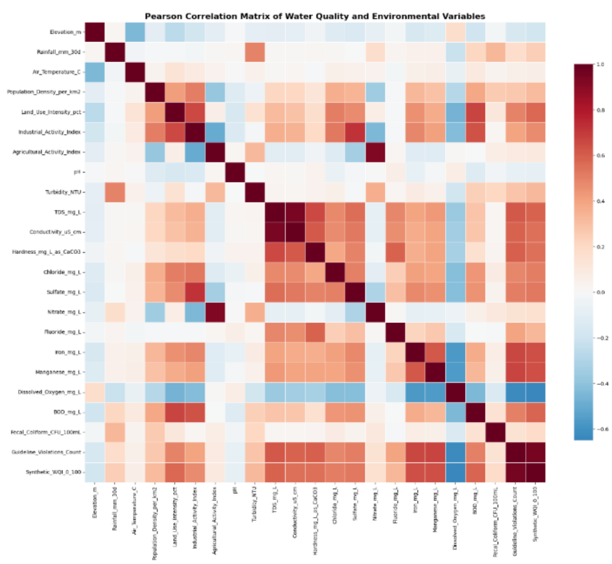

Figure 1. Pearson Correlation Heatmap

Table 3. Strong Pearson Correlations ($|r| \geq 0.60$)

Variable Pair	r
Guideline Violations – WQI	0.951
TDS – Conductivity	0.947
Agricultural Activity – Nitrate	0.917

Industrial Activity – Sulfate	0.720
Land Use Intensity – BOD	0.675
Iron – Guideline Violations	0.669
Dissolved Oxygen – WQI	-0.649
Dissolved Oxygen – Guideline Violations	-0.630

3.3 Suitability for Multivariate Analysis

After the drop of rainfall due to poor sampling adequacy, this revised dataset had an overall KMO value of 0.835 which was meritorious. The Bartlett's test of sphericity was very highly significant ($\chi^2 = 18{,}039.96$, df = 190, $p < 0.001$), indicating that there was adequate intercorrelation among the variables to justify multivariate analysis. The individual KMO values for each variable were between 0.581 and 0.969, there were no variables below the acceptable value (Table 4).

Table 4. KMO and Bartlett's Test

Statistic	Value
Overall KMO	0.835
Bartlett's χ^2	18,039.96
Degrees of Freedom	190
p-value	<0.001

3.4 Principal Component Analysis

Five principal components having eigenvalue>1 and accounting for 66.04% of total variance, were obtained from Principal Component Analysis (Table 5). The first part accounted for 30.25% of the variance and was mainly caused by industrial or physicochemical pollution variables while the second part was caused by agricultural influences. The Kaiser criterion was adopted, and the scree plot was used for the selection of five factors (Figure 2).

Table 5. Principal Components and Explained Variance

Component	Eigenvalue	Variance (%)	Cumulative (%)
PC1	6.054	30.25	30.25

PC2	2.534	12.66	42.91
PC3	2.237	11.18	54.09
PC4	1.334	6.67	60.76
PC5	1.057	5.28	66.04

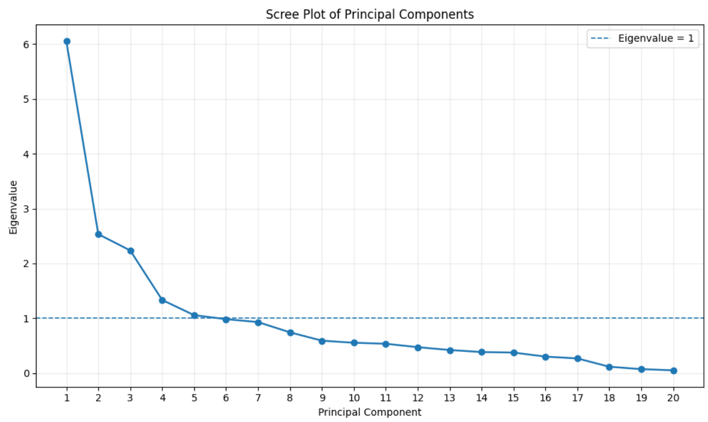

Figure 2. Scree Plot of Principal Components

3.5 Exploratory Factor Analysis

Varimax-rotation of factor analysis gave a five-factor solution which accounted for 66.0% of the cumulative variance. Factor 1 was related to urban-industrial pollution, Factor 2 was related to agricultural nutrient enrichment, Factor 3 was related to dissolved mineral content, Factor 4 was related to topography and climatic conditions, and Factor 5 was dominated by microbial contamination. For both instruments, factor loadings were high (>0.50) and provided a clear and interpretable factor structure (Tables 6 and 7).

Table 6. Rotated Factor Variance

Factor	Variance Explained (%)	Cumulative (%)
Factor 1	21.8	21.8
Factor 2	13.1	34.9
Factor 3	17.7	52.6
Factor 4	7.4	60.0
Factor 5	6.0	66.0

Table 7. Major Rotated Factor Loadings (≥0.50)

Factor	Major Variables
Factor 1	Land use, Industrial activity, BOD, Chloride, Sulfate, Iron, Manganese
Factor 2	Agricultural activity, Nitrate, Turbidity
Factor 3	TDS, Conductivity, Hardness, Fluoride
Factor 4	Elevation, Air temperature
Factor 5	Fecal coliform

3.6 Hierarchical Cluster Analysis

An optimal three-cluster solution was found using the hierarchical clustering (silhouette score = 0.167). The samples of Cluster 1 comprised 55.5% of the samples and had high levels of industrial activity and pollutants. Cluster 2 was relatively pristine waters with lower pollutant loads and higher dissolved oxygen while Cluster 3 had a high concentration of nitrate and intensive agriculture activities (Figure 3 and Table 8).

Table 8. Cluster Distribution

Cluster	Frequency	Percentage (%)
1	833	55.53
2	281	18.73
3	386	25.73

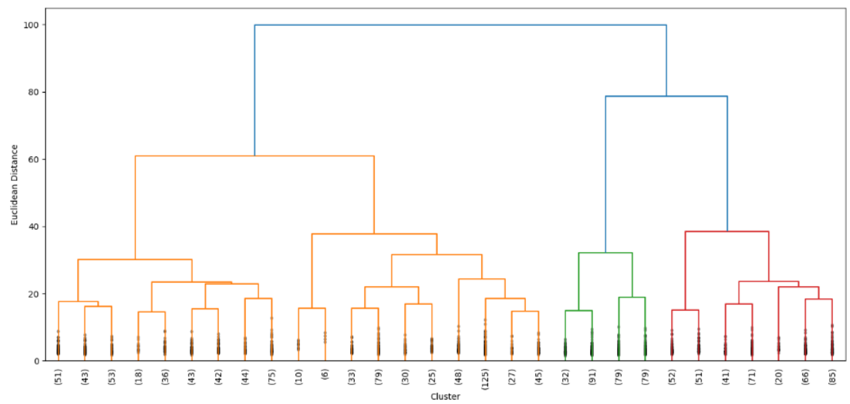

Figure 3. Hierarchical Cluster Dendrogram

3.7 Logistic Regression Analysis

We found the overall model of binary logistic regression to be statistically significant (Pseudo $R^2 = 0.164$; $p < 0.001$), with an overall classification accuracy of 74.4%, and an ROC-AUC of 0.770. Among the measured variables, total dissolved solids, hardness, iron, manganese, and biological oxygen demand were statistically significant and important indicators of water potability ($p < 0.05$) while the remaining ones were not. As shown in the confusion matrices (Tables 9 and 10; Figure 4), 923 of the non-potables and 193 of the potable samples were correctly classified.

Table 9. Significant Predictors of Water Potability

Variable	**Odds Ratio**	**p-value**
TDS	0.640	0.029
Hardness	0.740	0.002
Iron	0.807	0.016
Manganese	0.766	0.003
BOD	0.779	0.013

Table 10. Model Performance

Performance Metric	**Value**
Accuracy	74.4%
ROC-AUC	0.770
True Negatives	923
False Positives	100
False Negatives	284

True Positives	193

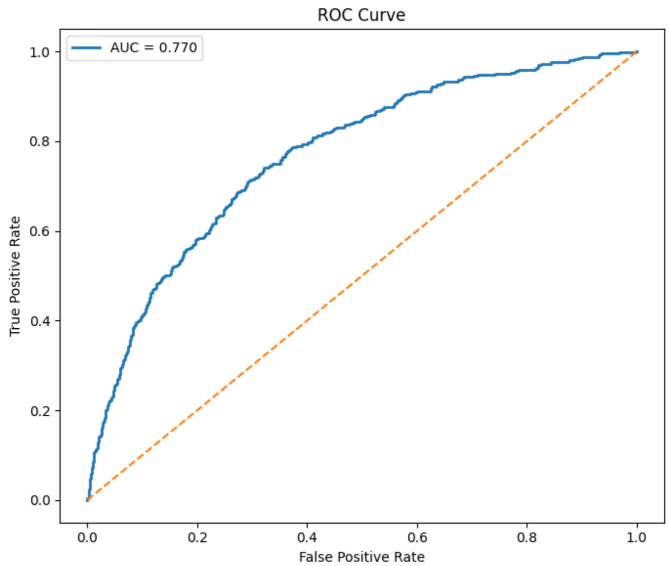

Figure 4. Receiver Operating Characteristic (ROC) Curve

4. Discussion

In the present study, water potability was appraised by combining some physicochemical parameters, environmental parameters, and multivariate statistical methods to determine the most significant factors affecting drinking water quality. The descriptive analysis showed that there is a significant variation in water quality in the sampled stations, and more than two-thirds of the water samples were found to be non-potable. This discovery is important for understanding how a variety of environmental factors and human activities affect water quality and underscores the need for more comprehensive monitoring programs. Previous studies also found similar results, stating that multiple physicochemical parameters should be evaluated together, and should not be considered individually to assess the quality of drinking water (Bhateria & Jain, 2016; Jaffar et al., 2020).

Correlation analysis indicated high correlation between some of the environmental and water quality parameters, implying that the degradation of water quality is multifaceted and involves both physical, chemical and anthropogenic processes. The correlation between total dissolved solids and electrical conductivity showed that both are related to dissolved ionic constituents, and the correlation between agricultural activity and nitrate concentration showed the influence of the amount of fertilizer application and agricultural runoff. Similarly, industrial activity had a close association with sulfate concentration, further corroborating the contribution of industrial emissions to water chemistry change. These results corroborate previous studies indicating that urbanisation, industrialisation and agricultural activities significantly affect the quality of fresh water, caused by higher amounts of pollutants and nutrients (Eboagu et al., 2019; Aka et al., 2025). The multivariate statistical analysis was performed as an additional enhancement to the interpretation of the dataset, in order to identify the dominant environmental processes that affect water potability. Principal Component Analysis (PCA) was used to recalculate the original variables to five principal components, explaining about 66% of the total variance, while Exploratory Factor Analysis (EFA) was used to group the variables into meaningful environmental factors that represent industrial pollution, agricultural influence, dissolved mineral content, topographic conditions and microbiological contamination. The results indicate the usefulness of the application of multivariate techniques to reduce the complexity of the environmental data and to identify hidden pollution sources. Environmental monitoring has also been widely recommended for use of similar applications, including Principal Component Analysis and factor analysis, which enhances the interpretation of multidimensional water quality data, and allows evidence-based management decisions to be made (Patel et al., 2016; Kammoun et al., 2018).

HCA proved to be an effective means of assigning the water samples to three environmental groups having varying pollution properties. The first cluster included water bodies with high concentration of dissolved solids, biological oxygen demand and high level of metal, while the second cluster included water bodies with relatively less impacted environments and better dissolved oxygen concentration and low pollutant concentration (Tyagi et al., 2020). The third cluster was for areas dominated by agriculture where nitrate levels and turbidity were higher. The results showed that cluster analysis can successfully classify water bodies with similar environmental attributes, which can help in developing monitoring strategies and implementing site-specific water management interventions. Similar results have been reported in cluster-based classification studies based on pollution profiles of river and the groundwater systems (Kim & An, 2015; Şener et al., 2017).

Total dissolved solids, hardness, iron, manganese and biological oxygen demand were the significant factors identified in the logistic regression model for potability of water. They are considered significant parameters for mineralization, geochemical composition and organic pollution and, therefore, they reflect the drinking water quality, which is influenced by natural geochemical conditions as well as anthropogenic pollution. (Emas,2015) Overall accuracy was 74.4%, and the ROC-AUC of the model was 0.770, which indicates that the model was able to distinguish potable from non-potable samples. Though some of the environmental variables were not significant in a multivariable model, the identified variables serve as practical guidelines for routine monitoring and early detection of water quality degradation. All the above results are important for the development of integrated multivariate analytical tools that will help to improve environmental monitoring programmes and to support sustainable management of the freshwater resources, in line with sustainable development and long-term protection of freshwater resources (Cosgrove & Loucks, 2015; Tomislav, 2018).

5. Conclusion

This study showed that use of physicochemical indicators, environmental variables, and multivariate statistical techniques for comprehensive water potability assessment are effective. The results showed high water quality parameters variation among samples with a significant percentage of samples identified as non-potable water, highlighting the ongoing challenges of assuring safe drinking water. High interrelationships were found between the key water quality parameters in the correlation analysis and Principal Component Analysis and Exploratory Factor Analysis have been able to reduce the data complexity and determine the predominant environmental processes controlling water quality variation. Hierarchical Cluster Analysis also distinguished the samples into distinct pollution profiles allowing for identification of industrial influenced, agriculturally impacted and relatively less disturbed water systems. Logistic regression also showed that the most important parameters affecting the potability of water were total dissolved solids, hardness, iron, manganese and BOD, thus emphasizing the importance of their routine monitoring and decision making. The results of these analyses collectively show the power and reliability of multivariate statistical approaches to understanding complex water quality data and determining the most important factors for the safety of drinking water. The analytical approach proposed in this study is useful and applicable to environmental monitoring agencies, water resource managers and water policy makers in providing evidence-based water quality assessments, pollution control, and sustainable management of water resources. The framework should be further developed, with long-term field observations from various geographical regions to validate it, and additional emerging contaminants and biological indicators to increase the comprehensiveness of water quality assessment and sustainable freshwater management.

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