

The Application of Principal Component Analysis in the Assessment of Surface Water Quality of Mati River, Albania

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Abstract—Principal Component Analysis (PCA) was applied to surface water quality data to identify pollution sources and assess their contribution to variations in water quality. Surface water samples were collected from 5 distinct sampling points along the Mati River in Albania, during the period from September 2024 to October 2025. 14 physico-chemical water quality parameters were analyzed: Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD₅), Chemical Oxygen Demand (COD), Total Dissolved Solids (TDS), pH, conductivity, temperature, sulphates, nitrogen forms, chloride, phosphates (PO₄³⁻), and total phosphorus (P-tot). Water quality was assessed based on site and season, with water quality classes determined and pollution issues identified. Pearson correlation and PCA were employed to evaluate the relationships between all parameters. PCA results indicated that the first 3 principal components (PC1, PC2, and PC3) accounted for approximately 96% of the total variance, effectively representing the underlying structure of the water's physicochemical properties. The analysis revealed that water quality along the Mati River is primarily influenced by 3 main factors: mineralization, organic pollution, and nutrient loading. PCA demonstrates that the primary determinants of water quality variability are chemical variables associated with pollution and mineralization. In contrast, biological and physical parameters play a secondary role in differentiating locations. The analysis reveals that the strength of these variables and their contributions to the principal components facilitate the identification of key influencing factors and provide clear interpretations of the environmental conditions.

Keywords—Mati River, principal component analysis, correlation, water quality, physico-chemical parameters

I. INTRODUCTION

Surface water resources represent a critical component of environmental sustainability, socio-economic development, and public health protection, particularly in river basins undergoing increasing anthropogenic pressure [1]. Rivers serve as primary sources of freshwater for drinking water supply, irrigation, industrial use, and ecosystem maintenance. However, rapid population growth, urban expansion, agricultural intensification, and industrial development have significantly altered the physicochemical characteristics of surface waters worldwide, leading to widespread degradation of water quality. In this context, systematic assessment and interpretation of surface water quality are essential for sustainable water resources management [2, 3].

Surface water quality remains a delicate issue, impacted by urban development, industry, agriculture, and natural phenomena such as precipitation, erosion, and geological breakdown, all contributing to the water's suitability for various uses like drinking and recreation [4]. Determining the connection between nonpoint source contaminants and

surface water quality requires an understanding of how land use and/or land cover affect water quality. Hydrological factors are greatly impacted by land-use change [5]. The expansion of human populations along with commercial and industrial activities has led to significant contamination of surface water from various sources [6]. Increased pollution results in decreased water quality, endangering public health, disrupting aquatic ecosystems, hindering economic growth, and affecting social welfare [7].

Traditional univariate approaches are often insufficient to capture the complexity of water quality datasets, which typically consist of numerous interrelated physicochemical parameters measured across multiple locations and time periods [8]. Multivariate statistical techniques, such as correlation analysis and Principal Component Analysis (PCA), provide powerful tools for reducing dimensionality, and revealing hidden patterns in water quality variations [9]. Research utilizing PCA has been shown to be effective in revealing hidden pollution sources and assessing parameter impacts, thereby aiding in identifying key variables driving changes in surface water quality [10]. PCA and related multivariate statistical methods are valuable for constructing robust water quality assessments and exploring relationships between dependent and independent variables within a data set.

PCA, in particular, enables the identification of dominant pollution sources, the grouping of correlated parameters, and the assessment of the relative influence of natural and anthropogenic factors on water quality [11]. By transforming original variables into a smaller set of uncorrelated principal components, PCA enhances data interpretability while minimizing information loss.

Numerous studies have demonstrated the effectiveness of PCA and related multivariate methods in surface water quality assessments [12, 13]. For instance, Ustaoglu *et al.* [14] and Xue *et al.* [15] employed principal component analysis to identify sources of pollution that impact surface water, such as the flow of agricultural inorganic fertilizers, soil erosion, and domestic wastewater discharge. Given the spatial and temporal variability in water chemistry, establishing a monitoring program is essential for reliable quality assessments. Consequently, monitoring efforts involve frequent sampling across multiple locations and analyzing various physicochemical parameters, generating extensive data requiring complex interpretation [16]. Hence, for the protection and management of water resources, monitoring the water quality and its spatiotemporal variation in rivers is essential [17].

In river basins similar to the Mati River, PCA has proven

especially valuable for distinguishing between geogenic influences and anthropogenic pressures, thereby supporting evidence-based decision-making in water management [18]. Given the pronounced spatial and temporal variability of water chemistry in river systems, robust monitoring programs involving frequent sampling and multi-parameter analysis are essential for accurate water quality evaluation [19]. In Albania, despite the strategic importance of the Mati River located in northern of country (Fig. 1), comprehensive studies integrating multivariate statistical analyses for water quality assessment remain limited.

In the Mati River basin, land-use changes and hydrological alterations have significantly affected runoff dynamics, sediment transport, and nutrient fluxes, increasing the vulnerability of surface waters to contamination. Identifying the relative contribution of these factors is a major challenge in water quality assessment, particularly in river systems characterized by heterogeneous pollution sources [20–22]. This study contributes to Sustainable Development Goal 6 (SDG 6) by providing evidence on pollution sources and seasonal dynamics in the Mati River, supporting data-driven water management that enhances access to clean and safe water [23].

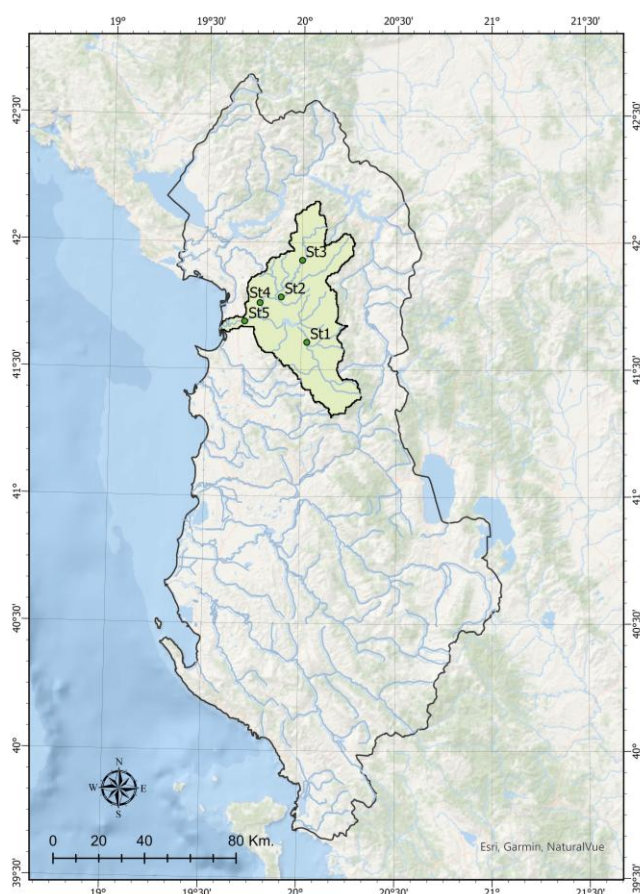


Fig. 1. Watershed of Mati River and monitoring stations.

II. MATERIALS AND METHODS

A. Study Area

The Mati River spans 144 km in length and encompasses a watershed area of 2441 km² [24], is one of the country's most important river systems, playing a vital role in regional water supply, agriculture, hydropower production, and ecosystem

services. The main tributaries of the Mati River are the Fani and Uraka, originating in the mountainous areas of northeastern Albania and flowing into the Adriatic Sea. The Fani acts as the primary tributary of the Mati River and is formed by the Great Fani and the Small Fani [25]. The Mati River has an average multi-annual discharge of 103 m³/s, corresponding to a modulus of 42.2 L/(s·km²). The hydrographic network of the Mati River catchment basin is composed of a considerable number of large and small streams. The Mat River catchment basin is composed of limestone, clay, and flysch rocks. In its lower course, the Mati passes through waters of Quaternary gravel deposits as well as artesian waters. As a result of the above conditions, the Mati River catchment basin is distinguished by a high degree of water content [22]. Hydrographically, the Mati River basin is distinguished by a dense network of water courses (Fig. 1), particularly in its middle and lower sections, where ultrabasic formations dominate. Additionally, the presence of various water bodies makes this basin an interesting subject for study. Besides numerous streams, the basin also contains several lakes, primarily created for hydroelectric and agricultural purposes, varying in size from medium to small. Drought is a slow-onset, creeping natural hazard and a recurrent phenomenon in the Mati watershed region [21, 26].

B. Analytical Procedures

The dataset was obtained in accordance with the Water Framework Directive of a river monitoring program employing a fixed sampling frequency [19]. Water samples were collected from 5 monitoring stations along the Mat River, selected to represent the surface water quality of the entire basin, as shown in Fig. 1. The monitoring sites were strategically chosen to capture potential pollution hotspots associated with mining activities operating within the basin (St2 and St3), as well as areas influenced by human activities, including urban settlements and agricultural practices (St1, St4, and St5).

Surface water samples were collected from the midpoint of bridges at each station to ensure representativeness of the river's overall water composition. Sampling commenced with the first monitoring campaign in October 2024, followed by a second campaign in January 2025. The third and fourth monitoring campaigns were conducted in March and June 2025, respectively. This sampling design enabled seasonal coverage, capturing both low-flow and high-flow hydrological conditions of the river.

At each monitoring station, a minimum of 2 samples were collected during each campaign, and all physicochemical analyses were performed in triplicate to ensure analytical accuracy and data reliability.

The physicochemical parameters were analyzed, known as Dissolved Oxygen (OD), Biochemical Oxygen Demand (BOD₅), Chemical Oxygen Demand (COD), Total Dissolved Substances (TDS), pH, chlorides (Cl⁻), conductivity, temperature, phosphates (PO₄³⁻), and total phosphorus, using the Standard Methods for the Examination of Water and Wastewater [27].

C. Principal Component Analysis (PCA)

This method is recognized as one of the most effective multivariate statistical methods for identifying linear relationships within a collection of variables. PCA serves as

a tool for pattern recognition that seeks to clarify the variance found in a sizable dataset of interrelated variables by reducing it to a smaller set of variables. PCA delivers insights regarding the essential parameters with minimal loss of the original information content. The principal components can be represented with Eq. (1).

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

where:

- X—original value of a variable.
- μ—average of all values of that variable.
- σ—standard deviation, which shows how spread out the values are around the mean.
- Z—standardized value.

III. RESULT AND DISCUSSION

A. Descriptive Statistics

Table 1 displays the range, minimum, maximum, mean, and standard deviation of the variables examined. It is evident that Conductivity (Conduc.), TDS, SO₄²⁻, and Cl⁻ are the key parameters, exhibiting high mean concentrations of 350 μS/cm, 160 mg/L, 55 mg/L, and 10.12 mg/L, respectively. This indicates a shared source for these variables. The mean pH values ranged from 8.23 to 8.34, with an average measurement of 8.29 mg/L, which means that the values are consistent across measurements. For the sulphates, a greater distribution is observed (SD = 10.64), indicating a significant variation among the samples. On the other hand, NH₄⁺, NO₂⁻, PO₄³⁻, and total phosphorus (P-tot), present low values, indicating that these nutrients are present in low concentrations. The concentrations of OD, BOD₅, and COD varied from 8.71 mg/L to 9.20 mg/L, 1.09 mg/L to 1.72 mg/L,

and 0.75 mg/L to 1.06 mg/L, respectively, with average values of 8.90 mg/L, 1.50 mg/L and 0.85 mg/L. The order of prevalence is OD > COD > BOD₅, indicating a lower level of anthropogenic impact on the surface water.

Table 1. Descriptive statistics of the parameters

Category	Mean	SD	Sum	Min	Max
Temp. (°C)	16.4	0.91	82	15.3	17.5
Conduc. (μS/cm)	267	56.99	1335	193	350
Cl ⁻ (mg/L)	7.81	1.44	39.05	6.38	10.12
SO ₄ ²⁻ (mg/L)	40.4	10.64	202	26	55
TDS (mg/L)	137.2	21.51	686	110	160
pH	8.29	0.047	41.45	8.23	8.34
OD (mg/L)	8.90	0.19	44.54	8.71	9.20
BOD ₅ (mg/L)	1.50	0.26	7.13	1.09	1.72
COD (mg/L)	0.85	0.126	4.23	0.75	1.06
NH ₄ ⁺ (mg/L)	0.016	0.004	0.079	0.011	0.022
NO ₂ ⁻ (mg/L)	0.047	0.008	0.233	0.036	0.05
NO ₃ ⁻ (mg/L)	0.29	0.102	1.42	0.11	0.38
PO ₄ ³⁻ (mg/L)	0.017	0.005	0.083	0.008	0.022
P-tot (mg/L)	0.025	0.004	0.12	0.021	0.032

The results of the Pearson correlation analysis revealed strong positive relationships between COD and OD (*r* = 0.97), as well as between BOD₅ and OD (*r* = 0.93), suggesting a common origin of the correlating elements, as well as the chemical or physical processes that these physicochemical parameters undergo during their residence in water, such as the formation of soluble complexes, sedimentation processes, and interaction with suspended matter, etc. (Table 2).

Furthermore, a strong positive correlation was also noted between nutrients and Temperatures (Temp.) [28]. On the other hand, the strong negative correlations between BOD₅ and temperatures (*r* = -0.97), as well as between NO₂⁻ and BOD₅ (*r* = -0.90), indicate the distorted relationship between nitrogen forms and BOD₅ in the presence of oxidative-reductive processes [29].

Table 2. Pearson correlation coefficients

	Temp.	Conduc.	Cl ⁻	SO ₄ ²⁻	TDS	pH	OD	BOD	COD	NH ₄ ⁺	NO ₂ ⁻	NO ₃ ⁻	PO ₄ ³⁻	P-tot
Temp.	1													
Conduc.	0.45	1												
Cl ⁻	0.005	0.86	1											
SO ₄ ²⁻	-0.009	0.26	0.07	1										
TDS	-0.16	0.70	0.67	0.64	1									
pH	-0.65	0.13	0.63	-0.27	0.23	1								
OD	-0.84	-0.53	-0.02	-0.45	-0.27	0.76	1							
BOD ₅	-0.97	-0.40	0.10	-0.13	0.08	0.80	0.93	1						
COD	-0.70	-0.61	-0.13	-0.61	-0.47	0.67	0.97	0.82	1					
NH ₄ ⁺	0.72	0.83	0.66	-0.16	0.18	0.02	-0.51	-0.59	-0.46	1				
NO ₂ ⁻	0.89	0.47	0.01	0.40	0.04	-0.67	-0.89	-0.90	-0.83	0.57	1			
NO ₃ ⁻	0.74	0.25	-0.006	-0.59	-0.34	-0.40	-0.45	-0.69	-0.28	0.63	0.37	1		
PO ₄ ³⁻	0.50	0.17	0.19	-0.76	-0.55	0.13	0.03	-0.30	0.21	0.66	0.19	0.71	1	
P-tot	-0.34	-0.41	-0.01	-0.76	-0.63	0.61	0.80	0.53	0.89	-0.07	-0.53	0.014	0.61	1

The eigenvalue is a measure of the information that each PC conveys about the dataset.

In the analysis of the physicochemical parameters of water quality along the Mati River, the first Principal Component (PC1) explains 47.62% of the total variability, showcasing that nearly half of the variation can be attributed to interrelated factors such as salt concentration, conductivity, and pH levels.

The PC2 accounts for an additional 26.96%, bringing the cumulative explained variability to 74.58%, while the PC3 component accounts for 21.39% of the variability. This indicates that these 3 components together encapsulate over

95% of the dataset's information, which is advantageous for effective data representation and thereby renders the first three components adequate for comprehensively depicting the behavior of the parameters studied.

Table 3. Eigenvalues of the correlation matrix

Category	Eigenvalue	Percentage of Variance	Cumulative
1	6.67	47.62%	47.62%
2	3.77	26.96%	74.58%
3	2.99	21.39%	95.97%
4	0.56	4.03%	100.00%
5	0	0.00%	100.00%

In contrast, components 4 and 5 provide negligible contributions, with 4.03% and 0.00%, respectively, suggesting that they primarily reflect noise or random variation rather than meaningful data variance (Table 3).

B. Principal Component Analysis (PCA) Results and Interpretation

PCA was applied to the physicochemical parameters of water with the aim of identifying the key factors that influence its quality and the spatial distribution of monitoring stations [16]. Fig. 2 presents a 3D plot from the PCA. It illustrates the eigenvalues for each principal component [30]. The analysis of PCA reveals that the 3 components (PC1, PC2, and PC3) account for approximately 95.97% of the total variance in the data, sufficiently representing the structure of the physicochemical variables of water. The other components PC4 and PC5, do not possess considerable values (eigenvalue scree plot < 1 , according to Kaiser's criterion). In PCA, the modulus of the loading vector signifies its length, which is influenced by the loadings associated with it. This modulus serves as a metric to quantify the total variance explained by the corresponding component within the dataset.

The parameters COD, BOD₅, pH, OD, and P-tot are grouped to the left of the PC1 axis. A strong positive correlation is observed between BOD₅, COD, and OD, suggesting a common source of organic pollution. On the other hand, TDS and SO₄²⁻, who are situated to the left, in the opposite direction of PC2, also exhibit close connections, reflecting characteristics of natural mineralization, or geological influences and anthropogenic influences [10]. These parameters are associated with organic pollution and biochemical processes in water. High values of these parameters imply the presence of organic matter and increased biological activity [31].

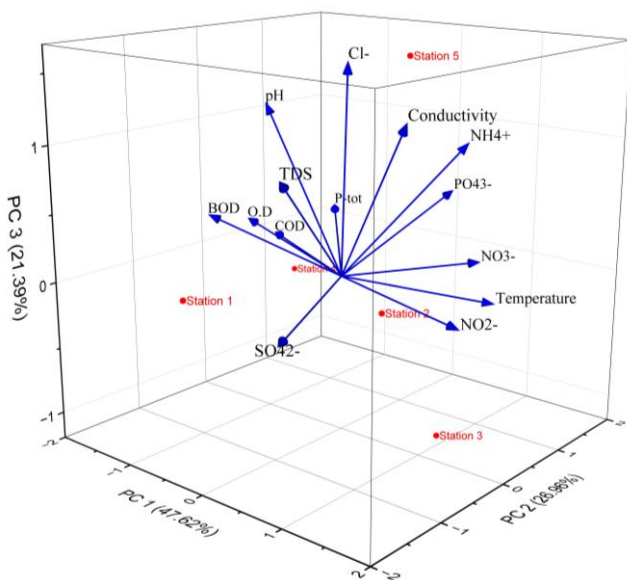


Fig. 2. Principal component analysis, 3D presentation.

The parameters NO₃⁻, NH₄⁺, NO₂⁻, PO₄³⁻, and conductivity are positioned closer to the center but oriented in a similar direction. This component is associated with eutrophication processes and elevated nutrient loads in the water, and reflects anthropogenic influences such as agricultural runoff and polluted inflows. The relationship between modulus (represented by conductivity/electrical modulus in this study)

and discharge was examined using both multivariate ordination (PCA) and station-wise measurements. The PCA biplot shows that conductivity (modulus) is strongly aligned along the same principal component as nutrient ions (PO₄³⁻, NO₃⁻), while discharge is oriented in an opposing or weakly associated direction. This spatial separation indicates a negative relationship between modulus and discharge. Stations with higher discharge (e.g., Station 5) tend to exhibit lower or only moderately elevated modulus values, while stations with lower discharge (e.g., Station 4) show relatively higher modulus. The observed discharge values exhibit a wide range among stations (≈ 193 – 350), indicating substantial hydrological variability, while modulus (conductivity) remains relatively stable with only minor fluctuations (8.23–8.33), suggesting limited spatial variability in ionic strength.

The pH and P-tot contribute less to the differentiation of samples, as their variations were more limited across all stations. The results of the PCA indicate that water quality is primarily influenced by 3 main groups of factors: mineralization, organic pollution, and nutrient loading. These groups of factors elucidate the spatial variation of the monitoring stations and suggest diverse sources of pollution within the aquatic system [32].

The PC3 reflects local or seasonal influences, such as water inflow, precipitation, or local discharges. St1 is located further down on the left, partially associated with TDS and SO₄²⁻. St1 is linked to natural resources or the geological influence on the composition of water. St2 is near the centre and possesses intermediate characteristics, lacking a clear dominance of any particular group of parameters. St3 and St5 are situated close to one another in the upper right section, where NO₃⁻, NH₄⁺, and PO₄³⁻ predominate. They exhibit the impact of agriculture or discharges containing nutrient substances (fertilizer runoff). St4 is found isolated on the left side and is strongly influenced by organic parameters (COD, BOD₅, OD). St4 represents an area with a high load of organic pollution, near an urban or industrial discharge. Variables characterized by longer arrows, such as conductivity, nitrate (NO₃⁻), temperature, and phosphate (PO₄³⁻), exhibit large moduli, indicating their significant contributions to the primary data structure and their effective representation by PCA. Conversely, variables represented by shorter arrows show a more constrained influence on the PCA outcomes. PC1 has a strong correlation with conductivity, NO₃⁻, and temperature, which may indicate underlying gradients associated with anthropogenic influences or water mineralization processes. In contrast, PC2 is more closely linked with pH, Dissolved Oxygen (DO), and Biological Oxygen Demand (BOD₅), suggesting a relationship with biological activities and oxidative conditions in the data. PC3 adds a layer of differentiation for certain secondary variables, contributing further information and context to the overall data structure.

PC1 distinguishes areas with organic pollution (to the left) from those with natural mineral composition (to the right).

PC2 differentiates the influence of nutrients from geochemical factors.

The stations, as illustrated in Fig. 2, form 3 possible groups.

- (i) The group of organic pollution: St4.
- (ii) The group of nutrients: St3 and St5.

(iii) The group with natural influence: St1 and partially St2.

The Eigenvalues for each principal component are shown in Fig. 3. PC1 exhibited a higher eigenvalue (≈ 6.7), indicating its predominant contribution to the structure of the variables [33].

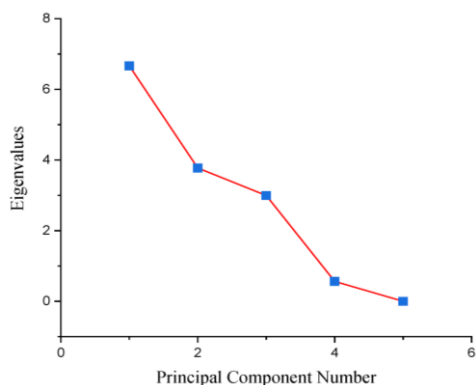


Fig. 3. The eigenvalues for each principal component.

These factors account for the majority of the spatial variation among the stations and suggest that the waters of this basin are influenced by various sources of pollution, including both natural and anthropogenic processes.

IV. CONCLUSION

The first 3 components explain nearly 96% of the total variability, indicating strong correlations among the physicochemical parameters. Variations in water quality along the Mati River are therefore influenced by a limited number of factors, including industrial and organic pollution, geographical conditions, and water inflow. The first component is primarily associated with overall pollution, parameter concentrations, COD, and BODs. The second component reflects natural factors such as temperature, pH, and dissolved oxygen. The third component captures local or seasonal influences, including water inflow, precipitation, and local discharges.

Water quality varies substantially between stations, and pollution sources are heterogeneous along the river course. Certain sections are dominated by industrial or anthropogenic impacts, whereas others are driven mainly by natural processes.

PC1 differentiates stations affected by organic pollution from those characterised by mineral or naturally derived compositions, while PC2 separates nutrient-related influences from geochemical factors. Based on these patterns, the stations can be grouped into 3 categories: (i) sites characterised by organic pollution (St4); (ii) sites influenced by nutrient enrichment (St3 and St5); and (iii) sites shaped predominantly by natural factors (St1 and, to a lesser extent, St2). This classification highlights spatial differences in human influence on water quality across the study area. Understanding these distinctions is essential for implementing targeted management strategies that address the specific environmental challenges at each station. PCA analysis indicates that key chemical variables, namely conductivity, NO_3^- , temperature, and PO_4^{3-} , are the primary factors driving the variance in the dataset. In contrast, biological parameters like BOD and DO play a role in secondary differentiation among the data points. The

sampling stations positioned in alignment with the arrows representing these variables exhibit higher values, which implies that various environmental influences affect the regions under investigation. Ultimately, PCA serves as a valuable tool for identifying the dominant variables impacting water quality and for clustering sampling stations, which aids in understanding the factors that control the quality of water in the studied areas.

Overall, the study represents a contribution to SDG 6 by providing empirical evidence on the main pollution sources and their seasonal dynamics in the Mati River. These insights support data-driven water management and policy measures aimed at enhancing access to clean and safe water resources. The results demonstrate a clear inverse relationship between modulus and discharge, whereby increased discharge leads to dilution of dissolved ions and reduced modulus, while low-discharge conditions promote solute accumulation and higher modulus values. This relationship is consistently supported by both station-level observations and PCA ordination.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

A.H. and E.Ç. conducted the research; B.P. analyzed the data; A.S. cartographer and digitalization; E.Ç. wrote the paper, Supervision; A.H. Review & Editing. All authors had approved the final version.

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