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Spatiotemporal Variation of River Water Quality in the Katse Reservoir Catchment in Lesotho: A Correlation Analysis Using Multiple Indices

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Abstract

Accurate river water quality assessment requires precise knowledge of human activities in the catchment. The water quality of the Katse Reservoir inflow rivers (KRIRs) is affected by mining effluents and livestock waste to varying degrees. This study compared the cumulative impact of human activities on the KRIRs through a correlation analysis and agglomerative hierarchical clustering of the water quality index (WQI) and the eutrophication index (EI) during the first decade (FD) (2003 to 2013) and the second decade (SD) (2014 to 2024). The study found that the water quality parameters selected to compute the WQI (NO_3^-, PO_4^{3-}, NH_4^+, NO_2^-, Fe^{2+}, Cd^{2+}, Pb^{2+}, EC, and pH) fluctuated within the water quality standards except for chemical oxygen demand (COD) and *Escherichia coli* (*E. coli*). Dissolved inorganic nitrogen, dissolved inorganic phosphorus, dissolved oxygen, and COD were used to compute the EI. The results from all water quality sites (WQS) showed that water was unsuitable for domestic use (WQI < 50). WQS-E and WQS-D were suitable for industrial use (51 < WQI < 75), whereas WQS-A, WQS-B and WQS-C were unsuitable for any use before treatment (100 < WQI). *E. coli* contributed significantly to the WQI, with strong correlations in the FD (r = 0.98) and in the SD (r = 0.94) ($p < 0.023$). Nitrates contributed significantly to the EI in the SD (r = 0.67). The correlation between WQI and EI increased from r = 0.45 in the FD to r = 0.81 in the SD at a significance level of $\alpha = 0.05$. The study effectively highlighted the evolution of pollution from diffuse to point sources in the SD at WQS-A. These findings can be used to forecast water quality responses to future land use activities and guide management strategies to curb pollution at source.

Keywords: eutrophication; rivers; water quality; nutrients; pollution; *E. coli*; correlation

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1. Introduction

Freshwater resources such as natural lakes, manmade reservoirs, rivers, and groundwater serve as vital water supply sources whose availability and quality require proper management [1]. However, the quality of these water resources has come under pressure from the growing population, climate change, urbanization, and industrial development [2,3]. The fitness of water for domestic use, irrigation, livestock drinking, and industrial use depends on a set of criteria including hygiene, water clarity, and chemical composition [4]. Consequently, monitoring water quality is a priority for countries to predict pollution and plan for a safer water supply [5].

A focus on the Katse Reservoir (KR) catchment in the Lesotho highlands indicated that diamond mining, as predicted by Pottinger [6], and livestock rearing [7] bring an influx of

nutrients, which are ingredients for eutrophication. Eutrophication is a progressive process by which aquatic ecosystems slowly become enriched with plant nutrients and experience increased production of organic matter [8]. The water quality of the Katse Reservoir inflow rivers (KRIRs) was concluded to be good by previous researchers in the first decade (FD) [8–10]. However, the opening of mines in 2011 led to intense human activity, with noticeable water quality degradation in the second decade SD [11–14]. Hence, Lintern et al. [15] suggest that it is important to identify spatial and temporal variation in river water quality of extensive catchments to develop effective water quality management strategies.

Mining generates waste and releases toxic chemicals, including cadmium (Cd^{2+}), nitrates ($NO_3{}^-$) and lead (Pb^{2+}) into the environment [12,16]. Ammonium nitrate-rich explosives used to blast the ore increase the $NO_3{}^-$ content of the mining effluent released into the rivers [17]. The influx of nitrates from mining activities creates potential for eutrophication even at low phosphorus concentrations [18]. Furthermore, mine residues inside tailings reservoirs contain unrecovered toxic metals which frequently overflow as acid mine drainage (AMD) into nearby rivers during heavy rainfall [16]. Cacciuttolo et al. [19] confirmed the water quality and socio-economic-related risks of discharging tailings slurry into surface water.

In addition to mining, livestock amplifies *Escherichia coli* (*E. coli*) and nutrient concentrations in the rivers through defecation and urination [7]. Livestock rearing competes with Lesotho's priority to utilize the highland landscape to collect and preserve both the quality and the quantity of the water for supply to South Africa [7,14]. According to Omoregie et al. [20], livestock waste brings nitrogen compounds into aquatic systems and accelerates eutrophication. Therefore, this study incorporated *E. coli* as a microbiological parameter in the WQI, to align with Indicator 6.3.2 of Sustainable Development Goals (SDGs) 6, which requires the application of methods that focus on physicochemical characteristics of water, including biological parameters such as *E. coli* [21].

The application of multiple indices informs early decision-making by authorities to avert the sudden emergence of water quality degradation [22,23]. The indices have an advantage over conventional descriptive statistics in that they collate several variables into a unitless value [24], which is easy to understand, interpret, and compare with the water suitability scale [25]. However, Kachroud et al. [26] hold a different opinion, arguing that there is high uncertainty linked to converting several water quality parameters into a single index value. This study explored a correlation analysis between WQI and EI to reduce the uncertainty in the application of indices. The WQI was developed by Horton [27]. Researchers who modified and applied the WQI selected water quality parameters based on the pollutants of interest and the source of pollution to analyze spatial and temporal trends in water quality at the catchment level [28–33]. The EI was used by various researchers to assess the eutrophication status of various ecosystems, including rivers [34–36].

This study filled critical research gaps by assessing the impacts of human activities on water quality in the KRIRs by coupling multivariate statistics with a correlation analysis of multiple indices. The findings include a water use suitability profile and recommendations for water quality assurance. Research gaps still existed following a critical review of parameter selection, WQI conceptualization, and the application and performance of WQI by Uddin et al. [37]. Thus, this study leveraged identified knowledge gaps and took a unique research direction by assessing spatiotemporal trends in water quality through the application of multivariate statistics and Pearson correlation over two decades to outline the evolution of water pollution from diffuse to point source.

Thus, the application of Pearson correlation to compare the degree of agreement between WQI and EI in the FD and SD and clarify the source of pollution, whether diffuse or point source, distinguished this study from previous research. Compared with single-index approach studies [28,30,33], multiple indices effectively captured spatiotemporal variation in water quality caused by multiple environmental stressors at the catchment scale [35,36,38]. This study aims to analyze spatial and temporal trends in water quality using multivariate statistics to inform stakeholders about the water fitness for use and curb pollution at source. The aim will be achieved through the following objectives: (1) to determine the fitness for various uses of the five KRIRs using the WQI and (2) to determine the eutrophication status of the five KRIRs using the EI over two decades.

2. Materials and Methods

2.1. Study Area Description and Water Sampling Sites

The study area is located in the Lesotho highlands, and it has a temperate subtropical climate with an average rainfall of 710 mm [39,40]. Snowfall is common in winter, with temperatures as low as −12 °C, while summers are rainy, with temperatures averaging around 35 °C [11,39]. The Katse Reservoir is a key structure in the Lesotho Highlands Water Project (LHWP) located at 29.33698° S, 28.5062° E in the Lesotho highlands below the confluence of the Malibamatšo River and Bokong River [14]. Geographic coordinates were taken using a Garmin eTrex® 10 GPS device (Garmin Asia Corporation, New Taipei City, Taiwan) at each WQS along the respective rivers as indicated in Table S1. KR has a catchment area of 1869 km^2, with the dam wall constructed along the Malibamatšo River [8], which receives effluent from diamond mines upstream of WQS-A [8,13]. The catchment also receives water from the tributaries that flow through the sampling points WQS-C, WQS-D, and WQS-E (Table S1).

In addition to mining, Lesotho, being a major exporter of wool and mohair products, has a high livestock density in the highlands [40]. The sub-catchment that overlays the river that runs through the WQS-C has densely populated communities with cattle kraals located close to the river (Figure 1). The other three rivers, which were sampled at WQS-B, WQS-D, and WQS-E, were associated with dispersed livestock grazing. This study confirmed the assertion by Lewis et al. [40] and Hoag [7] that rainfall runoff from livestock kraals and dipping sites dispersed in the upper catchment releases *E. coli* into the KRIRs. Table S1 shows the coordinates of the WQS on the KRIRs, while Figure 1 shows their spatial location in the KR catchment.

2.2. Data Collection

2.2.1. Criteria for the Selection of Water Quality Parameters

The criteria for the selection of water quality parameters (WQPs) were based on their indicative properties, water use fitness for various purposes, influence on eutrophication, prevalent anthropogenic activities in the catchment, influence on human health, and ecosystem health [2]. Eleven WQPs were selected, namely nitrates (NO_3^-), orthophosphates (PO_4^-), ammonium (NH_4^+), nitrite (NO_2^-), iron (Fe^{2+}), cadmium (Cd^{2+}), lead (Pb^{2+}), electrical conductivity (EC), chemical oxygen demand (COD), potential of hydrogen (pH), and *Escherichia coli* (*E. coli*) for computing the WQI. The study adopted expert knowledge of the catchment to select the most likely WQPs that constitute pollutants from cattle kraals and mining effluent, which are the most prevalent activities in the KD catchment. The adopted method for selecting parameters followed the assertion by Banda and Kumarasamy [41] that WQPs can be selected based on data availability, expert opinion, environmental significance of the parameter, and water use purpose without following a particular procedure or standard. The eutrophication index was calculated using physical and chemical parameters,

COD, dissolved oxygen (DO), dissolved inorganic nitrogen (DIN), and dissolved inorganic phosphorus (DIP) [42]. DIN is the total limiting concentration of NO_3^-, NO_2^-, and NH_4^+, while DIP is the concentration of orthophosphate. The DIN and DIP values are standards for DIN and DIP, respectively [43].

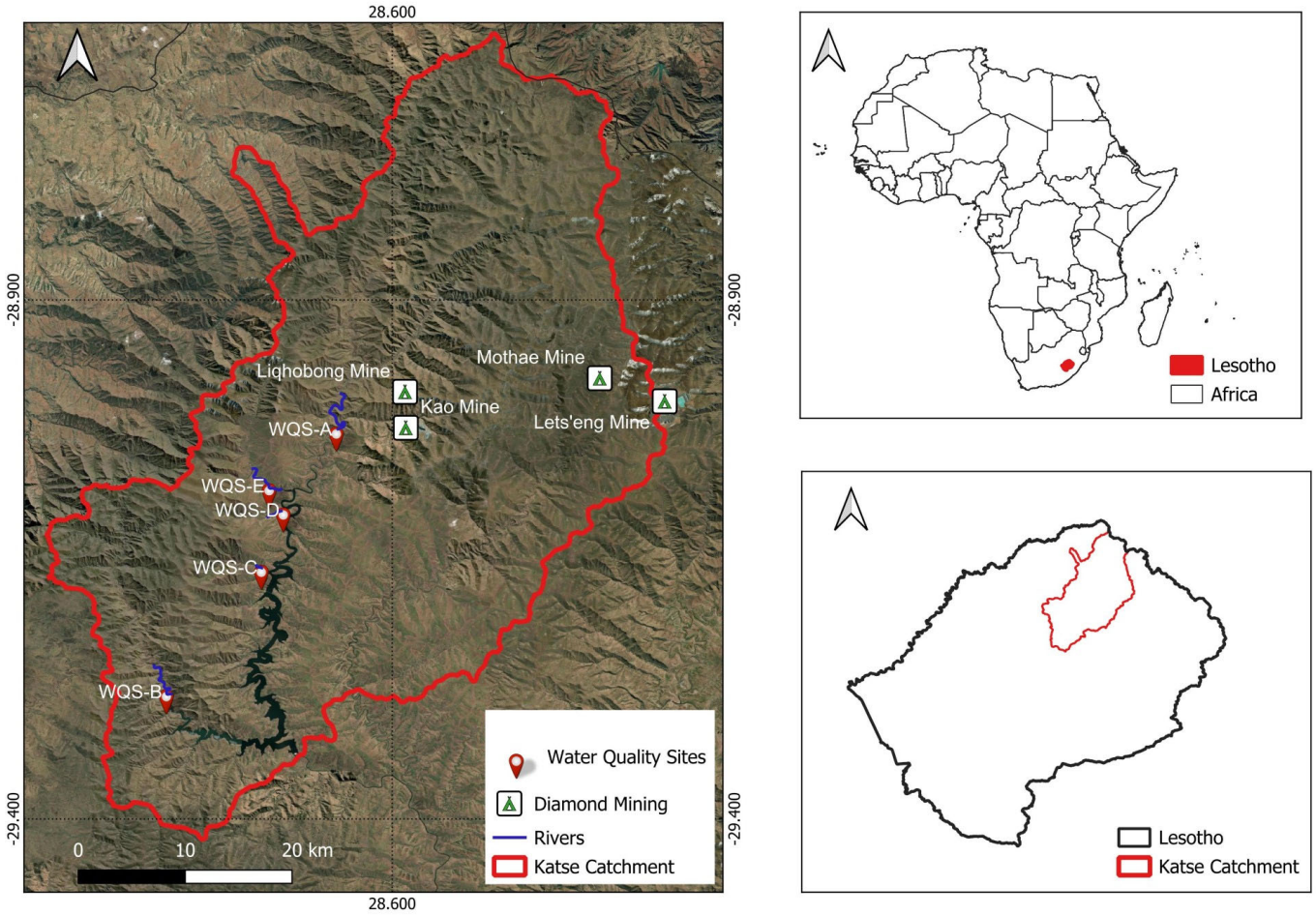


Figure 1. Map showing the Katse Reservoir catchment and water quality sites at inflow rivers: WQS-A, WQS-B, WQS-C, WQS-D, WQS-E.

2.2.2. Water Sampling and Laboratory Analysis

The water samples were collected from selected WQS in January, April, July and October of each year. All the water samples were analyzed at the chemistry and hydrobiology sections of the Randwater Laboratory, which is accredited by the South African National Accreditation System (SANAS) under the International Organization for Standardization (ISO) ISO/IEC 17025:2017 [44]. The Randwater Method numbers 1.1.2.16.1, 2.1.3.01.2, and 1.1.2.15.1 were followed to measure DO, EC, and pH on site at every WQS using a multiparameter probe instrument (YSI Sonde Model 6600, YSI Incorporated, Yellow Springs, OH, USA) [11] placed directly in the flowing stream of water at each WQS [11,45,46]. The water samples were taken from the WQS in rivers using 500 mL polypropylene bottles and stored in a SnoMaster SMDZ-LP96D Freezer (SnoMaster, Johannesburg, South Africa) [14] during transportation to the laboratory.

A UV-visible spectrophotometer (Thermo Scientific Evolution 300, Thermo Fisher Scientific Incorporated, Berlin, Germany) [14] was used for the analysis of PO_4^{3-}, NH_4^+, NO_3^-, and NO_2^-. COD was determined using the spectroscopy method 410.4 using the Thermo Scientific GENESYS 30 VIS Spectrophotometer (Thermo Fisher Scientific Incorporated, Berlin, Germany) [11,14], based on methods described by the American Public

Health Association [47]. Water samples were taken in January, April, July, and October for the study period from 2003 to 2024.

Water samples for *E. coli* were collected in clean, sterile, labeled 500 mL polypropylene bottles preserved with 1.8% mass per volume of sodium thiosulphate pentahydrate solution. The Colilert-18® Quanti-Tray® method (IDEXX, Westbrook, ME, USA) was used for the detection of *E. coli* within 24 h of sampling [45]. The proposed study used *E. coli* as a biological pollution indicator due to its association with livestock waste.

2.3. Data Analysis

2.3.1. Multivariate Statistical Analysis

This study adopted an integrated methodological approach combining the Pearson correlation and agglomerative hierarchical clustering analysis (AHCA) method. The WQI and EI average data were analyzed over two decades from 2003 to 2024 using agglomerative hierarchical clustering (AHC) to find patterns that show temporal variations and whether pollution was point-source or diffuse [38,48,49]. The R code using the hclust function for hierarchical cluster analysis (The R Core Team, Vienna, Austria) [50] was developed with assistance from ChatGPT (ChatGPT Team, Newark, DL, USA) [51]. A Pearson correlation was performed on the averages of selected physical and chemical WQPs and between WQI and EI at a significance level ($\alpha < 0.05$) in the FD and the SD. The result confirmed the time-varying nature of the water quality of aquatic systems at the catchment level with respect to anthropogenic activities occurring [32]. The selected approach further aggregated data to minimize the effect of short-term fluctuations on long-term trends and effectively elucidated evolution from rainfall-dependent diffuse to point-source pollution induced by mining activities [38].

2.3.2. Time Series Analysis

Time series analysis is a statistical technique that transforms a sequence of data collected over a continuous period. It is widely used for establishing trends that reveal a pattern over an extended period [52]. The current study applied time series analysis to illustrate changes in the WQI and EI average values over a continuous period of time from 2003 to 2024 to uncover a pattern and sporadic changes in water quality over the two decades.

2.3.3. Water Quality Index Rating Procedure Method

Globally, researchers who assessed the water quality status of different freshwater ecosystems such as groundwater, rivers, and lakes using the WQI applied the weighted arithmetic index approach because it proved objective by providing weights for each WQP based on its significance in the assessment [28,32,33,41,49,53,54]. The results in this current study were compared to South African National Standards (SANS 241:2015) [55] for drinking water and the South African Department of Water Affairs and Forestry (DWAF) water quality guidelines for livestock watering [56], or the more stringent standard where two standards were available (Table 1). The standards were used to provide an indication of fitness for human consumption and livestock drinking. According to Tripathi and Singal [54], policymakers and water managers adopt the WQI because it provides a distinct indication of the pollution levels of aquatic systems, including whole catchments [32], rivers [30,33], reservoirs [53], and groundwater [49,57].

The importance of a parameter was determined based on its health significance and availability in a natural environment according to principles confirmed by Nombuyiselo et al. [48]. A weight of 2 was assigned to chemical oxygen demand, lead, EC, and pH according to the degree of significance and based on principles confirmed by Nzama et al. [58], with a weight of 3 assigned to nitrite, iron, orthophosphates, and

ammonium. A weight of 4 was assigned to cadmium and nitrate, while *E. coli* was assigned a weight of 5 because of its impact on the health of animals and human users of river water [59] (Table 1).

Table 1. Weighted significance rating for selected water quality variables.

Water Quality Variable	Units	Relative Weights (w*i*)	Weighted Significance Rating (W*i*)	SANS 2015:241 [55]	DWAF [56]
EC	mS/m	2	0.06	170	154
Cd^{2+}	mg/L	4	0.12	11	*
COD	mg/L	2	0.06	5	*
E. coli	MPN/100 mL	5	0.15	0	200
Fe^{2+},	mg/L	3	0.09	2	10
NO_3^-	mg/L	4	0.12	11	100
Pb^{2+},	mg/L	2	0.06	0.02	*
PO_4^{3-}	mg/L	3	0.09	0.1	*
NH_4^+,	mg/L	3	0.09	1.5	*
NO_2^-,	mg/L	3	0.09	0.09	*
pH	pH units	2	0.06	8	*
		33	1		

* No available guideline values under livestock and watering DWAF [56].

The ultimate score derived from the calculation of the scores is divided by the sum of the weights derived for all WQP to get the weighted significance rating (w*i*) [53,58]. The assigned parameter weights influence the aggregated overall index value. The Weighted Arithmetic Water Quality Index (WAWQI) was calculated following the 5 steps below:

Each selected parameter was allocated a weight based on its impact on the overall water quality (a weight of 1 to 5), where one (1) depicts the least impact while five (5) refers to the most severe impact.

Determine the weighted significance rating (W*i*) for each parameter using Equation (1).

$$W_i = \frac{Wi}{\sum_{i=1}^{n} Wi} \quad (1)$$

where w*i* is the relative weight of the *i*th parameter, and *n* is the sum of rated parameters.

As a control measure, the weighted significance ratings should add up to 1 because the overall effect of the water quality parameters should add to 100% [41]. All the parameters except for pH were assigned a quality rating scale Q*i* by dividing their concentration (C*i*) by their respective South African National Standard (SANS 241:2015) [55] (S*i*) and multiplying by 100 [53]. The results are then presented as percentages using Equation (2).

$$Qi = \left[\frac{Ci}{Si}\right] \times 100 \quad (2)$$

where Q*i* denotes the quality rating, and C*i* is the concentration of the parameter. Q*i* is zero when the water samples show no pollution, and Q*i* = 100 when the parameter goes above the permitted quality range. Thus, an increase in Q*i* signifies more contamination in the water sample.

Calculate the sub-index S*i* for each parameter using Equation (3).

$$Si = Wi \times Qi \quad (3)$$

Sub-indices are applied to translate various WQP units into a single unitless value comparable to the WQI class shown in Table 2 [2].

Table 2. Water use suitability classification based on the water quality index value (adapted from Mnyango et al. [53]).

Class	WQI Value	Rating of Water Quality	Possible Uses
Class 1	<25	Excellent	Domestic usage, irrigation, and industrial usage
Class 2	26–50	Good	Domestic usage, irrigation, and industrial usage
Class 3	51–75	Poor	Irrigation and Industrial usage
Class 4	76–100	Very poor	Irrigation
Class 5	>100	Unsuitable	Proper treatment is required before use

The sub-indices are aggregated as in Equation (4) to give a single unitless value as a water quality rating of each river.

$$WQI = \sum_{i=1}^{n} Si \quad (4)$$

The water quality values are categorized using five water quality classes as presented in Table 2 [33,53].

2.3.4. Eutrophication Index

The eutrophication state of the rivers was evaluated using the eutrophication index of Liu et al. [34]. The EI was used to evaluate the eutrophication status of the KRIRs using three water quality parameters based on Equation (5): DIN, DIP, and COD [59].

$$EI = \frac{COD \times DIP \times DIN}{4500} \times 10^6 \quad (5)$$

where:

COD = the concentration of COD;
DIN = the concentration of total dissolved inorganic nitrogen; and
DIP = the concentration of dissolved inorganic phosphorus.
The EI is classified into two categories as follows [35]:
EI < 0: Zero eutrophication and EI > 0: Eutrophication.

3. Results

3.1. Statistics of Biophysical and Chemical Water Quality Parameters

Statistics were calculated for the eleven selected water quality parameters, namely potential of hydrogen (pH), electrical conductivity (EC), chemical oxygen demand (COD), cadmium (Cd^{2+}), iron (Fe^{2+}), lead (Pb^{2+}), *E. coli*, nitrate NO_3^-, nitrite (NO_2^-), ammonium (NH_4^+), and orthophosphate (PO_4^{3-}) at each water quality site (WQS). The eleven water quality parameters, namely NO_3^-, PO_4^{3-}, NH_4^+, NO_2^-, Fe^{2+}, Cd^{2+}, Pb^{2+}, EC, COD, and pH, selected to compute the WQI, fluctuated within the water quality standards except for COD and *E. coli* (Table S2). WQS-A measured the highest Fe^{2+} concentration at 0.051 mg/L.

The concentration of NO_3^- ranged from 0.338 mg/L to 2.47 mg/L with an average of 0.945 mg/L at WQS-A in the SD. Although the range is within the recommended maximum permissible limit of 6 mg/L of the South African water quality guidelines for livestock watering [56], it is higher than the NO_3^- range in the FD, which was from 0.148 mg/L to 0.473 mg/L with an average value of 0.225 mg/L at WQS-E.

At WQS-C, *E. coli* ranged between 91.29 MPN/100 mL and 3002 MPN/100 mL, with an average of 964.3 MPN/100 mL, in the FD. Comparatively, it was relatively higher than the average *E. coli* in the SD, which ranged between 315 MPN/100 mL and 2420 MPN/100 mL with an average of 1075.02 MPN/100. The highest average concentrations of *E. coli* (964.3 MPN/100 mL) and COD (6.32 mg/L) were recorded at WQS-C. The highest averages of NO_3^- (0.39 mg/L) and EC (8.32 mS/m) were recorded at WQS-D. Site WQS-E recorded the highest average PO_4^{3-} concentration of 0.055 mg/L. In the SD, PO_4^{3-} ranged between 0.02 mg/L and 0.08 mg/L, which was lower than the range between 0.01 mg/L and 0.13 mg/L in the FD. It was observed that pH was lower in the SD (8.10 to 8.44) than in the FD (8.17 to 8.43). Notably, most WQPs displayed fluctuations in all five inflow rivers. Average values were higher in the SD relative to the FD and complied with the standards [55,56], which are alert triggers for water managers to implement corrective measures should they be exceeded [60]. The statistics are summarized in Table S2.

3.2. Correlation Between Water Quality Parameters

The Pearson correlation coefficient between different WQPs was calculated at a significance level ($\alpha = 0.05$), and the results are shown in a correlation coefficient matrix in Table 3a,b. A strong positive correlation existed between pH, *E. coli*, and physicochemical parameters in the SD compared to the FD. During the FD, the correlation matrix in Table 3a shows that *E. coli*, EC, COD, pH, NO_3^-, NO_2^-, and Pb^{2+} were positively correlated with WQI, with correlation coefficients of 0.98, 0.65, 0.44, 0.30, 0.27, 0.02, and 0.01, respectively, in descending order. Among these parameters, *E. coli* showed the highest correlation with WQI in the FD and SD. The WQI showed weaker correlations with WQPs in the SD. The correlation between NO_3^- and WQI increased significantly from 0.02 to 0.27 from the FD to the SD. During the SD, the correlation between pH and other WQPs, such as NO_3^-, COD, Fe^{2+}, and PO_4^{3-}, decreased significantly. The correlation between EI and WQI increased from r = 0.45 in the FD to r = 0.81 in the SD (Table 3a,b).

3.3. Variations in Water Quality Index from 2003 to 2024 at Katse Reservoir Inflow Rivers

Figure 2 shows the time series analysis of WQI from 2003 to 2024 in the Katse Reservoir inflow rivers. The average WQI shows a notable fluctuation in the WQI value for WQS-C, including 1232 in 2007. This is attributed to high *E. coli* values at the WQS-C site relative to other sampling points (Table S2). WQS-D and WQS-E displayed low WQI values relative to WQS-C, WQS-A, and WQS-B. WQS-C and WQS-D had significantly higher *E. coli* at 3002 MPN/100 mL and 1224.4 MPN/100 mL, respectively (Table S2). WQS-C showed relatively high *E. coli* in the FD compared with the SD. This resulted in high WQI values in the FD (Figure 2).

3.4. Variations in Eutrophication Index from 2003 to 2024 at Katse Reservoir Inflow Rivers

The time series analysis of EI demonstrated that NO_3^- contributes to eutrophication in the rivers, as documented by Rossouw et al. [61]. The EI shows a significant increase in the SD due to the release of NO_3^- into the Malibamatšo River that flows through the WQS-A (Figure 3).

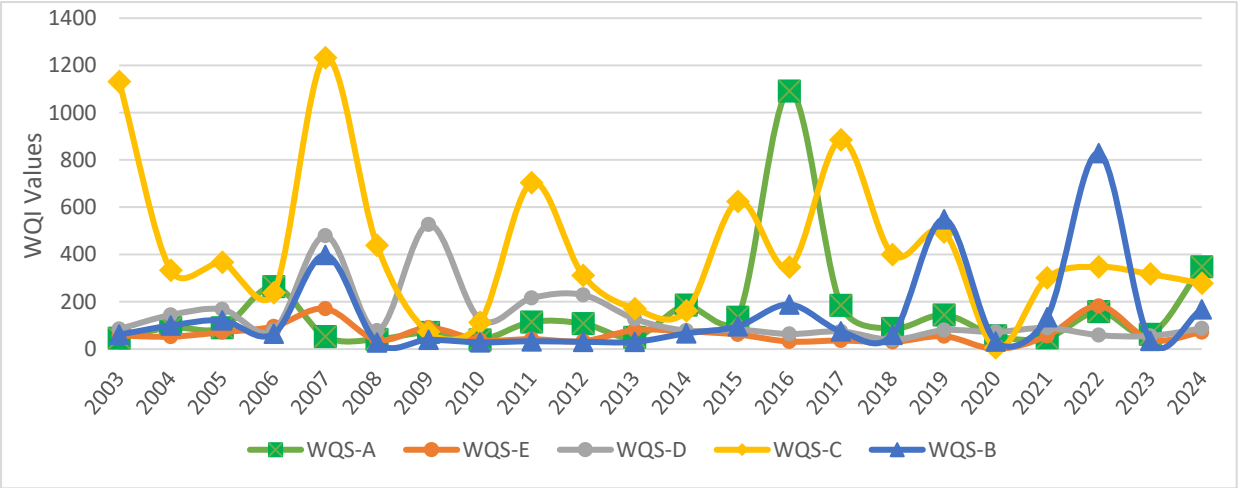


Figure 2. Time series analysis of the water quality index at Katse Reservoir inflow rivers from 2003 to 2024.

Table 3. Correlation matrix for selected water quality parameters, water quality index and eutrophication index for the first decade and the second decade at a significance level of 5% ($\alpha = 0.05$). The blue, white, and green colors depict strong, weak, and no correlation, respectively.

(a)	EC	Cd^{2+}	COD	*E. coli*	Fe^{2+}	NO_3^-	Pb^{2+}	PO_4^{3-}	NH_4^+	NO_2^-	pH	WQI	EI
EC	1.00												
Cd^{2+}	0.39	1.00											
COD	−0.49	−0.93	1.00										
E. coli	0.58	−0.34	0.39	1.00									
Fe^{2+}	−0.43	−0.45	0.38	−0.21	1.00								
NO_3^-	0.70	0.91	−0.95	−0.09	−0.43	1.00							
Pb^{2+}	0.66	0.90	−0.90	−0.08	−0.25	0.97	1.00						
PO_4^{3-}	−0.19	0.51	−0.27	−0.24	−0.70	0.21	0.12	1.00					
NH_4^+	−0.13	0.77	−0.78	−0.82	−0.29	0.57	0.49	0.53	1.00				
NO_2^-	0.27	−0.70	0.50	0.57	0.48	−0.37	−0.32	−0.91	−0.80	1.00			
pH	0.76	0.64	−0.72	0.15	−0.82	0.78	0.63	0.33	0.40	−0.27	1.00		
WQI	0.65	−0.21	0.27	0.98	−0.38	0.02	0.01	−0.10	−0.71	0.44	0.30	1.00	
EI	−0.16	−0.59	0.75	0.57	0.52	−0.56	−0.40	−0.35	−0.84	0.50	−0.69	0.45	1.00

(b)	EC	Cd^{2+}	COD	*E. coli*	Fe^{2+}	NO_3^-	Pb^{2+}	PO_4^{3-}	NH_4^+	NO_2^-	pH	WQI	EI
EC	1.00												
Cd^{2+}	−0.04	1.00											
COD	−0.09	−0.94	1.00										
E. coli	0.58	−0.67	0.40	1.00									
Fe^{2+}	−0.37	−0.61	0.82	−0.12	1.00								
NO_3^-	0.54	−0.37	0.52	0.16	0.47	1.00							
Pb^{2+}	0.25	−0.33	0.02	0.78	−0.51	−0.39	1.00						
PO_4^{3-}	−0.39	−0.58	0.73	−0.05	0.95	0.29	−0.44	1.00					
NH_4^+	−0.20	0.33	−0.57	0.13	−0.63	−0.92	0.57	−0.39	1.00				
NO_2	0.31	−0.05	0.24	−0.15	0.16	0.76	−0.33	−0.14	−0.84	1.00			
pH	0.47	0.73	−0.62	−0.43	−0.42	0.33	−0.46	−0.52	−0.28	0.51	1.00		
WQI	0.57	−0.71	0.47	0.96	−0.09	0.27	0.77	−0.12	−0.03	0.09	−0.38	1.00	
EI	0.87	−0.43	0.32	0.73	−0.12	0.67	0.38	−0.24	−0.42	0.51	0.18	0.81	1.00

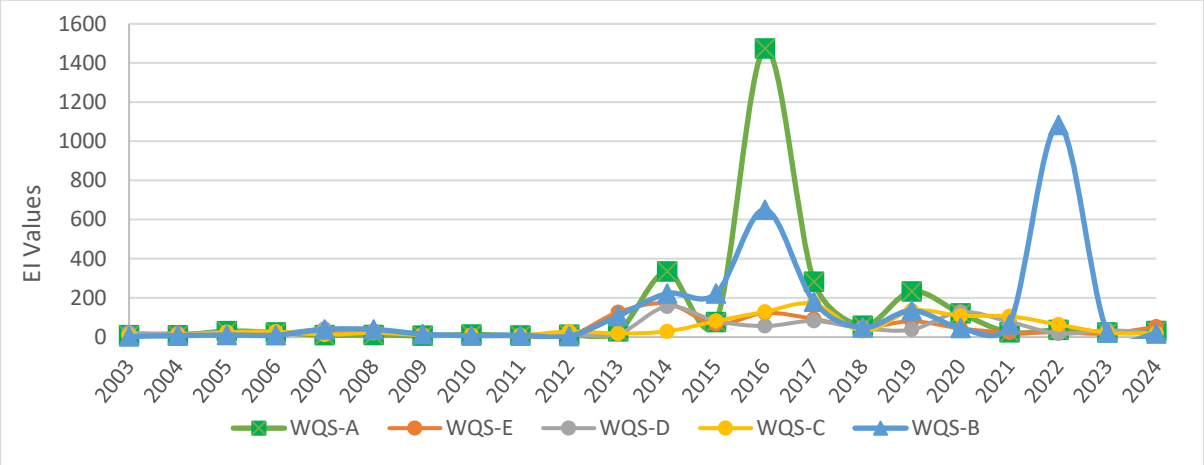


Figure 3. Time series analysis of eutrophication index at Katse Reservoir inflow rivers from 2003 to 2024.

3.5. Statistics for Water Quality Index and Eutrophication Index

Table 4 shows that the range of EI minimum values was significantly higher in the SD (17.5 to 23.5) compared to the FD (3.2 to 7.8). This observation is attributed to higher levels of nutrients in the KR catchment in the SD. WQS-A was more polluted compared to other water quality sites due to mining activities in the SD. This is evidenced by the average WQI of 87.6 in the FD, which is significantly lower compared to the WQI of 227.4 in the SD. Similarly, the average EI value for the FD was 14.5, significantly lower compared to the WQI of 245.2 in the SD.

Table 4. Statistics for water quality index and eutrophication index at Katse Reservoir inflow rivers.

Decade	Index	Descriptive Statistic	Water Quality Sites					Color Code
			WQS-A	WQS-B	WQS-C	WQS-D	WQS-E	
2003–2014	WQI	MIN	38.5	27.4	71.8	77.5	33.3	high
		MAX	263.8	398.0	1232.5	527.1	170.8	
		AVG	87.6	84.8	464.4	205.1	69.7	
		STDV	64.5	108.5	394.9	156.2	40.0	medium
	EI	MIN	6.8	3.9	3.2	7.8	4.0	
		MAX	29.7	126.5	107.3	28.5	41.2	
		AVG	14.5	22.7	22.9	16.2	18.3	
		STDV	8.6	35.2	30.6	7.9	10.7	low
2014–2024	WQI	MIN	47.1	32.0	5.0	39.4	0.4	high
		MAX	1092.1	828.8	884.5	89.6	182.4	
		AVG	227.4	203.0	378.0	70.9	57.8	
		STDV	299.1	253.4	232.1	15.2	46.5	medium
	EI	MIN	23.5	17.5	17.5	17.5	17.5	
		MAX	1474.1	170.3	1083.4	169.4	156.2	
		AVG	245.2	67.5	245.2	80.9	66.9	
		STDV	422.5	46.9	330.9	52.5	44.2	low

Both the WQI and EI average annual values indicate low pollution between 2020 and 2023 due to a reduction in mining intensity from 2019 to 2021, when the mining sector diminished by 24.6% in the third quarter of 2020 and resumed full-scale operations in 2024 [62]. Based on the combined result of both WQI and EI, the heatmap in Table 4 shows water quality status in the sequence WQS-E > WQS-A > WQS-D > WQS-C > WQS-B, from low pollution to high pollution in the FD. The impact of human activities such as mining

and livestock rearing degraded the water quality and induced a change to a new sequence WQS-E > WQS-D > WQS-B > WQS-C > WQS-A.

3.6. Correlation Between Water Quality Index and Eutrophication Index

This study employed a Pearson correlation to investigate the degree to which changes in physical and chemical parameters affected both the WQI and the EI. The findings of the study indicate that mining significantly impacted the water quality status at WQS-A. Notably, the results reveal that most WQSs displayed a strong positive correlation between WQI and EI in the SD relative to the FD. WQI and EI showed a negative correlation in the FD at WQS-C ($r = -0.24$, $p < 0.023$). Conversely, a statistically significant and strong positive correlation existed between WQI and EI ($r = 0.93$, $p < 0.023$) at WQS-A in the SD, mainly due to its location downstream of mining operations (Table 5).

Table 5. Correlation matrix for water quality index and eutrophication index from 2003 to 2024 at a significance level of 5% ($\alpha = 0.05$).

Pearson's Correlation Matrix at $\alpha = 0.05$					
		2003–2013	2014–2024		
WQS	**Indices**	**EI**		**Color Description**	
WQS-A	WQI	0.07	0.93	1	Strong Correlation
WQS-B		0.01	0.38	0.5	
WQS-C		−0.24	−0.11	0	Weak correlation
WQS-D		0.30	0.48	−0.5	
WQS-E		0.02	0.73	−1	No correlation

3.7. Water Use Classification for Katse Reservoir Inflow Rivers at Water Sampling Sites

Table 6 indicates that all the rivers in the Katse catchment were unsuitable for domestic use (WQI < 50). WQS-E and WQS-D were suitable for industrial use (51 < WQI < 75), while WQS-A, WQS-B and WQS-C were unsuitable for any use before treatment (100 < WQI) in the SD.

Table 6. Classification of water quality sites for various possible uses in the first decade and in the second decade.

Class	WQI Value	Category	Possible Uses	FD	SD
Class 1	<25	Excellent	Domestic		
Class 2	26–50	Good	Domestic		
Class 3	51–75	Poor	Industrial	WQS-E	WQS-E, WQS-D
Class 4	76–100	Very poor	Irrigation	WQS-A, WQS-B	
Class 5	>100	Unsuitable	Treatment is required before use	WQS-C, WQS-D	WQS-A, WQS-B, WQS-C

3.8. The Hierarchical Cluster Analysis of the Years Based on Water Quality Index and Eutrophication Index

Hierarchical cluster analysis classifies and groups sampling sites with similar characteristics, with the quality gradually decreasing from the first group to the last group [33,48] and enables multiscale assessment using different indices over time [38]. The classification

of monitoring years into the three classes, namely high quality (cluster 1), medium quality (cluster 2), and low quality (cluster 3), follows the assignment of years from 2003 (year 1) to 2024 (year 22) with units from 1 to 22, respectively (Figure 4).

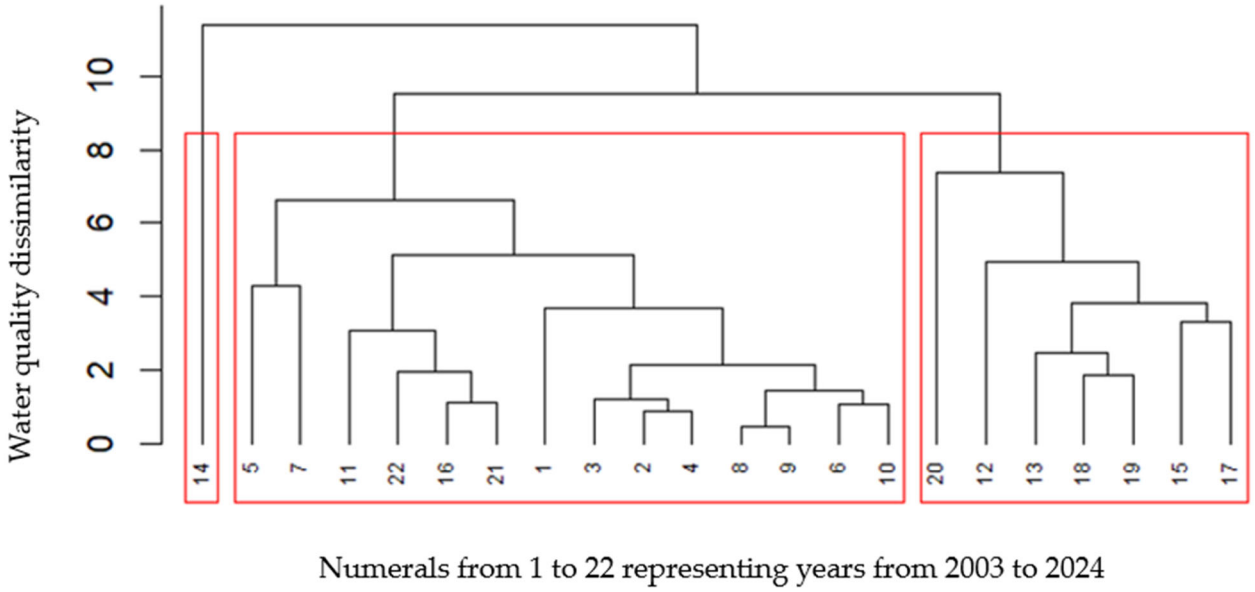


Figure 4. Hierarchical clustering dendrogram of WQI and EI over monitoring years from 2003 (numeral 1) to 2024 (numeral 22), showing the delineation of the low water quality cluster (14), high water quality cluster (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 16, 21, 22), and medium water quality cluster (12, 13,15, 17, 18, 19, 20) at the Katse Reservoir water quality sites. The classification of years from numeral 1 (2003) to numeral 22 (2024) was interpreted based on the contribution of WQI and EI to quality status in those years.

4. Discussion

4.1. Trends Analysis of Biophysical and Chemical Water Quality Parameters

In the FD, spatial variations in concentrations were evident, yet no identifiable trends indicated point-source pollution. Hence, the pollution mostly emanated from diffuse sources because no set of variables showed elevated concentrations at any particular WQS [38]. WQS-A showed evidence of shifting from non-point source pollution in the FD to point source pollution in the SD because of the following observed trends in nitrates (0.22 mg/L to 0.95 mg/L), COD (5.99 mg/L to 8.66 mg/L), and orthophosphates (0.03 mg/L to 0.85 mg/L). This observation reveals that diamond mining activity has significantly impacted the water quality at WQS-A through the release of metals and nitrate-laden effluent. In particular, the rise in nitrates is attributed to ammonium nitrates embedded in the explosives used in blasting the mine pit [17]. The nitrates in mining effluents are attributable to high values of WQI (1092.1) and EI (1474.1) at site WQS-A in the SD (Table 4). The influx of nitrates detected at WQS-A creates the potential for eutrophication even at low phosphorus concentrations [18]. It is also attributable to the high correlation (r = 0.93) between the two indices at WQS-A in the SD (Table 5).

Overall, nutrient and metal concentrations were relatively higher in the SD than in the FD due to a point source of pollution in the catchment. This is supported by the elevated correlation coefficients in the second decade from 2014 to 2024 (Table 5). It was evident from this study that *E. coli* and nitrates were the most influential parameters with high fluctuations in concentrations. The elevated concentrations of *E. coli* provide scientific evidence of the impacts of cattle kraals and sheep shearing sheds at site WQS-C. The relatively low pH in the SD at all WQSs indicates increased acidity from mining discharge such as mine slurry and seepage (Table S2). According to Winde and Newman-Portela [16],

pH is reduced by oxidation of iron sulfide due to exposure to water and oxygen. The effluent with a low pH is called AMD, and it is linked to high EC and elevated toxic trace metals such as lead and cadmium [16].

The Pearson correlation matrix revealed an inverse correlation between Cd^{2+}, Fe^{2+}, and Pb^{2+} attributable to possible chemical reactions between cadmium and these heavy metals [63]. The strong positive correlation between COD and NO_3^- indicated that these WQPs have the same point sources of pollution, notably mining effluents and runoff from sheep shearing sheds where livestock waste emanates [7,13]. WQS-C is located within a catchment where livestock density is higher close to rivers. Hence, the relatively higher WQI values at WQS-C agree with the observation by Cadraku and Shala [4] that the release of waste into rivers outweighs the natural cleansing ability of the rivers where pollution activity is higher close to rivers.

4.2. Impact of Anthropogenic Activities on the Water Quality Index and Eutrophication Index

4.2.1. Influence of Anthropogenic Activities on the Water Quality Index

Spatial and temporal variations in water quality parameters reveal an impact on the WQI and EI from FD to SD due to changes in the intensity of pollution from various sources in the KR catchment. The river at WQS-D was the most compliant with SANS (241:2015) [55] and DWAF [56] relative to the five rivers, as confirmed by Mathebula [11]. WQS-A and WQS-B showed increased WQI values that suggest low water flows and a low dilution factor, which explains the high concentrations of pollutants in 2016 [48].

While *E. coli*, EC, COD, pH, nitrate, nitrite, and lead contributed significantly to WQI, in the FD, *E. coli* displayed a strong positive correlation and the biggest influence on WQI in the FD (r = 0.98) and SD (r = 0.96). Nevertheless, *E. coli* is a nitrifying bacterium that benefits the catchment through removal of nitrogen and COD from livestock wastewater before entering the Katse Reservoir [64–66]. This observation is consistent with findings by Pan et al. [66] that although *E. coli is* naturally found in various ecosystems, researchers have shown an interest in developing *E. coli* strains for wastewater treatment.

Notably, high *E. coli* levels observed at WQS-C are attributed to fecal matter from livestock kraals located close to the river. Environmental managers should construct retaining walls for livestock wastewater bunding through stakeholder collaborations as corrective action to reduce the concentrations of *E. coli* [67]. Nevertheless, the possibility that rural communities in the Katse Reservoir practice open defecation is negligible, in contrast to residents of the Otamiri River in Nigeria [28]. Authorities in the KR catchment improved sanitation facilities in the vicinity of all five rivers as early as 2004 through a water and sanitation (WATSAN) program implemented by the Lesotho Highlands Development Authority (LHDA) [68].

4.2.2. Influence of Anthropogenic Activities on the Eutrophication Index

Nutrients also revealed a notable relationship with both WQI and EI. The change in the correlation between nitrates and WQI was significant because it increased from the FD (r = 0.02) to the SD (r = 0.27). While a negative correlation existed between nitrates and EI in the FD at r = − 0.56, a strong positive correlation existed between nitrates and EI in the SD at r = 0.67 (Table 5). The observed change is attributed to the release of mining effluent that is rich in nitrates from explosives used to blast the mine pit [17]. Research shows that eutrophication is caused by the enrichment of water bodies with nutrients, most of which emanate from catchment activities including mining and livestock waste dispersed in the catchment [61]. Nitrates contributed significantly to the EI in the SD (r = 0.67), attributable to mining effluent entering the river sampled at WQS-A (Table S2). Recent research offered innovative bioremediation technologies that incorporate microorganisms to reduce the

nutrient content of mining effluent before discharge into the environment [64,65]. These technologies provide pollution mitigation and protect aquatic ecosystems from toxic mine tailings discharge [16].

4.3. Water Use Suitability of Katse Reservoir Inflow Rivers

The water in rivers sampled at WQS-A, WQS-B and WQS-C was unsuitable for any use before treatment (100 < WQI) (Table 6). This limitation has implications for socio-economic development in the Katse reservoir catchment. Despite the observed limitation, the two rivers that flow through WQS-D and WQS-E were suitable for irrigation and industrial use in the SD. These findings indicate a need for catchment-scale environmental policymaking that entails advanced bioremediation for mining effluent, spatial outline of the distribution of pollution hotspots using remote sensing, and relocation of livestock posts from riverbanks. This can be facilitated through active engagement with scientists, policymakers, environmental managers and water consumers [3,38,60]. This study suggests setting alert trigger concentrations for *E. coli*, NO_3^- and EC as a corrective measure to improve water suitability for various uses, protect water resources and public health in the Katse Reservoir catchment [32]. Environmental managers should institute adaptive management to evaluate the effectiveness of these corrective measures to secure the economic, environmental and social value of the Katse Reservoir inflow rivers [60].

4.4. Correlation Between WQI and EI

The negative correlation between WQI and EI in the FD at WQS-C ($r = -0.24$, $p < 0.023$) highlights the effectiveness of using different indices to assess pollution emanating from various sources. This assertion is supported by the high WQI attributable to high levels of *E. coli* despite the low EI values. The strong positive correlation between WQI and EI in the SD reported in this study is consistent with conclusions by Son et al. [35] that agreement between indices supports decision-making and indicates point-source pollution due to concentrated pollutants. There is a marked upward trend in the correlation between WQI and EI at all the WQSs from FD to SD due to deteriorated water quality status across the catchment (Table 5). The heatmaps in Tables 4 and 5 are comparable in their depiction of WQSs with the greatest water quality deterioration. WQS-A and WQS-C are the most impacted sites attributable to NO_3^- and *E. coli* concentrations, respectively.

4.5. Grouping of Years Between 2003 and 2024 Based on Water Quality Status

Consistent with studies by Chen and He [38], the temporal agglomeration and correlation between WQI and EI indicated that the impact of mining activities shifted pollution from diffuse in the FD to point source in the SD. The year 2016, represented by the numeral 14, had the worst water quality because it was reported as a drought year with low flows in rivers in Lesotho [69]. This was also supported by the results in Figures 2 and 3, where WQS-A and WQS-B indicated elevated WQI and EI values due to a low dilution factor caused by low flows and high pollutant concentration. According to Nombuyiselo et al. [48], elevated flow in rivers dilutes the concentration of pollutants, while low flow increases pollutant concentration, hence the low dilution factor in 2016.

High water quality years comprise the FD years between numeral 1 (2003) and numeral 11 (2013) because of exposure to low pollution. The numerals 21 (2023) and 22 (2024) have been classified in the low pollution high water quality cluster due to their relatively low exposure to pollution from the mines following a period of care and maintenance at the mines to lessen the spread of the COVID-19 pandemic from 2020 to 2021 [61]. In contrast, low water quality years included the years 2014 (numeral 12), 2015, 2016 (numeral 13), and 2022 (numeral 20), because of exposure to higher pollution from mining seepage and slurry discharge (Table 7).

Table 7. Clustering water quality monitoring years from year 1 (2003) to year 22 (2024) between low-quality and high-quality classes.

Classification	Cluster	WQI	EI	Numerals Representing Years from 2003 to 2024
High quality	1	105	19	1,2,3,4,5,6,7,8,9,10,11,21,16,22
Medium Quality	2	140	138	12,13,15,17,18,19,20
Low quality	3	329	487	14

5. Limitations and Future Considerations

This study successfully identified mining activity and livestock waste as point sources of pollution at WQS-A and WQS-C using water quality data. However, the selected methodology does not distinctly specify the underlying driver of water quality degradation. Hence, it is necessary to explore remote sensing and satellite imagery in future research to outline the spatial distribution of diffuse sources of pollution and to determine the direct cause of water quality degradation, as supported by Chen and He [38]. Additionally, it was observed that a large increase in one parameter affects the entire result, and neither index reveals the impact of short-term, localized changes in water quality [2]. To alleviate this limitation, it is recommended that future research apply hydrological water quality models such as the Soil and Water Assessment Tool and Hydrological Simulation Program to simulate water quality and hydrological processes to identify and quantify water pollution at the catchment scale [3,70]. A future research direction would be to leverage recent advances in continuous real-time monitoring of the quality and quantity of mine water with higher accuracy using the Internet of Things (IoT) remote sensing, with the objective of processing and reusing mine water [71,72].

6. Conclusions

The application of indices in this study linked mining activities to water quality deterioration. Furthermore, the indices classified the KR inflow rivers into a simple water-use suitability scale that non-technical stakeholders can understand. The application of correlation analysis and agglomerative hierarchical clustering along with multiple indices in this study effectively identified spatiotemporal variation in water quality status influenced by human activities in the Katse Reservoir catchment, advanced previous studies, and contributed to filling the scientific knowledge gap. The Malibamatšo River, at WQS-A (Table S1), shifted from diffuse to point-source pollution due to increased mining activity in the SD. Most studies reported results without distinctly identifying the impacts of climate change and hydrodynamics on water quality [28,30,33]. In contrast, it is argued that this study, through the application of hierarchical cluster analysis, identified 2016 as the year in which drought impacted the water quality of the KRIRs, consistent with climate reports [69].

The water in the Katse Reservoir catchment was concluded to be unsuitable for domestic usage (WQI < 50). Furthermore, the two rivers sampled at WQS-E and WQS-D were concluded to be suitable for industrial use and irrigation (51 < WQI < 75), whereas those flowing through WQS-A, WQS-B and WQS-C were unsuitable for any use before treatment (100 < WQI) in the SD. *E. coli* contributed significantly to the WQI, while nitrates contributed significantly to the EI in the SD, attributable to mining effluent entering the river sampled at WQS-A. Eutrophication increased significantly from the FD to the SD in the KRIRs. Collaboration with stakeholders in the KR catchment is recommended for constructing retaining walls around livestock kraals and for implementing bioremediation technologies that incorporate microorganisms to reduce the nutrient content of mining effluent before discharge into the environment. Development of policy frameworks in consultation with all stakeholders will improve water quality at the catchment scale. The

findings provide long-term sustainable environmental management initiatives that mitigate pollution at source to protect public health and aquatic ecosystems from toxic mine tailings discharge and livestock waste.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/environments13090481/s1, Table S1: The site codes, GPS coordinates, and river names of the Katse Reservoir inflow rivers; Table S2: Statistics for water quality parameters from 2003 to 2024.

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Abbreviations

The following abbreviations are used in this manuscript:

AHCA	Agglomerative hierarchical cluster analysis
AMD	Acid mine drainage
COD	Chemical oxygen demand
DIN	Dissolved inorganic nitrogen
DIP	Dissolved inorganic phosphorus
DO	Dissolved oxygen
DWAF	Department of Water Affairs and Forestry
EI	Eutrophication index
FD	First decade
ISO	International Organization for Standardization
KR	Katse Reservoir
KRIRs	Katse Reservoir inflow rivers
LHDA	Lesotho Highlands Development Authority
SANAS	South African National Accreditation System
SD	Second decade
TOC	Total organic carbon
UNEP	United Nations Environmental Programme

WHO	World Health Organization
WQI	Water quality index
WQP	Water quality parameters
WQS	Water quality site

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