

Article

Assessment of the Impact of Coal Mining on Water Resources in Middelburg, Mpumalanga Province, South Africa: Using Different Water Quality Indices

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Abstract: The objective of this study was to assess the water quality status of the surface water and groundwater resources in the Middelburg area, South Africa. The assessment was addressed using combined water quality indices, investigating selected chemical parameters over four different seasons for a period of five years from 2017 to 2021. A combination of the Canadian Council of Ministers of the Environment water quality index and the comprehensive pollution index was used to analyze the water quality status of surface water and groundwater of the town of Middelburg, situated near coal mining activities in Mpumalanga, South Africa. The combination of the indices indicated that some surface water monitoring sites ranged between poor to fair water quality. Groundwater monitoring points also showed a poor to fair ranking. The comprehensive pollution index confirmed that some sites showed very poor water quality in the summer seasons, exceeding expected limits for the period 2017 to 2021. The principal component analysis further showed that both surface water and groundwater sites had high levels of contamination with increased chemical parameters. The results were compared against the different water quality guidelines. In an extensive monitoring program, water management systems must be properly implemented to mitigate impacts on water resources.



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Keywords: coal mining; acid mine drainage; water quality; pollution indices; multivariate analysis

1. Introduction

In most developing countries around the world, including South Africa, the mining industry effectively contributes to their socioeconomic development. Over centuries, mining has been an economic driver contributing to the gross domestic product, providing employment and business opportunities. However, the industry also poses a big threat to the natural environment [1,2]. Most mining countries have been victims of water pollution and unrehabilitated land [3]. This has resulted in water quality contamination becoming a significant environmental challenge in many countries around the world. The expansion of coal and gold mining in California has not only contributed to industry growth and success in the United States but also increased detrimental impacts on the environment [4]. In Spain, the Tinto River has experienced endless pollution from mining impacts such as acid mine drainage (AMD) [5]. In China, the Coal Industry Association also showed a reduction in coal mines from approximately 80,000 to 5800; however, most of the closed mines have resulted in environmental challenges and deteriorating water quality [6].

The government of South Africa has set laws and policies through the Department of Environmental Affairs and the Department of Water and Sanitation, previously known as the Department of Water Affairs and Forestry, to ensure that mining does not impact the environment. However, there has not been a significant improvement in the degradation of the environment. The availability and quality of South Africa's water resources are under strain from trends in natural and anthropogenic activities including urbanization, intensive agricultural practices, and significant industrial developments such as mining

operations [7]. Since the majority of these rapidly expanding water users are located upstream of sizable rivers and dams, the effects of their effluent discharges and return flows on water resources are substantial [8]. The aquatic ecosystem, human health, and other water users all suffer significant effects from the decline in the quality of water resources. Increased salinity, heavy metals, nutrients, organic debris, and sedimentation are a few of the frequent water quality issues [9].

To determine the amount of good water quality needed for residential use, the sustainable environmental or ecological flow of rivers, and the quality of water sources for various applications, it is crucial to monitor water quality and anthropogenic disturbances on water resources. Additionally, utilizing assessed factors, the water quality indices (WQIs) were created to depict the current water quality status of watercourses. Nevertheless, certain WQI models are not generic since they create uncertainty in the process of converting vast volumes of water quality data into a single index because they are typically created in accordance with site-specific rules for a specific region [10].

Numerous academics from around the world have used these indices to evaluate the state of surface water and groundwater bodies. This includes the Horton index, the National Sanitation Foundation WQI, the Scottish Research Development Department index, the water quality index of the Canadian Council of Ministers of the Environment (CCME–WQI), the Bascarón WQI, the fuzzy interface system, the Malaysian WQI and the West Java WQI [10–12], the comprehensive pollution index (CPI), organic pollution index (OPI), eutrophication index (EI), trace metal pollution index (TPI) [13], and the National Sanitation Foundation–Environmental Sanitation Technology Company of the State of São Paulo WQI [14].

Previous studies used a modified pollution index to determine the water quality status of the Loskop Dam, South Africa, and reported nutrient enrichment and heavy metal pollution [15]. Son et al. [13] evaluated the water quality of the Cau River using a combination of indices, including the WQI, CPI, OPI, EI, and TPI. They found significant eutrophic conditions and organic pollution downstream. Tang et al. [16] used the comprehensive pollution index to assess the water quality of Qilu Lake. Matta et al. [17] used the CPI to assess the water quality of the Henwal River in India and found moderate and severe contamination at many sampling sites. Using a combination of indices (CPI, OPI, EI, and TPI), Mishra et al. [18] assessed the Surha Lake in India and discovered that it was eutrophic and moderately polluted. Lumb et al. [19] evaluated the water quality of the Mackenzie Great Bear Sub-basin using the CCME–WQI and found turbidity and trace metal contamination. In the Norte Chico zone of north-central Chile, Espejo et al. [20] also applied the water quality status of four watersheds (Huasco Basin, Elqui Basin, Choapa Basin, and Limarí Basin) using the CCME–WQI. They found that, overall, the water quality was fairly acceptable, with the Limarí Basin having particularly good quality.

Although these tools have been modified and applied in various reservoirs, the WQIs have been used to address these issues to better assess the general water quality for both surface water and groundwater; however, not much work has been conducted at the catchment level of the study area. For this study, a combination of both the CCME–WQI and CPI was used to understand the overall water quality at the study area. There are very limited studies where combined indices were used to assess coal mining impacts in water resources [21]. The main reasons for selecting the CCME–WQI in the study was because it is an easy application to use, and it offers flexibility in selecting the variables to analyze in the model [22] as well as its ability to identify the space and time of dynamics in water quality and provide a number to represent water quality in a specific area of interest and time. The CCME–WQI can also simplify a complex dataset to be easier to understand. Furthermore, the index can also communicate the water quality status to decision makers and the public at large.

The CPI is another essential technique for scientific reflection of the kinds and levels of pollution in water systems. The CPI was also used in Bangladesh to assess the Karnaphuli

River, where severe pollution was identified from different wastes generated from various industries situated at the banks of the river [23].

With the social and economic development of the town of Middelburg, South Africa, and the upper Olifants River catchment largely influenced by coal mining, McCarthy [24] confirmed that approximately 50 million liters per day of AMD were decanting from defunct mines. The water quality in the Loskop Dam situated just downstream of the town of Middelburg has over time shown contamination, with groundwater being impacted by mining taking place upstream [25]. Furthermore, Adler and Rascher [26] mentioned that the impacts of AMD found in the Witbank and Middelburg regions of South Africa included environmental, political, and socioeconomic impacts. The environmental impacts included pollution of surface water through heavy metals, affecting aquatic life [3,26,27]. Therefore, there was a need to assess the groundwater and surface water quality status of the Middelburg region and to determine their pollution sources.

According to Atangana [28] and Oberholster et al. [15], it is imperative to develop tools such as water monitoring indices that may be utilized to detect and mitigate pollution in these types of catchments. An effective way to enhance data interpretation and analysis is to assess the present status of water quality in the watershed using a variety of water quality indices (e.g., CCME–WQI and CPI) in combination with water quality guidelines. Using the pollution indices (CPI and CCME–WQI), in relation to the water quality guidelines can provide better scientific evidence on the level and extent of pollution in water resources, which will be essential for decision makers. Very little is known about the use of combined WQIs in catchments impacted by AMD in South Africa; it will therefore be important to improve monitoring data analysis and interpretation. The study therefore aimed at achieving the following objectives:

1. To use existing water quality monitoring data for both surface water and groundwater sampling points in the Middelburg region and compare it with the water quality resource objectives of the study area;
2. To use different water quality indices (CCME–WQI and CPI) in combination with the water quality guidelines to determine the impacts of coal mining activities on surface water and groundwater quality around the study area;
3. To evaluate the interrelationship trends of the surface water and groundwater quality data;
4. To provide possible and efficient mitigation measures for the protection of water resources from coal mining and other related land-use activities.

2. Materials and Methods

2.1. Description of Study Area

The case study is situated approximately three kilometers south of the town of Middelburg near the N4 National Road and the R35 Middelburg–Bethal Provincial Road within the Steve Tshwete Local Municipality of the Nkangala District in the Mpumalanga Province, South Africa. The mining industry around the area has been contributing effectively to the socioeconomic development of the country by providing employment opportunities. The study area falls within the summer rainfall regions of the Mpumalanga province, where a typical Highveld climate with warm summers are observed at the range of 12 °C to 29 °C and winters from −3 °C to 20 °C. The Mpumalanga Highveld has distinct wet and dry seasons, with about 91% of the area's mean annual rainfall experienced from October to April [29].

The topography of the study area is mostly characterized by subdued relief and consists of gently shallow sand slopes [30]. Most of the coal mines in and around the area are exploiting coal, which occurs in shallow depths, influencing the dominating use of opencast mining methods [31]. The area is underlain by sediments of the Ecca Group that forms part of the Karoo Supergroup. The Ecca Group consists mainly of dark grey shale that is carbonaceous in some instances, with interbedded whitish sandstone and greyish gritstone as well as occasional coal bands [32].

The area falls within the Olifants Water Management Area 2 (WMA 2). The water management area is characterized by extensive agricultural and mining activities, mostly associated with coal deposits dominating the northern part of the area [25]. The catchment in which the study area falls consists of perennial streams situated on both the eastern and western side, draining towards the major rivers, namely the Olifants and Klein-Olifants Rivers. Within the B11H quaternary catchment, the tributaries flow in a north–west direction to the confluence with the Olifants River; at B12D, the streams flow north–east to the Klein-Olifants River, which then drains to the major Olifants River. Figure 1 shows the regional and drainage locality of the study area.

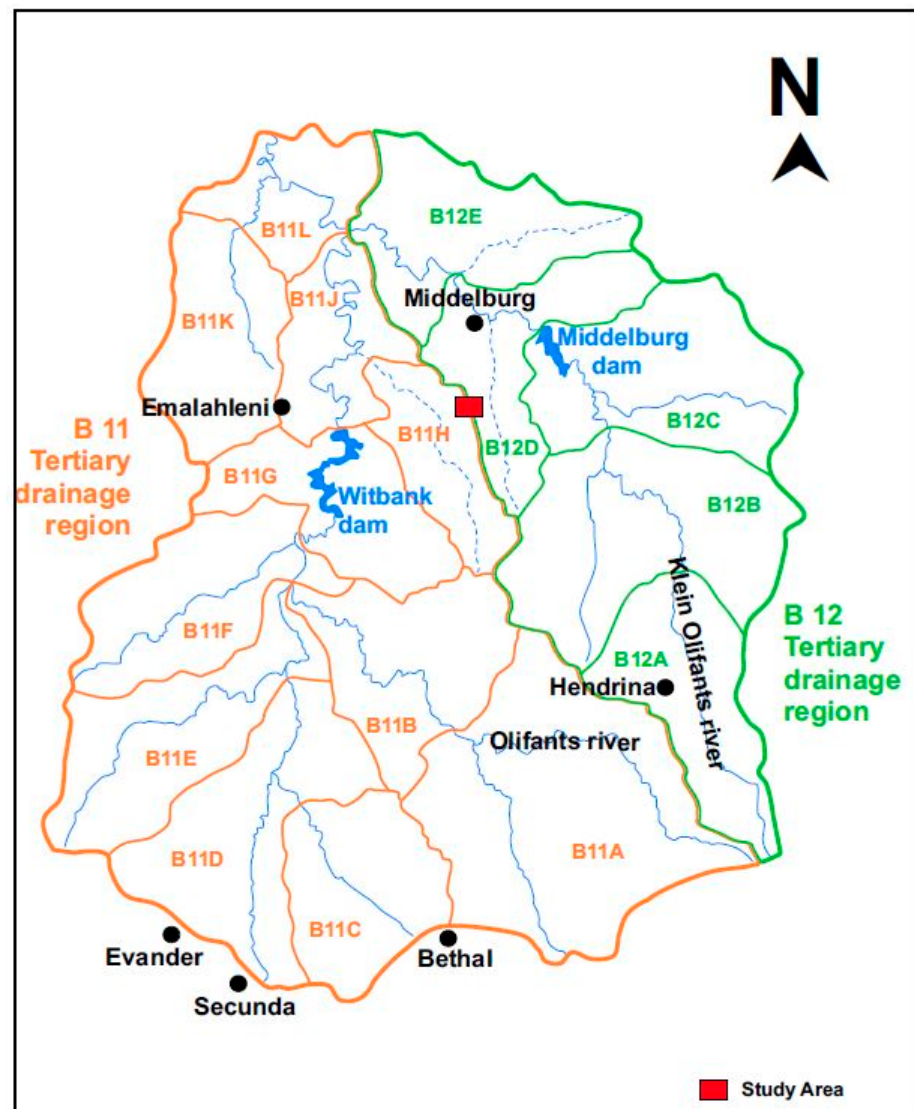


Figure 1. Regional and drainage regions of the study area, South Africa.

2.2. Field Sampling and Analysis

Due to increasing water pollution caused by mining activities, especially in the coal-fields, authorities such as the Department of Water and Sanitation have enforced the importance of water quality management, which entails monitoring. The National Water Act 36 of 1998 has further introduced an integrated water resource management concept, compromising all water resources aspects such as water quality monitoring [33].

For the current study, historical data from the surface water and groundwater monitoring points, as shown in Figures 2 and 3, were utilized to achieve the objectives set. The data were obtained from an established monitoring program on a monthly basis for

surface water and on a quarterly basis for groundwater for a period of five years from 2017 to 2021. The monitoring program was developed to provide the mining companies with the necessary information to assess the successes and failures of their water management strategies and comply with monitoring commitments stipulated in issued licenses and environmental permits. Using historical data provided answers and different perspectives on issues [34,35]. The water quality data were compared against the following standards to assess the level of contamination: resource quality objectives (RQO) [36], target water quality range (TWQR) [37,38], the CCME–WQI [39], and the guidelines of the Australian and New Zealand Environment and Conservation Council and the Agriculture and Resource Management Council of Australia and New Zealand (ANZECC/ARMCANZ) [40].

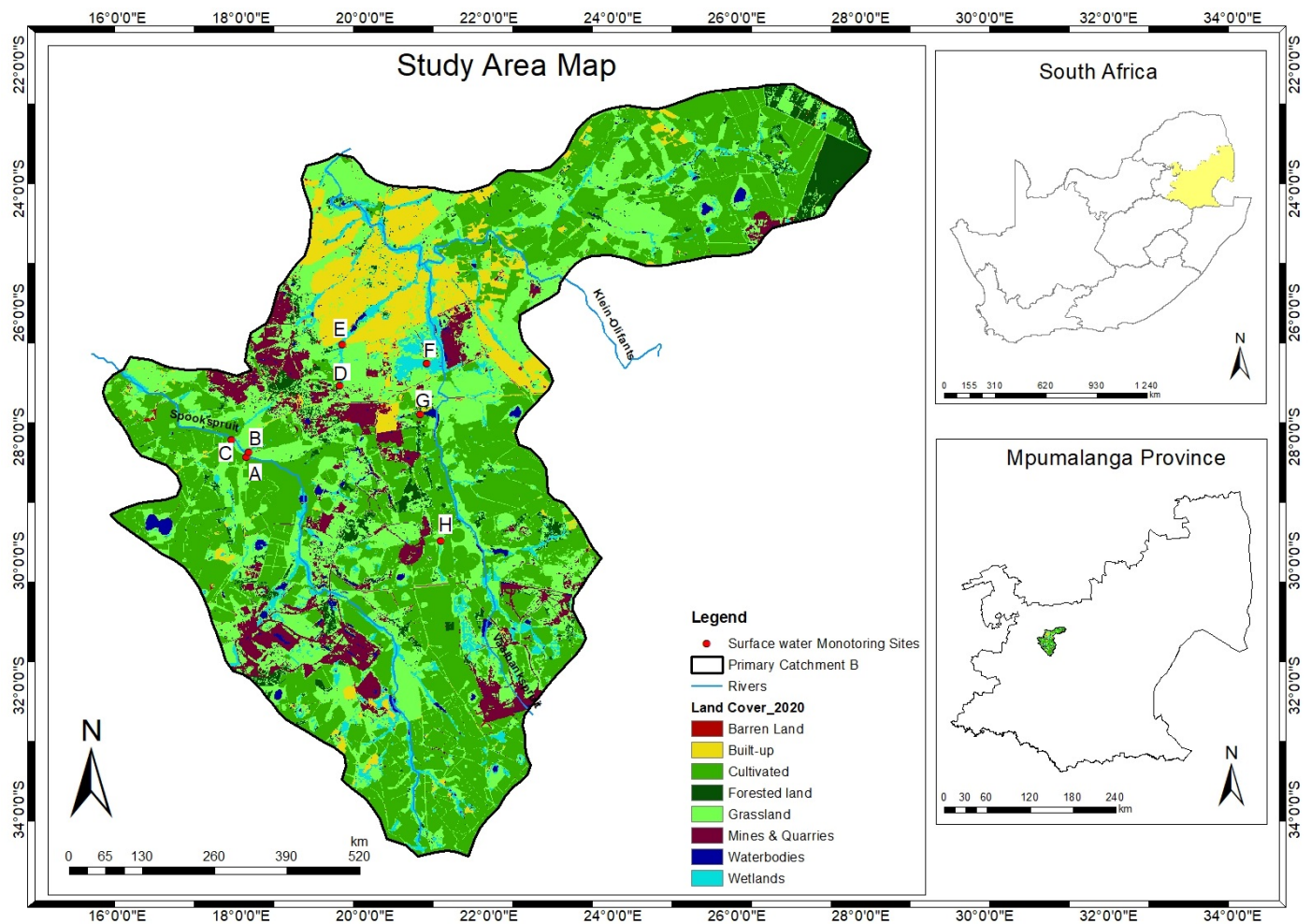


Figure 2. Surface water monitoring sites sampled from 2017 to 2021 (A–H sampling sites) [41].

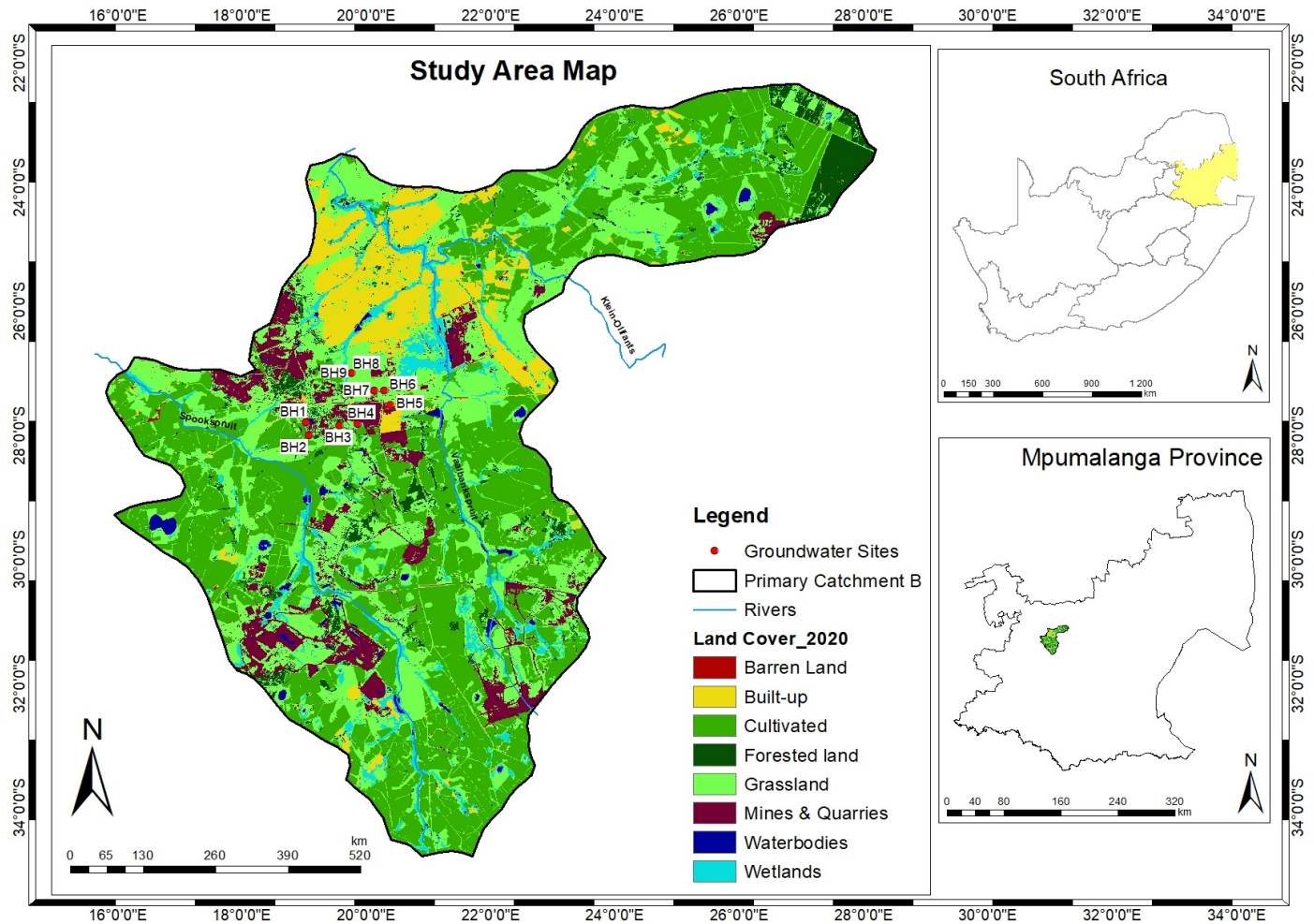


Figure 3. Groundwater sampling sites sampled from 2017 to 2021 (BH = borehole) [41].

2.3. Surface Water

The sampling procedure followed for the monitoring was the grab sampling method, which involved dipping a plastic bailer into the water to collect samples from the center of the streams, which were collected in clear, marked, sterilized one-liter plastic bottles. The bailer was rinsed with water from each sampling site to prevent cross-contamination. Monitoring of surface water was conducted on a monthly basis from 2017 to 2021 at eight sampling sites. The name of the sample, date, and time of collection were marked on each of the sampling bottles using a permanent marker. Water quality sampling was conducted during the day, and no on-site analysis was conducted. The samples were then transported in a cool insulated container under strict protocols within 24 h to an accredited laboratory for analysis, namely the Regen Waters Laboratory in Witbank, Mpumalanga, which is accredited for the chemical and microbiological analysis of water samples in terms of the South African National Accreditation System.

2.4. Groundwater

Contrary to surface water, groundwater monitoring was conducted during the day on a quarterly basis from 2017 to 2021 at eight boreholes using the grab sampling method. A plastic bailer tied with a rope was used, which involved dipping it into the borehole to collect samples from the borehole, which were collected into clear, marked, sterilized one-liter plastic bottles and labelled similarly to those of the surface water. The bailer was also rinsed with water from each sampling site to avoid the possibility of cross-contamination.

All water samples were kept in a cool insulated container under strict protocols to be tested within 24 h.

All collected samples were then transported to an accredited laboratory, Regen Waters Laboratory, in Witbank, Mpumalanga, for analysis in terms of the South African National Accreditation System. The analyses were conducted following the methods specified by the South African Bureau of Standards. For nutrient analysis such as chloride, nitrate, and ammonia, the laboratory used the procedures for the analysis of chloride, nitrate, and ammonia and methods such as spectroscopy and inductively coupled plasma–optimal emission spectrometry (ICP–OES). Furthermore, the inductively coupled plasma–mass spectrometry (ICP–MS) was used by Regen Waters Laboratory for metal analyses due to its sensitivity, as it detects very low concentrations.

2.5. Selection of Sampling Sites

The sampling sites were strategically selected to determine potential contamination of water courses. Surface water monitoring sites were selected from upstream and downstream of coal mining and related activities to monitor the water quality before and after the study. Groundwater boreholes around the area were assessed for any plume movement away from the mining and related activities. All sampling sites depicted a good representation of what the study aimed to achieve.

Figure 2 indicates the location and description of the surface water monitoring points, and Figure 3 shows the location of the boreholes sampled at the groundwater sampling sites.

2.6. Data Analysis

2.6.1. Water Quality Analysis

The Department of Water Affairs and Forestry [36] established the RQO of different catchments and the TWQR [37,38] portraying the maximum limits for concentrations of the variables allowed in surface water. The CCME [39] as well as the ANZECC/ARMCANZ [40] guidelines were also used to assess the level of water quality in the study area. The World Health Organization's [42] guidelines for drinking water quality was used to specifically assess the potential risks on groundwater in the receiving environment.

2.6.2. Water Pollution Indices

Understanding the source of pollution will help to recommend mitigation and management measures to reduce any further potential risks [43]. The available water quality dataset was used to provide empirical evidence in making future environmental decisions. The WQIs also represented the quality levels using the analyzed parameters. The CCME–WQI was used to understand the overall water quality for surface water resources. The benefit of using this index is its ability to identify water quality over space and time. It can also simplify complex water quality data to be easily understandable [22].

The following equations for the CCME–WQI were used:

$$CCME-WQI = 100 - \frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732} \quad (1)$$

where

F1 (scope) represents the number of variables whose objectives were not met.

$$F_1 = \left(\frac{\text{Number of failed variables}}{\text{Total number of variables}} \right) \times 100 \quad (2)$$

F2 (frequency) represents the number of items by which the objectives were not met.

$$F_2 = \left(\frac{\text{Number of failed tests}}{\text{Total number of tests}} \right) \times 100 \quad (3)$$

F3 (amplitude) represents the amount by which the objectives were not met.

$$Amplitude = \left(\frac{nse}{0.01_{nse} + 0.01} \right) \quad (4)$$

Excursion:

$$Normalised\ sum\ of\ excursions(nse) = \frac{\sum_{i=1}^n excursion}{Number\ of\ tests} \quad (5)$$

$$Excursion = \left(\frac{Failed\ test\ value}{Guideline\ value} \right) - 1 \quad (6)$$

As indicated above, the understanding of water quality is important for managing the environment and possible mitigation of pollution. The CPI is another method that can be used to evaluate water quality [13]. The CPI technique is good for scientific reflection of the kinds and extent of pollution in water systems. The pollution index (PI) was used to undertake the groundwater assessment in this study to identify the coal mining impacts.

The CPI method is obtained from the following formula:

$$CPI = \frac{1}{n} \sum_{i=1}^n PI \quad (7)$$

where

PI represents pollution index of individual parameters.

N is the number of parameters.

$$PI = \left(\frac{C_i}{S_i} \right) \quad (8)$$

where

C_i is the measured concentration of ith parameter

S_i is the standard value of ith parameter.

The WQIs and values were classified into different categories as shown in Table 1.

Table 1. Water quality index ratings [44].

Water Quality Indices	CCME-WQI	Comprehensive Pollution Index
Excellent	91–100	<0.2
Good	71–90	0.21–0.40
Poor/fair	51–70	0.41–1.00
Very poor/marginal	26–50	1.01–2.0
Unsuitable/poor	0–25	> 2.01

2.6.3. Statistical Analysis

All water quality analyses for surface water and groundwater samples were calculated and standardized using Microsoft Excel 2016 and are represented as mean and standard deviation. For this research, multivariate statistical techniques were also employed to characterize, assess, and verify the seasonality of temporal and regional fluctuations induced by human causes connected to surface water and freshwater quality. The water quality datasets of the study sites, which includes all the parameters, were analyzed using a multivariate approach such as principal component analysis (PCA) and regression analysis. Using the IBM SPSS program version 13, a constrained variant of the linear ordination approach of PCA, also known as a redundancy analysis (RDA), was carried out. Microsoft Excel 2016 was used for the regression analysis.

2.6.4. Principal Component Analysis

According to various researchers, the PCA is a crucial technique for establishing links between environmental quality and landscape [45]. The variation in a collection of response factors such as water quality variables explained by a set of explanatory variables such as land use of watersheds was summarized by the RDA.

It is further used to reduce data and to extract principal components for analyses of relationships between variables. PCA can reduce the number of correlated variables to a smaller set of orthogonal factors, making it easier to interpret a given multidimensional system by displaying the correlations among the original variables. PCA and derivative methods have been widely applied to various environmental streams, such as water, air, and soil, to identify sources of pollution through natural versus anthropogenic activities.

2.6.5. Multiple Linear Regression

Statistical methods such as the multiple linear regression model were used to measure the strength of the relationship between a measured dependent variable and independent variables of water quality parameters. The collected data from the surface and groundwater quality monitoring station were analyzed to assess the differences in values at the different sampling points.

Multiple linear regressions can be expressed using the following equation:

$$\gamma = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon \quad (9)$$

where

γ represents the dependent variable.

$x_1 \dots, x_2$ represents several independent variables.

$\beta_0 \dots \beta_n$ represents the regression coefficient.

ε represents the random error.

According to Bhatnagar and Devi [46], the coefficient of determination (R^2) measures the model's goodness of fit with the measured variables, which indicates the percentage of variance for the developed models, as shown in Equation (15).

Equation (10): The coefficient of determination:

$$R^2 = \frac{\sum_{i=1}^N (Y_i - \bar{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (10)$$

where

SSR is the regression sum of squares.

SST is the observed variance.

SSE is sum of squares of the residuals.

R^2 can be adjusted to reflect the different independent variables used and is expressed as in Equation (10) above.

Equation (11): The independent variables:

$$Adjusted R^2 = 1 - \frac{N-1}{N-K-1} \frac{SSE}{SST} \quad (11)$$

Root mean square error is also used to evaluate the performance of the developed model, as shown in Equation (12).

Equation (12): The root mean square error:

$$Root Mean Square Error = \sqrt{\frac{1}{n} \sum_{i=1}^N (x_i - \hat{x}_i)^2} \quad (12)$$

The x_i is the actual value.

$\hat{x}_i$ is the predicted value, and n is the number of observations.

R^2 , adjusted R^2 , and root mean square error can be obtained directly from the output data results.

3. Results

3.1. Water Chemistry

Generally, surface water monitoring sites become contaminated rapidly due to exposure to various anthropogenic activities and natural causes. Looking at the average concentrations of the chemical variables from the analyzed water quality data, all the surface water monitoring points in the study showed some level of contamination that can be associated with coal mining and related activities.

Total dissolved solids (TDS) is a measure of organic and inorganic materials dissolved in water, such as salts, metals, ions, and different minerals. Anthropogenic activities are known to produce TDS in water. Agricultural runoff and mining impacts such as AMD can increase the presence of TDS in a water course. The increase in TDS at monitoring sites A and B exceeded the permissible limits in all different seasons, as shown in Figure 4. All other sites were below the selected guideline. A maximum average of 1373 mg/L was analyzed during the spring season and an average of 1217 mg/L recorded for TDS in summer.

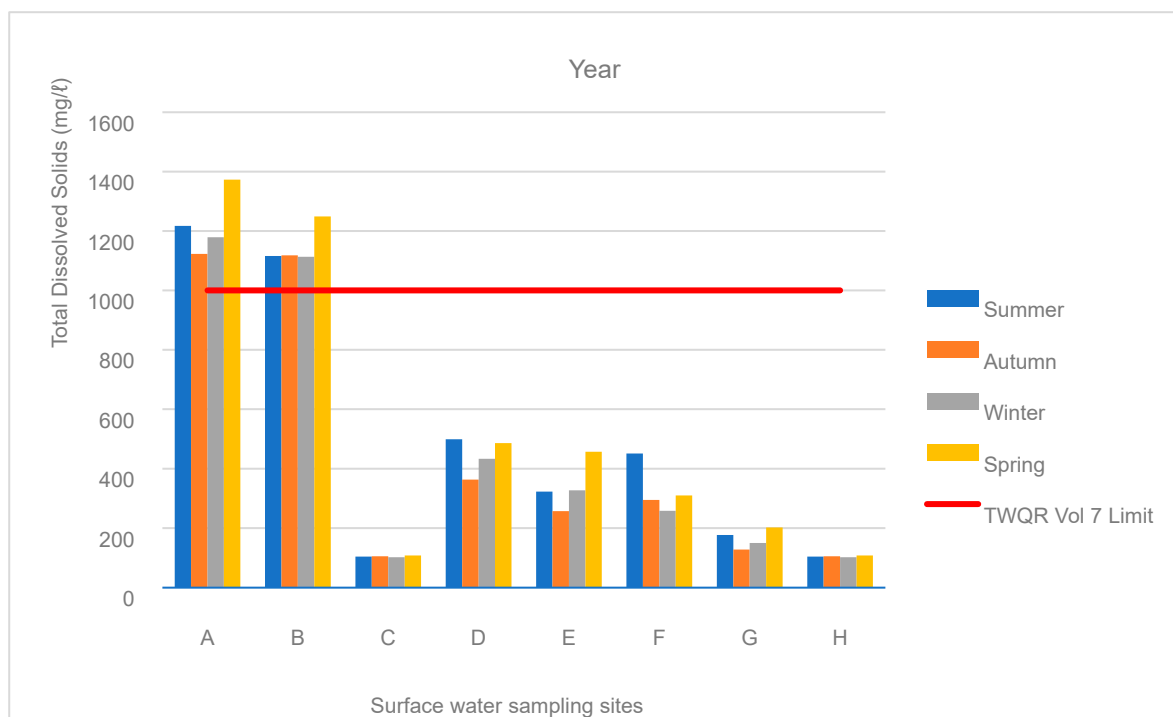


Figure 4. Average total dissolved solids (mg/L) from 2017 to 2021.

Sulfates represent another naturally occurring variable on the earth from different rock and soil types. Mining activities are likely to produce SO_4 in abundance, which is washed off to rivers and groundwater resources in the vicinity. The concentration of SO_4 at monitoring sites A and B was recorded as higher than the 500 mg/L limit of the RQO guideline [36] in all the seasons, ranging from 725 mg/L to 1174 mg/L for the entire five years of monitoring (see Figure 5 and Table 2).

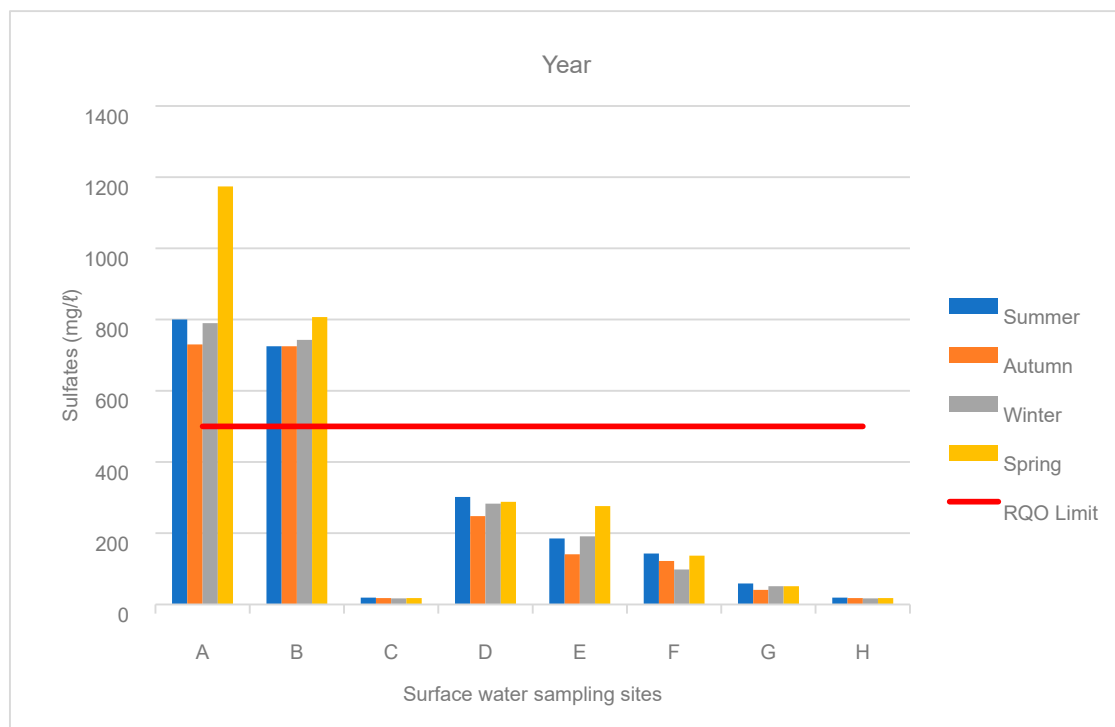


Figure 5. Average sulfates (mg/L) from 2017 to 2021.

Monitoring site B also recorded an elevated average concentration of electrical conductivity (EC) in the seasons above 30 mS/m when compared to the ANZECC/ARMCANZ [40] guidelines. Most of the surface water monitoring sites located away from the mining activities, such as C, G, and H, showed an improved water quality. Monitoring points D, E, and F had an average concentration exceeding the ANZECC/ARMCANZ [40] permissible limits in all the seasons for each point, as shown in Figure 6. Table 2 indicates the average concentrations of EC in all surface water monitoring sites.

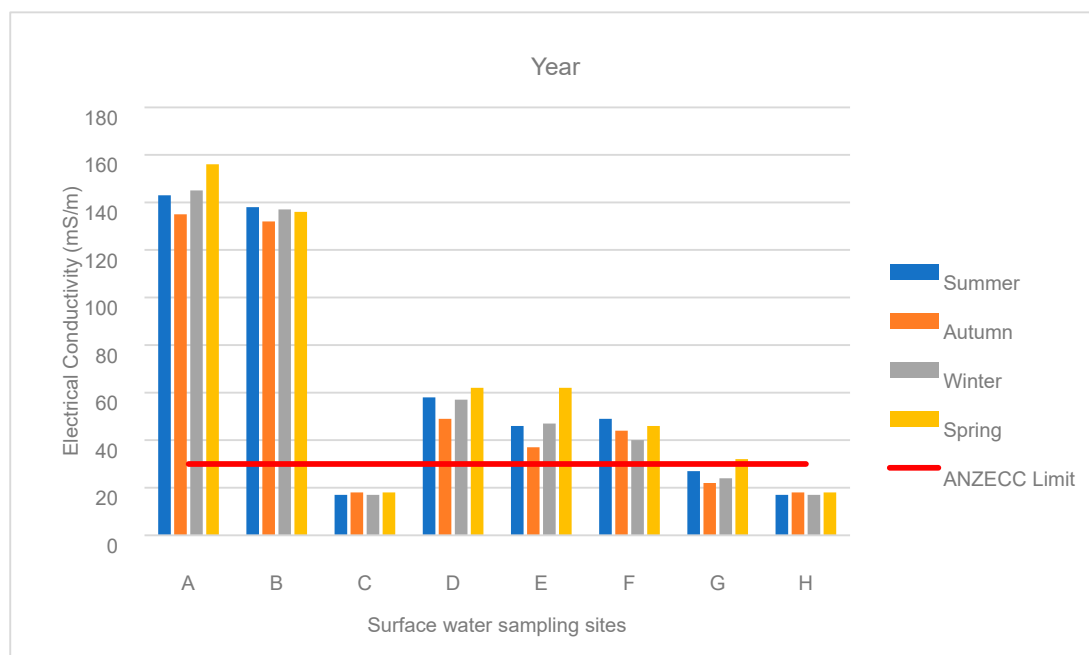


Figure 6. Average electrical conductivity (mS/m) from 2017 to 2021.

Sodium (Na), magnesium (Mg), and calcium (Ca) are largely found on the Earth’s surface and absorbed by water as it moves across different soil and rock types. All sampling points fell within all the expected limits. Figures 7 and 8 provide graphical presentations of Ca and Mg, respectively.

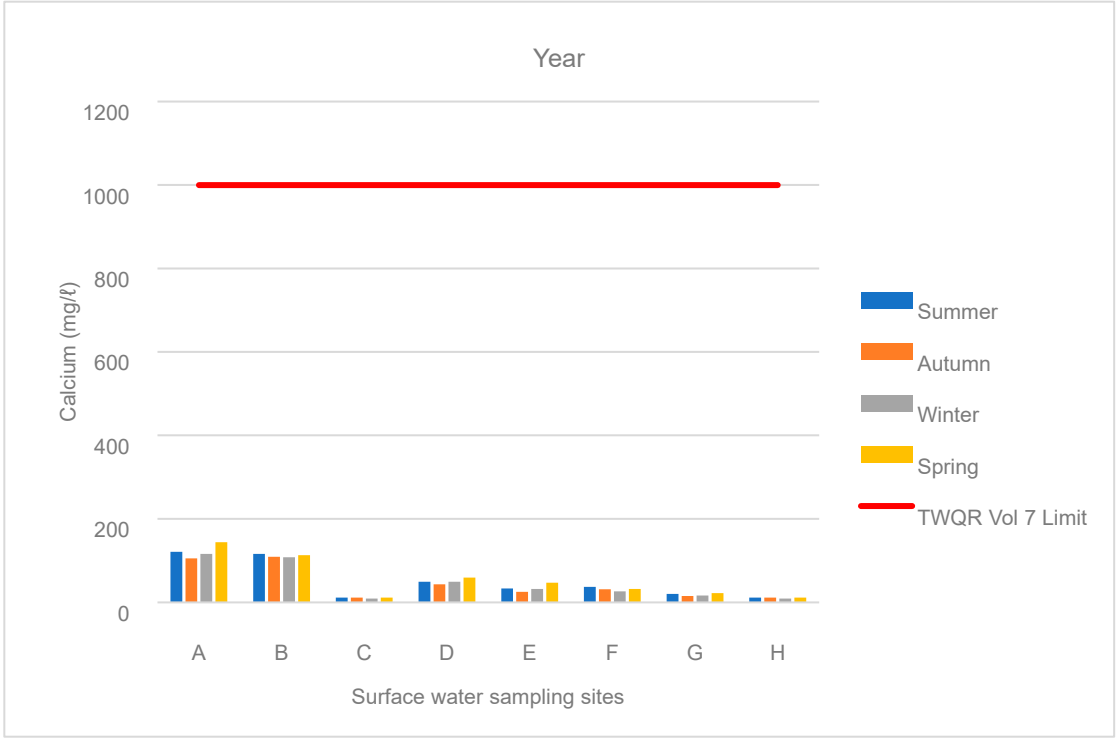


Figure 7. Average calcium (mg/L) from 2017 to 2021.

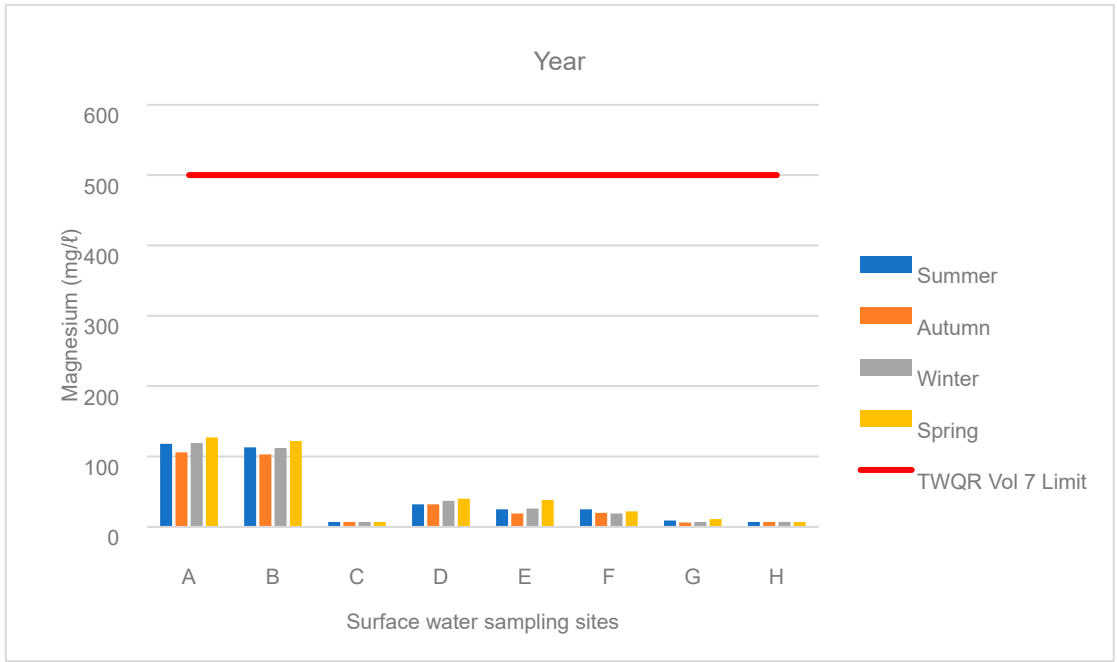


Figure 8. Average magnesium (mg/L) from 2017 to 2021.

pH determines the acidity and alkalinity in water. It is expressed as a negative log of the concentration of H+ ions. All the monitoring sites showed a pH level falling within the

8.0–9.0 range. Only monitoring site D indicated acidic conditions of six in all the seasons found below the expected limits (see Figure 9).

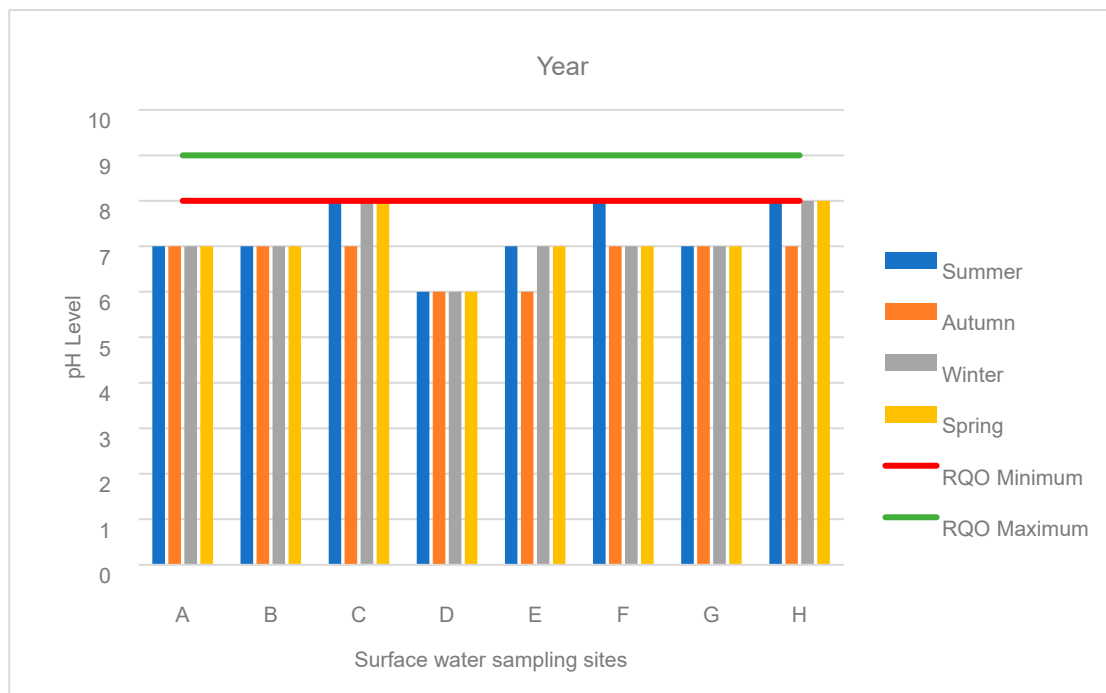


Figure 9. Average pH Level from 2017 to 2021.

Table 2. Average surface water quality results over four seasons for a period of five years (2017–2021) in Middelburg, South Africa.

Points	Season	TDS (mg/L)	SO ₄ (mg/L)	Ca (mg/L)	Mg (mg/L)	Na (mg/L)	Fe (mg/L)	Mn (mg/L)	EC (mg/L)	pH	Al (mg/L)
		1000 ***	500 *	1000 ***	500 ***	2000 ***	0.3 ****	0.18 **	30 *****	8.0–9.0 *	5 **
A	Summer	1217	800	121	118	39	0.1	1	143	7	0.1
	Autumn	1123	730	105	106	38	0.04	0.4	135	7	0.03
	Winter	1179	790	116	119	36	0.03	0.1	145	7	0.03
	Spring	1373	1174	144	127	44	0.1	0.3	156	7	0.04
B	Summer	1160	725	116	113	37	0.1	1	138	7	0.1
	Autumn	1118	725	109	103	37	0.1	0.1	132	7	0.04
	Winter	1113	743	108	112	36	0.1	0.1	137	7	0.04
	Spring	1249	807	113	122	42	0.01	0.2	136	7	0.1
C	Summer	104	19	11	7	13	1	2	17	8	0.2
	Autumn	105	18	11	7	13	1	0.2	18	7	0.1
	Winter	102	17	9	7	14	0.2	0.03	17	8	0.1
	Spring	108	18	11	7	14	0.2	1	18	8	0.1
D	Summer	499	302	49	32	10	18	5	58	6	1
	Autumn	363	248	43	32	7	1	3	49	6	0.1
	Winter	433	283	49	37	11	3	3	57	6	0.3
	Spring	486	288	59	40	13	2	3	62	6	1
E	Summer	323	185	33	25	19	0.2	0.4	46	7	0.04
	Autumn	257	141	25	19	17	0.2	0.2	37	6	0.2
	Winter	327	191	32	26	20	0.0	0.2	47	7	0.02
	Spring	457	276	47	38	25	0.1	0.4	62	7	0.1

Table 2. Cont.

Points	Season	TDS (mg/L)	SO ₄ (mg/L)	Ca (mg/L)	Mg (mg/L)	Na (mg/L)	Fe (mg/L)	Mn (mg/L)	EC (mg/L)	pH	Al (mg/L)
		1000 ***	500 *	1000 ***	500 ***	2000 ***	0.3 ****	0.18 **	30 *****	8.0–9.0 *	5 **
F	Summer	451	143	37	25	63	0.2	1	49	8	0.1
	Autumn	295	122	31	20	26	0.2	0.2	44	7	0.2
	Winter	258	98	26	19	26	0.1	0.1	40	7	0.1
	Spring	310	137	32	22	27	0.1	0.3	46	7	0.1
G	Summer	177	59	20	9	17	1	0.3	27	7	0.1
	Autumn	128	41	15	6	14	1	0.02	22	7	0.03
	Winter	150	51	16	7	18	0.1	0.01	24	7	0.03
	Spring	202	51	22	11	24	1	0.4	32	7	0.2
H	Summer	104	19	11	7	13	0.5	2	17	8	0.2
	Autumn	105	18	11	7	13	1	0.2	18	7	0.1
	Winter	102	17	9	7	14	0.2	0.0	17	8	0.1
	Spring	108	18	11	7	14	0.2	1	18	8	0.1

* RQO [36]; ** TWQR [37]; *** TWQR [38]; **** CCME [39]; ***** ANZECC/ARMCANZ [40].

Groundwater does not become contaminated as rapidly as surface water; however, mining activities such as blasting and seepages of dirty mine water can contribute to its pollution. The overall groundwater quality at the study area was poor to fair, with certain parameters exceeded their required limits from the WHO guidelines [42].

TDS concentrations were very low in most groundwater sampling sites in comparison to the WHO guidelines [42]. Monitoring site BH 2 was most contaminated, with TDS concentrations ranging from 1961 mg/L to 2456 mg/L, exceeding the 600 mg/L limit, as shown in Table 3 below. BH 7 and BH 9 also had some elevated average concentrations in autumn (1.046 mg/L) and summer (1048 mg/L) in the monitoring period of five years, as indicated in Figure 10.

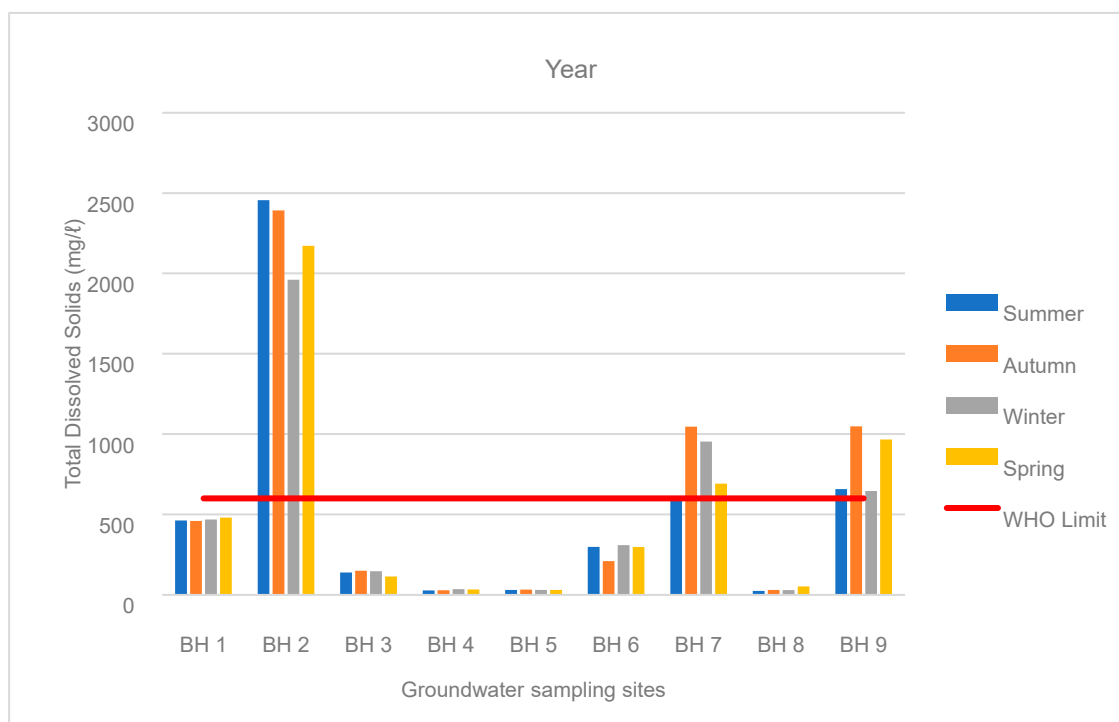


Figure 10. Average total dissolved solids (mg/L) from 2017 to 2021.

Borehole BH 1 had an increased SO₄ concentration (296 mg/L to 315 mg/L) higher than the 250 mg/L of the WHO (2017) benchmark [42]. BH 9 also indicated an exceedance

in all the seasons: spring (438 mg/L), summer (674 mg/L), autumn (445 mg/L), and winter (650 mg/L) (Figure 11 and Table 3).

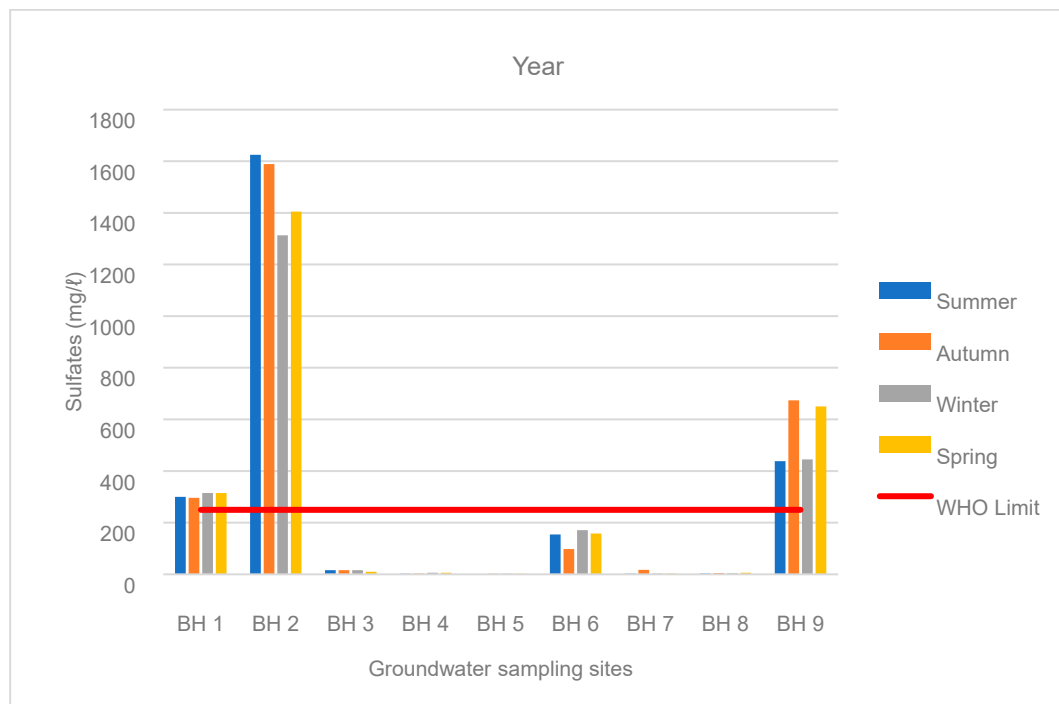


Figure 11. Average sulfates (mg/L) from 2017 to 2021.

The EC of all groundwater monitoring sites was within the WHO guidelines [42]. Monitoring sites BH 2 and BH 7 had increased average concentrations in all five years in all the seasons but still complied with the WHO guidelines [42] (Figure 12 and Table 3).

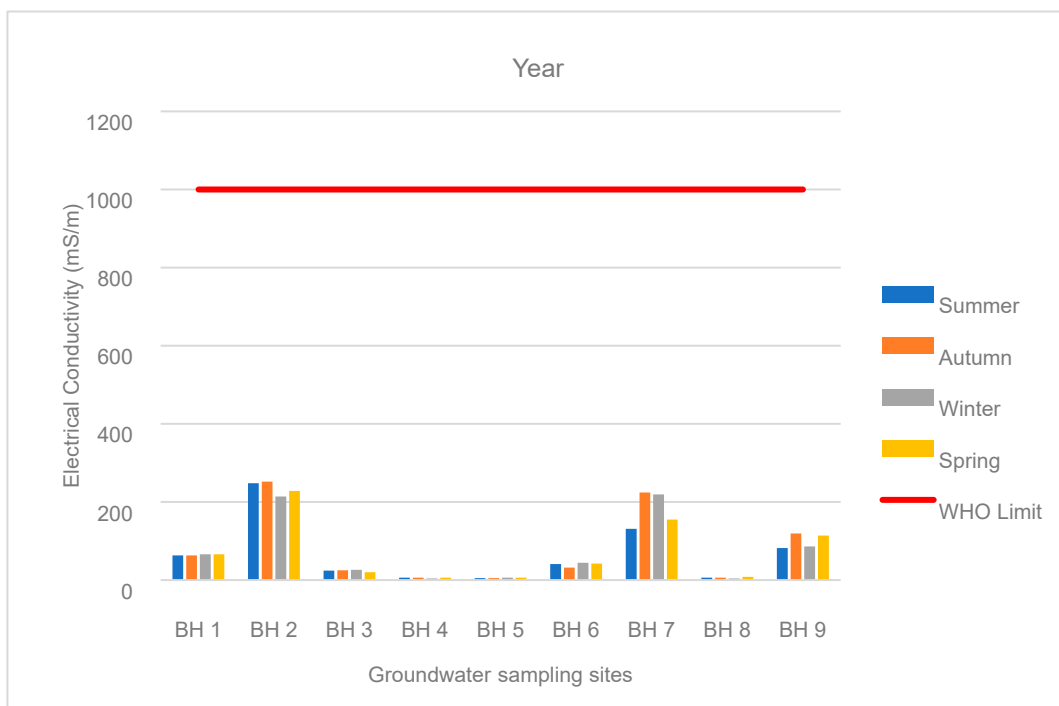


Figure 12. Average electrical conductivity (mS/m) from 2017 to 2021.

Monitoring site BH 2 had higher concentrations in comparison to the WHO [42] limits. This site showed a level of contamination that can be associated with the mining activities in the vicinity. Figure 13 and Table 3 show site BH 7 with a high average Ca concentration during the spring season in the five years of monitoring.

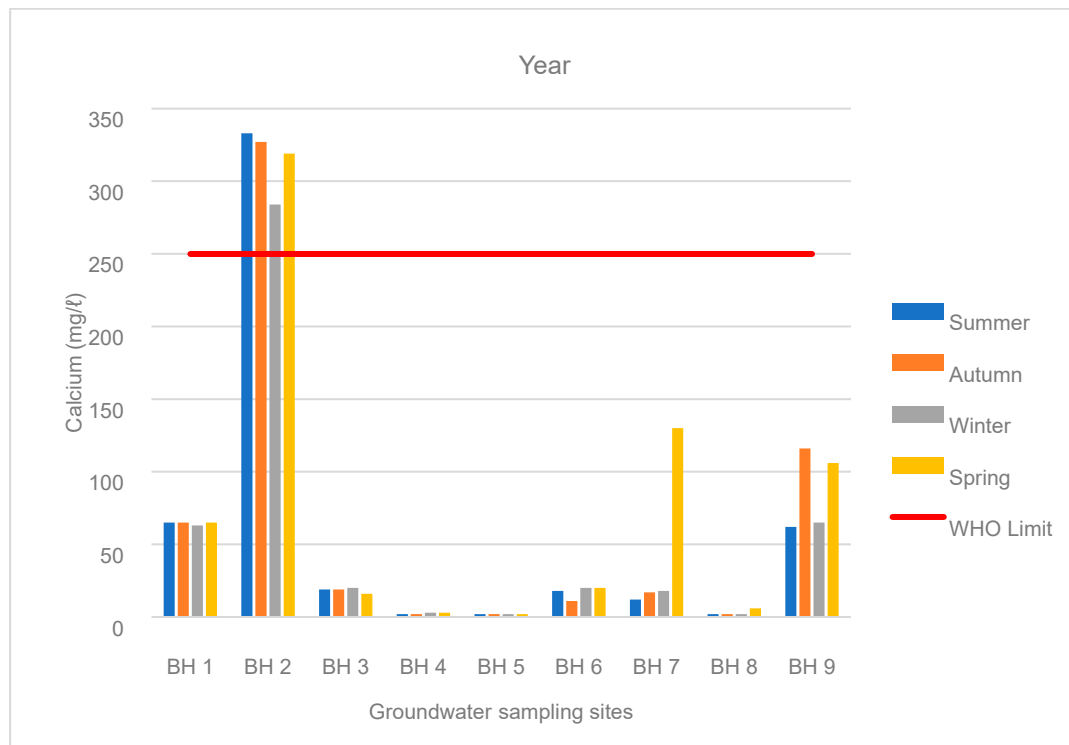


Figure 13. Average calcium (mg/L) from 2017 to 2021.

Table 3. Average groundwater quality results over four seasons for a period of five years (2017–2021) in Middelburg, South Africa.

Points	Season	TDS (mg/L)	SO ₄ (mg/L)	Ca (mg/L)	Mg (mg/L)	Na (mg/L)	Fe (mg/L)	Mn (mg/L)	EC (mg/L)	pH	Al (mg/L)
		600	250	250	300	200	0.3	0.1	1000	6.5–8.5	0.9
BH 1	Summer	462	300	65	9	12	0.1	0.2	63	7	0.05
	Autumn	459	296	65	29	14	0.1	0.1	63	7	0.1
	Winter	468	315	63	33	13	0.1	0.1	66	8	0.0
	Spring	480	315	65	33	14	0.0	0.1	66	8	0.0
BH 2	Summer	2456	1625	333	167	72	3	10	248	5	2
	Autumn	2392	1589	327	158	75	9	9	252	6	2
	Winter	1961	1313	284	122	67	3	6	214	6	0.2
	Spring	2172	1405	319	139	76	3	7	228	6	3
BH 3	Summer	139	16	19	10	11	0.1	0.0	24	7	0.2
	Autumn	150	16	19	9	17	0.1	0.1	25	7	0.2
	Winter	147	16	20	10	12	0.1	0.0	26	7	0.2
	Spring	114	10	16	8	11	0.0	0.0	20	7	0.1
BH 4	Summer	27	2	2	1	5	1	0.3	6	5	0.02
	Autumn	28	3	2	1	5	0.4	0.2	6	6	0.02
	Winter	35	6	3	2	5	2	0.1	4	6	0.03
	Spring	33	6	3	2	5	0.1	0.1	6	5	0.01

Table 3. Cont.

Points	Season	TDS (mg/L)	SO ₄ (mg/L)	Ca (mg/L)	Mg (mg/L)	Na (mg/L)	Fe (mg/L)	Mn (mg/L)	EC (mg/L)	pH	Al (mg/L)
		600	250	250	300	200	0.3	0.1	1000	6.5–8.5	0.9
BH 5	Summer	30	1	2	1	4	1	0.4	5	6	0.01
	Autumn	32	2	2	1	5	1	0.2	5	6	0.1
	Winter	30	2	2	1	5	0.1	0.2	6	6	0.03
	Spring	30	2	2	1	4	0.2	0.2	6	6	0.02
BH 6	Summer	298	154	18	21	30	7	0.4	41	6	0.1
	Autumn	209	98	11	13	26	2	0.2	32	6	0.1
	Winter	309	171	20	23	29	2	1	44	6	0.1
	Spring	297	158	20	22	30	1	0.3	42	6	0.1
BH 7	Summer	595	2	12	21	23	0.2	0.1	131	7	0.02
	Autumn	1046	17	17	15	28	2	0.1	224	8	0.1
	Winter	953	3	18	14	35	1	0.1	219	8	0.03
	Spring	691	3	130	13	24	1	0.1	155	8	0.1
BH 8	Summer	24	3	2	1	5	0.1	0.01	6	7	0.03
	Autumn	30	5	2	1	5	0.1	0.02	6	6	0.1
	Winter	29	4	2	1	5	0.1	0.02	4	6	0.1
	Spring	52	6	6	3	7	0.1	0.01	8	6	0.1
BH 9	Spring	658	438	62	59	14	6	2	82	6	0.1
	Summer	1048	674	116	90	21	22	4	119	7	0.04
	Autumn	646	445	65	65	14	3	2	86	6	0.03
	Winter	966	650	106	91	20	5	4	114	6	0.04

3.2. Canadian Council of Ministers of the Environment Water Quality Index

The results of the CCME–WQI were determined using the calculations and formulas shown in Section 3 above. Most of the surface monitoring sites in the study area indicated a fair to excellent water quality throughout all the seasons of the monitoring period of five years, as shown by the index. Monitoring sites A and B ranged between 59% and 72%, showing a fair quality, while monitoring site D had a very poor quality during the summer and winter seasons between 2017 and 2021 at 36% and 48%, respectively. A very good to excellent quality was determined in monitoring points E, F, G, and H, where in all the seasons, the WQI ranged between 73% and 100%.

The scope (F1) represented the number of variables whose objectives were not met, ranging from 0% to 66% in all the surface water monitoring points, as shown in Table 4. The frequency (F2) of monitoring sites A and B was high in all the monitoring seasons for the period of five years, which depicted a poor to fair water quality in comparison with the CCME index. The highest amplitude (F3) was recorded in monitoring site D during the summer and winter seasons between 2017 to 2021 at 90.5% and 72.5%, respectively, showing very poor analyzed water quality.

Table 4. CCME–WQI over four seasons for a period of five years (2017–2021) in Middelburg, South Africa.

Monitoring Points	Seasons	F1	F2	F3	CCME–WQI	WQI Ranking
A	Summer	40	30	40.7	62.8	Poor/fair water quality
	Autumn	40	28	31.7	66.4	Poor/fair water quality
	Winter	40	28.6	32	66.1	Poor/fair water quality
	Spring	50	29	40	59.3	Poor/fair water quality
B	Summer	40	28	38	64.2	Poor/fair water quality
	Autumn	30	24.6	29.3	71.9	Good water quality
	Winter	40	30.8	36.8	63.9	Poor/fair water quality
	Spring	40	29.3	33.3	65.5	Poor/fair water quality

Table 4. Cont.

Monitoring Points	Seasons	F1	F2	F3	CCME–WQI	WQI Ranking
C	Summer	20	9.3	46	70.5	Poor/fair water quality
	Autumn	20	6.66	14	85.4	Good water quality
	Winter	10	1.9	0.97	94	Excellent water quality
	Spring	10	0.67	2.6	94	Excellent water quality
D	Summer	60	20.6	90.5	36.2	Very poor water quality
	Autumn	50	13.3	42.6	61.3	Poor/fair water quality
	Winter	50	16.6	72.5	48.3	Very poor water quality
	Spring	40	16	65.3	54.8	Poor/fair water quality
E	Summer	30	11.3	16.8	79.1	Good water quality
	Autumn	30	10.6	10.7	80.6	Good water quality
	Winter	20	10.6	8.3	86.1	Good water quality
	Spring	40	13.3	19.1	73.3	Good water quality
F	Summer	30	10.7	23.2	77.2	Good water quality
	Autumn	30	10	10.8	80.7	Good water quality
	Winter	13	8.7	4.3	87.2	Good water quality
	Spring	30	11.3	15.9	79.3	Good water quality
G	Summer	30	13.3	32.1	73.5	Good water quality
	Autumn	10	2	12.3	90.8	Good water quality
	Winter	10	2	12.2	90.8	Good water quality
	Spring	0	0	0	100	Excellent water quality
H	Summer	20	7.3	46.7	70.4	Poor/fair water quality
	Autumn	20	6	17.9	84.1	Good water quality
	Winter	0	1.3	0.6	99.2	Excellent water quality
	Spring	20	4	15.9	85.0	Good water quality
Water quality indices		CCME–WQI				
Excellent		91–100				
Good		71–90				
Poor/fair		51–70				
Very poor/marginal		26–50				
Unsuitable/poor		0–25				

Monitoring borehole BH 1 showed a marginal or very poor quality in summer with a score of 40, improving during the other seasons to a good state ranging from 86 to 90. Borehole BH 2 also highlighted some level of pollution during all seasons, with all results falling within the very poor range over the whole monitoring period from 2017 to 2021. Furthermore, monitoring boreholes BH 3, BH 4, BH 5, and BH 8 showed good to excellent results, with scores between 80 and 100, with no indication of contamination that may be associated with the dominating mining activities at these points. However, BH 9 was contaminated and very poor during the summer and autumn seasons, with an improvement to a fair state in the winter and spring seasons.

The scope for F1 represented the number of variables whose objectives were not met, ranging from 0% to 60% in all the groundwater monitoring points, as shown in Table 5. The frequency (F2) of monitoring point BH 3 (0%) and BH 8 (0%) was low over all the monitoring seasons for the period of five years, which indicated an excellent water quality related to the guidelines. The highest amplitude (F3) was recorded in BH 1 during the summer season at 97.2%, indicating very poor analyzed water quality.

Table 5. CCME–WQI over four seasons for a period of five years (2017–2021) in Middelburg, South Africa.

Monitoring Points	Seasons	F1	F2	F3	CCME–WQI	WQI Ranking
BH 1	Summer	30	18	97.2	49.3	Very poor water quality
	Autumn	20	10	10.9	85.6	Good water quality
	Winter	10	10	10.6	89.8	Good water quality
	Spring	10	10	10.8	89.7	Good water quality
BH 2	Summer	60	48	88.2	32.4	Very poor water quality
	Autumn	60	44	87.3	33.7	Very poor water quality
	Winter	60	40	82.9	36.5	Very poor water quality
	Spring	60	44	84.7	34.8	Very poor water quality
BH 3	Summer	0	0	0	100	Excellent water quality
	Autumn	0	2	1.9	98.3	Excellent water quality
	Winter	0	0	0	100	Excellent water quality
	Spring	0	0	0	100	Excellent water quality
BH 4	Summer	20	8	23.3	81.6	Good water quality
	Autumn	20	8	10.6	86.1	Good water quality
	Winter	10	4	31.8	80.5	Good water quality
	Spring	10	2	0.6	94.1	Excellent water quality
BH 5	Summer	20	10	21.4	82.0	Good water quality
	Autumn	20	8	13.9	85.1	Good water quality
	Winter	10	4	2.3	93.6	Excellent water quality
	Spring	60	10	8.6	64.5	Poor/fair water quality
BH 6	Summer	20	22	70.9	55.5	Poor/fair water quality
	Autumn	20	14	35.6	75.0	Good water quality
	Winter	10	30	43.5	68.9	Poor/fair water quality
	Spring	60	18	19.6	62	Poor/fair water quality
BH 7	Summer	40	16	27.8	70.3	Poor/fair water quality
	Autumn	20	16	53.7	65.5	Poor/fair water quality
	Winter	20	14	48.1	68.8	Poor/fair water quality
	Spring	30	16	27.3	74.8	Good water quality
BH 8	Summer	0	0	0	100	Excellent water quality
	Autumn	0	0	0	100	Excellent water quality
	Winter	0	0	0	100	Excellent water quality
	Spring	0	0	0	100	Excellent water quality
BH 9	Summer	50	26	67.1	49.4	Very poor water quality
	Autumn	50	28	90.8	37.9	Very poor water quality
	Winter	40	24	68.0	52.3	Poor/fair water quality
	Spring	50	26	54.4	54.7	Poor/fair water quality
Water quality indices		CCME–WQI				
Excellent		91–100				
Good		71–90				
Poor/fair		51–70				
Very poor/marginal		26–50				
Unsuitable/poor		0–25				

3.3. Comprehensive Pollution Index

The surface water monitoring sites A, B, and C were very poor in the summer seasons, indicating some improvement during the rest of the seasons and falling within the permissible ranges of the CPI. All of monitoring site D's readings were greater than the suitable limit of 2.01, as shown in Table 6. However, all the findings at monitoring sites E, F, G, and H were compliant with the CPI limits, highlighting a fair to good state of water quality.

Table 6. Comprehensive pollution index and water quality index over four seasons for a period of five years (2017–2021) in Middelburg, South Africa.

Sampling Points	Comprehensive Pollution Index			
	Summer	Autumn	Winter	Spring
A	1.2 Very poor	1.0 Very poor	0.97 Poor	1.2 Very poor
B	1.1 Very poor	0.9 Fair	0.9 Fair	0.9 Fair
C	1.2 Very poor	0.5 Poor	0.3 Good	0.5 Poor
D	9.4 Very poor	2.2 Very poor	3.1 Very poor	2.8 Very poor
E	0.6 Fair	0.5 Fair	0.4 Good	0.7 Fair
F	0.8 Fair	0.5 Fair	0.4 Fair	0.5 Fair
G	0.8 Fair	0.4 Good	0.2 Excellent	0.8 Fair
H	1.2 Very poor	0.5 Poor	0.3 Good	0.5 Poor
BH 1	0.5 Fair	0.5 Fair	0.5 Fair	0.5 Fair
BH 2	8.2 Very poor	7.6 Very poor	5.4 Very poor	6.2 Very poor
BH 3	0.2 Excellent	0.3 Good	0.2 Excellent	0.2 Excellent
BH 4	0.5 Fair	0.3 Good	0.7 Fair	0.2 Excellent
BH 5	0.5 Fair	0.4 Good	0.3 Good	0.3 Good
BH 6	3.0 Very poor	0.9 Fair	1.3 Very poor	0.6 Fair
BH 7	0.7 Fair	1.6 Poor	1.3 Very poor	1.1 Very poor
BH 8	0.1 Excellent	0.1 Excellent	0.1 Excellent	0.1 Excellent
BH 9	3.5 Very poor	10.4 Very poor	2.6 Very poor	0.1 Excellent
Water quality indices	CPI			
Excellent	<0.2			
Good	0.21–0.40			
Poor/fair	0.41–1.00			
Very poor/marginal	1.01–2.0			
Unsuitable/poor	>2.01			

All of groundwater site BH 1's readings fell within the fair range over all seasons, while BH 2 was very polluted, ranging from 5 to 8. Boreholes BH 3 to BH 5 had good to excellent water quality. No impacts associated with coal mining could be identified in these boreholes using the comprehensive pollution index. BH 6 experienced different levels, with exceedances in the summer and winter seasons at 2.9 and 1.3, respectively. BH 9 was also contaminated, exceeding the permissible limits in terms of the CPI.

3.4. Comparison between the Two Indices

The CCME–WQI for surface water was found within the range of 36.2 to 100, showing different water qualities at different monitoring sites. Most sites that were located closer to coal mining activities in the study area showed poor to fair water quality scores, and those further away indicated an excellent water quality score. Boreholes BH 2 and BH 9 were contaminated, with low WQI scores between 32.4 to 54.7 in the different seasons. BH 8 had an excellent water quality at 100% in all the monitoring seasons. Similar to CCME–WQI, the CPI depicted some level of pollution in surface water monitoring points that exceeded the limits. Points in close proximity of the study area, like site A, had very poor CPI.

3.4.1. Multivariate Statistical Analysis Results

Principal Component Analysis

The analyses were conducted on the z-scores scale, ensuring that transformed data were normally distributed and that there were no non-normality issues hindering the interpretation of findings. The three components accounted for 78.6% of the total variance.

The PCA plotting diagrams (Figures 14–24) isolate the components elements that are pertinent in explaining the water quality variations at different sites. Panel-crossing this information with the descriptive analysis performed earlier, the sources of contamination at each site can be reasonably inferred, having on one side parameters whose roles are significant in the resulting quality and on the other their measured levels at each site.

In the surface water monitoring site A, three major components are shown: Component 1's group of elements included TDS (0.943), SO_4 (0.623), EC (0.926), Mg (0.847), Na (0.808), and Ca (0.845). Component 2 also indicated a remarkably high concentration of Mn and Al, respectively. Component 3 also showed an increased concentration of Fe (0.852). According to the PCA analysis and the locality of site A, the sources of contamination can be associated with the mining industry and the natural sources of the soil (Figure 14).

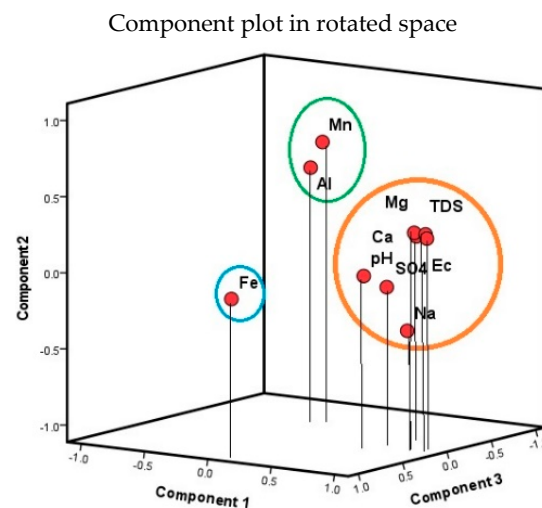


Figure 14. Principal component analysis—component plot for surface water monitoring at site A from 2017 to 2021.

The extracted components accounted for 86.6% of the total variance. Monitoring site B also had three components identified in the analyses in common with component 1, having a group of elements that included TDS (0.984), Mg (0.970), Na (0.678), SO_4 (0.976), EC (0.957), and Ca (0.969). These variables can be associated with anthropogenic activities occurring upstream of the sampling point. Component 2 had an increased level of Mn (0.734). Component 3 had Al at 0.853 and Fe at 0.765. Considering the location of sampling site B, the possibility of seepages from the notable mining activities could contribute to the elevations analyzed (Figure 15).

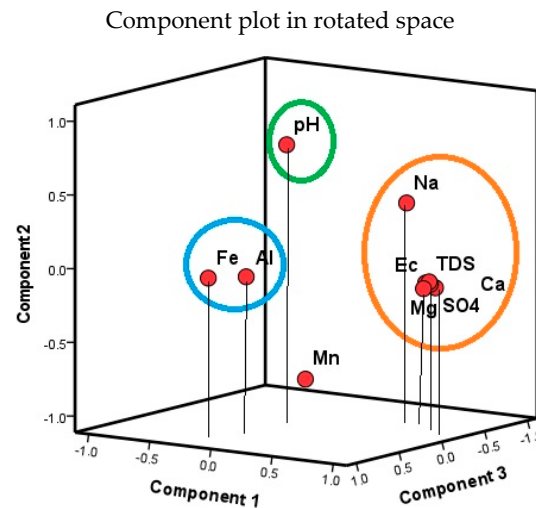


Figure 15. Principal component analysis—component plot for surface water monitoring at site B from 2017 to 2021.

The extracted components accounted for 33.27% of the total variance. At site C, four components were identified, with a group of parameters including TDS, Ca, Mg, EC, SO_4 , and Na, showing a strong correlation with the PCA. Component 2 showed the elements Fe (0.846) and Al (0.778). Component 3 accounted for 11.77% of the total variance. The group of elements identified included Mn and Al. For component 4, the group had pH accounts that formed 11.5% of the total variance. These variables were already present in the soil; however, they were elevated through anthropogenic activities such as mining (Figure 16).

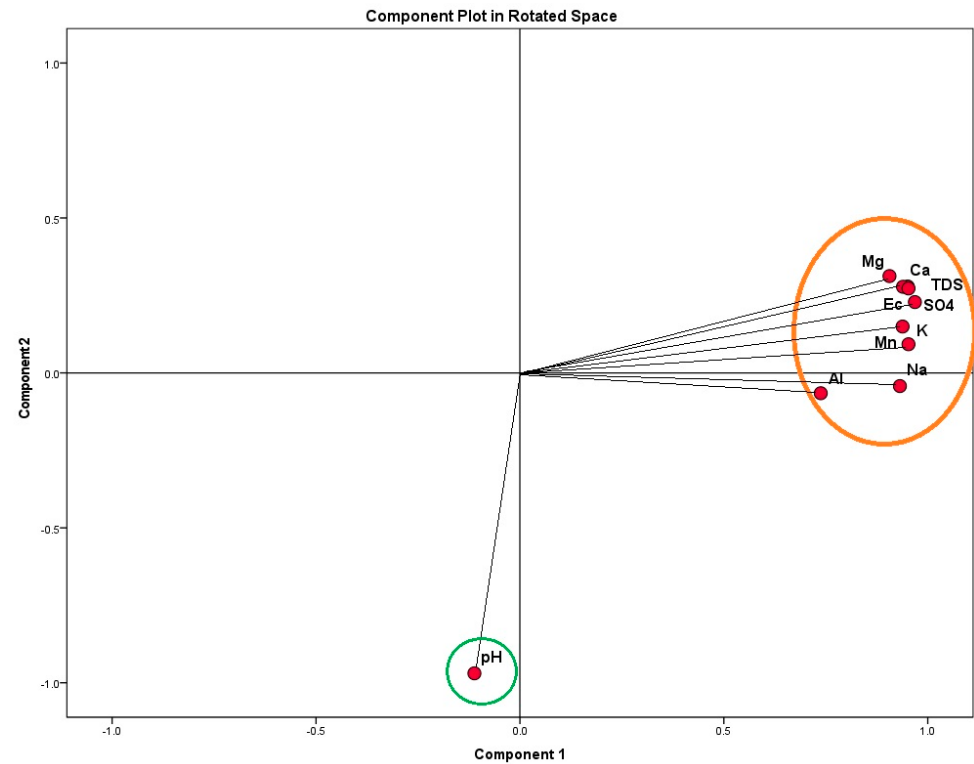


Figure 16. Principal component analysis—component plot for surface water monitoring at site D from 2017 to 2021.

There were two components that were extracted from site D, where component 1 had a group of elements—TDS, SO_4 , Ca, Na, Mn, and EC—that showed a remarkably high

concentration in the PCA. Component 2 explained a total variance of 10%. Mining activities are assumed to have contributed to the water quality status at this site (Figure 17).

The extracted components accounted for 78.5% of the total variance. The group of elements in the first component had a total variance of 60.8%, explained with a strong and high mean concentration of TDS, SO_4 , Ca, Mg, Na, and EC in the PCA at site E. In component 2, the elements Fe, Mn, and Al explained a total variance of 17.7%. The source of these variables could be associated with anthropogenic activities, mainly coal mining activities, and some are mostly found naturally occurring on the surface.

In monitoring site F, component 1 had high concentrations of SO_4 (0.899), Ca (0.941), Mg (0.936), and EC (0.960). Component 2 had a group of elements that included TDS (0.835), Na (0.950), and Mn (0.686). Component 3 had concentrations primarily of Fe (0.905) and Al (0.903). The dominance of these variables could be associated with mining and industrial activities closer to the monitoring point.

The extracted components accounted for 80.3% of the total variance. In monitoring site G, the first component explained 49.5% of the total variance and a high value of EC (0.960), Ca (0.941), Mg (0.936), and SO_4 (0.899). The second component had 16.8% of the total variance, containing an elevated concentration of Na (0.950) and TDS (0.835). Fe and Al had increased levels at 0.905 and 0.903. This explained 14% of the total variance. This point indicates that anthropogenic activities like mining and industrialization could be impacting the resources in the area (Figure 17).

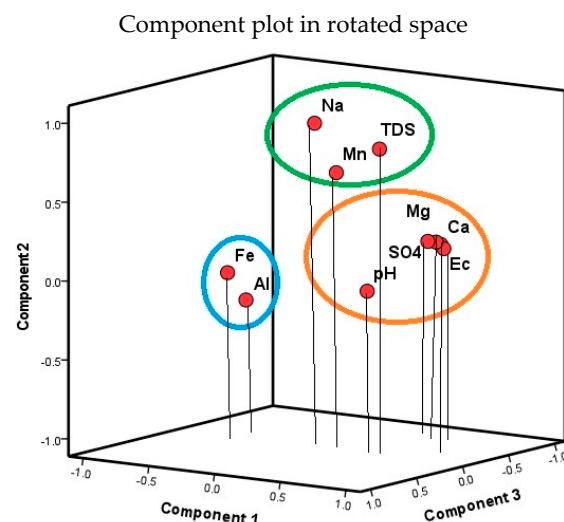


Figure 17. Principal component analysis—component plot for surface water monitoring at site G from 2017 to 2021.

The extracted components accounted for 80.9% of the total variance. The component of site H had high concentrations of TDS, EC, Na, Mg, and Ca, which accounted for a total variance of 54.6%. Component 2 had Fe (0.897) and Al (0.771) with a total variance of 16.3%. The third component had a total variance of 10%, with a high concentration of Mn and SO_4 at 0.901 and 0.501, respectively (Figure 18).

The extracted components accounted for 86.6% of the total variance. The groundwater monitoring site BH 1 showed that the first component consisted of increased concentrations of SO_4 , EC, TDS, Ca, and Mg, accounting for a total variance of 58.9%. Component 2 had a group of elements that included Fe, Mn, and Al, with 16.4% of the total variance. Component 3 had a total variance of 11.3% with the level of pH (0.867) and the concentrations of Na (0.684) and Al (0.510) (Figure 19).

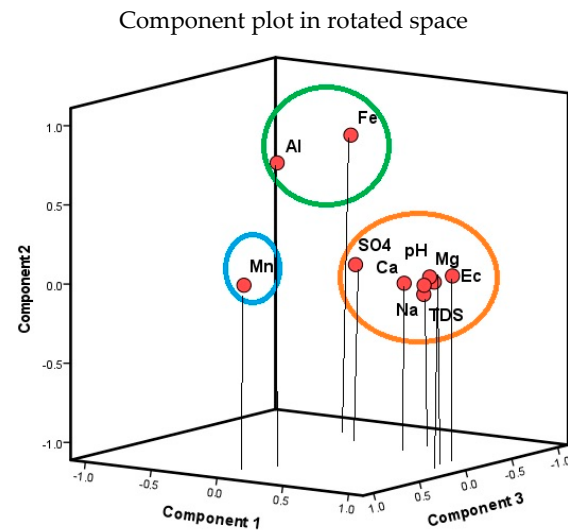


Figure 18. Principal component analysis—component plot for surface water monitoring at site H from 2017 to 2021.

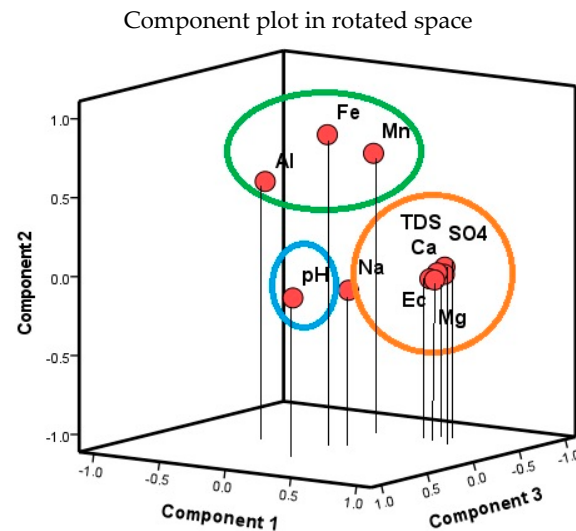


Figure 19. Principal component analysis—component plot for groundwater monitoring at site BH 1 from 2017 to 2021.

Borehole 2 only had two components from the PCA. Component 1 had a high concentration of EC (0.973), Ca (980), TDS (0.46), and SO_4 (942). The total variance explained was 65.6%. Component 2 had high metals with Mn (0.831), Al (0.733), and Fe (0.717), which accounted for 17.5% of the total variance (Figure 20).

The extracted components accounted for 80.1% of the total variance. Two components were determined in BH 3. The group of elements identified in this component included EC (0.977), TDS (0.968), Mg (0.949), and Ca (0.937), accounting for 60.8% of the total variance. Component 2 had elevated concentrations of metals such as Fe (0.933), Mn (0.841), and Al (0.673), with a total variance of 19.3%.

The extracted components accounted for 78% of the total variance. The analysis at BH 4 resulted in three components, where component 1 had an increased concentration of Na (0.923), TDS (0.899), and Mg (0.865), accounting for a total variance of 52.5%. Component 2 had a total variance of 13.5%, with high concentrations of Al, Fe, and SO_4 . Component 3 had a dominance of Mn and Fe at 0.915 and 0.645, respectively, with 12% of the total variance.

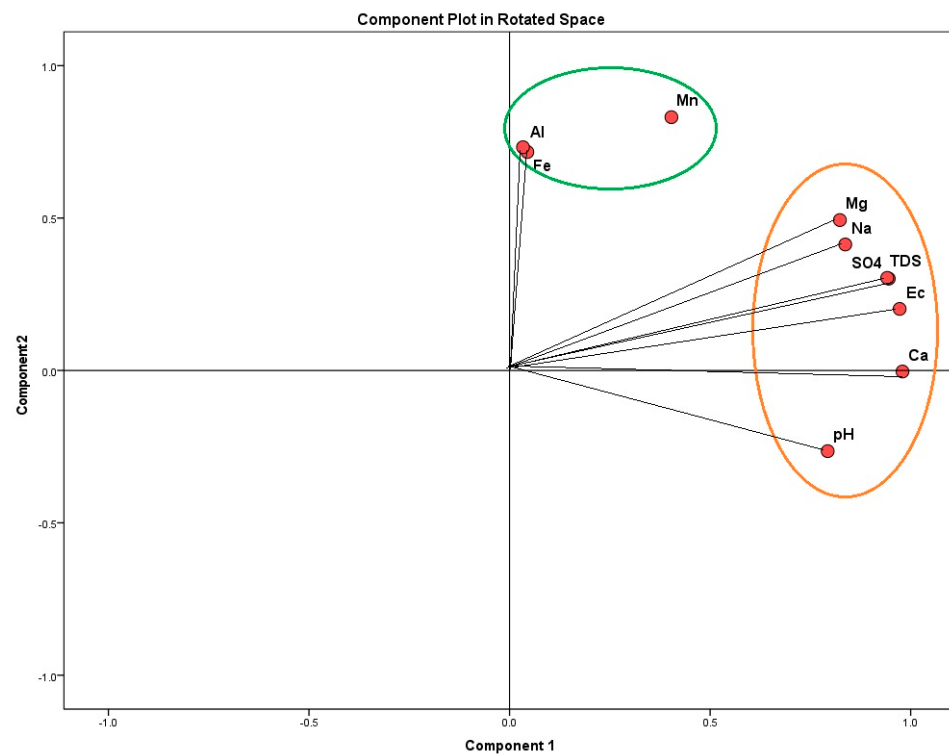


Figure 20. Principal component analysis—component plot for groundwater monitoring site BH 2 from 2017 to 2021.

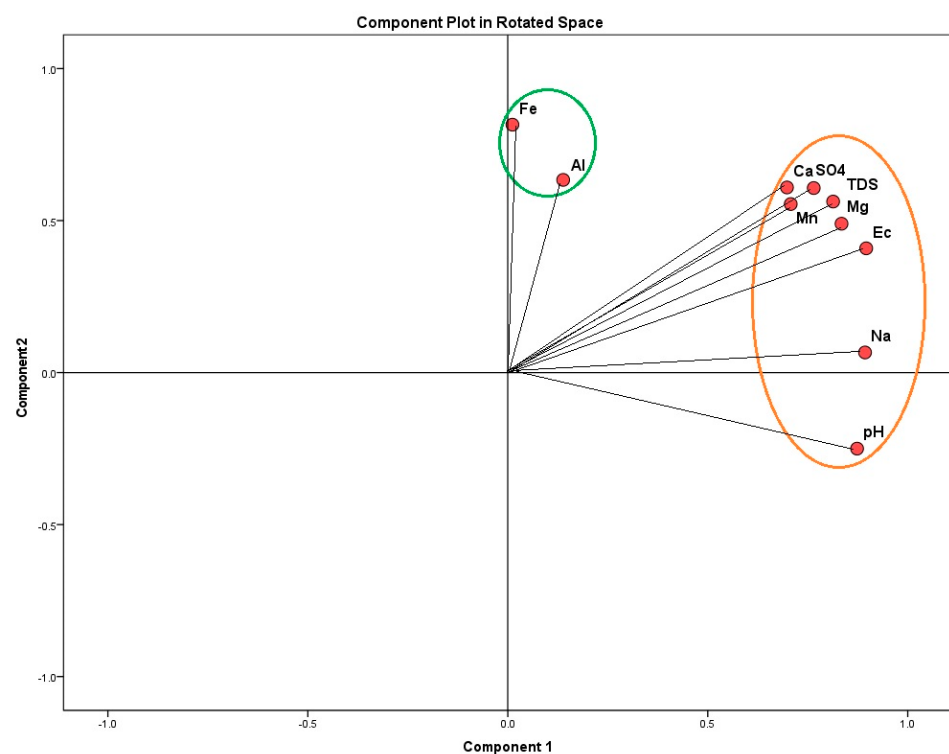


Figure 21. Principal component analysis—component plot for groundwater monitoring at site BH 6 from 2017 to 2021.

The extracted components accounted for 82.4% of the total variance. In BH 5, the group of elements that was found with high concentrations at the first components included TDS, Mg, pH, EC, and SO₄. Component 1 accounted for a total variance of 52.4%. The

second component had a total variance of 17.1%, while component 3 had 12.9% of the total variance.

The extracted components accounted for 81.8% of the total variance. Two components were identified in this analysis at monitoring site BH 6. Component 1 had high concentrations of Na, EC, pH, Mg, and TDS, with 68% of the total variance explained. Component 2 had a total variance of 13.8%, with an increase in Fe, Al, Ca, and SO₄ (Figure 21).

The extracted components accounted for 66.6% of the total variance. Borehole 7 consisted of a group of elements that included TDS (0.945), EC (0.940), and Na (0.819), which explained a total variance of 39%. Component 2 had 16.6% of the total variance, with a dominance of pH, Ca, and Mg. The third component had high Al, Fe, and Mn, which accounted for 11% of the total variance (Figure 22).

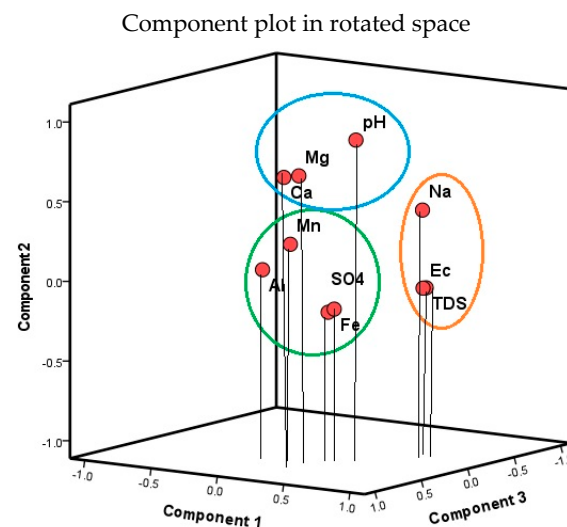


Figure 22. Principal component analysis—component plot for groundwater monitoring at site BH 7 from 2017 to 2021.

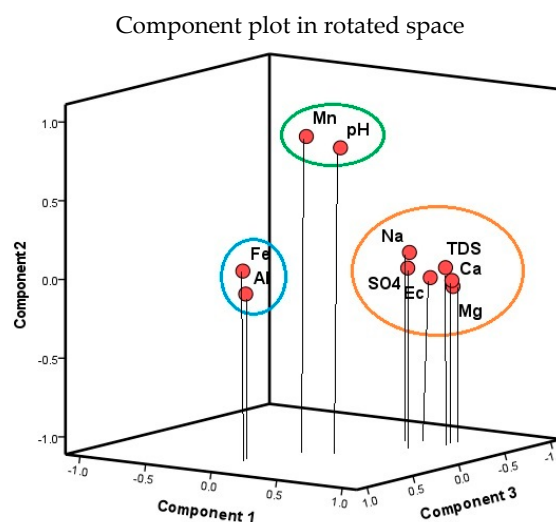


Figure 23. Principal component analysis—component plot for groundwater monitoring at site BH 8 from 2017 to 2021.

The extracted components accounted for 83.9% of the total variance. In BH 8, component 1 had a group of elements that contributed elevated TDS (0.989), Ca (0.983), EC (0.959), and Mg (0.976), with a total variance of 56%. Component 2 had an explained total variance of 16%. Component 3 only had Al (0.833) and Fe (0.760), with high concentrations

at a total variance of 11.9%. The source of contamination at this point could be associated with natural sources such as the soils or the stratigraphical units (Figure 23).

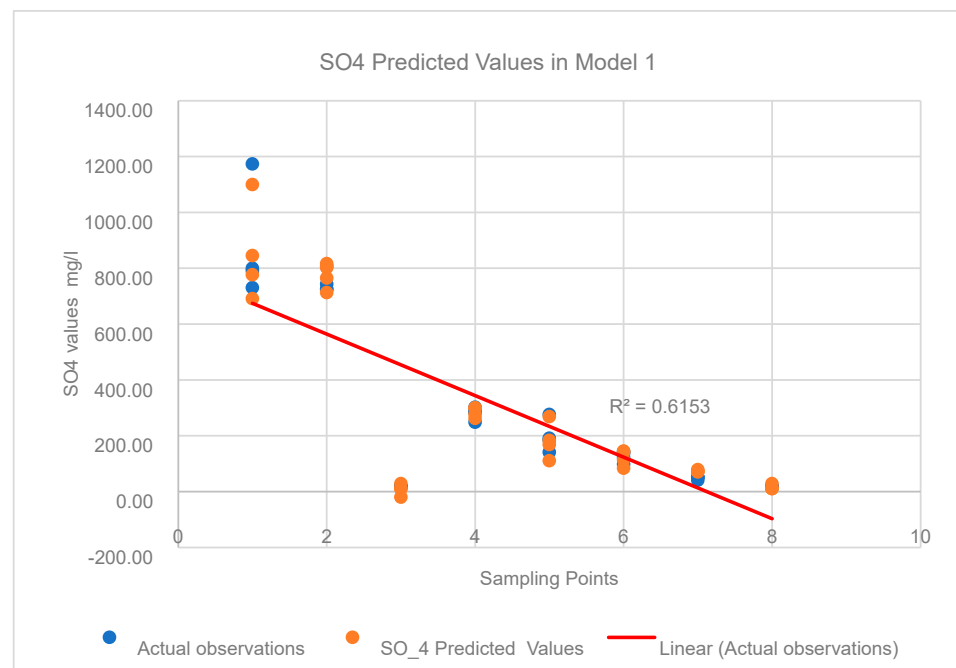


Figure 24. Predicted sulfate values in model 1 for both surface water and groundwater monitoring sites from 2017 to 2021.

Monitoring site Fihu BH 9 only had two components from the PCA. Component 1 had increased concentrations of TDS (0.982), SO_4 (0.982), Ca (0.984), Mn (0.982), Na (0.942), and Mg (0.945), explaining a total variance of 76%. The second component had high levels of pH (0.835) and Al (0.691), accounting for a total variance of 11.5%.

Linear Regression Analysis

The data were classified by the four seasons, where the average concentrations were calculated for each of the surface water and groundwater sampling points and each of the water chemical parameters. Four candidate regression models were fitted using the sulfate concentration as the dependent variable and the others as independent variables. The model was developed to assess the SO_4 ratio against the dependent variables.

In model 1, the p -values of EC, Ca, and Fe were smaller than 0.05, indicating an effective model and presenting a good fit (Figure 24). The R^2 of 0.615 in the model shows that the dependent variables explained the variability of SO_4 as an independent variable, showing a strong correlation.

$$\begin{aligned} \text{SO}_4 = & 53.12487 - 4.81874 \text{ Ph} - 6.65227 \text{ Ec} + 0.587389 \text{ TDS} + 11.77652 \text{ Ca} \\ & - 1.93564 \text{ Mg} - 2.77687 \text{ Na} - 166.58\beta_7 \text{ Al} + 13.40986 \text{ Fe} \\ & - 27.9553 \text{ Mn} \end{aligned} \quad (13)$$

The R^2 value of the second model indicates that the water parameters pH, EC, TDS, Ca, Mg, Na, Al, Fe, and Mn explained 0.6153 of the variability of SO_4 . The greater R^2 value indicated the strong relationship between the independent and dependent variables. The p -values of EC, Ca, Al, Fe, and Mn were below 0.05. The best fit of the model is presented below.

$$\begin{aligned} \text{SO}_4 = & 2.206989808 \text{ Ph} - 6.42775334 \text{ Ec} + 0.621488677 \text{ TDS} \\ & + 11.81236424 \text{ Ca} + 2.483595419 \text{ Mg} + 3.021507737 \text{ Na} \\ & + 170.3619 \text{ Al} + 13.15460242 \text{ Fe} + 25.64761114 \text{ Mn} \end{aligned} \quad (14)$$

Of the five variables of the model, only the last one was not significant. The R^2 value was at 0.6153, showing EC, Ca, Al, Fe, and Mn as a strong fit for the model. The p -values less than 0.05 also confirmed the good fit of the model. The presentation of the model is indicated in Equation (15) and Figure 25.

$$SO_4 = -22.2575 - 5.74723 EC + 14.19187Ca - 199.464 Al + 17.56244 Fe - 18.3914 Mn \quad (15)$$

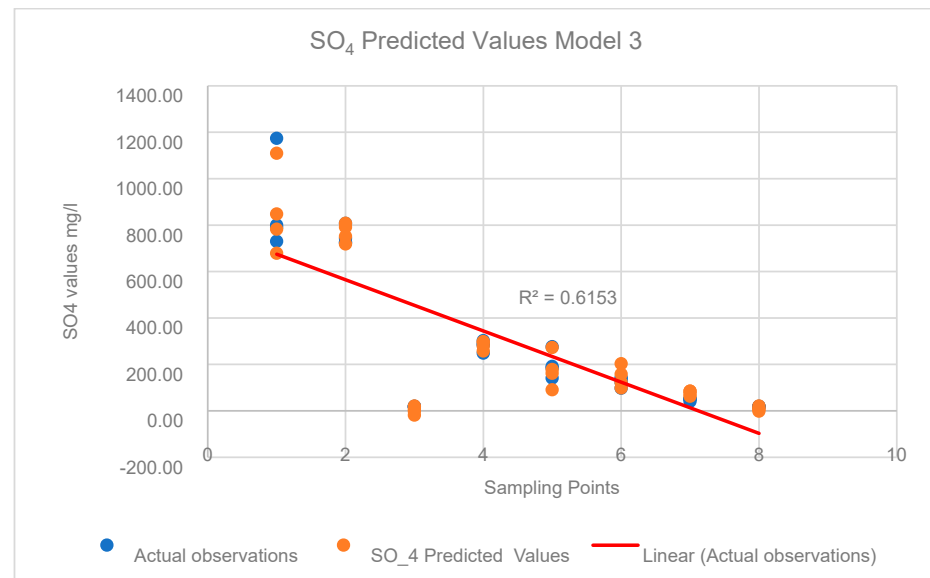


Figure 25. Predicted sulfate values in model 3 for both surface water and groundwater monitoring sites from 2017 to 2021.

In model 4 of the analysis, a strong correlation was determined, showing a good fit with an R^2 of 0.6153. (Figure 26). The R^2 in the model showed that dependent variables explained the 99% variability of the independent variable, indicating a strong correlation with the dependent variables. The p -values of EC, Ca, Al, Fe, and Mn were all below 0.05. The best fit of the model is presented below.

$$SO_4 = -7.39536 EC + 15.98919Ca - 231.237 Al + 20.5739 Fe - 23.9072 Mn \quad (16)$$

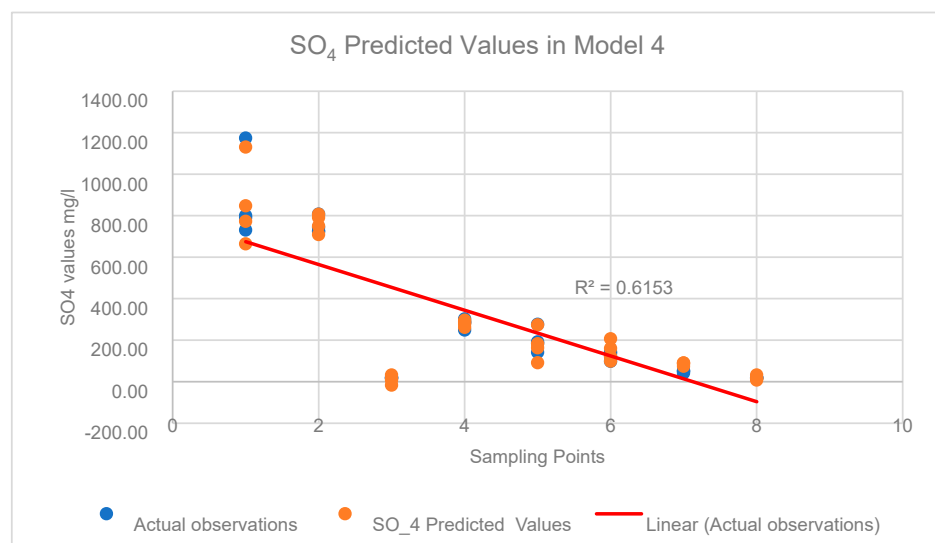


Figure 26. Predicted sulfate values in model 4 for both surface water and groundwater monitoring sites from 2017 to 2021.

4. Discussion

The current study was effective in determining if indeed anthropogenic activities such as coal mining do have an impact on water resources by using different WQIs. The use of the CCME–WQI and CPI has been utilized by developed countries with extensive mining activities, such as the United States, Spain, and China. In Spain, the continuous impacts of mining were determined in the Tinto River [5]. Using these indices, the China Coal Industry Association showed levels of poor water quality as a result of closed mines [6]. Oberholster et al. [15] indicated a higher concentration of Cl in the Loskop Dam greater than what the South African, Canadian, Australian, and New Zealand guidelines suggest.

In the present study, a full analysis of the water quality data was conducted to determine the extent to which the study area has been impacted by the coal mining activities in its vicinity. The water quality displayed high levels of the analyzed parameters, which are associated with mining and related activities, which are widespread in the proximity of the town of Middelburg. The analyses of metals and physicochemical parameters that were conducted using the WQIs indicated an in-depth understanding of the impact of coal mining and related activities. The study indicated that some water quality parameters from the used data collected from the year 2017 to 2021 indeed exceeded the limits from the RQO [36], TWQR [37,38], CMME [39], and ANZECC/ARMCANZ [40] guidelines.

The water quality status of monitoring sites A and B showed some pollution from mainly SO_4 , total dissolved solids, and electrical conductivity. Groundwater monitoring boreholes BH 1, BH 2, BH 6, BH 7, and BH 9 were the most contaminated when compared with the WHO guidelines [42].

The use of the selected and combined indices (CCME–WQI and CPI) was a success in determining the water quality status of both the surface water and groundwater resources, confirming the presence of pollution from anthropogenic activities such as coal mining. The outcome of the current study can be related to the study by Hamlat et al. [47], who applied different WQIs in assessing the water quality in the Tafna catchment in Algeria. Their study aimed at determining the status and trends of the water quality in the Tafna catchment, although this was not limited to the impacts of coal mining.

The use of these indices has provided evidence that mining activities have an impact on water resources. The CCME–WQI of the surface monitoring points A and B ranged from 63 to 64 points, respectively, and were found within the poor to fair range in the summer season. The CPI for both points was between 1.1 and 1.2, which lies within the very poor range. These two points were notably in the vicinity of mining sites. The sampling points that were situated at a distance from the coal mining activities, such as sites E, F, G and H, had CCME–WQI scores ranging from 86 to 100 in the winter, indicating a good to excellent water quality. The CPI was between 0.2 and 0.4, found within the limits for good status. Boreholes BH 1, BH 2, and BH 6 experienced a poor CCME–WQI over all the seasons. The CPI also indicated poor qualities. The application of different WQIs was effective in determining the impacts of anthropogenic activities in the study area.

The CCME–WQI and CPI have provided reliable results of the degree of contamination by mining and related activities [14]. A study conducted by Atangana et al. [28] obtained similar results when applying CCME and CPI to assessment the surface water quality in the Vaalwaterspruit, a stream in Mpumalanga, South Africa. Good and fair results for the CCME–WQI and CPI best categorized the water quality, which deteriorated more in the downstream area due to nutrients (fluoride), trace metals (Al, Fe, and Mn), and particulate matter caused by mining activities in the area during the four-year (2017–2021) study period.

In the absence of similar studies within the catchment, the study conducted at the uMngeni River in South Africa, using the CCME–WQI, indicated that the index is critical in identifying influential parameters affecting water quality in water resources. The use of the CCME–WQI effectively simplified the complex dataset to be easier to understand. It is mostly used because it is an easy application to use, and it offers flexibility in selecting the variables to analyze in the model [22]. The CPI technique is essential for scientific reflection

of the kinds and levels of pollution in water systems. The use of a combination of these indices can be applied in South Africa and the continent at large to predict water quality impacts from coal mining activities and manage it on catchment levels.

Application of the PCA statistical analysis using the SPSS software identified the dominance of parameters such as TDS, SO_4 , Mg, EC, and Ca in most of the surface water points. These findings showed consistency in interpretation, similar to the analyses undertaken by Atangana et al. [28], indicating that some of the variables are sourced from anthropogenic activities such as mining. These chemical parameters are naturally occurring on the ground, with a strong correlation when exposed through anthropogenic activities. Point D also showed an increase in SO_4 , TDS, Ca, Na, Mn, and EC, accounting for a total variance of 80.2%. In groundwater, BH 1, BH 2, and BH 3 showed a total variance ranging between 59% and 61%, indicating a strong correlation.

The analyses from the linear regression were used for the water quality variables that were found to have significant high levels in the models. The regression analyses carried out for the water quality parameters indicated a better and higher level of significance in the correlation coefficients. From the analyses, it was evident that the analyses parameters significantly correlated with the sulfates in all models, with all R^2 at 0.9.

5. Conclusions and Recommendations

The present study provided an overview of the current state of water quality and showed that anthropogenic activities such as coal mining and related activities impacted the water resources in the Middelburg area during the years 2017–2021. The study used historical water quality data for a period of five years, and the data were analyzed using WQIs such as CCME–WQI and CPI and multivariate statistics. Water quality results indicated elevated concentrations of the chemical parameters, contamination that can be associated with coal mining and related activities through the high concentration of TDS, SO_4 , and EC in both surface and groundwater samples.

The two indices applied in the study were found to generate fair results in evaluating the water quality status of the surface and groundwater and could be considered by the water utility manager in assessing the water quality status of water resources impacted by acid mine drainage. The CCME–WQI index results showed surface water quality of fair to excellent quality throughout all seasons, with groundwater showing some level of contamination in some boreholes. The CPI result also indicated some improvement at some of the surface water points and also picked up pollution in some of the monitoring boreholes, mostly during the summer and winter seasons. Addressing the sampling area pollution point sources by the use of multivariate analysis, PCA identified contamination in both surface water and groundwater that could be associated with the mining industry, with some natural occurrences in some of the chemical parameters. The linear regression analysis also identified the dominance of SO_4 in most of the sampling points, which could also be linked to mining activities. In view of the above, the combination of the above indices suggested that there was contamination in water quality, showing increased concentrations of the analyzed chemical parameters. Using both indices can effectively predict water quality pollution by coal mines. The indices can be included in the water quality monitoring programs to supplement water quality data by simplifying large datasets.

It is recommended to enforce an extensive monitoring program on water resources and compare them against the guidelines of the Department of Water and Sanitation (previously Department of Water Affairs and Forestry), together with the guidelines for the indices. Mining companies must improve in the application of their water management systems and regularly monitor their effectiveness. It is also important that the government improve the implementation of the environmental legislations. Various treatment options are available to deal with the contamination arising from mining activities if managing their activities is not productive. A passive treatment system associated with constructed wetlands may pose real solutions for addressing pollution arising from abandoned mines and small-scale mines.

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