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Original Research Paper

Inter-Annual Comparative and Correlation Analysis of Seasonal Limnological Characteristics of Urmil Dam (Singhpur Barrage), Madhya Pradesh, Central India

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Abstract

Freshwater reservoirs are strongly influenced by seasonal hydrological changes, yet integrated assessments combining annual comparisons and multivariate statistical analysis remain limited for Singhpur Barrage Reservoir, Madhya Pradesh, India. This study evaluated physicochemical water-quality variations across winter, summer, and monsoon during 2024–25 and 2025–26 using 24 observations. Descriptive statistics, normality testing, parametric and non-parametric comparisons, Spearman correlation, principal component analysis, and hierarchical cluster analysis were applied. Significant seasonal variation occurred in electrical conductivity, pH, chloride, alkalinity, fluoride, iron, total hardness, calcium, magnesium, sulphate, sodium, and potassium. Summer generally exhibited higher ionic and mineral concentrations, while monsoon conditions were associated with increased suspended matter and reduced transparency. Annual differences were mainly observed for water temperature, chloride, and selected mineral-related variables. Strong positive correlations were found among conductivity, sulphate, magnesium, potassium, iron, and hardness, whereas transparency showed a strong negative relationship with suspended solids. Five principal components explained 87.206% of the total variance, although the low KMO value indicated that the PCA findings should be interpreted cautiously. Hierarchical clustering identified mineral, ionic, physical, optical, and general physicochemical groups. The findings highlight the importance of seasonal and long-term monitoring for sustainable reservoir management and water-resource planning.

Keywords: Singhpur Barrage Reservoir, physicochemical water quality, seasonal variation, multivariate statistical analysis, principal component analysis, hierarchical cluster analysis

1. Introduction

1.1 Importance of Freshwater Reservoirs

Freshwater reservoirs play a vital role in regional water-resource systems due to their functions of irrigation, drinking-water supply, fisheries, flood control, conservation of biodiversity, recreation and livelihoods. They play a significant role in the ecology and economic value in area with seasonality of water availability, especially in semi-arid and in area with monsoon. Reservoirs also act as a dynamic aquatic environment where all inputs from the hydrological processes, catchment processes, sediment transport and human activities are in constant interaction. Hence, it is essential to maintain the quality of the water in the reservoir for human consumption as well as for maintaining the aquatic productivity and ecosystem stability. Monitoring of water quality per season is therefore crucial in sustainable reservoir management as the degradation in water quality could impact both the domestic use and irrigation efficiency, fish production, and ecological health (Mamun et al., 2021; Liu et al., 2020).

1.2 Importance of Physicochemical Assessment

Physicochemical parameters are an immediate indicator of the status and functioning of freshwater systems. The temperature of the water affects metabolic processes, solubility and rates of chemical reactions, and tolerance levels to biological organisms, and pH affects nutrient availability, metal mobility and biological tolerance. Electrical conductivity is an indicator of the number of ions in the solution and total dissolved solids (TDS) is a measure of both inorganic and organic matter in the solution. Turbidity and transparency are a measure of the optical quality of water and are influenced by

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suspended particles, erosion, number of plankton and runoff. TOTAL HARDNESS, CALCIUM, MAGNESIUM, CHLORIDE, SULPHATE, SODIUM, POTASSIUM, IRON, ALKALINITY and FLUORIDE are useful in determining mineral dissolution, geology of the catchment area, evaporation and potential anthropogenic inputs. These variables assessed in combination, can help identify if the water in the reservoir is suitable for aquatic life and various human activities. Such integrated multidimensional physicochemical were found to be successful in the Indian and international studies of surface waters (George et al., 2017; Gyimah et al., 2021).

1.3 Seasonal Variation in Tropical Reservoirs

It has been observed that the water chemistry in tropical reservoirs is drastically altered during the different seasons of winter, summer and monsoon season. Typically, water chemistry, evaporation and temperatures are lower under winter conditions. In summer, high temperature and evaporation can change these parameters including the concentration of dissolved salts, conductivity, hardness and pH. Monsoon rainfall can have both positive and negative consequences (diluting effects) on some of the dissolved constituents, but also a positive influence on increasing the concentration of turbidity and suspended solids, nutrient input and ions from catchment surface runoff. Flow conditions can thus vary seasonally, and change the physical and chemical characteristics of reservoir waters. Past research has indicated that monsoon intensity and drought, inflow and seasonal runoff are significant drivers of variations in the water-quality patterns of reservoirs, lakes and rivers (Ouyang et al., 2006; Sharma & Ravichandran, 2021). Seasonal and spatial assessments are especially beneficial as a single annual mean could mask short-term declines and/or hydrological changes (Lencha et al., 2021; Niu et al., 2021).

1.4 Importance of Multivariate Statistical Analysis

Typically, there will be many related variables in water-quality data that will complicate the interpretation of the data if only univariate techniques are used. Correlation analysis can be used to determine positive and negative relations between parameters, and can help to identify common hadrochemical controls. PCA is a method that will make a large number of variables into a smaller number of variables representing the dominant sources/processes. For hierarchical cluster analysis to group together variables for similar behaviour, distinguishing mineral, ionic, physical and optical characteristics can be done. Many of these methods have been applied to the surface water to recognize temporal patterns, pollution sources and hadrochemical association (Shrestha & Kazama, 2007; Singh et al., 2004). Multivariate methods also help in better interpretation as it helps to distinguish natural geochemical influences from any seasonal or anthropogenic effects (Goswami &Kalamdhad, 2024; Singh et al., 2005).

Objectives of the study

Although several Indian rivers, lakes, and reservoirs have been examined using seasonal and multivariate approaches, integrated interannual evaluation of Singhpur Barrage remains limited.

- To assess the seasonal variation in the physicochemical characteristics of Singhpur Barrage during winter, summer, and monsoon across the two monitoring years.
- To compare the water-quality parameters of Singhpur Barrage between 2024–25 and 2025–26 and identify statistically significant interannual differences.
- To examine relationships and dominant patterns among the physicochemical parameters using correlation analysis, principal component analysis, and hierarchical cluster analysis.

2. Materials and Methods

2.1 Study Area

The study was carried out at Singhpur Barrage near Singhpur-Lavkushnagar, Chhatarpur district, Madhya Pradesh in Central India. The reservoir was built in 2017-2018 to be used for irrigation, water supply and flood-control. It occupies around 6000ha with an average depth of around 10m, a maximum depth of almost 12m and a gross capacity of around 24.5 million m³. The catchment covers an area of almost 257.71 km² and is served by small streams and the surface run-off from the catchment during the rainy season. The regional hydrology is of a monsoonal nature, with the catchment inflow and rainfalls mainly happening during the rainy season, and relatively low in the winter and summer seasons. It is believed that these seasonal variations will affect the reservoir's dilution, evaporation, sediment loads and ionic concentrations.

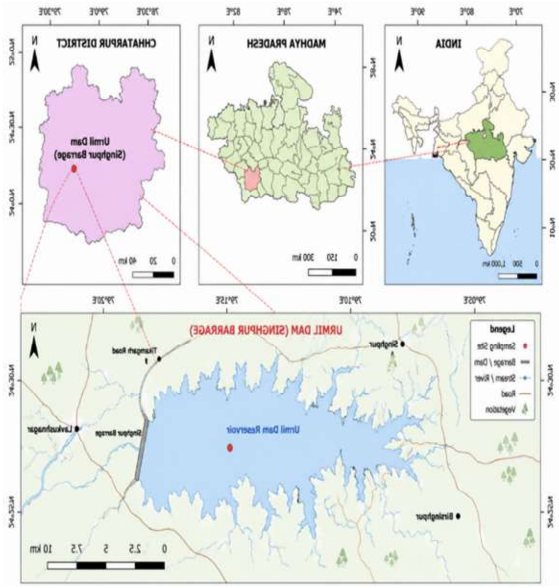

Figure 1. Location map of Singhpur Barrage, Chhatarpur District, Madhya Pradesh, India.
Source: OpenStreetMap Contributors. (2026). OpenStreetMap. https://www.openstreetmap.org

2.2 Sampling Design

Monitoring took place over two years (2024–25 and 2025–26) and water-quality observations were evaluated for those two monitoring years. Collection of samples was laid out in three seasons namely winter, summer and monsoon. Twelve observations were made each season (4 sample sites x 3 seasons) and twenty-four observations were made in the combined data set. The site-level observations were used as seasonal replicates to make interannual and seasonal statistical comparisons.

2.3 Water Sample Collection

The water samples were taken using clean properly labeled containers from selected sampling location. Field parameters were noted at or near the sampling stations and samples collected for laboratory determination were preserved under appropriate conditions and sent quickly to the laboratory to minimize any changes in the physical, chemical or biological characteristics of the sample. To prevent contamination in the collection, storage and transportation, standard precautions were adhered to.

2.4 Physicochemical Analysis

Water temperature, electrical conductivity, turbidity, transparency, total dissolved solids, total suspended solids, depth, pH chloride, alkalinity, fluoride, iron, total hardness, calcium, magnesium, sulphate, sodium and potassium were measured. The temperature was measured with the help of a thermometer, the pH, conductivity and TDS were measured by the suitable meters, transparency was measured by observation of Secchi-disc and TSS by filtration and gravimetric measurement. The chloride, alkalinity and hardness were evaluated by titrimetric methods while fluoride, iron, calcium, magnesium, sulphate, sodium and potassium were evaluated by laboratory testing. Nitrate was not used in the final multivariate analyses due to not being analytically suitable for stable multivariate interpretation.

2.5 Statistical Analysis

Descriptive statistics were: mean, standard deviation, minimum, maximum and coefficient of variation. The Shapiro – Wilk test was used to test for normality. Independent-samples t-test and Mann–Whitney U test were used to analyze interannual differences. One-way analysis of variance (ANOVA) and Kruskal–Wallis tests were used to compare for seasonal differences followed by pairwise comparisons when appropriate. Association between variables were tested by spearman's rank correlation. Due to limited sampling adequacy, principal component analysis was used as exploratory and hierarchical cluster analysis used average linkage between groups and correlation-based similarity.

Table 1. Summary of sampling and statistical design

Component	Description
Study period	2024–25 and 2025–26
Seasons	Winter, summer, monsoon
Sampling sites	Four sites per season
Total observations	24
Variables retained	18 physicochemical parameters
Year comparison	t-test and Mann–Whitney U
Seasonal comparison	ANOVA, Kruskal–Wallis, pairwise tests
Multivariate analysis	Spearman correlation, exploratory PCA, hierarchical clustering

3.1 Descriptive Statistics

The results of descriptive analysis in Table 2 revealed that there was a significant difference between the physicochemical characteristics of Singhpur Barrage Reservoir during the different seasons. Generally, the water temperature, electrical conductivity, total dissolved solids and pH and most of the ionic parameters were higher in the summer and the suspended solids were slightly higher (with lower transparency) in the monsoon.

Table 2. Seasonal descriptive statistics of physicochemical parameters

Parameter	Winter, mean ± SD	Summer, mean ± SD	Monsoon, mean ± SD
Water temperature	26.86 ± 4.52	29.63 ± 1.60	30.88 ± 0.83
Electrical conductivity	367.63 ± 40.64	1013.88 ± 47.06	839.38 ± 79.02
Turbidity	3.19 ± 0.52	2.88 ± 0.37	3.00 ± 0.41

Transparency	1.83 ± 0.10	1.88 ± 0.21	1.71 ± 0.22
Total dissolved solids	151.38 ± 13.67	171.88 ± 15.84	161.63 ± 7.03
Total suspended solids	17.75 ± 1.04	17.75 ± 2.05	18.75 ± 2.05
Water depth	10.75 ± 0.89	10.75 ± 0.89	10.75 ± 0.89
pH	7.21 ± 0.31	7.61 ± 0.10	7.35 ± 0.36
Chloride	32.73 ± 1.70	202.25 ± 178.16	194.88 ± 171.28
Total alkalinity	123.13 ± 6.06	283.50 ± 5.26	290.00 ± 1.20
Fluoride	0.19 ± 0.11	0.25 ± 0.03	0.17 ± 0.01
Iron	0.16 ± 0.03	0.57 ± 0.38	0.33 ± 0.05
Total hardness	164.63 ± 41.98	328.75 ± 127.71	198.13 ± 35.95
Calcium	47.63 ± 4.24	111.38 ± 57.22	43.50 ± 8.42
Magnesium	6.08 ± 0.45	24.69 ± 18.91	12.44 ± 6.18
Sulphate	5.44 ± 0.50	80.00 ± 75.75	10.46 ± 2.38
Sodium	14.13 ± 1.36	17.63 ± 1.19	15.88 ± 1.13
Potassium	3.71 ± 0.34	4.78 ± 0.23	4.50 ± 0.32

Note: *Values are presented as mean ± standard deviation; n = 8 observations per season.*

Water temperature increased from 26.86 ± 4.52°C in winter to 30.88 ± 0.83°C in the monsoon. Electrical conductivity was minimum in winter and maximum in summer which suggest that the ionic concentration was higher during dry season as compared to rainy season. The other parameters, such as, total hardness, calcium, magnesium, sulphate, chloride, sodium and potassium also exhibited their maximum mean values during summer. By contrast, there was little difference in turbidity between the seasons and water depth was constant. The overall descriptive results indicate that under summer conditions dissolved minerals were concentrated and monsoon conditions helped in increasing suspended matter and decreasing the water clarity.

Figure 2 illustrates the seasonal variation in the mean values of the measured physicochemical parameters across the study period.

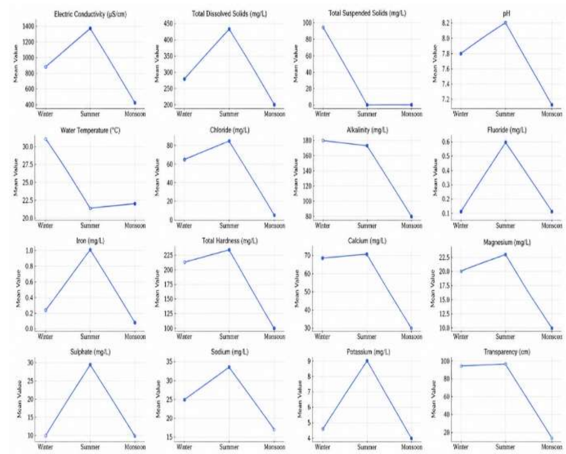

Figure 2. Seasonal mean profile plot showing variations in the physicochemical parameters of Singhpur Barrage Reservoir across winter, summer, and monsoon seasons.

3.2 Normality Assessment

The Shapiro-Wilk test was used to test the normality of the distribution for the variables of the physicochemical parameters in each year–season group. No significant deviation from normality ($p > .05$) was observed for majority of the parameters as given in the Table 3. But, the water temperature distribution in summer of 2024–25, monsoon of 2024–25 and monsoon of 2025–26 was found to be non-normal. The alkalinity was found to be non-normal during summer and monsoon of 2025–26 and pH deviated slightly during monsoon of 2025-26. Thus, in the following comparisons both parametric and non-parametric tests were taken into account.

Table 3. Physicochemical parameters showing significant Shapiro–Wilk results

Study year	Season	Parameter	Shapiro–Wilk statistic	*p*-value	Interpretation
2024–25	Summer	Water temperature	0.630	.001	Non-normal
2024–25	Monsoon	Water temperature	0.630	.001	Non-normal
2025–26	Monsoon	Water temperature	0.729	.024	Non-normal
2025–26	Monsoon	pH	0.753	.041	Non-normal
2025–26	Summer	Alkalinity	0.630	.001	Non-normal
2025–26	Monsoon	Alkalinity	0.630	.001	Non-normal

Note: *Only statistically significant Shapiro–Wilk results are shown. All remaining parameters had* p *> .05.*

3.3 Comparison Between Years

Table 4 showed that most of the variables were relatively stable when compared between the two monitoring years while only few physicochemical parameters were significantly different. The water temperature, chloride content, Fe, total hardness, Mg and SO4 contents were found to differ significantly ($p < 0.05$) using the independent samples t-test. However, the electrical conductivity, turbidity, transparency, total dissolved solids, total suspended solids, water depth, pH, alkalinity, fluoride, calcium, sodium and potassium concentrations in the water did not show significant differences among the study years. The Mann–Whitney U test confirmed these results and revealed significant differences between the years for water temperature, and chloride concentration, but not for the other parameters. Overall, the results suggest that there were little variations in the hydrochemical characteristics of the reservoir from one year to the other, except for some of the mineral related parameters and temperature.

Table 4. Comparison of physicochemical parameters between the two study years

Parameter	**Independent *t*-test (*p*)**	**Mann–Whitney U (*p*)**	**Interpretation**
Water temperature	<0.001*	<0.001*	Significant
Electrical conductivity	0.886	0.644	Not significant
Turbidity	0.295	0.224	Not significant
Transparency	0.676	0.772	Not significant
Total dissolved solids	0.370	0.298	Not significant
Total suspended solids	0.823	0.815	Not significant
Water depth	1.000	1.000	Not significant
pH	0.380	0.930	Not significant
Chloride	<0.001*	0.028*	Significant
Alkalinity	0.954	0.487	Not significant
Fluoride	0.822	0.908	Not significant
Iron	0.024*	0.174	Significant (*t*-test only)
Total hardness	0.037*	0.184	Significant (*t*-test only)
Calcium	0.104	0.470	Not significant
Magnesium	0.004*	0.141	Significant (*t*-test only)
Sulphate	0.027*	0.106	Significant (*t*-test only)
Sodium	0.338	0.350	Not significant
Potassium	0.743	0.467	Not significant

Note: *Variables with* p *< 0.05 are considered statistically significant. Both parametric and non-parametric tests were performed because selected variables showed deviations from normality.*

3.4 Seasonal Variation

One-way Analysis of Variance (ANOVA) and Kruskal–Wallis test was used to determine the existence of seasonal variation. In Table 5 the results of ANOVA indicated the significance of the difference between the water temperature, electrical conductivity, total dissolved solids, pH, chloride, alkalinity, iron, total hardness, calcium, magnesium, sulphate, sodium and potassium contents of the water samples collected in different seasons. Most of the ionic and mineral related parameters like Electrical conductivity, pH, chloride, alkalinity, fluoride, iron, hardness, calcium, magnesium, sulphate, sodium and potassium showed a significant seasonal variation which was confirmed by Kruskal-Wallis test. There was no significant difference between the mean values of turbidity, transparency, TSS or water depth for the respective seasons. Results generally suggest that the primary factor affecting the dissolved ions, mineral concentration and water chemistry was the seasonal conditions while the physical characteristics of the reservoir were relatively constant.

Table 5. ANOVA and Kruskal–Wallis results for seasonal variation

Parameter	**ANOVA, *F***	**ANOVA, *p***	**Kruskal–Wallis, *H***	**KW, *p***	**Interpretation**
Water temperature	4.278	0.028*	3.615	0.164	Significant by ANOVA
Electrical conductivity	265.341	<0.001*	19.565	<0.001*	Significant
Turbidity	1.028	0.375	1.834	0.400	Not significant
Transparency	1.795	0.191	2.312	0.315	Not significant
Total dissolved solids	5.175	0.015*	5.930	0.052	Significant by ANOVA
Total suspended solids	0.842	0.445	1.558	0.459	Not significant
Water depth	0.000	1.000	0.000	1.000	Not significant

pH	4.186	0.030*	12.927	0.002*	Significant
Chloride	3.607	0.045*	13.284	0.001*	Significant
Alkalinity	3257.001	<0.001*	19.309	<0.001*	Significant
Fluoride	2.888	0.078	6.642	0.036*	Significant by KW
Iron	6.828	0.005*	15.148	0.001*	Significant
Total hardness	9.320	0.001*	11.330	0.003*	Significant
Calcium	10.335	0.001*	15.488	<0.001*	Significant
Magnesium	5.426	0.013*	15.322	<0.001*	Significant
Sulphate	7.257	0.004*	16.640	<0.001*	Significant
Sodium	16.269	<0.001*	14.406	0.001*	Significant
Potassium	26.837	<0.001*	15.988	<0.001*	Significant

Note: ANOVA degrees of freedom were 2 and 21; Kruskal–Wallis degrees of freedom were 2. An asterisk indicates statistical significance at $p < 0.05$.

3.5 Pairwise Seasonal Comparison

Pairwise Mann Whitney tests were carried out for parameters and results in Table 6 that indicated there was significant seasonal variation (Bonferroni adjusted $\alpha = 0.0167$). There were significant differences in electrical conductivity and alkalinity among each of the three season comparisons. The seasonal differences between winter and the warmer seasons were the only significant ones for the elements chloride, iron, magnesium, sulphate and potassium. Phenological variations (winter and summer) were also observed for the parameters pH, total hardness, calcium and sodium. The fluoride, calcium and sodium concentration were significantly different in the summer–monsoon comparison. These results show that the greatest seasonal difference was in winter compared to summer, overall.

Table 6. Significant pairwise seasonal comparisons

Parameter	Winter–Summer	Winter–Monsoon	Summer–Monsoon
Electrical conductivity	<0.001*	<0.001*	0.001*
pH	<0.001*	0.105	0.021
Chloride	<0.001*	0.002*	0.442
Alkalinity	<0.001*	<0.001*	0.002*
Fluoride	0.442	1.000	<0.001*
Iron	<0.001*	<0.001*	1.000
Total hardness	0.002*	0.065	0.028
Calcium	<0.001*	0.442	<0.001*
Magnesium	<0.001*	0.001*	0.130
Sulphate	<0.001*	<0.001*	0.105
Sodium	<0.001*	0.021	0.015*
Potassium	<0.001*	0.001*	0.083

Note: Values are exact two-tailed p*-values. An asterisk indicates significance after Bonferroni correction at* $p < 0.0167$.

3.6 Correlation Analysis

The heatmap of the Spearman correlation shown in Figure 2 revealed some of the strong relationships between the various physicochemical parameters. The electrical conductivity was highly and positively correlated with potassium ($r_s = 0.882$), sulphate ($r_s = 0.822$) and magnesium ($r_s = 0.821$) and thus, a higher conductivity also yielded a higher ionic content of the water. Chloride was also highly correlated with sulphate ($r_s = 0.891$) and there was a strong positive correlation between iron and sulphate ($r_s = 0.899$). The highest positive correlation value was between Mg and SO_4 ($r_s = 0.958$). Transparency on the other hand had a very strong negative correlation with total suspended solids ($r_s = -0.975$) and a strong negative correlation with depth ($r_s = -0.843$). So there was a negative correlation with water clarity as the amount of suspended matter increased. The overall correlation matrix implies that ionic and mineral parameters were related each other while optical transparency parameters decreased with increasing physical particulates parameters.

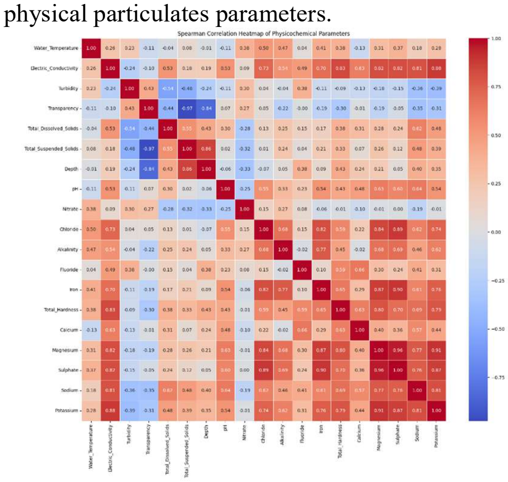

Figure 2. Spearman correlation heatmap showing associations among the physicochemical parameters of Singhpur Barrage Reservoir

3.7 Principal Component Analysis

Table 7 shows the results of the Kaiser–Meyer–Olkin and Bartlett test which were used to determine the suitability of the physicochemical data for principal component analysis. Based on the results of Bartlett's test of sphericity, the correlation between the variables was sufficient as shown by the result of the Bartlett's test which was statistically significant, $\chi^2(171) = 648.660$, $p < 0.001$. But, the overall sampling adequacy (KMO value) was 0.426 which is a weak value. Thus, the results from the PCA should be considered exploratory and not confirmatory.

Table 7. KMO and Bartlett's test

Test	Result
Kaiser–Meyer–Olkin measure	0.426
Bartlett's approximate χ^2	648.660
Degrees of freedom	171
Significance	<0.001

Table 8 shows the 5 principal components that had eigenvalues > 1. When considered together, they accounted for 87.206% of the total variance, which meant that a relatively few dimensions could account for most of the variance in the water quality of the reservoirs.

Table 8. Principal component retention and variance explained

PCA result	Value
Number of components retained	5
Retention criterion	Eigenvalue > 1
Cumulative variance explained	87.206%
Interpretation	Exploratory five-component solution

In Figure 3, it is seen that the first 5 components had high reduction in eigenvalues and then it levelled off, which indicated the retention of 5 components. These components were, in general, an index of mineral and hardness, ionic composition, physical water properties, optical properties and a relatively independent physicochemical change. Due to the low KMO value and small sample size, caution needs to be used to interpret the components.

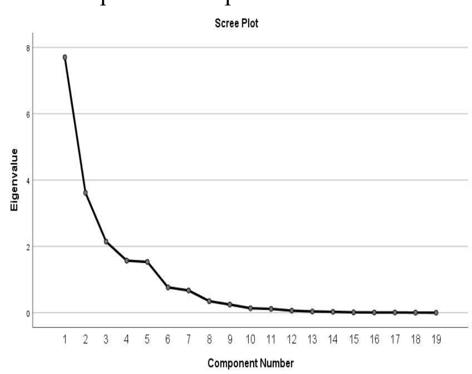

Figure 3. Scree plot showing the eigenvalues of the principal components extracted from the physicochemical parameters.

3.8 Hierarchical Cluster Analysis

Figure 4 shows the results of hierarchical cluster analysis (HCA) based on average linkage which led to five interpretable clusters of physicochemical parameters. Hardness and mineral ions (Fe, sul, Mg, TH, Ca and chloride) were part of Cluster I. They are grouped on the basis of mineral enrichment and hardness process which have very close association. Cluster II included electrical conductivity, alkalinity, potassium and sodium which were in general the general ionic composition of the reservoir. The total suspended solids, depth and total dissolved solids (TDS) were grouped together in Cluster III and interpreted as a physical-characteristics group. Turbidity and transparency were combined in Cluster IV, which was related to optical water-quality conditions. There was an inverse relationship between these variables that corresponded to an increase in turbidity and suspended matter leading to a decrease in water clarity. The group of water temperature, pH and fluoride (Cluster V) was quite independent and clustered with the other groups at later cluster levels. The two groups with the highest similarity coefficient (0.968) are the initial groups of iron and sulphate. This group was then followed by the fusion of this cluster with magnesium at 0.947. The other strong association found was between electrical conductivity and alkalinity (0.940) and total hardness and calcium (0.936). Later the groups of mineral-ions and hardness joined each other at 0.915. The dendrogram results generally confirmed the correlation results as there was a commonality between mineral, hardness and ionic parameters behaviour.

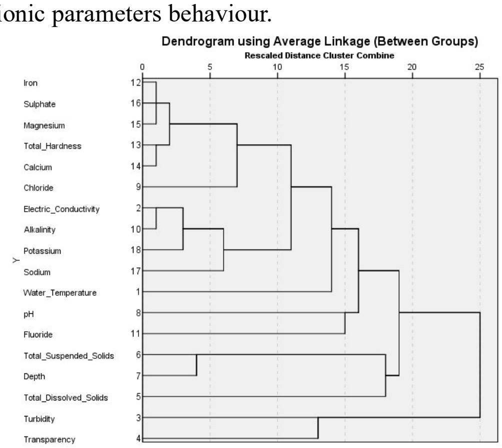

Figure 4. Hierarchical cluster dendrogram showing the grouping of physicochemical parameters based on average linkage.

4. Discussion

4.1 Seasonal Water-Quality Dynamics

Physicochemical attributes of Singhpur Barrage were distinctly different in terms of electrical conductivity, pH, chloride, alkalinity, fluoride, iron, total hardness, calcium, magnesium, sulphate, sodium and potassium with respect to the different seasons. This difference suggests that, the hydrodynamic conditions of the season are very important in controlling the ionic composition and mineral balance of the reservoir. Generally, the electrical conductivity, alkalinity, hardness, calcium and sodium were found to be higher in summer as compared to other seasons, which could be attributed to increase in evaporation, decrease in dilution and concentration of dissolved constituents in summer. Similar enrichment of dissolved ions has been found in surface water in tropical regions where high temperature and low flow causes a high concentration of mineral ions (George et al., 2017; Sharma & Ravichandran, 2021). No different hydrochemical response was observed under the monsoon conditions. Both rainfall and catchment runoff can help to dilute some of the dissolved constituents and lead to an increase in the amount of suspended matter, soil derived minerals and dissolved ions entering the reservoir. The seasonal differences that were found for the sulphate, magnesium, iron, chloride and potassium suggest an impact of run-off and catchment weathering. Lakes and reservoirs have experienced changes in water chemistry due to changes in inflow, flood pulses and nutrient transport that are similar to the monsoon related changes observed in these ecosystems (Mamun et al., 2021; Lencha et al., 2021). Turbidity, transparency, total suspended solids, depth and temperature, however, failed to produce any statistically significant seasonal differences in the Kruskal–Wallis analysis and it is suggested that the variability within seasons and/or among sampling sites may have limited the ability to make statistically significant comparisons between these data and those collected at the other sites.

4.2 Annual Variability

When compared to 2025–26, the interannual difference showed a few changes in the physicochemical parameters in 2024–25. This variation could be due to variations in rainfall, the inflow to reservoirs, evaporation, catchment runoff, water residence time and local human activity. The hydrological conditions (annual) may change the ion concentrations and sediment transport even in the same seasons. Ouyang et al. (2006) also found that seasonal effects can compound the effects of precipitation and flow conditions to result significantly different surface-water quality conditions from year to year. Changes in the relative importance of chemical parameters has also been reported in multivariate water-quality investigations where climatic and watershed factors varied the relative importance of the chemical parameters (Gyimah et al., 2021). Thus, the 2-year comparison provides added support to the study, and demonstrates that a single year of monitoring does not adequately reflect the water quality of the reservoirs.

4.3 Hydrochemical Relationships

Spearman's correlation method was used to identify significant relationships between variables and the results showed that there were some good correlations between the measured variables. The electrical conductivity had high positive correlation with the alkalinity, potassium, sulphate, hardness and sodium, suggesting that the conductivity was more influenced by the mineral ions dissolved in water. The high positive correlation of iron, magnesium and sulphate indicates that they are probably from a similar geochemical and/or catchment source. The total hardness was highly related with calcium and this showed that the calcium was a major contributor to the total hardness in the reservoir. Such relationship is similar to the previous study where strong correlation between strong ion–conductivity and hardness-calcium were identified to be common hydrochemical controls (Giri et al., 2019; Singh et al., 2020). A significant negative correlation was found between transparency and TSS, which is ecologically sound as increased suspended particles will decrease the transparency. Suspended solids were found to be significantly positively correlated with depth, which may be due to higher accumulation and/or resuspension at deeper depths. Correlation analysis can be employed in this regard to detect such correlated activity, but doesn't necessarily prove causality. Other uses of the same applications have helped to differentiate the natural mineralization, sediment effects and potential anthropogenic impacts in surface-water systems (Kazi et al., 2009; Singh et al., 2022).

4.4 Principal Controlling Factors

Based on the findings from principal component analysis, five components were extracted which had a total variance of 87.206% suggesting that a few latent processes accounted for most of the variance in the data. These components were most probably related to mineralization, chemistry associated with hardness, dynamics of suspended material and seasonality of physicochemical effects. But the value of Kaiser–Meyer–Olkin was 0.426 which was below the acceptable limit of 0.5 and hence indicated poor sampling adequacy. The results from the PCA are exploratory and the low KMO values from Bartlett's test suggests that the test results should be interpreted accordingly. Shrestha and Kazama (2007) pointed out that PCA can be useful to reduce the complexity of water-quality data and Goswami and Kalamdhad (2024) showed the usefulness of PCA in finding the dominant processes and potential patterns of water quality sources. In the current study, PCA is still useful, but, with such a small sample size, one cannot be general.

4.5 Hydrochemical Grouping

Five parameter groups were obtained by hierarchical cluster analysis that were easily interpretable. There was a cluster of minerals/hardness related variables: Iron, sulphate, magnesium, hardness, calcium, and chloride. The variables of electrical conductivity, alkalinity, potassium and sodium constituted an ionic-strength cluster. The physical and solids-related conditions were TSS, depth and TDS and those of optical quality were turbidity and transparency. Another group consisting of water temperature, pH and fluoride was identified that captured general physicochemical regulation. This grouping is in accordance with the results of Singh et al., (2004) and Vega et al., (1998) that showed cluster analysis could be used to present similarities between water-quality variables and to show the common controlling mechanisms.

4.6 Implications for Reservoir Management

The results show that the continuous monitoring and seasonally monitoring is essential for Singhpur Barrage. The parameters related to Ionic concentration, Hardness, Alkalinity, Sulphate should be given special attention during the summer and monsoon season. Rainfall, inflow, land-use activity and sediment movement also should be monitored to enhance the interpretation of changes from year to year. The dimensionally identified parameter clusters could also help to reduce the number of indicators to be monitored in the future by choosing the representative indicators from each hydrochemical group. To support a sustainable management of the reservoirs, long term observation of the reservoir, catchment protection and control of runoffs, as well as periodic evaluation of water suitability for irrigation, fisheries and domestic purposes are recommended.

5. Conclusion

In the present study, it was observed that different physicochemical parameters of the Singhpur Barrage are different in different seasons and years. Results indicated that electrical conductivity, pH, chloride, alkalinity, fluoride, iron, total hardness, calcium, magnesium, sulphate, sodium and potassium had significant seasonal differences, reflecting the high influence of evaporation, rainfall, runoff and dilution and of mineral inputs from the catchment on the water chemistry of the reservoir. Summer season was generally characterized by higher mineral enrichment and ionic concentration while during monsoon period both dilution and transport of dissolved and suspended matter effects were observed. The comparison was also done between the water quality in the reservoirs in 2024-25 and 2025-26, demonstrating that water quality in reservoirs is not consistent from year to year. This variability may have been caused by alteration of the rainfall, inflow, the water residence time, evaporation, and the catchment activity. The conductivity data were highly correlated with the alkalinity, hardness, calcium, magnesium, sulphate, sodium, potassium and iron data, which suggested common hydrochemical controls between conductivity and these variables, and transparency was negatively correlated with suspended solids, reflecting the expected optical responses. The complex data set was reduced to five components which accounted for the majority of the total variance (but with low sampling adequacies, caution needs to be used in interpretation). The data were analyzed using hierarchical cluster analysis (HCA) which revealed different clusters of mineral, ionic, solids related, optical and general physicochemical. In general the results give a valuable base line data for Singhpur Barrage. On-going seasonal and multi-year monitoring is recommended focusing on conductivity, alkalinity, hardness, major ions, suspended solids and change in relation to rainfall. Combining water-quality monitoring and catchment management and planning for use of reservoirs, will aid sustainable irrigation, fisheries and domestic usage and long-term ecological conservation. Continuation of monitoring should be conducted for a longer time frame and incorporate more sampling sites, hydrological parameters and biological parameters. More and larger data sets would have enhanced the accuracy of PCA and better allowed identification of natural and anthropogenic influences on the water quality of the reservoirs.

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