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Post-mining Water Quality of the Bhadra River in Kudremukh National Park, the Western Ghats of Karnataka, India

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ABSTRACT

Nineteen water quality parameters of the Bhadra River were evaluated one year after the cessation of mining to assess conditions within Kudremukh National Park (KNP). Cluster analysis grouped the monitoring stations into three categories: upstream, adjacent to and downstream of the mined area. The Bhagavathi stretch, located upstream, reflected water quality largely governed by natural factors. In contrast, the mining zone along the Bhadra River near Lakya and Malleswara showed clear impacts from effluents released from the Lakya dam, which stores mining tailings, along with surface runoff from disturbed areas. Downstream stations at Nellibedu and Kalasa were influenced by a combination of runoff from mined regions, agricultural activities and natural inputs. Principal Component Analysis (PCA) extracted four components explaining 87.524% of the total variance, effectively reducing the dataset from 19 variables to four, achieving a 78.947% reduction with a 16.629% information loss. Subsequent factor analysis further refined the dataset by minimizing the effect of less significant variables. Spatial factor analysis indicated moderate pollution at Nellibedu and high pollution at Malleswara. However, pollution levels declined downstream from Nellibedu to Kalasa, attributed to the river's natural self-purification capacity. Despite the cessation of mining in the Aroli-Gangamoola ranges of the Kudremukh hills, suspended solids (SS) remained a dominant pollutant even after one year. Along with total solids and electrical conductivity, SS continued to adversely affect the downstream water quality of the Bhadra River within KNP.

Keywords Cluster analysis, Factor analysis, Iron ore mining, Karnataka, Lotic water body, Principal component analysis.

INTRODUCTION

Kudremukh National Park (KNP) lies in the upper catchments of both east-flowing rivers such as the Bhadra and Tunga, and west-flowing rivers including the Swarna, Gurpura, and Nethravathi. Spread over an area of 600.32 km² between 75°01′–75°25′ E and 13°01′–13°29′ N, the park extends across the districts of Chikkamagaluru, Dakshina Kannada, and Udupi,

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and is recognized for its high ecological significance. KNP supports a rich diversity of both terrestrial and aquatic wildlife (Gopi 2007, Subramanian 2007, ZSI 2007, Thippeswamy and Malathi 2008, Thippeswamy 2024). Aquatic organisms inhabiting lotic systems, such as rivers, streams and rivulets, are especially sensitive to variations in water quality (Sugunan 1995). The Bhadra Reservoir, which impounds water from the river, sustains a variety of commercially important fishes (Sukumaran and Das 2005), including major and minor carps, catfishes, feather backs and other freshwater species, in addition to insectivorous and weed fishes. The structure and composition of these biological communities, both in the reservoir and in flowing (lotic) systems, are strongly governed by environmental conditions. In particular, upstream physico-chemical factors (Thippeswamy *et al.* 2020) and biological variables (Thippeswamy and Malathi 2008) play a crucial role in shaping these ecosystems (Sugunan 1995).

In the Aroli and Malleswara regions of the Kudremukh hills, magnetite quartzite deposits were mined for nearly three decades by the Kudremukh Iron Ore Company Limited (KIOCL) within an enclosed area of Kudremukh National Park in the Western Ghats. Kudremukh Iron Ore Company Limited (KIOCL), a public sector enterprise, discontinued its open cast mining operations following a judgment by the Supreme Court of India, citing considerable environmental impacts (Murthy and Seshadri 2011, Sridhar 2015). Surface mining is widely recognized for disturbing extensive land areas and generating large volumes of sediment. Sediment production from surface-mined regions can be 100 to 2000 times greater than that from forested areas and more than ten times higher than that from grazing lands. Consequently, water quality deteriorates due to surface runoff and leachates arising from the substantial quantities of tailings generated during iron ore mining and subsequent processing activities (Curtis 1971). Spatial and temporal variations in river water quality are closely associated with the environmental conditions prevailing within the catchment areas of rivers and streams.

Several studies conducted during the active mining period, prior to December 2005, reported that the Bhadra River, both near the mining area and in downstream stretches, exhibited elevated levels of suspended sediments and iron concentrations compared to the upstream regions. Consequently, the river water in the downstream sections was deemed unsuitable for human consumption (Krishnaswamy *et al.* 2006, Shubharekha *et al.* 2018, Thippeswamy *et al.* 2020). Even after the cessation of mining activities, the downstream water quality remained unfit for consumption due to persistently high sediment loads and iron concentrations (Mahesh *et al.* 2011). For instance, biological oxygen demand (BOD) values of 7.6 mg/l and 11.44 mg/l were recorded in December 2014 at Jamble village, located downstream of the Kudremukh Iron Ore Company Limited mining area, and at Balehole, situated further downstream, respectively (Divya 2015). Despite these preliminary findings, comprehensive information on the water quality of the Bhadra River following the closure of open-cast iron ore mining operations by KIOCL remains limited. Some studies have examined the water quality of the Bhadra River and its tributaries (Shubharekha *et al.* 2018, Thippeswamy *et al.* 2020, 2024) before the defunct of mining operations, as well as the adjacent Tunga River and its tributaries (Malathi and Thippeswamy 2013) in the Western Ghats. Globally, river water quality monitoring data have been widely analyzed using multivariate statistical techniques (Pejman *et al.* 2009, Varol *et al.* 2012, Chounlamany 2017, Ioele *et al.* 2020, Jo *et al*. 2022, Ali *et al.* 2024), including applications in the Indian subcontinent (Singh *et al.* 2004, Dutta *et al.* 2018, Thippeswamy *et al.* 2020, 2024). In this study, we present an assessment of river water quality in the upper reaches of the Bhadra River following the cessation of mining activities, using statistical analysis.

MATERIALS AND METHODS

Study area

The Bhadra River originates at Gangamula on Varaha Parvata in the Aroli–Gangamula region, at an elevation of about 1198 m above mean sea level (MSL) in the Western Ghats, within Kudremukh National Park, India. The park lies in the upper catchment of both East-flowing rivers such as the Bhadra and Tunga River, and west-flowing rivers including the Swarna,

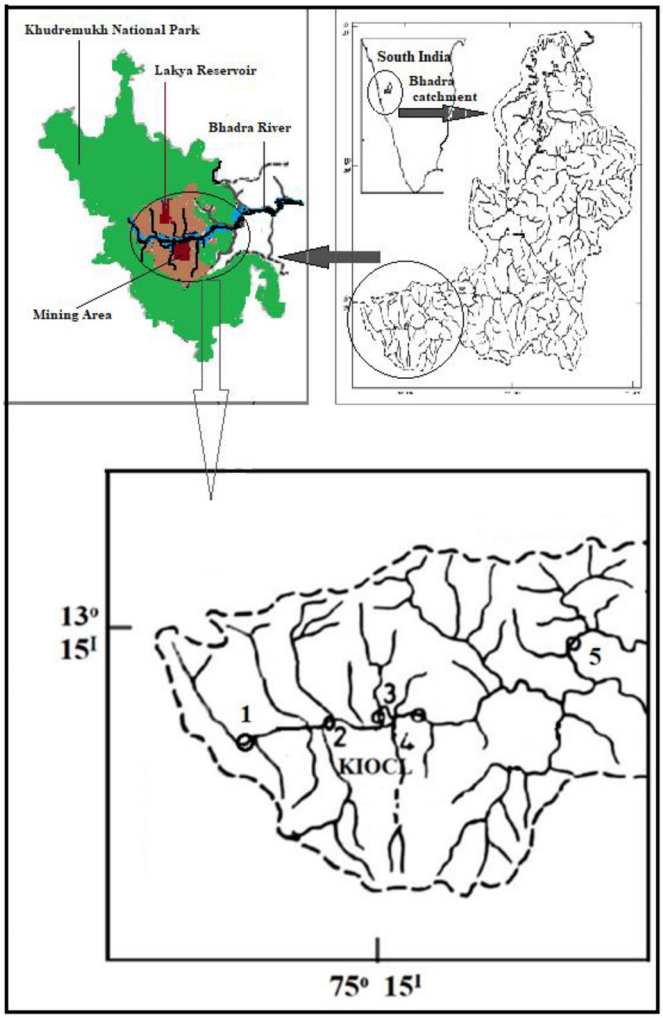


Fig. 1. Location of sampling stations for collection of water sample in the river Bhadra from Kudremukh National Park in the Western Ghats.

Gurpura and Nethravathi. The Bhadra River initially flows eastward through the KIOCL mined area and the Kudremukh Township, which was developed following the rehabilitation of Malleshwara village. It then gradually turns northeast and eventually joins the Tunga River at Kudli, north of Shivamogga. From this confluence, the combined flow forms the Tungabhadra River, a major tributary of the Krishna River. The total length of the Bhadra River is approximately 138 km, spanning elevations from 606 to 1679 m above MSL, and it exhibits a sub-montane character. Geologically, the basin is composed of Precambrian Archean formations of the Dharwar schist belt. The river is fed by numerous tributaries, streams, rivulets and perennial flows originating from shola forests in the upper reaches. The river basin in the Western Ghats receives heavy and consistent rainfall exceeding 500 cm annually during the monsoon season (June–August). A dam has been constructed across the Bhadra River at Lakkavalli village, near Shivamogga, primarily for irrigation purposes. The upper reaches of the Bhadra River, extending from Nellibedu to Kalasa town, comprise patches of natural forest interspersed with areas influenced by human activities such as agriculture, including extensive coffee plantations, tea gardens, paddy fields, as well

Table 1. Location of sampling stations for collection of water sample from the upstream Bhadra river basin in the Western Ghats, Karnataka.

Station No.	Name	River	Code	Coordinates
1	Bhagavathi	Bhadra	Bag 1	13°11'58"N 75°11'50"E
2	Lakya	Bhadra	Lak 2	13°12'45"N 75°14'06"E
3	Mallesh-wara	Bhadra	Mal 3	13°12'48"N 75°15'14"E
4	Nellibedu	Bhadra	Nel 4	13°12'22"N 75°16'59"E
5	Kalsa	Bhadra	Kal 5	13°13'47"N 75°20'49"E

as areca nut and coconut cultivation.

A total of five sampling stations were established along the main course of the river (Fig. 1) for water sample collection and their geographic coordinates are provided in Table 1. Station 1, located at Bhagavathi near the summer camp within Kudremukh National Park, represents a relatively undisturbed site characterized by tropical evergreen forest conditions. Station 2 at Lakya is situated near the discharge point of the Lakya Dam, which was constructed to store tailings from open-cast mining operations. Station 3 at Malleshwara (Kudremukh Township) lies adjacent to the defunct mining site and associated activities of KIOCL, and is therefore influenced by anthropogenic factors. Stations 4 and 5, located at Nellibedu and Kalasa respectively, are influenced by a combination of natural forest conditions, agricultural practices, and human settlements. These five stations were strategically selected along the Bhadra River to capture a range of agro-climatic and environmental conditions, including non-mined areas at Bhagavathi (upstream) and at Nellibedu and Kalasa (downstream), as well as areas adjacent to the mined region at Lakya and Malleshwara associated with KIOCL.

Sample and sampling procedures

Water samples were collected from five sampling stations located in the upstream reaches of the Bhadra River during the winter season (December 2006 to February 2007) at monthly intervals. Water temperature (WT) was measured in situ at each sampling site using a calibrated mercury thermometer and expressed in degrees Celsius. Surface water samples were collected from just below the water surface using pre-cleaned polyethylene containers. The collected samples were preserved under refrigerated conditions and transported to the laboratory for subsequent physico-chemical analysis. For the determination of dissolved oxygen (DO), water samples were fixed immediately in the field using Winkler's reagents and analyzed within five hours of collection to ensure accuracy and minimize alteration.

Analytical methods

Dissolved oxygen (DO) in river water was determined using the Winkler method as prescribed by American Public Health Association (APHA 1995). The hydrogen ion concentration (pH) was measured using a calibrated pH meter. Total solids (TS), dissolved solids (DS) and suspended solids (SS) were estimated following standard procedures (APHA 1995, Trivedy and Goel 1986). Electrical conductivity (EC) was measured using a water analysis kit (SYSTRONICS 371; ISO 9001:2008, Ahmedabad) in accordance with standard protocols (APHA 1995). Total hardness (TH) was determined by the EDTA titrimetric method, while total alkalinity (TA), chloride (Cl), calcium (Ca) and magnesium (Mg) were analyzed using standard methods (APHA 1995). Sodium (Na) and potassium (K) concentrations were determined using a flame photometric technique (spray and burning method) with a photometer (SYSTRONICS 127; ISO 9001:2008, Ahmedabad), following the procedures outlined in APHA (1995). Total Kjeldahl nitrogen (TKN) was estimated using the Kjeldahl method, sulfate (SO_4^{2-}) by the turbidometric method, total phosphorus (TP) by spectrophotometry, silicate (Si) by the molybdosilicate method and iron (Fe) by the phenanthroline method (APHA 1995). Water temperature (WT) is expressed in degrees Celsius, electrical conductivity (EC) in $\mu S\ cm^{-1}$ and the concentrations of TS, DS, SS, DO, TH, TA, Cl, Ca, Mg, Na, K, TKN, TP, SO_4, Si and Fe in mgl^{-1}.

Statistical procedures

Quality assurance of analytical data was ensured through standardization procedures, blank determinations and analysis of duplicate samples. All statistical and mathematical analyses were performed using

IBM SPSS Statistics (Meyers *et al.* 2013). Cluster Analysis (CA), Principal Component Analysis (PCA) and Factor Analysis (FA) were conducted on field and laboratory data after standardization using z-score transformation, in order to minimize errors arising from variations in data dimensionality and to render the dataset dimensionless. The Kolmogorov-Smirnov test was employed to assess the goodness-of-fit of the data to a normal distribution. In the present study, the results indicated that the measured water quality variables did not follow a normal distribution. The Kaiser-Meyer-Olkin test (KMO) and Bartlett's test of sphericity were also performed (Shrestha and Kazama 2007). A KMO value close to 1 suggests that PCA and FA are appropriate for the dataset; in the present study, the spatial dataset yielded a high KMO value of 0.875, indicating suitability for multivariate analysis. Bartlett's test of sphericity evaluates whether the correlation matrix is an identity matrix, which would imply that variables are uncorrelated (Varol and Sen 2009). In this study, the significance level of Bartlett's test was less than 0.05, indicating statistically significant correlations among the variables.

Correlation analysis -Water quality data of the river were analyzed using Spearman's rank correlation coefficient to evaluate relationships among the measured variables, with statistical significance assessed at the 0.01 and 0.05 levels.

Cluster analysis (CA) - Hierarchical agglomerative cluster analysis (HCA) was applied to the water quality dataset using Ward's method with Euclidean distance as the similarity measure for spatial clustering, following data standardization. This approach is based on analysis of variance (ANOVA) and aims to minimize the within-cluster sum of squares at each step of clustering. Additionally, HCA was performed using the between-group linkage method with correlation coefficient as the similarity measure for variable (sample) clustering. Cluster analysis was thus conducted on both variables and sampling stations to generate variable (sample) and spatial (station) dendrograms, respectively (Vega *et al.* 1998, Otto 1998, Helena *et al.* 2000).

Principal component analysis (PCA) - Principal Component Analysis (PCA) derives eigenvalues and eigenvectors from the correlation matrix of the original variables. The resulting principal components are orthogonal (uncorrelated) variables obtained by transforming the original correlated variables through multiplication with eigenvectors, which represent the loadings or weightings. In the present study, the dataset was subjected to PCA to determine the number of components that sufficiently explain the observed correlations among variables. PCA was also employed for pattern recognition, enabling the reduction of a large set of interrelated variables into a smaller number of independent components. These components represent linear combinations of the original variables and account for most of the variance in the dataset (Helena *et al.* 2000).

Factor analysis (FA) - The initial steps of the procedure are identical to those described for PCA, involving the extraction of eigenvalues and eigenvectors from the correlation matrix of the original variables. The dataset was subsequently subjected to Factor Analysis, which derives a new set of variables, termed variance factors (VF's), through rotation of the axes defined by PCA. Factor analysis further refines the results by reducing the influence of less significant variables identified in PCA and the resulting variance factors may represent latent, unobservable or hypothetical variables. The dataset was processed using varimax rotation to obtain variance factors (VF's) and corresponding factor scores (FS) for both variables and sampling stations (Vega *et al.* 1998).

RESULTS AND DISCUSSION

The descriptive statistics, including mean values and standard deviations (SD), along with the minimum and maximum ranges of climatic factors and water quality variables recorded at the sampling stations during the study period, are summarized in Table 2. At Station 1, located within KNP where relatively undisturbed natural conditions prevail, the lowest values of WT, TS, DS, EC and Cl were observed during December; DO, TA and Fe during January and pH, Ca, K, Fe, TP and TKN during February. In contrast, the highest concentrations of Na and K were recorded during December, while WT and Cl reached their peak values during February at this station. The minimum silicate concentration was recorded at Station 3 in January, a site characterized by

Table 2. The descriptive values of water quality variables in the upper reaches of river Bhadra. Abbreviations for months and stations: D, December'06; J, January'07; F, February'07; B1, Bhagavathi; L2, Lakya; M3, Malleswara; N4, Nallibedu, K5, Kalasa. Unites for variables are given in the text.

Parameters	Code	Mean	Std deviation	Minimum	Month and Station	Maximum	Month and Station
Water temperature	WT	29.15	5.39	17.00	D, B1	34.70	F, B1
Total solids	TS	37.33	11.63	20.00	D, B1; D, N4	60.00	J, M3; F, M3
Dissolved solids	DS	0.026	0.007	0.014	D, B1	0.038	F, M3
Suspend solids	SS	37.30	11.63	19.97	D, N4	59.97	J, M3
Dissolved oxygen	DO	9.72	1.47	8.00	J, L2	12.96	D, N4
Conductivity	EC	55.41	14.73	34.60	D, B1	89.40	F, M3
Total alkalinity	TA	19.20	6.99	8.00	J, L2	30.00	D, M3
pH	pH	7.07	0.44	6.00	F, B1	7.73	D, N4
Chloride	Cl	10.98	2.37	8.52	D, L2	14.2	F, L2; F, M2, F, N4, F, K5
Total hardness	TH	13.60	6.88	5.00	F, N4; F, K5	26.00	J, M3
Calcium	Ca	4.50	1.38	2.41	F, B1	7.21	J, M3
Magnesium	Mg	9.11	6.03	0.99	F, N4; F, K5	18.79	J, M3
Sodium	Na	1.37	0.34	1.00	F, K5	2.40	D, B1
Potassium	K	0.45	0.55	0.10	F, B1; F, K5	2.40	D, B1
Silicate	Si	27.79	20.03	12.00	J, M3	70.30	D, K5
Iron	Fe	2.12	0.91	0.83	J, B1; F, B1	3.47	J, M3
Sulfate	SO_4	3.05	1.81	1.04	F, K5	7.70	D, M3
Total phosphate	TP	0.39	0.03	0.35	D, K5; F, N4	0.43	J, M3; J, N4, J, K5
Total Kjeldahl nitrogen	TKN	0.19	0.20	0.02	F, B1	0.74	D, N4

intensive anthropogenic disturbances associated with mining and related activities. Notably, this station also exhibited the highest values of TS, DS, SS, EC, TA, TH, Ca, Mg, Fe and TP during the study period. Elevated levels of DO, pH, Cl, TP and TKN were observed at Station 4 (Nellibedu), situated immediately downstream of mining and associated activity zones. Furthermore, Station 5 recorded the maximum concentrations of TH, Mg, Na, K and SO_4, along with relatively higher levels of Cl, Si and TP throughout

Table 3. Correlation coefficient values of water quality variables in the upper reaches of river Bhadra in the Western Ghats. Values in italic indicate correlation is significant at the 0.05 level and values in bold indicate correlation is significant at the 0.01 level.

Variable	WT	TS	DS	SS	DO	EC	TA	pH	Cl
WT	1.000								
TS	.530	1.000							
DS	**.680**	.578	1.000						
SS	.357	**.948**	.324	1.000					
DO	**-.690**	-.416	-.219	-.376	1.000				
EC	**.755**	**.731**	**.874**	.540	-.284	1.000			
TA	.029	.019	.457	-.157	.494	.299	1.000		
pH	**-.659**	-.438	-.267	-.405	**.819**	-.289	.405	1.000	
Cl	**.869**	.622	**.808**	.417	-.463	**.845**	.128	-.526	1.000
TH	-.468	.085	-.318	.288	.151	-.246	-.426	.267	-.412
Ca	-.187	.396	-.231	.566	-.129	-.006	-.487	-.069	-.029
Mg	-.462	.067	-.268	.243	.168	-.254	-.364	.288	-.418
Na	-.481	-.574	-.298	-.490	.248	-.371	-.187	.281	-.546
K	-.315	-.141	-.156	-.066	.283	-.037	-.007	.179	-.364
Si	-.507	**-.780**	-.258	**-.821**	**.643**	-.502	.504	.578	-.505
Fe	-.016	.343	.406	.235	.365	.419	.448	.510	.172
SO_4	-.416	.151	.083	.141	.598	.113	.399	.469	-.219
TP	.293	.365	-.151	.517	-.620	.051	**-.801**	-.581	.152
TKN	-.263	-.038	.162	-.091	.524*	.129	.406	.625*	-.106

Table 3. Continued.

Variable	TH	Ca	Mg	Na	K	Si	Fe	SO_4	TP	TKN
WT										
TS										
DS										
SS										
DO										
EC										
TA										
pH										
C1										
TH	1.000									
Ca	.605	1.000								
Mg	**.983**	.496	1.000							
Na	.398	-.080	.373	1.000						
K	.359	.049	.300	**.701**	1.000					
Si	-.214	**-.668**	-.137	.354	.110	1.000				
Fe	.223	.067	.275	-.253	.091	.001	1.000			
SO_4	.306	-.031	.336	.107	.458	.290	.577	1.000		
TP	.423	.508	.347	.035	.139	**-.755**	-.293	-.403	1.000	
TKN	.068	.032	.126	-.144	-.233	.237	.565*	.361	-.622*	1.000

the study period. Comparable trends in water quality variation have been reported from the Bhadra River basin (Shubharekha *et al.* 2018) as well as the adjacent Tunga River basin (Malathi and Thippeswamy 2013).

Correlation analysis

The correlation matrix of the measured water quality variables is presented in Table 3. Analysis of samples collected from the study area using a two-tailed correlation approach revealed multiple interrelationships among the variables, with statistically significant associations identified for 38 out of 190 possible variable pairs. These correlations suggest that the environmental variables can be organized into relatively homogeneous groups based on their interaction

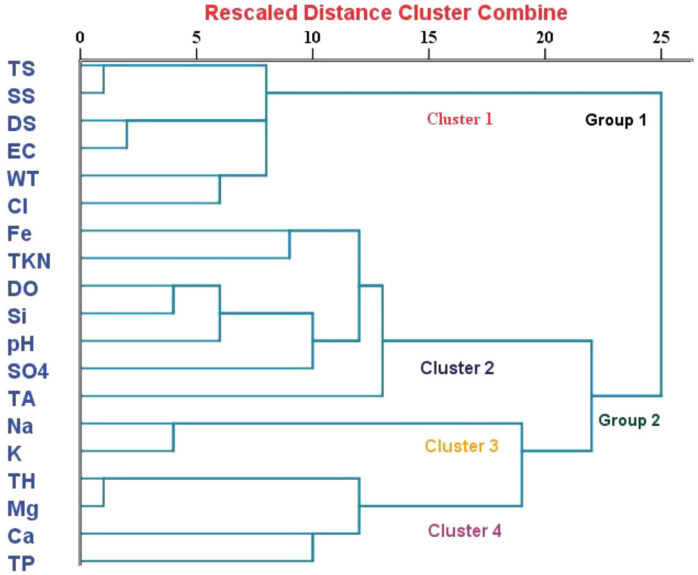


Fig. 2. Dendrogram showing the clusters of water quality variables in the upper reaches of the river Bhadra in the Western Ghats.

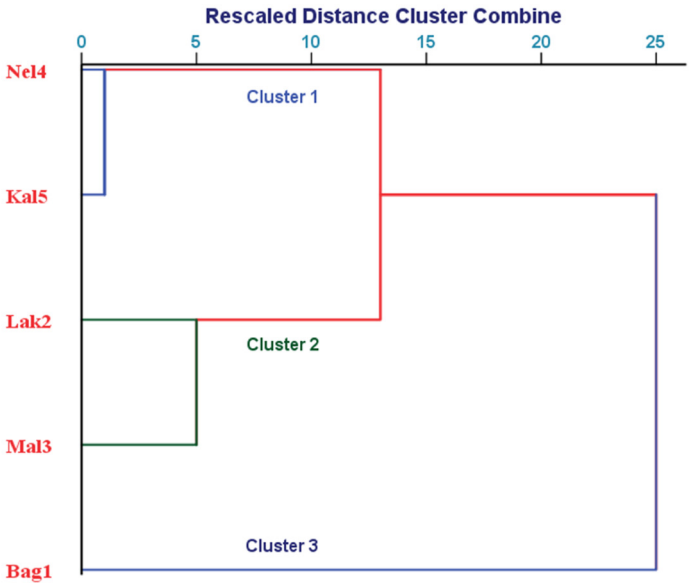


Fig. 3. Dendrogram showing the clustering of sampling sites according to characteristics of river water in the upper reaches of the river Bhadra in the Western Ghats.

patterns, thereby facilitating subsequent analyses. Further examination of the correlation matrix indicated that, among the significant relationships, 24 were positive and 14 were negative, all at either the 5% or 1% levels of significance ($p < 0.05$ or $p < 0.01$). In contrast, a substantial proportion of the variable pairs (133) exhibited correlations below the 5% significance threshold. This predominance of weak or non-significant correlations underscores the need for applying robust multivariate statistical techniques for a more comprehensive interpretation of the dataset.

Cluster analysis

Cluster analysis elucidates the inherent structure of a dataset without requiring prior assumptions, by classifying objects into groups or clusters based on their similarity or proximity (Vega *et al.* 1998). Among the available techniques, hierarchical clustering is widely employed and it was used to generate a dendrogram of water quality parameters in the present study, as illustrated in Fig. 2. The hierarchical cluster analysis (HCA) performed using average linkage between groups, delineated four distinct but interrelated clusters. The resulting dendrogram broadly segregated the variables into two principal groups: Group 1 comprising a single cluster and Group 2 encompassing three clusters. Cluster 1 grouped physico-chemical parameters such as TS, SS, DS, EC, WT and Cl, indicating similarity in their sources and behavior. This cluster was further linked to the clusters within Group 2. The second group exhibited further subdivision into two subgroups. Subgroup 1 consisted of Cluster 2, which included variables such as Fe, TKN, DO, Si, pH, SO_4 and TA, representing predominantly non-point source pollution, particularly from agricultural runoff and within this cluster, TA emerged as a relatively distinct variable. Cluster 2 showed linkage with Clusters 3 and 4. Cluster 3 comprised parameters Na and K, reflecting similarity in their sources, and was further connected to Cluster 4. Cluster 4 included variables such as TH, Mg, Ca and TP, which are primarily associated with soil-derived contributions, indicating a common origin.

Euclidean distance is commonly used to quantify the similarity between two samples, wherein the "distance" reflects the difference between their analytical values (Otto 1998). In the present investigation, spatial cluster analysis based on this measure generated a dendrogram (Fig. 3), grouping the five sampling stations within the river basin into three dis-

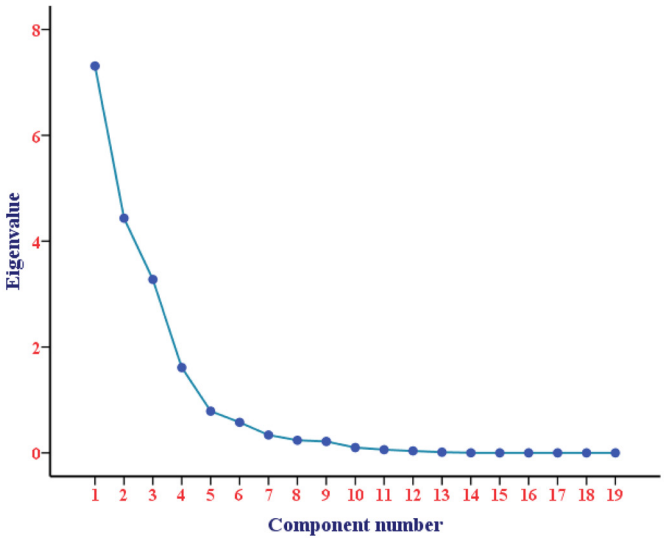


Fig. 4. Scree plot of eigenvalues.

tinct clusters. Cluster 1 comprised two downstream stations influenced by mining activities, namely Nellibedu (Station 4) and Kalasa (Station 5). Cluster 2 included two stations located adjacent to the mined area, Lakya (Station 2) and Malleshwara (Station 3). In contrast, Cluster 3 consisted solely of Bhagavathi (Station 1), representing an upstream, non-mined region characterized by natural forest conditions. The grouping pattern indicates that stations within each cluster share similar environmental characteristics and are influenced by comparable source factors. Station 1 (Bhagavathi) is distinctly separated from the other stations, forming an independent Cluster 3 under Group B, and reflects the relatively undisturbed natural background of tropical evergreen forests within KNP. Cluster 2, represented by Stations 2 and 3 located near the KIOCL mining area, is influenced by multiple inputs, including leachates from the Lakya dam tailings on the left bank and surface runoff from mining operations on the right bank of the Bhadra River, in addition to upstream natural water contributions from Station 1. These shared influences explain their close association within the same cluster and their linkage with Cluster 1. Clusters 1 and 2 together form Group A in the dendrogram, indicating similarity in anthropogenic influences, although they remain distinctly different from Cluster 3. Cluster 1 stations, situated in the lower reaches of the mined region, are subject to both natural and anthropogenic impacts. These include the natural background of tropical forest ecosystems as well as human activities such as coffee plantations, paddy cultivation and other commercial crops cultivated in valley and hilly terrains, particularly along the right bank near Samse and the Kudremukh region, with intermittent patches of tropical evergreen forests on the left bank. Additionally, Stations 4 and 5 receive cumulative inputs from upstream natural waters (Station 1), as well as leachates from Lakya dam tailings and surface runoff originating from the mined areas, further contributing to their clustering pattern.

Principal component analysis

Principal Component Analysis (PCA) facilitates the interpretation of relationships among the most influential factors governing the data structure (Padro *et al.* 1993), while enabling dimensionality reduction with minimal loss of original information (Hotelling 1933). It also aids in identifying the key components that influence aquatic systems and account for variations in water quality, thereby serving as an effective tool for formulating appropriate water resource management strategies (Varol and Sen 2009, Varol *et al.* 2012). The Scree plot generated in the present study (Fig. 4) was utilized to determine the

Table 4. Loadings of the first four principal components for data set of water quality variables in the upper reaches of river Bhadra in the Western Ghats. Description of different codes for environmental variables is given in Table 2. PC stands for principal component. Values in bold indicate (> 0.50 criteria) loadings for identification of eigenvectors.

Variable	PC 1	PC 2	PC 3	PC 4
WT	**0.952**	-0.076	0.061	-0.133
TS	**0.793**	0.15	0.458	0.191
DS	**0.661**	0.64	0.05	0.131
SS	**0.792**	0.149	0.459	0.191
DO	**-0.779**	0.518	0.2	-0.047
EC	**0.646**	0.603	0.158	0.318
TA	-0.174	**0.843**	-0.313	0.237
pH	**-0.733**	0.373	0.357	-0.186
Cl	**0.85**	0.218	-0.17	0.136
TH	-0.368	-0.381	**0.812**	-0.001
Ca	0.169	-0.386	**0.706**	-0.123
Mg	-0.467	-0.442	**0.674**	0.074
Na	**-0.7**	-0.314	-0.165	0.465
K	-0.531	-0.17	-0.029	**0.799**
Si	**-0.918**	0.303	-0.09	-0.018
Fe	0.052	**0.714**	0.577	0.02
SO_4	-0.354	0.502	**0.524**	0.397
TP	0.427	**-0.788**	0.331	0.174
TKN	-0.293	**0.594**	0.404	-0.476
Eigen values	7.308	4.433	3.276	1.611
% of variance	38.469	23.332	17.243	8.479
Cumulative %	38.469	61.801	79.044	87.524

Table 5. Loadings of the first four principal components, with varimax rotation, for data set of water quality variables in the upper reaches of river Bhadra in Karnataka. Description of different codes for environmental variables is given in Table 2. VF stands for variance factor. Values in bold indicate (> 0.50 criteria) loadings for identification of eigenvectors.

Variable	VF 1	VF 2	VF 3	VF 4
WT	**0.665**	-0.513	0.039	-0.476
TS	**0.899**	-0.143	0.222	-0.14
DS	**0.824**	0.106	-0.376	-0.185
SS	**0.898**	-0.143	0.223	-0.14
DO	-0.319	**0.877**	-0.075	0.205
EC	**0.904**	0.107	-0.28	-0.004
TA	0.176	0.519	**-0.741**	0.214
pH	-0.332	**0.839**	0.143	0.071
Cl	**0.715**	-0.391	-0.33	-0.213
TH	-0.128	0.279	**0.905**	0.165
Ca	0.194	-0.037	**0.794**	-0.149
Mg	-0.252	0.218	**0.828**	0.278
Na	-0.556	0.008	0.056	**0.721**
K	-0.201	0.03	0.049	**0.952**
Si	-0.611	**0.667**	-0.183	0.305
Fe	0.554	**0.729**	0.06	-0.067
SO_4	0.273	**0.715**	0.138	0.453
TP	0.188	-0.668	**0.676**	0.064
TKN	0.006	**0.825**	0.048	-0.383
Eigen value	5.563	4.963	3.658	2.445
% of variance	29.279	26.121	19.255	12.868
Cumulative %	29.279	55.401	74.656	87.524

optimal number of principal components required to adequately represent the underlying data structure (Cattell 1966). The PCA performed on the entire dataset extracted four principal components, which together explained 87.524% of the total variance (based on extraction sums of squared loadings), in the water quality dataset. The criterion of eigenvalues greater than 1 was employed to select the number of significant components capable of explaining the observed correlations among variables. The remaining unexplained variance accounted for 12.476%, attributable to residual or unmeasured factors. The eigenvalues and their respective contributions indicate that a relatively small number of components (four) effectively summarize the variability present in a larger set of variables (nineteen). For interpretative purposes, component loadings exceeding 0.50 were regarded as significant in identifying the dominant eigenvectors. The detailed component structure, including loadings and percentage variance explained, is presented in Table 4.

Factor analysis

Factor analysis is employed to identify the underlying factors responsible for correlations among variables and to further simplify the dataset derived from PCA by minimizing the influence of less significant variables. This is achieved through rotation of the PCA-defined axes, based on established statistical principles, resulting in a new set of variables termed variance factors (VF's). The corresponding VF's, their loadings and the proportion of variance explained are presented in Table 5. For interpretative purposes, variance factors (VF's) with loadings exceeding 0.50 were considered in identifying significant eigenvectors. Furthermore, factor loadings exceeding 0.70 were classified as strong, while those between 0.50 and 0.70 were considered moderate, and both were treated as statistically significant.

Variance Factor 1 (VF1), accounting for 29.279% of the total variance, exhibited strong positive load-

ings (> 0.70) for EC, TS, DS, SS and Cl along with a moderate positive loading for WT. These associations suggest contributions from natural water sources in non-mined regions, as well as non-point source inputs from forested and agricultural areas, including soil erosion due to weathering and surface runoff from mining-affected upper reaches of the river basin. Overall, this factor is predominantly characterized by physicochemical parameters. Variance Factor 2 (VF2) explained 26.121% of the total variance and was characterized by strong positive loadings on DO, pH, TKN, Fe and SO_4 along with a moderate positive loading on Si. This factor reflects the influence of organic matter and nutrient inputs primarily derived from agricultural runoff and human settlements along the riverbanks, in addition to natural contributions such as sulfate, thereby representing non-point sources of pollution. Surface runoff from both mined and non-mined areas, including disturbed and relatively undisturbed landscapes, contributes to the elevated loadings of Fe, pH, SO_4 and Si. Additionally, leachates originating from mining operations and tailings, particularly in the KIOCL areas near Lakya and Malleshwara, further enhance Fe and SO_4 concentrations. Increased turbidity, associated with higher levels of suspended solids and mineral content, influences aquatic respiration and reduces dissolved oxygen availability due to increased oxygen demand for the decomposition of organic matter and oxidation of dissolved ions. This process also leads to the accumulation of free carbon dioxide, thereby altering pH levels. The elevated DO levels observed in this factor may be attributed to natural re-aeration processes, including atmospheric oxygen mixing facilitated by turbulent flow conditions over riverbeds composed of granite rocks, cobbles and pebbles, as well as through riffles, eddies and intermittent pools with cascading flow. Furthermore, VF2 highlights nutrient enrichment, particularly TKN, arising from extensive agricultural practices in the basin, including coffee, tea, paddy, areca nut and coconut cultivation, where the application of fertilizers and organic manures is prevalent. Contributions from mining-affected areas further reinforce the significance of this factor in representing nutrient and organic pollution inputs.

Variance Factor 3 (VF3) accounted for 19.255% of the total variance and was characterized by strong positive loadings (> 0.70) on TH, Ca, Mg and a strong negative loading on TA along with a moderate positive loading on TP. These loadings suggest that this factor is primarily influenced by the mineral composition of water derived from natural sources, including soil weathering and surface runoff, as well as inputs from mining-affected areas such as those associated with KIOCL. Accordingly, VF3 represents non-point source contributions. The elevated TP loading can be attributed to agricultural activities within the river basin, where the application of fertilizers and organic manures in paddy fields, coffee plantations and tea estates is widespread. Runoff from these cultivated areas enhances phosphorus input into the river system. Additionally, this factor is distinguished by a pronounced negative loading on TA, indicating an inverse relationship with the other associated variables. Variance Factor 4 (VF4) explained 12.868% of the total variance and exhibited strong positive loadings on K (0.952) and Na (0.721). These associations indicate contributions primarily from the natural mineral composition of water, including inputs from soil weathering and surface runoff originating from both KIOCL mining areas and agricultural fields. Additionally, the use of inorganic fertilizers, particularly potash, in agricultural practices contributes to the enrichment of these ions. The accumulation of such minerals in the river water is reflected in their high loadings within this factor.

The application of factor analysis to the water quality dataset, comprising 19 variables across five sampling stations, has facilitated the identification of major sources and types of river water contamination. These include soluble salts and physical parameters of natural origin, as well as nutrient-related pollutants from non-point sources, and organic and mining-related pollutants of anthropogenic origin within the studied river stretch. Comparable investigations have been undertaken to assess river water quality (Singh *et al.* 2004, Mendiguchia *et al.* 2004). However, to achieve a more comprehensive understanding of pollution sources and their dynamics, it is essential to generate water quality datasets that incorporate both spatial and temporal variability across the entire river basin. Such extended analyses are particularly important for clearly delineating the nature and origin of pollutants in the post-mining phase of the basin.

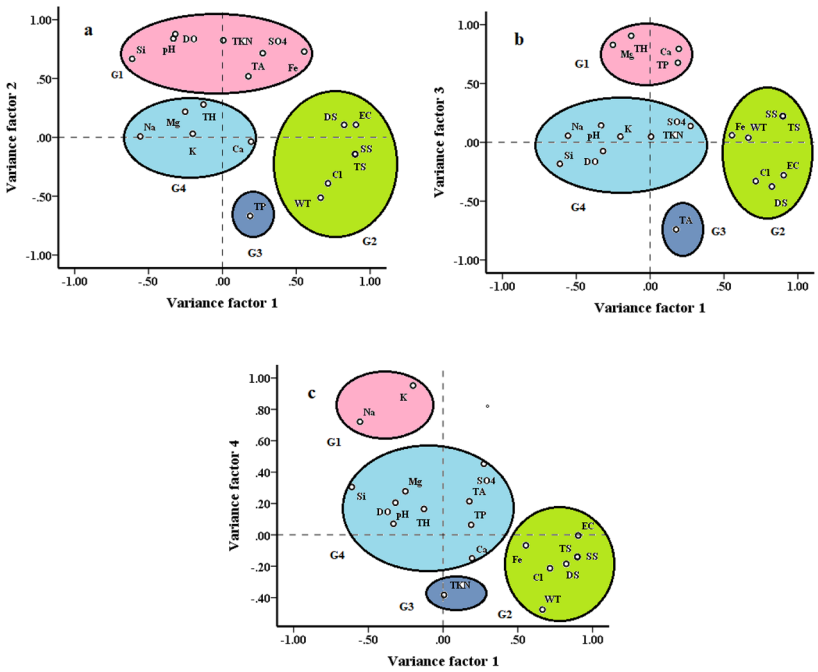


Fig. 5. Plots between the loadings of VF 1 and VF 2 (a), VF 1 and VF 3 (b) and VF 1 and VF 4 (c) for data set of water quality variables in the upper reaches of the river Bhadra in the Western Ghats. Description of different codes for water quality variables is given in Table 2. G represents possible groups of loadings.

The relationships between (a) VF 1 and VF 2, (b) VF 1 and VF 3 and (c) VF 1 and VF 4 are illustrated in Fig. 5. These plots reveal four distinct strong environmental gradients within the VF plots, indicating the presence of four possible groups.

1. Group 1 in Fig. 5a comprised Si, pH, DO, SO_4, TA, Fe and TKN, exhibiting high loadings on VF 2 and low loadings on VF 1, and corresponded to the same set of variables as Cluster 2 of CA (Fig. 2). In Fig. 5b, Group 1 included Mg, TH, Ca and TP, characterized by high loadings on VF 2 and low loadings on VF 1, matching the variables in Cluster 4 of the dendrogram (Fig. 2). Similarly, Group 1 in Fig. 5c consisted of Na and K, showing high positive loadings on VF 2 and low negative loadings on VF 1, and aligned with the variables in Cluster 3 of the dendrogram (Fig. 2).

2. Group 2 in Fig. 5a comprised WT, TS, DS, SS, EC and Cl, showing high loadings on VF 1 and low loadings on VF 2, except WT, and corresponded to the same variables as Cluster 1 of the dendrogram (Fig. 2). In Fig. 5b and Fig. 5c, these groups also included the above variables along with Fe, all exhibiting high loadings on VF 1 and low loadings on VF 2. Fe is associated with Cluster 2 of the dendrogram (Fig. 2).

3. Group 3 is represented by TP in Fig. 5a, TA in Fig. 5b and TKN in Fig. 5c, each showing low positive loadings on VF 1 and high negative loadings on VF 4. TP is associated with Cluster 4, while TA and TKN belong to Cluster 2 (Fig. 2). Furthermore, TP and TA are linked to VF 3, whereas TKN is related to VF 2 (Table 5). These observations suggest that TP, TA and TKN originate from sources other than natural and mining influences.

4. Group 4 is represented by Na, K, Ca, Mg and TH in Fig. 5a; Na, K, pH, DO, SO_4, TKN and Si in Fig. 5b and Ca, Mg, TH, pH, DO, SO_4, Si, TA and TP in Fig. 5c, all exhibiting low correlation on both coordinates. This group comprises variables from Cluster 2, Cluster 3 and Cluster 4 of Fig. 2, indicating ionic contributions from natural processes, anthropogenic

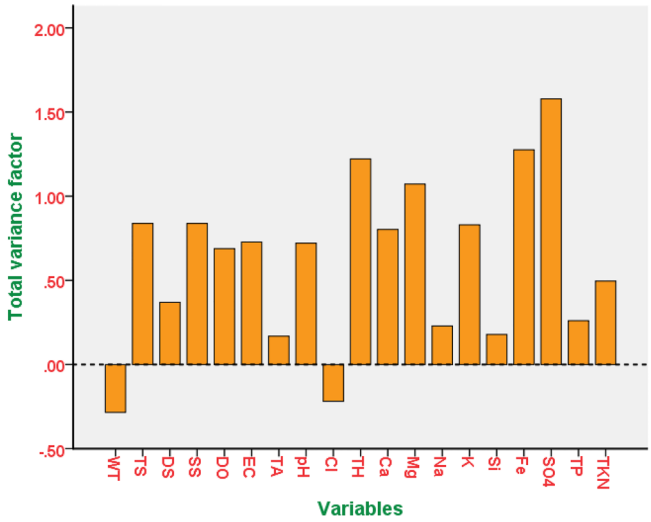


Fig. 6. Total eigenvectors for water quality variables in the upper reaches of the river Bhadra in the Western Ghats.

(mining) activities and inorganic sources (fertilizers). Notably, none of the variables from neither Cluster 1 of Fig. 2 nor Fe from Cluster 2 are represented in this group, suggesting distinct sources.

Eigenvector - The pooled eigenvector data, accounting for 87.524% of the total variance, are presented in Fig. 6. The results indicate four major categories of water pollution based on eigenvectors (Thippeswamy *et al.* 2020, 2024) in the present study. Variables with total eigenvector values < 0.50, namely WT (−0.285), Cl (−0.219), TA (0.168), Si (0.178), Na (0.229), TP (0.260), DS (0.369) and TKN (0.496), are regarded as normal variables that do not contribute to pollution in the river stretch, suggesting that the water remains normal or safe with respect to these parameters. Variables with total eigenvector values between > 0.50 and < 1.00, such as DO (0.688), EC (0.727), pH (0.729), Ca (0.802), K (0.830), SS (0.838) and TS (0.838), are considered low pollution causing variables, indicating that the water is slightly polluted due to their influence. Those with eigenvector values in the range of > 1.00 to < 1.50, Mg (1.072), TH (1.221) and Fe (1.276), are categorized as medium pollution causing variables, reflecting a moderate level of pollution in the river stretch. Furthermore, variables with eigenvector values > 1.50, such as SO_4 (1.579) in the present study, are classified as high pollution causing variables, indicating that the water is highly polluted due to their impact. The residual variance in the study was 12.476%, attributed to unexplained variables, which may include unmonitored parameters such as BOD, other metals.

Factor score - The pooled factor score data for the five water sampling stations are presented in Fig. 7. The results show negative factor score values (< 0) for the sampling sites at Bhagavathi (station 1), Lakya (station 2), and Kalsa (station 5), indicating that the water at these locations is not polluted. In contrast, the sampling site at Nellibedu (station 4) exhibits a positive factor score in the range of > 1.50 to < 3.00, suggesting a medium level of pollution during the present study period. The sampling site at Malleswara (station 3) shows a high positive factor score (> 4.50), indicating very high pollution levels. Factor score ranges of > 0.0 to < 1.50 and > 3.00 to < 4.50, which correspond to low and high pollution levels, respectively, as reported elsewhere (Thippeswamy *et al.* 2020, 2024), were not observed in the present study. Higher factor scores indicate a stronger influence of the corresponding factors on the sampling sites (Mendiguchia *et al.* 2004, Felipo-Sotelo 2007). Water at sampling station 1 (Bhagavathi), located in the upper reaches of the Bhadra River within the KNP area, was found to be normal. However, the sampling site at station 4 (Nellibedu), situated immediately downstream of the mined area, exhibited

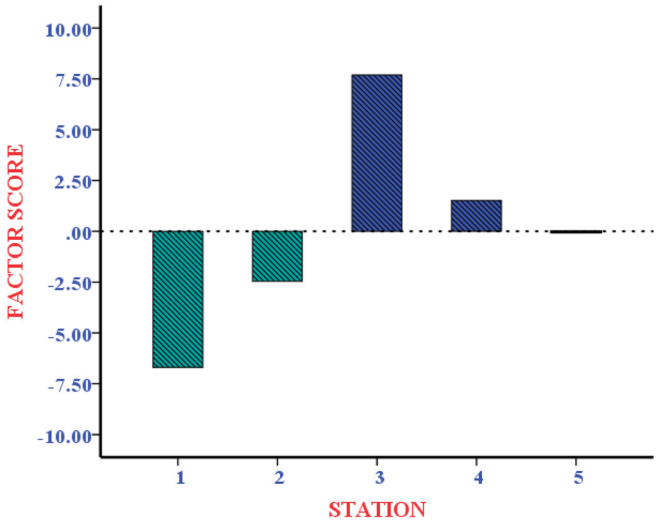


Fig. 7. Total factor scores for sampling stations located in the upper reaches of the river Bhadra in the Western Ghats.

moderate pollution due to runoff from the KIOCL mining area. Further downstream at Kalsa (station 5), water quality returned to normal conditions, likely due to self-purification processes such as mixing and settling occurring upstream. Based on five pollution categories defined by factor scores (Thippeswamy *et al.* 2020, 2024), three categories were identified in the present study: < 0.0 (safe/no pollution), > 1.50 to < 3.00 (medium pollution) and > 4.50 (very high pollution) (Table 6). Accordingly, the sampling stations at Bhagavathi, Lakya and Kalsa were classified under the safe category, with factor scores of −0.6914, −2.458 and −0.055, respectively. Station 4 at Nellibedu, located immediately downstream of the mining area, was categorized under medium pollution with a factor score of 1.514. Station 3 at Malleswara, located adjacent to the KIOCL mining area was classified under very high pollution, with a factor score of 7.691.

Water quality variables and health of the river stretch - Factor scores obtained from the five sampling sites during the winter season during the study period in the upper reaches of the Bhadra River are presented in Fig. 8. The results indicate four types of variables related water pollution:

1. Variables with total factor scores less than zero (< 0.0), such as DS (−7.296), TKN (−4.977), K (−3.663), TP (−3.380), Na (−1.607), Fe (−1.089) and SO_4 (−0.642), are considered normal variables that do not contribute to pollution in the river stretch, indicating that the water remains normal or safe with respect to these parameters.

2. Variables with total factor scores in the range of > 0.0 to < 1.50, namely Ca (0.059), Mg (0.656), pH (0.764), DO (1.210) and Cl (1.366), are regarded as low pollution causing variables.

3. Variables with total factor scores in the range of > 1.50 to < 3.00, namely TH (1.508), TA (2.090), Si (2.413), and WT (2.764), are classified as medium pollution–causing variables.

4. Variables such as SS (3.078), TS (3.078) and EC (3.667), with total factor scores in the range of > 3.00 to < 4.50, are considered high pollution causing variables.

Dissolved solids (DS), classified under water pollution category 1, exhibited the highest negative factor score (-7.296) during the entire winter season study period, indicating no pollution attributable by DS. The minimum and maximum concentrations of DS in the river water were 0.14 (D, B1) and 0.38

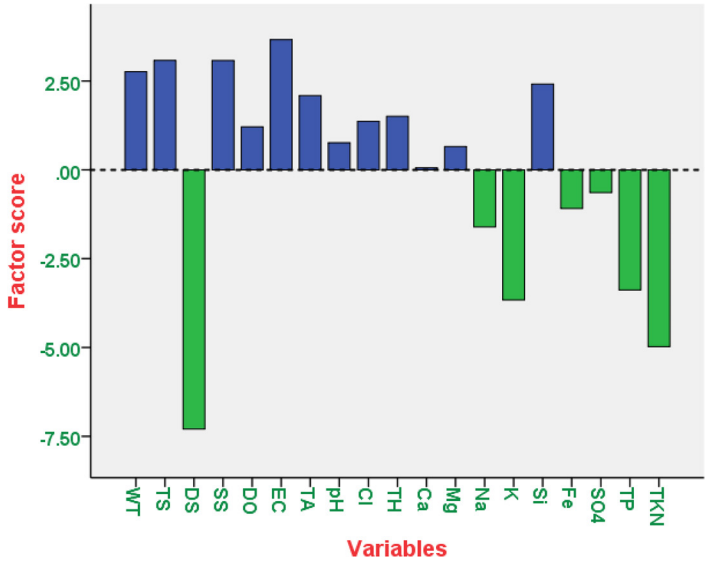


Fig. 8. Total factor scores for water quality variables in the upper reaches of the river Bhadra in the Western Ghats.

(F, M3) mg/l, respectively. DS showed a significant positive correlation ($r = > 0.680$; $P < 0.01$) with WT, EC and Cl, and a significant positive correlation with TS ($r = 0.578$; $P < 0.05$). Furthermore, DS (0.824) exhibited high positive loadings (> 0.665) with WT, TS, SS, EC and Cl on VF 1. However, these associated variables (WT, EC, Cl, TS) are generally linked to varying levels of water pollution rather than normal or safe water conditions in the river stretch. Previous studies (Krishnaswamy *et al.* 2006, Thippeswamy *et al.* 2020) have reported elevated sediment loads in the Bhadra River during mining activities, leading to pollution due to suspended sediments. The presence of water cat ions and anions (TKN, K, Na, SO_4), nutrients (TP) and metals (Fe) reflects a high mineral composition derived from natural processes and/or anthropogenic sources such as soil erosion and surface runoff from agricultural and mined areas. Despite this, these ions did not contribute to pollution in the river stretch, possibly due to reduced input from the defunct mining area into the main Bhadra River and dilution effects caused by the confluence of several tributaries and streams (Singsara, Bilegal, Hengaralu and Somavahini), as well as smaller rivulets, prior to Kalasa town (station 5). Consequently, station 5 indicates no pollution, suggesting that the river stretch undergoes natural self-rejuvenation in the study area.

The water cat ions and anions (Ca, Mg, Cl), which contribute to the high mineral composition of the river water derived from natural soil erosion and surface runoff from mined areas, are associated with low levels of pollution in the river stretch, along with physical parameters such as DO and pH. The presence of Ca is attributed to cat ion-exchange processes at the soil-water interface (Guo and Wang 2004) and the dissolution of Ca-bearing minerals (Pejman 2009, Varol *et al.* 2012). The total eigenvector loading for Ca (0.802) further indicates a low level of pollution with respect to this parameter in the river basin. During the study period, the pH of the water ranged from 6.00 (F, B1) to 7.73 (D, N4), with an average value of 7.065. Suspended particles, ranging from fine to coarse sizes, are prone to chemical reactions that lead to precipitation, resulting in reduced SS levels in river water, particularly under higher pH conditions (Wu and Kuo 2012). Additionally, pH influences coagulation and diffusion processes involving suspended particles in stream water. The maximum DO concentration (12.96 mg/l) was recorded at station 4 (Nellibedu) in the Bhadra River during December 2006 (Table 2). The riverbed at Nellibedu is characterized by small rocks, cobbles, and pebbles, with turbulent water flow that enhances DO levels through increased mixing with atmospheric oxygen. Dissolved oxygen is critical

Table 6. Classification of water pollution for different variables based on the factor score obtained from five sampling sites in the upper reaches of river Bhadra.

Sl. No.	Classification / category	Factor score	Stations
1	Safe / Normal	< 0.00	1, 2, 5
2	Low pollution	> 0.00 - < 1.50	–
3	Medium pollution	> 1.50 - < 3.00	4
4	High pollution	> 3.00 - < 4.50	3
5	Very high pollution	> 4.50	–

for sustaining aerobic biota, as it supports metabolic processes. Any variations in DO levels, whether due to anthropogenic or natural factors, are reflected in the overall DO content of the river water. The total eigenvector loading for DO (0.688) indicates a low level of pollution associated with this parameter in the river stretch. Such conditions in the upper reaches of the Bhadra River are maintained through natural self-purification processes, primarily driven by physical mixing. The river receives inputs from multiple tributaries, streams, rivulets and perennial flows from shola forests. The flow regime, characterized by riffles, swirling currents and intermittent pools, along with a riverbed composed of granite rocks, cobbles and pebbles, facilitates effective aeration and dilution, thereby contributing to improved water quality.

Ambient temperature plays a crucial role in the biological activities of aquatic organisms. Water temperature is a key parameter of river water quality, as it influences both chemical and biological processes. It also affects other variables such as pH, conductivity, gas saturation levels and different forms of alkalinity. During the present study period, water temperature (WT) ranged from 17°C (D, B1) to 34.70°C (F, B1). The highest average water temperature (29.83°C) was recorded at station 3, while the lowest (20.55°C) occurred at station 2 (Table 2). These observations indicate moderate thermal pollution in the river stretch, which may be attributed to geographical and agro-climatic conditions, anthropogenic influences and reduced water flow in the upper reaches of the river. Additionally, the time of observation also affects recorded water temperature. Variables such as TA, TH and Si in stream water contribute to the overall mineral composition, derived from natural and anthropogenic sources, including water cat ions and anions in the basin, soil erosion and surface runoff from agricultural and mined areas. This suggests the influence of non-point sources contributing to moderate pollution in the river stretch. The concentration of silicate was highest (70.30 mg/l) at station 5 during December 2006 and its total eigenvector loading (2.413) indicates a moderate level of pollution. The presence of silicate is attributed to soil erosion, agricultural runoff, runoff from mined areas and other anthropogenic activities within the river stretch.

High concentrations of suspended particles in a river can reduce its self-purification capacity, leading to deterioration in water quality. In the present study, a maximum SS value of 59.97 mg/l was recorded at station 3 during January 2007. The total VF loading for SS was 0.838 and its total factor score was 3.078, indicating a high level of pollution due to suspended solids in the river stretch. Several earlier studies conducted in the Bhadra River prior to the cessation of mining activities have reported elevated suspended sediment levels near the mining areas and in downstream stretches compared to the upper reaches (Krishnaswamy *et al.* 2006, Shubharekha *et al.* 2018, Thippeswamy *et al.* 2020). Notably, even one year after the discontinuation of mining activities in the Aroli–Gangamoola ranges of the Kudremukh hill region, SS continued to contribute significantly to high pollution levels in the river stretch. Thus, SS along with TS and EC have adversely affected the health of the Bhadra River in the downstream stretches of the mined area of KIOCL.

CONCLUSION

The present investigation provides baseline data following the cessation of mining activities by KIOCL in the KNP area and these findings contribute to understanding the rejuvenation of the Bhadra River. Cluster Analysis (CA) proved effective in classifying sources of water pollution as well as identifying the affected river stretches. The application of Principal Component Analysis (PCA) and Factor Analysis (FA) revealed that the Bhagavathi station, located in the upstream stretch of the mined area, remained unaffected by anthropogenic influences and was primarily governed by natural forest conditions, whereas water pollution increased in areas adjacent to the mining

zone. However, pollution levels declined progressively along the river course from Nellibedu, situated immediately downstream of the mined area, to Kalasa town further downstream, owing to natural self-purification processes operating within this stretch. Despite these findings, a comprehensive assessment of water quality across spatial and temporal scales over an extended period throughout the entire river basin, following the cessation of mining activities, is necessary to derive more conclusive insights into the overall water quality status of the basin.

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