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Multivariate statistical analysis to assess the surface water quality of a snow and glacier-fed river: A case from Alaknanda River basin

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ABSTRACT

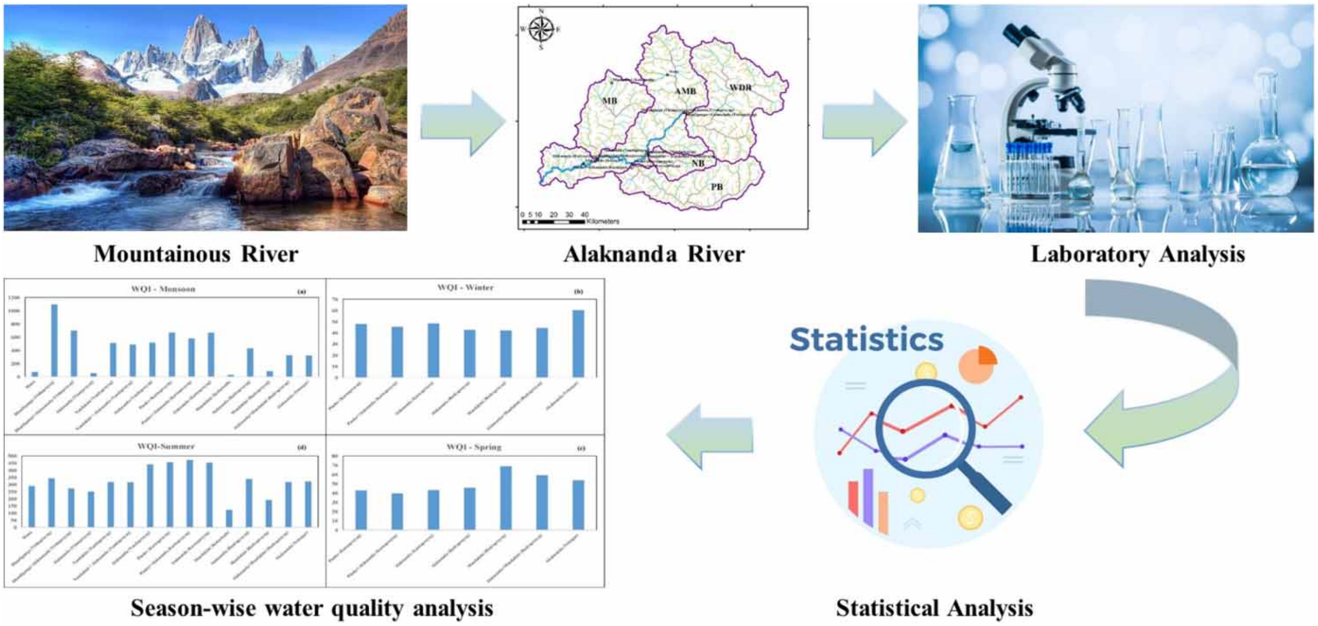
The water quality of Himalayan rivers has declined due to human activities, untreated effluent discharge, and poor sewage and drainage systems. The current study aimed to assess the water quality of these rivers using multivariate statistical analysis throughout four seasons. The analyses of 44 surface water samples taken during the monsoon, winter, spring, and summer seasons are well within the ranges acceptable for drinking and domestic use after the sedimentation. The suspended soils and turbidity are highly correlated and affect the water quality index (WQI). The WQI of headwater streams is good during low water flow seasons and poor during high water flow seasons. This is due to the number of melting glaciers and suspended solids/turbidity. Principal component analysis shows that in all the seasons, human activities such as road-cutting projects across the river and natural causes such as intense rainfall and melting of moraine-filled glaciers both impact the WQI. The findings of this study provide important information for future research and policy decisions aimed at improving the water quality of the Himalayan rivers.

Key words: glaciers, Himalaya, human activities, principal component analysis (PCA), WQI

HIGHLIGHTS

- Water quality indices were calculated from physicochemical parameters across 15 sampling locations and four seasons (monsoon, winter, spring, and summer).
- A strong positive correlation was observed between TSS-Turbidity, TA-TH, TSS-TA, and TSS-TH during different seasons.
- Winter and spring showed WQI values ranging from good to poor, with pH, EC, TA, TH, and DO having less impact on WQI compared to turbidity and TSS.
- PCA was used to identify latent variables affecting water quality parameters across different seasons.
- The findings of this study provide important information for future research and policy decisions aimed at improving the water quality of the Himalayan rivers.

GRAPHICAL ABSTRACT



INTRODUCTION

Anthropogenic activities have substantially impacted river systems, leading to a decline in water quality, a reduction in water availability, and a reduction in the capacity of aquatic life (Whitehead *et al.* 2009; Sharma *et al.* 2019; Sofi *et al.* 2022). Rivers contribute significantly to the sustainable socio-economic growth of a nation and makeup 0.006% of the global freshwater resources (Shiklomanov 2000; Grimm*et al.* 2008). With the exponential increase in population, tourism, agriculture, and urbanization, the Himalayan rivers are under extreme stress (Singh *et al.* 2020). The quality and quantity of rivers are seriously threatened by these human consequences and the ambiguous implications of climate change (Sharma *et al.* 2021). However, the water quality in high-altitude fluvial systems is significantly decreased by natural processes, including intense precipitation, rock or snow avalanche, glacier lake outburst, soil erosion, and agricultural activities (Kumar *et al.* 2020). Most of the population in the Himalayan area live along riverbanks and rely heavily on groundwater and river water for drinking, agriculture, and other household needs (Rani *et al.* 2021; Sofi *et al.* 2023). Poor waste management methods are in these places, particularly along the banks, and untreated or partially treated sewage is discharged into rivers, which subsequently impacts groundwater quality nearby (Sarkar & Paul 2016).

The change in the climate largely influences the movement of surface runoff via variability in the precipitation intensity and profound glacier retreat (Rani & Sreekesh 2019; Dubey & Goyal 2020). Furthermore, fluctuations in surface runoff, interflow, groundwater flow, and pumping in and out contribute significantly to river flow and the concentration of pollutants (Mirzaei Aminiyan *et al.* 2016; Thakur *et al.* 2018). A significant loss in snow and glacier retreat in the Himalayan regions has resulted in a freshwater shortage (Rani & Sreekesh 2019; Rautela *et al.* 2022a). Many non-natural variables affect river water quality in the Himalayan region, such as unprecedented urbanization, increasing tourism, shifting land use patterns, trash dumping, and agricultural runoff (Thakur *et al.* 2018). Water scarcity occurs downstream of the Himalayan rivers due to changing climatic conditions and other anthropogenic activities (Sati 2020). Therefore, identifying probable causes of impaired surface water quality is the foundation and requirement for water quality management (Tomar *et al.* 2022). In the headwater rivers, the installation of micro or small hydroelectric power plants with pondage can modify the flow characteristics, influencing its hydrodynamics and potentially altering sediment transport patterns, but it does not fundamentally transform a river into a lacustrine ecosystem (Sofi *et al.* 2022). Assessing water quality is imperative as it provides essential insights into the ecological health of these ecosystems and ensures the safety of water resources for both human and environmental needs. Multivariate statistical analysis plays a crucial role in this assessment by enabling the comprehensive evaluation of various parameters, helping identify patterns, correlations, and potential sources of pollution, which are instrumental in formulating effective strategies for maintaining and improving the water quality of these vital river systems (Kwan & Jo 2023).

In the field of traditional statistics, multivariate statistical analysis has become a well-established and powerful method for studying data from multiple variables at once. It is possible to evaluate the statistical laws governing relationships between many objects and various indicators using techniques such as cluster analysis (CA) (Corporal-Lodangco *et al.* 2014), discriminant analysis (DA) (Oda *et al.* 2020), principal component analysis (PCA) (Yang *et al.* 2013), and factor analysis (FA) (Aristizabal *et al.* 2019), when they are associated with one another. When it comes to chemical and physical measurements with multiple components, multivariate statistical analysis effectively reduces and interprets the data (Nnorom *et al.* 2019). It serves as a useful tool for identifying elements and sources that could influence water quality and aquatic systems (Chattopadhyay *et al.* 2012).

Monitoring surface and groundwater concerning WQI has been the subject of numerous studies (Bouza-Deaño *et al.* 2008; Wu *et al.* 2017; Nnorom *et al.* 2019; Valentini *et al.* 2021). It is not easy to understand and explain meaningful data from water chemistry due to several obscure human and natural factors (Pehlivan & Arslan 2007; Rani *et al.* 2021). In the above context, the present study uses a compound data set to generate a water quality index (WQI) to evaluate and assess the differences in overall quality between study sites and seasons. To compare drinking and domestic water standards with those provided by the Bureau of Indian Standards (BIS) and the World Health Organization (WHO), water samples were collected in four seasons (summer, monsoon, winter, and spring) from different sites from different altitudes. In addition to WQI and hydro-geochemical analyses, multivariate statistical techniques were used to understand complicated water quality grids to find solutions to pollution issues. In this way, the results of the study will provide important information about the river Akaknanda's surface water quality and contribute to thoughtful and sustainable water quality management.

MATERIALS AND METHODS

Study area

Alaknanda Basin is situated in the middle of the Indian Himalayan Region (IHR) (Figure 1). This region is one of the richest regions in terms of biological and water resources. The Alaknanda River is the significant upstream tributary of the river Ganga. The river originates from the Sathopath and Bhagirathi Kharak glaciers in the Chamoli district, Uttarakhand state of India. Then the river flows through various famous towns such as Badrinath, Jyosimath, Chamoli, Nandaprayag, Karanaprayag, Gauchar, Rudraprayag, and Srinagar situated along the banks, and after that, it merges in the Bhagirathi river at Devprayag. The Alaknanda Basin, which spans the latitudes of 30 ° 0′N–31 °10′ N and 78 °45′E–80 °20′ E and covers an area of 11,064 km^2, is thought to constitute the eastern portion of the Western Himalaya. Additionally, 433 km^2 of the basin's total area is covered by glaciers, and 288 km^2 is covered by fluvial terrain. The basin has a distinct range of climates, including subtropical, temperate, sub-alpine, and alpine, owing to the significant variance in height ranging from 446 to 7,801 m. High mountain peaks and glaciated valleys make up the distinctive topographic landscape of the basin, particularly in its northern region (Sharma & Mohanty 2018). The region's defining features are steep slopes, high relative relief, high stream frequency, and drainage density (Panwar *et al.* 2017). Additionally, the landscape's incised river basins and ridges with a north-south tendency are typical features (Ghosh *et al.* 2019).

Geology, hydrology, and drainage pattern

The Uttarakhand state is divided into three main stratigraphic zones as outer or sub-Himalayan zone, the central or lower Himalayan zone, and the higher Himalayan zone, which is formed by largely tertiary sediments, granite, and crystalline rocks of un-fossiliferous sediments and highly fossiliferous sediments, respectively (Panwar *et al.* 2017). Regarding geology, the Alaknanda basin is separated into three lithological sequences: the Tethyan Sedimentary Sequence, higher Himalayan crystallines, and lesser Himalayas in the upstream, middle, and downstream regions, respectively (Panwar *et al.* 2017). The primary rock formations of the Alaknanda River are granite, schist, dolomite, quartzite, phyllite, gneiss, limestone, and migmatites (Bickle *et al.* 2003). The primary structural faults across the Alaknanda basin are the Alaknanda fault, Main Central Thrust (MCT), North Almora Thrust (NAT), and South Tibetan Detachment System (STDS). The Alaknanda River basin consists dendritic drainage pattern with very high drainage density in the upstream sections of the river and its tributary. The river travels a total distance of 195 km with steep terrain and significant flow. Hydrologically, the Alaknanda River shows much diversity in terms of headwater contribution. The tributaries of western Dhauliganga, Nandakini, Pinder,

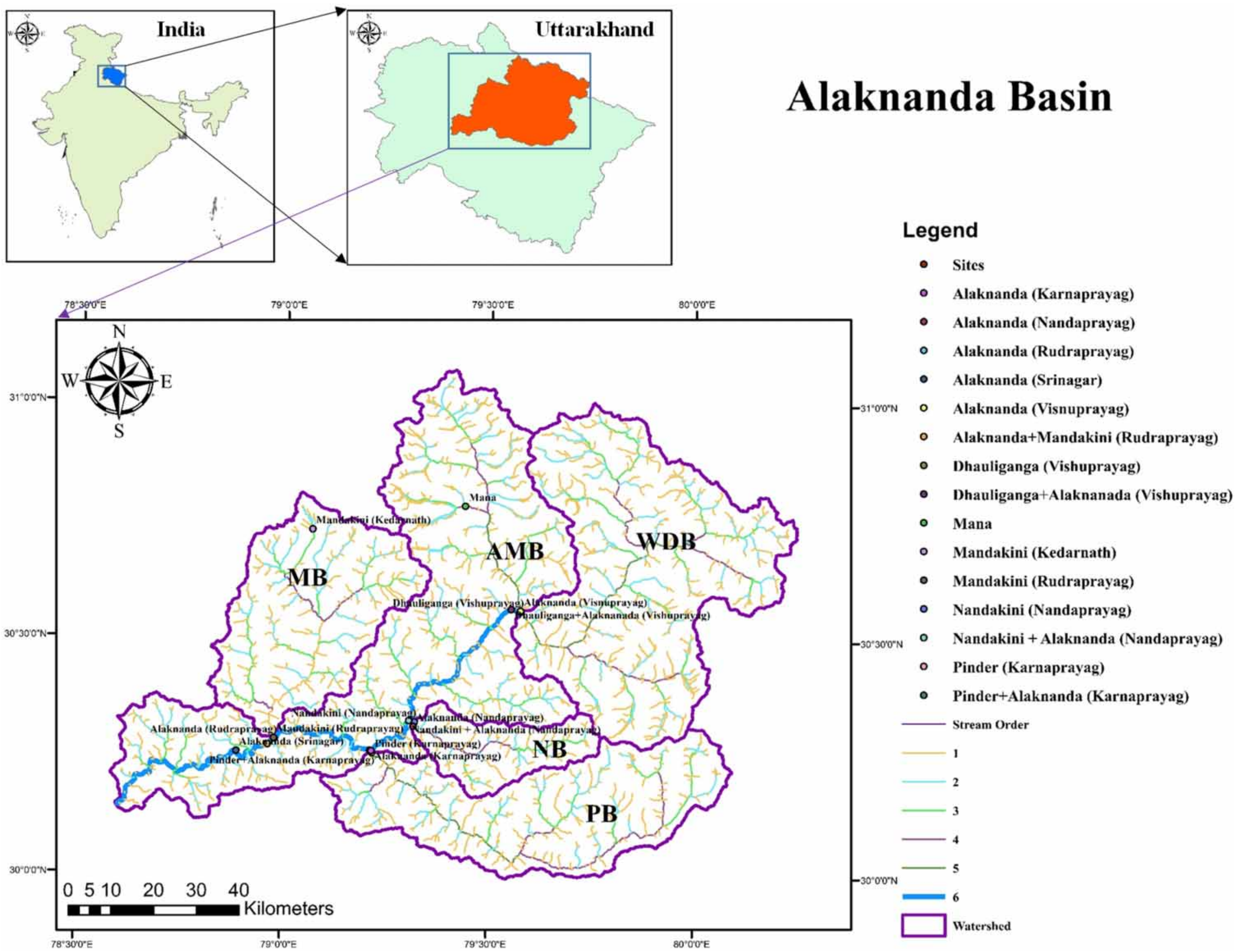


Figure 1 | Location map of the Alaknanda basin (where the basin is divided into five major sub-basin including sampling site and AMB, MB, WDB, NB, and PB denotes Alaknanda main basin, Mandakini basin, Western Dhaulignaga basin, Nandakini basin, and Pinder basin, respectively).

and Mandakini contribute a significant amount of snow and glacier melt to the Alaknanda River. Previous studies show that snow and glacier melt contributes 23–38% of total river flow. The observed streamflow at the Devprayag station ranges from 50 to 4,400 m^3/s (Rautela *et al.* 2022a). Also, at Devprayag gauging station, the Alaknanda River carries three times more total suspended sediments (TSS) than the Bhagirathi River (Panwar *et al.* 2017).

Data collection and data analysis

The water samples were collected from the 15 sites (mainly at Prayags) situated along the Alaknandariver and its tributaries (Figure 1). Three samples were taken from the river at each site during four seasons (monsoon, winter, spring, and summer) for the years 2021–2022. Samples were taken in 500 mL sterilized polyethylene bottles that had been cleansed with metal-free soap, rinsed with distilled water, and then immersed in 10% nitric acid for 24 h. To prevent changes in water quality and interference, all of the samples were maintained at 4 °C. Water samples were collected, preserved, transported, and analyzed using the techniques outlined in APHA-AWWA-WEF (1998). To keep the samples free from contact with the atmosphere, the polyethylene bottles used to store the samples were tape-sealed.

After samples were preserved, the physicochemical parameters were assessed in the laboratory according to the Bureau of Indian Standards (BIS 1991) and the American Public Health Association (APHA) (Eaton *et al.* 2005). For measuring pH, turbidity, dissolved oxygen (DO), and electrical conductivity (EC), we used pH meters, nephelometers, and conductivity meters (PC-II, Hach, USA). The laboratory also assesses other parameters using volumetric analysis.

Water quality index

WQI is the whetstone to judge surface and groundwater quality (Nihalani & Meeruty 2021). Physicochemical and biological parameters are plugged into an equation, and the resulting non-dimensional number indicates the palatability and reusability of the water. If the parameters exceed the permissible limits, the water can be branded unfit for utilization. Some of the prevalent WQI include the National Sanitation Foundation Water Quality Index (NSFWQI), the Oregon Water Quality Index (OWQI), and the Canadian Council of Ministers for Environment (CCME) WQI which involve a combination of physical, chemical, and biological parameters. However, among all the existing water quality indices, the weighted average method of water quality indexing is the most used due to its ease of operation and a higher degree of freedom (Sarkar & Majumder 2021). Even though this method has broader coverage, it is sometimes discouraged as other factors can influence the water quality, making the results erroneous. The 'weights' determine the relative importance of the discrete parameters (Gopolang & Letshwenyo 2019). Even though they fluctuate less, the factors with lower allowed limits typically have the potential to change the water quality to a greater extent; for this reason, they are given high weights. The formula for calculating WQI via the weighted arithmetic average method is as follows (Sarkar & Majumder 2021):

$$K = \frac{1}{\sum \frac{1}{\mathrm{Si}}}$$

where Si denotes the standard permissible limit for the parameters.

$$\mathrm{Qi} = \frac{\mathrm{Vi} - \mathrm{V0}}{\mathrm{Si} - \mathrm{V0}} * 100$$

Vi represents estimated values for the parameter, and V0 represents the parameter in ideal water conditions, generally considered zero except for pH and DO, which are 7 and 14.6 mg/L, respectively. The rating scale used in this study is presented in (Table 1).

To calculate the individual unit weight of the parameter, the following formula can be used:

$$\mathrm{Wi} = \frac{K}{\mathrm{Si}}$$

Finally, the WQI can be computed using the formula:

$$\mathrm{WQI} = \frac{\sum \mathrm{Qi} * \mathrm{Wi}}{\sum \mathrm{Wi}}$$

Table 1 | Water quality rating (Nihalani & Meeruty 2021)

S/No.	WQI
0–25	Excellent
26–50	Good
51–75	Poor
76–100	Very poor
Above 100	Unsuitable for drinking

Multivariate statistical analysis

Freshwater, marine water, and sediment quality have all been characterized using multivariate statistical techniques (Noori *et al.* 2010; Hamid *et al.* 2016). A multivariate statistical approach has recently been widely used to assess water quality (Kim *et al.* 2005; Barzegar *et al.* 2020). The correlation coefficient between two variables is calculated using the correlation analysis approach. The strength and importance of the two variables can be used to gauge the link between them. Correlation (r) indicates the strength, while probability levels show the importance (p values). Stronger relationships have higher correlation coefficients, but more significant relationships have lower p-levels.

PCA is a statistical method that uses a group of variables to extract linear relationships between them (Simeonov *et al.* 2003). PCA allows data analysis without sacrificing much information (Singh *et al.* 2005). According to the principal components (PCs) produced during the analysis, principal component 1 (PC1) explained the most variance in the original data. The factor loadings were classified as 'strong,' 'moderate,' or 'weak' based on absolute loading values of 0.75, 0.75–0.50, and 0.50–0.30 (Vieria *et al.* 2012), but loading does not indicate a component's relevance; rather, it indicates the relative significance of a variable within the component.

RESULTS AND DISCUSSION

Water quality parameters

The water quality indices were calculated from the physicochemical parameters obtained from the 15 sampling locations over four seasons (monsoon, winter, spring, and winter) with their average values and permissible and desirable limits (Tables 2 and 3). The average values of water quality parameters are below the desirable limits except for turbidity and TSS. The average values of TSS range from 0.04 to 9.36 g/L. The highest TSS has been measured in the Alaknanda River at the Karnapyarag site. However, the Pinder river contributes a significant amount of suspended solids to the Alaknanda River. There is an effect of storage reservoir also seen in the amount of TSS. The Mandakini River at Rudraprayag and Alaknanda River at Srinagar show less TSS than the other sites due to Singoli-Bhatwari and Alaknanda Hydro Electric Power plants. The higher concentration of suspended solids in the river water may affect the mechanical components of the turbine and cause wear and tear (Rautela *et al.* 2022b).

The pH values of all the sampling sites and seasons range from 7.1 to 8.25. The pH value is well correlated with the TSS. Similar sampling sites, as discussed above, have higher pH values. Higher pH levels influence aquatic life, mucous membranes, corrosion, and the flavor of water (Narasimha Rao *et al.* 2011). The DO in the sampling sites ranges from 5.25 to 10.26 mg/L. The sites at higher altitudes (Mana and Kedarnath) have significantly less DO than the downstream sites. However, the downstream regions have to DO more than 6 mg/L, which is desirable for aquatic animals. The significant amount of DO is the adequate dissolution of oxygen during river water's up and down movement. Throughout the investigation, EC accounted for 100% of the desired range, with mean values ranging from 92 to 156 μS/cm. The EC is somehow increased during the summer and monsoon seasons due to the melting of glaciers. The trends for EC measurements of river water samples at Pinder (Karnapyarag) and Alaknanda (Karnaprayag) are found to move parallel to each other, with higher values throughout the study interval.

Hardness is a characteristic of water that hinders soap from lathering properly. The main cations that contribute to hardness are calcium and magnesium. Strontium, iron, and manganese are additional cations that contribute to hardness. Carbonate and bicarbonate anions make up the majority of the anions that cause hardness. The mean concentration of hardness in the sampling sites ranges from 25 to 89 mg/L. The TH of the all-sampling sites falls within the desirable limits. Although water hardness alone has no harmful effects on health, a higher quantity of hardness in the water can lead to heart disease and kidney stone issues (Napacho & Manyele 2010). The Total Alkalinity (TA) of all the sampling sites ranged from 28 to 97 mg/L and fell within the desirable limits. Alkalinity in water is caused by carbonates, bicarbonates, and hydroxides, which might be dissolved sediments, salts, or rocks (Krishna Kumar *et al.* 2012). The presence of suspended solids, including clay, silt, colloidal organic matter, plankton, and other creatures, causes turbidity, which is a measurement of the purity of the water (Dorner *et al.* 2007). The turbidity of the sampling sites ranged from 3 to 18.1 NTU. During monsoons and summer, the samples' turbidity exceeds the desirable limit. However, the Pinder River shows very high turbidity during both summer and monsoon season and deliver a significant amount of suspended sediments to the Alaknanda River. The turbidity and TSS have been largely influenced by the melting of debris and moraine-covered glaciers and intense rainfall in the summer and monsoon seasons. TSS and turbidity are at the desirable

Table 2 | Site-wise water quality parameters (TSS, pH, DO, and EC), including their average, permissible, and desirable limits (in bold)

		TSS (g/L)				pH				DO (mg/L)				EC (micro-mho/cm)			
S.No.	**Sampling Site**	**Monsoon**	**Winter**	**Spring**	**Summer**	**Monsoon**	**Winter**	**Spring**	**Summer**	**Monsoon**	**Winter**	**Spring**	**Summer**	**Monsoon**	**Winter**	**Spring**	**Summer**
1	Mana	0.04	NA	NA	1.23	7.11	NA	NA	7.1	5.25	NA	NA	6.15	100	NA	NA	100
2	Dhauliganga (Vishnuprayag)	5.72	NA	NA	4.71	7.8	NA	NA	7.6	7.19	NA	NA	7.35	120	NA	NA	110
3	Dhauliganga + Alaknanada (Vishnuprayag)	4.04	NA	NA	3.52	7.6	NA	NA	7.5	7.15	NA	NA	7.39	140	NA	NA	130
4	Alaknanda (Visnuprayag)	0.48	NA	NA	3.36	7.26	NA	NA	7.3	7	NA	NA	7.52	110	NA	NA	115
5	Nandakini (Nandaprayag)	5.32	NA	NA	4.25	7.78	NA	NA	7.8	7.85	NA	NA	8.26	108	NA	NA	100
6	Nandakini + Alaknanda (Nandaprayag)	4.36	NA	NA	4.31	7.8	NA	NA	7.6	7.8	NA	NA	7.8	130	NA	NA	125
7	Alaknanda (Nandaprayag)	7.16	NA	NA	6.15	8.2	NA	NA	7.9	8	NA	NA	8.12	140	NA	NA	135
8	Pinder (Karnaprayag)	9.32	0.36	0.3	6.35	8.25	7.5	7.4	7.8	7.75	10.2	9.86	7.96	150	95	100	156
9	Pinder + Alaknanda (Karnaprayag)	8.12	0.24	0.2	6.64	7.92	7.6	7.5	7.9	8.1	10.4	10.2	8.29	120	98	95	125
10	Alaknanda (Karnaprayag)	9.36	0.32	0.25	6.33	8.25	7.5	7.5	7.8	8.05	10.3	9.82	8.36	145	96	98	149
11	Mandakini (Kedarnath)	0.04	NA	NA	1.31	7.15	NA	NA	7.2	6.1	NA	NA	6.25	95	NA	NA	98
12	Alaknanda (Rudraprayag)	5.68	0.24	0.3	4.36	8.1	7.6	7.4	8	7.65	10.2	9.95	7.95	125	95	102	136
13	Mandakini (Rudraprayag)	0.8	0.16	0.6	2.39	7.5	7.6	7.5	7.6	8.1	10.3	10.26	8.25	120	92	95	125
14	Alaknanda + Mandakini (Rudraprayag)	4.12	0.16	0.45	4.25	7.9	7.8	7.7	7.6	8.25	10.5	10.1	8.45	130	94	98	145
15	Alaknanda (Srinagar)	4.04	0.4	0.35	4.38	7.9	7.7	7.6	7.5	8.25	10.4	10.25	8.54	130	94	100	149
Average		**4.57**	**0.31**	**2.56**	**4.24**	**7.77**	**7.56**	**7.60**	**7.61**	**7.50**	**10.20**	**8.97**	**7.78**	**124.20**	**96.57**	**118.07**	**126.53**
Permissible limit		**20**				**–**				**–**				**2000**			
Desirable limit		**0.5**				**6.5–8.5**				**6.5–8**				**750**			

Table 3 | Site-wise water quality parameters (TH, TA, turbidity), including their average, permissible, and desirable limits (in bold)

		TH (mg/L)				TA (mg/L)				Turbidity (NTU)			
S.No.	**Sampling site**	**Monsoon**	**Winter**	**Spring**	**Summer**	**Monsoon**	**Winter**	**Spring**	**Summer**	**Monsoon**	**Winter**	**Spring**	**Summer**
1	Mana	47	NA	NA	46	42	NA	NA	45	3	NA	NA	7.5
2	Dhauliganga (Vishnuprayag)	67	NA	NA	65	62	NA	NA	52	15.5	NA	NA	9.5
3	Dhauliganga + Alaknanada (Vishnuprayag)	65	NA	NA	70	67	NA	NA	57	13	NA	NA	10.55
4	Alaknanda (Vishnuprayag)	63	NA	NA	65	58	NA	NA	56	2.5	NA	NA	8.5
5	Nandakini (Nandaprayag)	62	NA	NA	61	51	NA	NA	53	10.2	NA	NA	9.25
6	Nandakini + Alaknanda (Nandaprayag)	70	NA	NA	69	53	NA	NA	54	12.5	NA	NA	8.75
7	Alaknanda (Nandaprayag)	67	NA	NA	68	55	NA	NA	57	12.25	NA	NA	10.25
8	Pinder (Karnaprayag)	75	35	25	71	60	32	29	51	18.1	3	3	12.1
9	Pinder + Alaknanda (Karnaprayag)	89	40	38	86	63	35	28	53	15.5	4	3.5	10.45
10	Alaknanda (Karnaprayag)	68	38	40	71	55	35	33	57	17	4	3.5	11.65
11	Mandakini (Kedarnath)	50	NA	NA	55	45	NA	NA	47	2.95	NA	NA	7.95
12	Alaknanda (Rudraprayag)	75	38	36	72	61	34	36	58	15	3	4	12.5
13	Mandakini (Rudraprayag)	55	36	34	59	40	32	37	42	4.5	4.5	5	7.05
14	Alaknanda + Mandakini (Rudraprayag)	70	38	39	67	59	35	39	54	13.5	4	3.5	10.5
15	Alaknanda (Srinagar)	70	36	42	69	60	32	34	56	13.5	5	4.5	9.95
Average		**66.20**	**36.79**	**53.60**	**66.27**	**55.40**	**33.64**	**43.60**	**52.80**	**11.27**	**3.89**	**7.28**	**9.76**
Permissible limit		**600**				**600**				5			
Desirable limit		**200**				**200**				1			

limit during the winter and spring season, where the melting of snow and glaciers are negligible. The overall water qualities showed significant variation during monsoon and summer, maybe due to increased sediment transport during the season. The suspended solids content is the only factor seen beyond the permissible limit for most cases, impacting the water quality in the sampling sites.

Correlation matrix

The substantial link among the measures was developed by statistical analysis using Pearson's correlation coefficient between several river water quality metrics (Bhandari & Nayal 2008; Joshi *et al.* 2009). The data analysis produced an *R*-value, which is a correlation showing the linear relationship between the data pairs. A linear relationship indicates that if one variable rises or falls, the other one does so linearly as well. Correlation coefficients with values approaching +1 (positive correlation) indicate that while one variable rises, the other rises almost linearly. On the other hand, a correlation value that is close to −1 indicates that when one variable rises, the other falls almost linearly. Values approaching 0 denote a negligible or nonexistent linear connection between the variables (Mudgal *et al.* 2009). When data are unrelated, there is no connection between the data points. In Table 1, there is a strong positive correlation shown between the TSS-turbidity ($r = 0.915$), TA-TH ($r = 0.896$), TSS-TA ($r = 0.726$), and TSS-TH ($r = 0.827$) during the monsoon, winter, spring, and summer season, respectively (Table 4).

Moreover, there is also a less or negative correlation found between TA and DO ($r = 0.402$), TSS and TA ($r = -0.367$), EC and DO ($r = -0.507$), and TA and DO ($r = 0.451$) during monsoon, winter, and spring and summer season, respectively (Table 4). TSS and turbidity are strongly correlated with each other during the summer, spring, and monsoon seasons, whereas in the winter, there is no correlation between these two parameters. The results also indicate that the river has a

Table 4 | Correlation matrix of the water quality Parameter

Parameters	Season	pH	DO	EC	TH	TA	Turbidity	TSS
pH	Monsoon	1						
	Winter	1						
	Spring	1						
	Summer	1						
DO	Monsoon	0.764	1					
	Winter	0.801	1					
	Spring	0.484	1					
	Summer	0.746	1					
EC	Monsoon	0.819	0.642	1				
	Winter	−0.323	0.023	1				
	Spring	−0.254	***−0.507***	1				
	Summer	0.521	0.681	1				
TH	Monsoon	0.737	0.685	0.567	1			
	Winter	0.157	0.389	0.697	1			
	Spring	0.63	0.379	−0.119	1			
	Summer	0.723	0.665	0.596	1			
TA	Monsoon	0.528	***0.402***	0.554	0.767	1		
	Winter	0.147	0.382	0.625	**0.896**	1		
	Spring	0.509	0.217	0.118	0.354	1		
	Summer	0.478	***0.451***	0.468	0.634	1		
Turbidity	Monsoon	0.902	0.629	0.782	0.799	0.717	1	
	Winter	0.441	0.643	−0.314	−0.048	−0.183	1	
	Spring	0.145	0.686	−0.204	0.335	0.517	1	
	Summer	0.718	0.486	0.719	0.696	0.71	1	
TSS	Monsoon	0.925	0.608	0.743	0.766	0.574	**0.915**	1
	Winter	−0.377	−0.281	0.254	−0.391	***−0.367***	0.034	1
	Spring	0.345	0.481	−0.281	−0.077	**0.726**	0.669	1
	Summer	0.82	0.703	0.644	**0.827**	0.604	0.752	1

Bold values show strongly positive, negative correlation and no correlation.

significant amount of TSS concentration in the high flow period of the Alaknanda River and its tributaries, and the melting of snow and glaciers will affect the amount of TSS and turbidity of the riverine flow dynamics. The strong and weak negative correlation between the measures might be interpreted as the main causes of seasonal fluctuations in water quality.

WQI assessment

The WQI provides a comprehensive analysis of the quality of surface and ground water and its appropriateness for consumption. WQI's primary goal is to transform complicated data on water quality into usable information that regular people can use to understand the condition of water sources in a specific area. Figure 2 shows WQI values for different sites for different seasons. In monsoon and summer, the WQI for all the sites is very poor because the melt water in the river contains a significant amount of TSS. However, during the winter and spring, the WQI for maximum downstream sites will lie between good and poor. However, the other parameters, such as pH, EC, TA, total hardness (TH), and DO, do not largely affect the WQI compared to the turbidity and TSS. Dhauligangariver in Vishnuprayag shows the highest WQI among all the sampling sites (Figure 2). This might be because the flash flood occurred in February 2021; the river carries enough suspended solids and is delivered to the Alaknanda River. However, upstream sampling sites such as Mana and Kedarnath have good WQI during monsoon but increase in the summer. This will also indicate that melting snow and glaciers will significantly impact the WQI. The impact of storage reservoirs has also been observed. The storage reservoirs will reduce the flow velocity and allow the settling of the suspended sediments. The WQI of Alaknanda River at Srinagar and Mandakini River at Rudraprayag shows a significant effect of Alaknanda Hydro Electric and Singoli-Bhatwari Power plant, respectively. The results indicate the WQI will be largely affected by TSS and turbidity, and as per the drinking water quality standards, the riverine water is unsuitable for drinking. However, the river water will be used for drinking after some primary and secondary treatments.

Principal component analysis

A PCA was used to determine the latent variables influencing the water quality parameters of surface water samples. A second degree of statistical significance can also be ascribed to PCs with eigenvalues greater than 0.75 used for interpretation

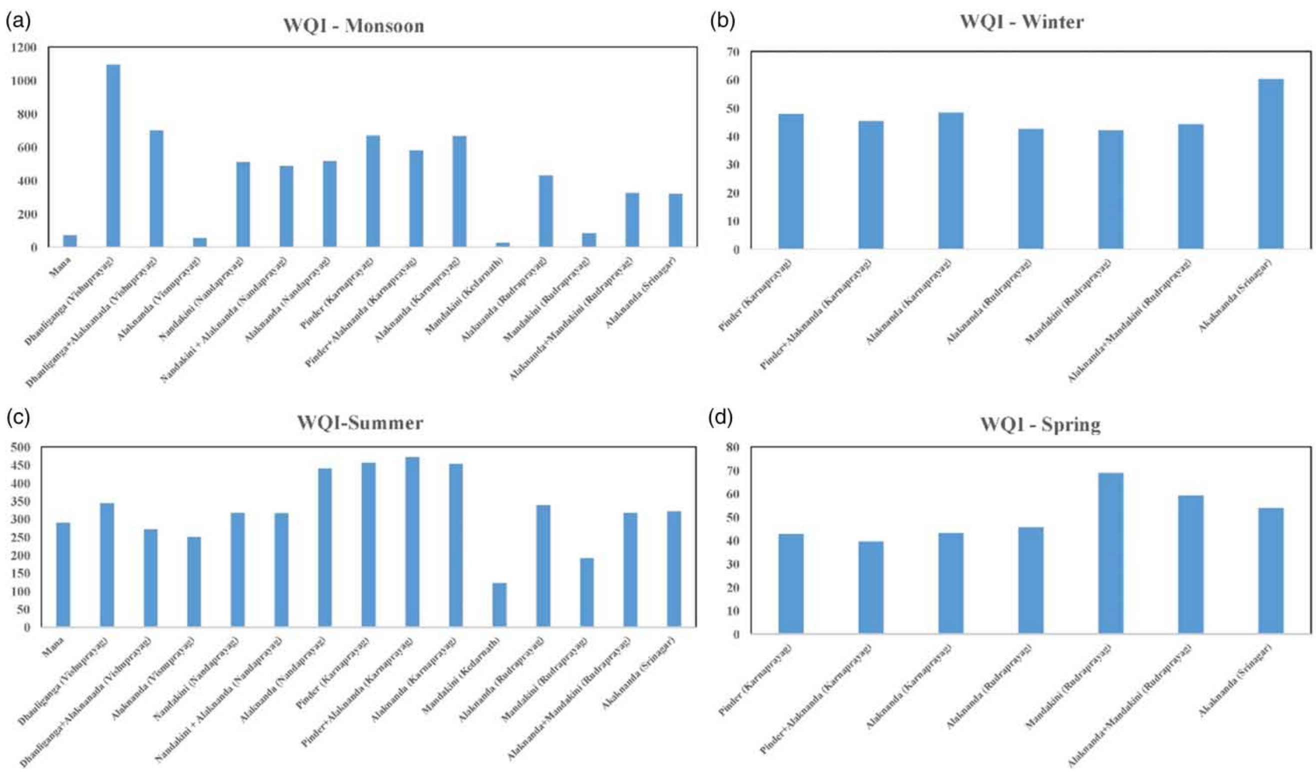


Figure 2 | Water quality of sampling sites of the Alaknanda River for (a) Monsoon season, (b) Winter Season, (c) Summer season, and (d) Spring season.

Table 5 | Eigenvalue, variance, and cumulative variance of the monsoon, winter, spring, and summer season

Monsoon			Winter			Spring			Summer		
Eigenvalue	Variance	Cumulative variance	Eigenvalue	Variance	Cumulative variance	Eigenvalue	Variance	Cumulative variance	Eigenvalue	Variance	Cumulative variance
5.2736	0.753	0.753	**2.852**	0.407	0.407	**3.279**	0.468	0.468	**4.9209**	0.703	0.703
0.7105	0.102	0.855	**2.3638**	0.338	0.745	**1.3217**	0.189	0.657	0.706	0.101	0.804
0.4795	0.068	0.923	**1.1112**	0.159	0.904	**1.2704**	0.181	0.839	0.5359	0.077	0.88
0.3427	0.049	0.972	0.4316	0.062	0.966	0.7253	0.104	0.942	0.3786	0.054	0.934
0.0992	0.014	0.986	0.1383	0.02	0.985	0.3416	0.049	0.991	0.2732	0.039	0.974
0.0572	0.008	0.995	0.1031	0.015	1	0.062	0.009	1	0.1431	0.02	0.994
0.0373	0.005	1	0	0	1	0	0	1	0.0424	0.006	1

Bold values show the eigen values which are not less than 1.

(Shrestha *et al.* 2007). Each primary component is reflected in the table as variance, cumulative variance, and commonality. PCA was performed using standardized datasets, and in the varimax rotated component matrix, only three PCs with eigenvalues larger than one could account for the variance whose eigenvalue is greater than 1. Table 5 presents eigenvalues and their corresponding variances for a PCA conducted across four different seasons: Monsoon, Winter, Spring, and Summer. Eigenvalues represent the amount of variance explained by each principal component in the PCA. In the Monsoon season, the first eigenvalue is 5.2736, explaining 75.3% of the variance, while the second eigenvalue is 0.7105, contributing an additional 10.2% to the cumulative variance of 85.5%. Similar patterns are observed in the other seasons, with the first eigenvalue explaining the majority of the variance. As we move through the seasons, the cumulative variance increases, indicating that the principal components are collectively capturing a higher percentage of the overall variability in water quality data. These eigenvalues and variances are crucial in PCA as they help determine how many PCs should be retained for analysis. However, Figure 3 displays a scree plot of all the PCs of different seasons retrieved using PCA.

In the monsoon season, PC1 explains approximately 3/4th, i.e., 75.30% of the total variance, and has a moderately positive correlation with pH; Turbidity and TSS suggest the natural weathering sources that affect the water quality parameters (Table 6). At the same time, PC2 and PC3 are insignificant in the monsoon season. In the winter season, PC1 explains 40.70% of the total variance, and a moderately positive correlation with DO, TH, and TA suggests the basin's lithogenic factors influence the water quality (Table 6). However, during the winter, the PC2 and PC3 hold significant variance values. PC2 explains 33.8% of the total variance. Moderately positive and negative correlated with the EC and turbidity.

In comparison, PC3 explains 15.9% of the total variance and is negatively correlated with the turbidity and TSS, respectively, showing that in the winter season, the water flowing in the river and its tributaries will not be much affected by the suspended sediments (Table 6). In the spring season, PC1 explains 46.8% of the total variance and is moderately positively

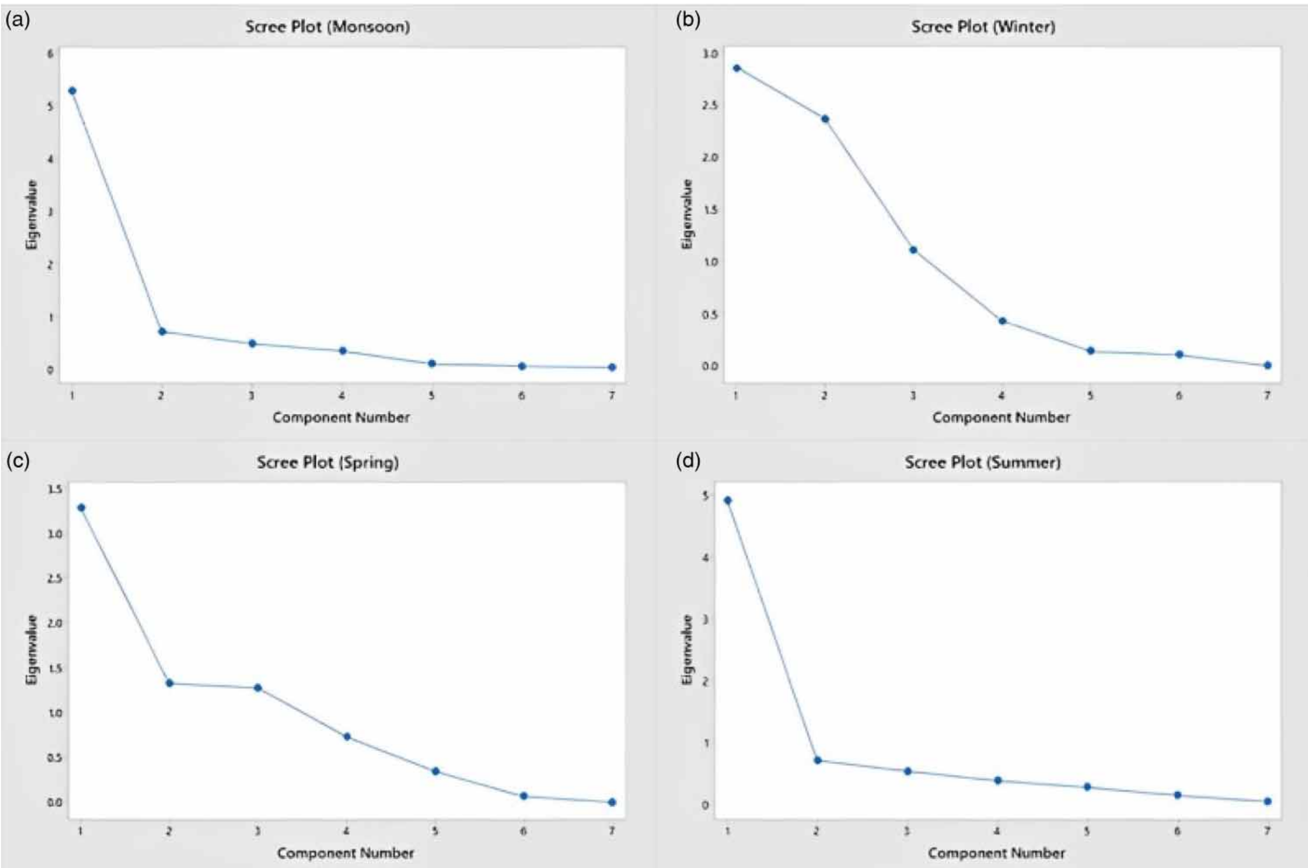


Figure 3 | Scree plot extraction principal components in (a) Monsoon, (b) Winter, (c) Spring, and (d) Summer seasons.

Table 6 | Varimax rotated matrix of analyzed water samples during monsoon winter, spring, and summer season

Eigenvectors Variable	Monsoon			Winter			Spring			Summer		
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
PH	**0.411**	− 0.298	0.122	0.323	−0.463	0.06	0.381	0.397	0.276	0.388	0.286	**0.408**
DO (mg/L)	0.338	**−0.412**	**− 0.725**	**0.444**	− 0.363	−0.259	**0.438**	0.16	−0.353	0.364	**0.544**	− 0.079
EC (micro-mho/cm)	0.367	−0.259	0.359	0.253	**0.504**	− 0.397	−0.226	−0.28	**0.651**	0.354	0.112	−0.82
TH (mg/L)	0.381	0.334	**−0.412**	**0.521**	0.266	−0.014	0.301	**0.56**	0.351	0.397	−0.022	0.266
TA (mg/L)	0.322	**0.741**	− 0.028	**0.504**	0.283	0.059	0.394	−0.317	**0.475**	0.33	**−0.679**	0.082
Turbidity (NTU)	**0.415**	0.072	0.254	0.119	**−0.481**	**− 0.459**	**0.434**	− 0.271	−0.13	**0.413**	− 0.377	−0.165
TSS (mg/L)	**0.401**	− 0.097	0.308	−0.306	0.133	**−0.747**	**0.421**	**− 0.501**	− 0.096	**0.414**	0.077	0.224

Bold values show strongly positive and negative correlation.

correlated with the DO, turbidity, and TSS, respectively, indicating the significant contribution of the TSS in the riverine flow. On the other hand, PC2 explains 18.90% of the total variance and moderately positively and negatively correlated with the EC and TA, respectively, while PC3 explains 18.10% of the total variance and moderately correlated with the EC and TA (Table 6). In the summer season, PC1 explains 70.30% of the total variance and is moderately positively correlated with the turbidity and TSS, respectively, while PC2 and PC3 are insignificant in the summer seasons because of the eigenvalue less than 1 (Table 6). In the summer, the turbidity and TSS affect the river's water quality, as we discussed earlier, the possible causes of the availability of TSS.

CONCLUSION

The current study clearly illustrates the use of multivariate statistical approaches in conjunction with WQI with graphical representation. Such instruments are used in the current study to comprehend the water quality parameters of the surface water of Alaknanda and its tributaries. The parameter values of all the water samples analyzed were well within the ideal ranges defined by BIS (1991) and WHO (2011), except somehow, TSS and turbidity of the water samples increased in the summer and monsoon season due to the intense glacier melting and erratic rainfall pattern. Except for all spots in summer and monsoon season where the TSS and turbidity were outside the acceptable range, the overall water quality is thus safe for domestic use with proper sedimentation. The higher suspended sediment concentration in the river water will negatively impact the aquatic biodiversity and runoff of river hydroelectric power plants in the downstream regions. According to the WQI, most water samples fell into the bad category throughout the summer and monsoon seasons, followed by the good category during the summer and spring. The PCA and correlation matrix highlight the key anthropogenic variables, such as agri-runoff and household wastewater runoff that are the primary influences on the water quality indicators. These factors include rock–water interaction, ion exchange, and the leaching of parent materials. The current study's findings will provide baseline information to the municipal corporations and planners of the cities situated at the river banks.

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DECLARATIONS

All authors have read, understood, and have complied as applicable with the statement on 'Ethical responsibilities of Authors' as found in the instructions for authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

AUTHORS STATEMENT

K. S. R. and D. K. conceptualized the whole article. K. S. R. and D. K. developed the methodology, K. S. R. and D. K. rendered support in formal analysis and investigation. K. S. R. wrote the original draft, K. S. R., D. K., B. G. R. G., A. R., B. S. K. and A. K. D. wrote the review and editing; D. K. and A. K. D. supervised the article.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

APHA 1998 *Standard Methods for the Examination of Water and Wastewater*, 20th edn. American Public Health Association, American Water Works Association and Water Environmental Federation, Washington DC.

Aristizabal, J. P., Giraldo, R. & Mateu, J. 2019 Analysis of variance for spatially correlated functional data: Application to brain data. *Spatial Statistics* **32**, 100381.

Barzegar, R., Moghaddam, A. A., Tziritis, E., Adamowski, J., Nassar, J. B., Noori, M. & Kazemian, N. 2020 Exploring the hydrogeochemical evolution of cold and thermal waters in the Sarein-Nir area, Iran using stable isotopes (δ18o and δD), geothermometry and multivariate statistical approaches. *Geothermics* **85**, 101815.

Bhandari, N. S. & Nayal, K. 2008 Correlation study on physico-chemical parameters and quality assessment of Kosi River water. *Uttarakhand. E-Journal of Chemistry* **5** (2), 342–346.

Bickle, M. J., Bunbury, J., Chapman, H. J., Harris, N. B., Fairchild, I. J. & Ahmad, T. 2003 Fluxes of Sr into the headwaters of the Ganges. *GeochimicaetCosmochimicaActa* **67** (14), 2567–2584.

BIS 1991 *Specifications for Drinking Water*, IS:10500: 1991, Bureau of Indian Standards, New Delhi, India.

Bouza-Deaño, R., Ternero-Rodríguez, M. & Fernández-Espinosa, A. J. 2008 Trend study and assessment of surface water quality in the Ebro River (Spain). *Journal of Hydrology* **361** (3–4), 227–239.

Chattopadhyay, T., Sharina, M., Davoust, E., De, T. & Chattopadhyay, A. K. 2012 Uncovering the formation of ultracompact dwarf galaxies by multivariate statistical analysis. *The Astrophysical Journal* **750** (2), 91.

Corporal-Lodangco, I. L., Richman, M. B., Leslie, L. M. & Lamb, P. J. 2014 Cluster analysis of North Atlantic tropical cyclones. *Procedia Computer Science* **36**, 293–300.

Dorner, S. M., Anderson, W. B., Gaulin, T., Candon, H. L., Slawson, R. M., Payment, P. & Huck, P. M. 2007 Pathogen and indicator variability in a heavily impacted watershed. *Journal of Water and Health* **5** (2), 241–257.

Dubey, S. & Goyal, M. K. 2020 Glacial lake outburst flood hazard, downstream impact, and risk over the Indian Himalayas. *Water Resources Research* **56** (4), e2019WR026533.

Eaton, A. D. & Franson, M. A. H. & American Water Works Association, Water Environment Federation 2005 *Standard Method for the Examination of Water and Wastewater*, 21st edn. American Public Health Association, Washington.

Ghosh, T. K., Jakobsen, F., Joshi, M. & Pareta, K. 2019 Extreme rainfall and vulnerability assessment: Case study of Uttarakhand rivers. *Natural Hazards* **99** (2), 665–687.

Gopolang, O. P. & Letshwenyo, M. W. 2019 *Water Quality Index of Waste Stabilisation Ponds and Downstream of Discharge Point*.

Grimm, N. B., Faeth, S. H., Golubiewski, N. E., Redman, C. L., Wu, J., Bai, X. & Briggs, J. M. 2008 Global change and the ecology of cities. *Science* **319** (5864), 756–760.

Hamid, A., Bhat, S. A., Bhat, S. U. & Jehangir, A. 2016 Environmetric techniques in water quality assessment and monitoring: A case study. *Environmental Earth Sciences* **75** (4), 1–13.

Joshi, D. M., Bhandari, N. S., Kumar, A. & Agrawal, N. 2009 Statistical analysis of physicochemical parameters of water of River Ganga in Haridwar district. *Rasayan Journal of Chemistry* **2** (3), 579–587.

Kim, J. H., Kim, R. H., Lee, J., Cheong, T. J., Yum, B. W. & Chang, H. W. 2005 Multivariate statistical analysis to identify the major factors governing groundwater quality in the coastal area of Kimje. *South Korea. Hydrological Processes: An International Journal* **19** (6), 1261–1276.

Krishna Kumar, S., Chandrasekar, N., Seralathan, P., Godson, P. S. & Magesh, N. S. 2012 Hydrogeochemical study of shallow carbonate aquifers, Rameswaram Island, India. *Environmental Monitoring and Assessment* **184** (7), 4127–4138.

Kumar, P., Mahajan, A. K. & Kumar, A. 2020 Groundwater geochemical facie: Implications of rock-water interaction at the Chamba city (HP), northwest Himalaya, India. *Environmental Science and Pollution Research* **27** (9), 9012–9026.

Kwon, H. G. & Jo, C. D. 2023 Water quality assessment of the Nam River, Korea, using multivariate statistical analysis and WQI. *International Journal of Environmental Science and Technology* **20** (3), 2487–2502.

Mirzaei Aminiyan, M., Mirzaei Aminiyan, F. & Heydariyan, A. 2016 Study on hydrochemical characterization and annual changes of surface water quality for agricultural and drinking purposes in semi-arid area. *Sustainable Water Resources Management* **2** (4), 473–487.

Mudgal, K. D., Kumari, M., Sharma, D. K., dev Mudgal, K. & Kumari, M. 2009 Hydrochemical analysis of drinking water quality of Alwar district, Rajasthan. *Nat Sci* **7** (2), 30–39.

Napacho, Z. A. & Manyele, S. V. 2010 Quality assessment of drinking water in Temeke District (part II): Characterization of chemical parameters. *African Journal of Environmental Science and Technology* **4** (11), 775–789.

Narasimha, R. C., Dorairaju, S. V., Bujagendra, R. M. & Chalapathi, P. V. 2011 Statistical analysis of drinking water quality and its impact on human health in Chandragiri, near Tirupati, India.

Nihalani, S. & Meeruty, A. 2021 Water quality index evaluation for major rivers in Gujarat. *Environmental Science and Pollution Research* **28** (45), 63523–63531.

Nnorom, I. C., Ewuzie, U. & Eze, S. O. 2019 Multivariate statistical approach and water quality assessment of natural springs and other drinking water sources in Southeastern Nigeria. *Heliyon* **5** (1), e01123.

Noori, R., Sabahi, M. S., Karbassi, A. R., Baghvand, A. & Zadeh, H. T. 2010 Multivariate statistical analysis of surface water quality based on correlations and variations in the data set. *Desalination* **260** (1–3), 129–136.

Oda, R., Suzuki, Y., Yanagihara, H. & Fujikoshi, Y. 2020 A consistent variable selection method in high-dimensional canonical discriminant analysis. *Journal of Multivariate Analysis* **175**, 104561.

Panwar, S., Agarwal, V. & Chakrapani, G. J. 2017 Morphometric and sediment source characterization of the Alaknanda River basin, headwaters of river Ganga, India. *Natural Hazards* **87** (3), 1649–1671.

Pehlivan, E. & Arslan, G. 2007 Removal of metal ions using lignite in aqueous solution – low cost biosorbents. *Fuel Processing Technology* **88** (1), 99–106.

Rani, S. & Sreekesh, S. 2019 Evaluating the responses of streamflow under future climate change scenarios in a Western Indian Himalaya Watershed. *Environmental Processes* **6** (1), 155–174.

Rani, M., Joshi, H., Kumar, K., Bhatt, D. K. & Kumar, P. 2021 Climate change scenario of hydro-chemical analysis and mapping spatio-temporal changes in water chemistry of water springs in Kumaun Himalaya. *Environment, Development and Sustainability* **23** (3), 4659–4674.

Rautela, K. S., Kumar, D., Gandhi, B. G. R., Kumar, A. & Dubey, A. K. 2022a Application of ANNs for the modeling of streamflow, sediment transport, and erosion rate of a high-altitude river system in Western Himalaya, Uttarakhand. *RBRH* **27**, e22.

Rautela, K. S., Kuniyal, J. C., Alam, M. A., Bhoj, A. S. & Kanwar, N. 2022b Assessment of daily streamflow, sediment fluxes, and erosion rate of a pro-glacial stream basin, Central Himalaya, Uttarakhand. *Water, Air, & Soil Pollution* **233** (4), 1–16.

Sarkar, K. & Majumder, M. 2021 Application of AHP-based water quality index for quality monitoring of peri-urban watershed. *Environment, Development and Sustainability* **23** (2), 1780–1798.

Sarkar, A. & Paul, B. 2016 The global menace of arsenic and its conventional remediation – a critical review. *Chemosphere* **158**, 37–49.

Sati, V. P. 2020 Water resources and change. *Himalaya on the Threshold of Change* **66**, 47–61.

Sharma, G. & Mohanty, S. 2018 Morphotectonic analysis and GNSS observations for assessment of relative tectonic activity in Alaknanda basin of Garhwal Himalaya, India. *Geomorphology* **301**, 108–120.

Sharma, P. J., Patel, P. L. & Jothiprakash, V. 2019 Impact of rainfall variability and anthropogenic activities on streamflow changes and water stress conditions across Tapi Basin in India. *Science of the Total Environment* **687**, 885–897.

Sharma, G., Lata, R., Thakur, N., Bajala, V., Kuniyal, J. C. & Kumar, K. 2021 Application of multivariate statistical analysis and water quality index for quality characterization of Parbati River, Northwestern Himalaya, India. *Discover Water* **1** (1), 1–20.

Shiklomanov, I. A. 2000 Appraisal and assessment of world water resources. *Water International* **25** (1), 11–32.

Shrestha, S. & Kazama, F. 2007 Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. *Environmental Modelling & Software* **22** (4), 464–475.

Simeonov, V., Stratis, J. A., Samara, C., Zachariadis, G., Voutsa, D., Anthemidis, A. & Kouimtzis, T. 2003 Assessment of the surface water quality in Northern Greece. *Water Research* **37** (17), 4119–4124.

Singh, K. P., Malik, A., Sinha, S., Singh, V. K. & Murthy, R. C. 2005 Estimation of source of heavy metal contamination in sediments of Gomti River (India) using principal component analysis. *Water, air, and Soil Pollution* **166** (1), 321–341.

Singh, S., Tanvir Hassan, S. M., Hassan, M. & Bharti, N. 2020 Urbanisation and water insecurity in the Hindu Kush Himalaya: Insights from Bangladesh, India, Nepal and Pakistan. *Water Policy* **22** (S1), 9–32.

Sofi, M. S., Hamid, A., Bhat, S. U., Rashid, I. & Kuniyal, J. C. 2022 Impact evaluation of the run-of-river hydropower projects on the water quality dynamics of the Sindh River in the Northwestern Himalayas. *Environmental Monitoring and Assessment* **194** (9), 626.

Sofi, M. S., Rautela, K. S., Muslim, M., Bhat, S. U., Rashid, I. & Kuniyal, J. C. 2023 Modeling the hydrological response of a snow-fed river in the Kashmir Himalayas through SWAT and Artificial Neural Network. *International Journal of Environmental Science and Technology* 1–14. https://doi.org/10.1007/s13762-023-05170-7.

Thakur, N., Rishi, M., Sharma, D. A. & Keesari, T. 2018 Quality of water resources in Kullu Valley in Himachal Himalayas, India: Perspective and prognosis. *Applied Water Science* **8** (1), 1–13.

Tomar, G., Malik, D. S., Sharma, A. K., Kamboj, V. & Kumar, V. 2022 Assessment of water quality and biodiversity status of Alaknanda River at Garhwal, Uttarakhand: A case study. In: *Environmental Pollution and Natural Resource Management* (Bahukhandi, K. D., Kamboj, N. & Kamboj, V., eds). Springer International Publishing, Cham, pp. 121–136.

Valentini, M., dos Santos, G. B. & Muller Vieira, B. 2021 Multiple linear regression analysis (MLR) applied for modeling a new WQI equation for monitoring the water quality of Mirim Lagoon, in the state of Rio Grande do Sul–Brazil. *SN Applied Science* **3**, 70.

Vieira, J. S., Pires, J. C., Martins, F. G., Vilar, V. J., Boaventura, R. A. & Botelho, C. M. 2012 Surface water quality assessment of Lis River using multivariate statistical methods. *Water, Air, & Soil Pollution* **223**, 5549–5561.

Whitehead, P. G., Wilby, R. L., Battarbee, R. W., Kernan, M. & Wade, A. J. 2009 A review of the potential impacts of climate change on surface water quality. *Hydrological Sciences Journal* **54** (1), 101–123.

WHO 2011 *World Health Statistics 2011, Report: Ambient (outdoor) Air Quality and Health*. World Health Organization, Geneva.

Wu, Z., Zhang, D., Cai, Y., Wang, X., Zhang, L. & Chen, Y. 2017 Water quality assessment based on the water quality index method in Lake Poyang: The largest freshwater lake in China. *Sci. Rep.* **7**, 17999.

Yang, J. S., Hu, X. J., Li, X. X., Li, H. Y. & Wang, Y. 2013 Application of principal component analysis (PCA) for the estimation of source of heavy metal contamination in sediments of Xihe River, Shenyang City. *Advanced Materials Research* **610**, 948–951.

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