Desalination and Water Treatment
www.deswater.com
doi: 10.1080/19443994.2015.1098570

57 (2016) 19121–19130
September

Study of water quality in Hindon River using pollution index and environmetrics, India

Saurabh Mishra[a], Amit Kumar[a,*], Prabhakar Shukla[b]

[a]*Biomass and Ecosystem Lab, Alternate Hydro Energy Centre, Indian Institute of Technology Roorkee, Uttarakhand, 247667, India, Tel. +91 7417575326; email: saurabhmishra20057@gmail.com (S. Mishra), Tel. +91 9045939559; email: amit.agl09@gmail.com (A. Kumar)*

[b]*Department of Civil Engineering, Motilal Nehru National Institute of Technology, Allahabad 211004, India, Tel. +91 7379400080; email: yaahoo.india@gmail.com*

Received 28 February 2015; Accepted 17 September 2015

ABSTRACT

The River Hindon, a main tributary of river Yamuna flows in the western part of Uttar Pradesh (UP), India. As it passes through the industrial and urban areas, it receives a huge amount of wastages. Therefore, the present study is concerned with the assessment of water quality of the river in 28 sampling sites using the comprehensive pollution index (CPI), considering the eleven physiochemical parameters such as biological oxygen demand, dissolved oxygen, total dissolve solids, total phosphate and four heavy metals (Fe, Cu, Zn and Cr). Besides this, a multivariate statistical analysis is also performed using water quality parameters to validate the results. The CPI was found to be 2.68–7.12 (CPI > 2), which is an indication of severely polluted water of Hindon river. The result reveals that water of the Hindon River is unfit for human use, irrigation and other life supporting activities which are mainly on account of direct discharge of untreated wastewater by industries and municipal sources. This study also illustrates that principal component analysis and cluster analysis is an important statistical tool for better management of water quality monitoring system.

Keywords: River Hindon; CPI; PCA; CA; Water quality

1. Introduction

Water is a vital and essential natural resource required for multiplicity of purposes. It is an essential life-supporting factor comprising of major bulk (70–90%) of all living cells [1]. Water quality is one of the major factors responsible for both health and the cause of disease in humans [2]. The availability of freshwater resources is important for meeting the requirement of a rapidly growing population and in spreading out economic activities of any country. In the recent years, due to remarkable increase of human populations, industrial expansion and direct discharge of untreated wastewater into surface water bodies, there is a rise in concentration nutrients which have led to eutrophication i.e. the deterioration in water quality [3]. Therefore, the water pollution has become an important issue to prevent and control worldwide [4,5]. It has become essential to implement regular monitoring and conservation programmes for various water bodies. In addition, the conventional water quality regulations are also

*Corresponding author.

required which includes quality classes based on crispy sets that are limited between various classes with inherent imprecision, i.e. each water quality parameter is to be equally valued in assessing the pollution in water bodies. But, since quality classes may vary from one sampling location to other, all of the water quality parameters may not be included in a single class thereby leading to difficulty in defining pollution at the sampling site. In this concern, a number of studies have been carried out on water pollution and heavy metal contamination in sediment and water of river Hindon [6,7] but a comprehensive study has not been done yet. The literature found that Hindon River is severely polluted and hence water is not suitable for use for domestic and other life supporting purposes [6,7]. So, in the present paper, a comprehensive pollution index (CPI) [8] has been evaluated to define the water pollution in river Hindon at various sampling sites. Furthermore, the application of environmetrics also called as multivariate statistical techniques like principal component analysis (PCA) and cluster analysis (CA) is performed to recognize possible sources that could influence water system so as to have a better understanding of water quality and ecological status of the study region. These techniques have been especially trustworthy for providing new and unique insights into the relations in a broad scale of pollution situations [9–11]. These techniques are very valuable tool for reliable management and conservation of water resources as well as speedy solution for pollution harms in water-bodies.

2. Material and methods

2.1. Details of study site

River Hindon, which falls in Indogangatic Plain, is one of the main tributaries of River Yamuna. It originates in the upper Sivalik Himalayan region near the Saharanpur district of U.P, India, at coordinates 35˚05´ N 77˚08´ E (origin) to 28˚04´ N 77˚04´ E (mouth). It flows through six different districts i.e. Saharanpur, Muzaffarnagar, Meerut, Baghpat, Gautambudh Nagar and Ghaziabad joined by its two main tributaries (Krishna and Kali). River Hindon covers the catchment area of 7,083 km^2 with length of 400 km before merging into river Yamuna just outside Delhi. River Kali merges with River Hindon near Atali village while River Krishna joins it near the Binauli village in Merrut district. River Kali and Krishna are extremely contaminated and carry a huge amount of industrial and domestic waste as they pass through inhabited and industrialized straps of U.P. The major industrial effluents like pulp and paper (Star paper mill), sugar distilleries (Cooperative distilleries) etc. enter into the river through various Nallas (Dhamola, Nagdev, Barnawa nalla etc.). The physiochemical monitoring of the river Hindon has been performed considering 28 sampling locations (S0, S00, S1, S2, S3 … S26), covering the stretch between Sharanpur to Delhi, during pre- and post-monsoon season (2013–2014). A map of the river Hindon is shown in Fig. 1 which indicates tall sampling locations at different points.

2.2. Sampling method

The samples were collected and analysed in the laboratory as per the water quality testing manual guidelines [12] with needed precautions for testimonial analysis. Some parameters like surface temperature, dissolved oxygen (DO) and pH were measured on site. Eleven physiochemical parameters were considered for analysis, such as pH, total dissolve solids (TDS), chemical oxygen demand (COD), biological oxygen demand (BOD), DO, turbidity, conductivity, total hardness (TH), sulphate, chloride, total phosphate (TP) and four heavy metals like Fe, Cu, Zn and Cr. All the WQ parameters are measured in mg/l except conductivity (μs/cm), turbidity (NTU), DO (% saturation) and surface temperature (˚C). The detection limit of Fe, Cu, Zn and Cr in aqueous was 0.03, 0.003, 0.004, and 0.002 mg/l respectively, analysed using spectroscope.

2.3. Comprehensive pollution index

This CPI has been applied to classify the water quality status by many of the research findings [8]. It is evaluated by the following equations as:

$$\mathrm{PI} = \frac{\text{Measured concentation of individual parameter}}{\text{standard permissible concentration of parameter}} \tag{1}$$

$$\mathrm{CPI} = \frac{1}{n}\sum_{i=1}^{n}\mathrm{PI} \tag{2}$$

where PI is the pollution index of individual water quality parameter considered, as shown in Fig. 2, n is the number of parameters and CPI is a comprehensive pollution index. The standard permissible concentrations of each parameter considered in the study were obtained from the Central Pollution Control Board (CPCB) norms of the Indian government for a general discharge of environmental pollutant [13–16]. CPI ranges from 0 to 2 which classifies water quality as:

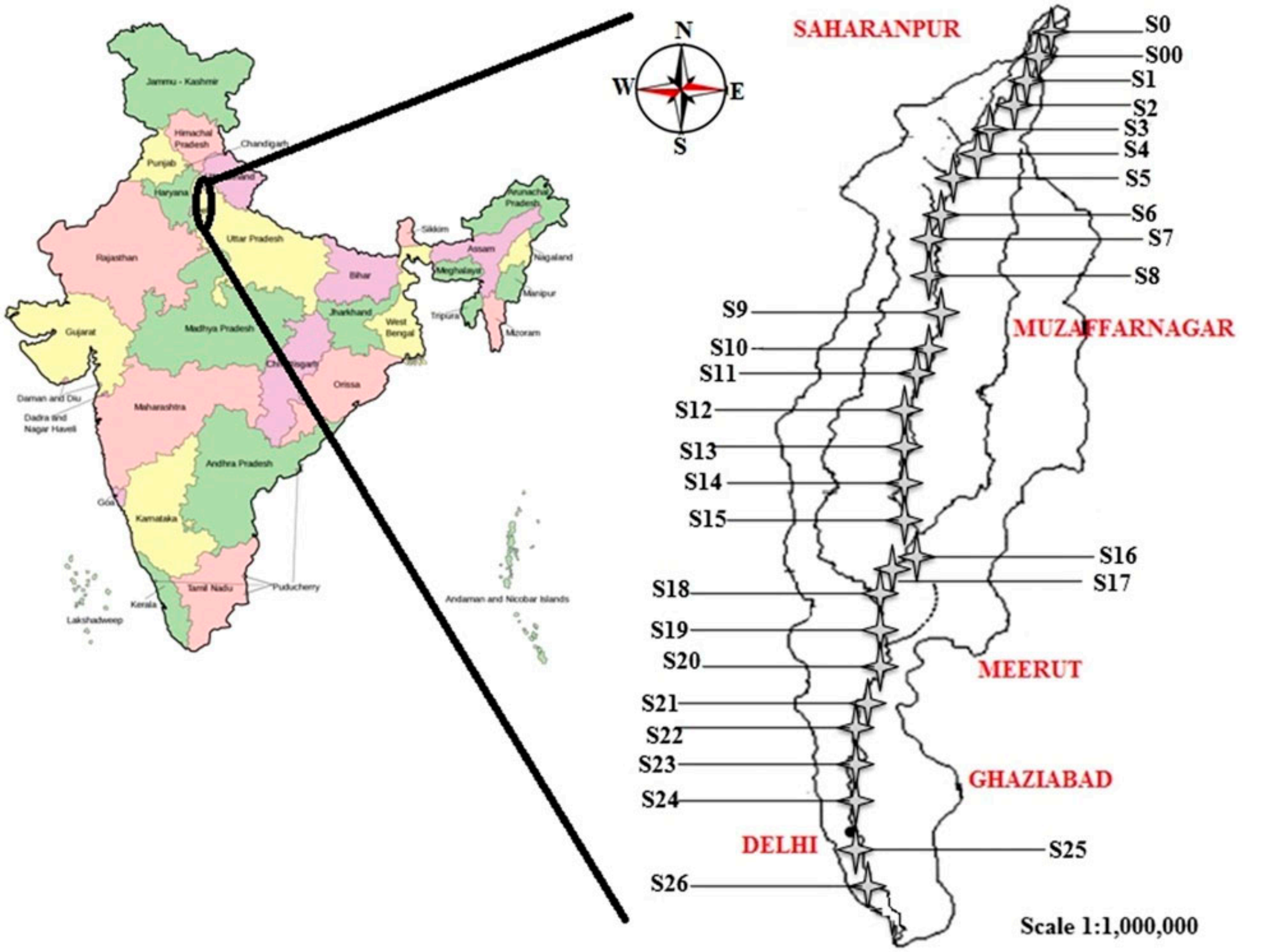


Fig. 1. Schematic diagram showing sampling locations in the stretch of Hindon River.

≤0.20 is Clean; 0.21–0.40 is Sub-clean; 0.41–1.00 is slightly polluted; 1.01–2.0 is moderately polluted; ≥2.01 is severely polluted.

2.4. Environmetrics

The Environmetrics, such as PCA and CA are getting applied in recent years for assessment of a large and complex water quality dataset of the river basin to draw meaningful information using SPSS 17.0 software.

2.4.1. Principal component analysis

PCA is a pattern recognition technique used to renovate the original variables into reduced and uncorrelated new variables (axes) termed as the principal components (PCs), a linear combination of the original variable [9,17,18]. The reduced variable dataset may assist in the recognition and explanation of trend in water quality varying due to geochemical, hydrologic processes and sources of pollution [19]; PCA depends upon an eigenvector disintegration of the correlation or covariance matrix. The eigenvalues of the PCs are the measure of their associated variance, the participation of the original variables in the PCs is given by the loadings, and the coordinates of the objects are called scores [20]. Here PCA was performed to take out significant PCs from dataset of water quality parameters at all the sampling sites in order to assess variations of water quality in river during pre- and post-monsoon, which would help in identifying the possible contributing sources by some trace metals.

2.4.2. Cluster analysis

This statistical technique is used to identify groups or clusters of similar sites based on similarities within

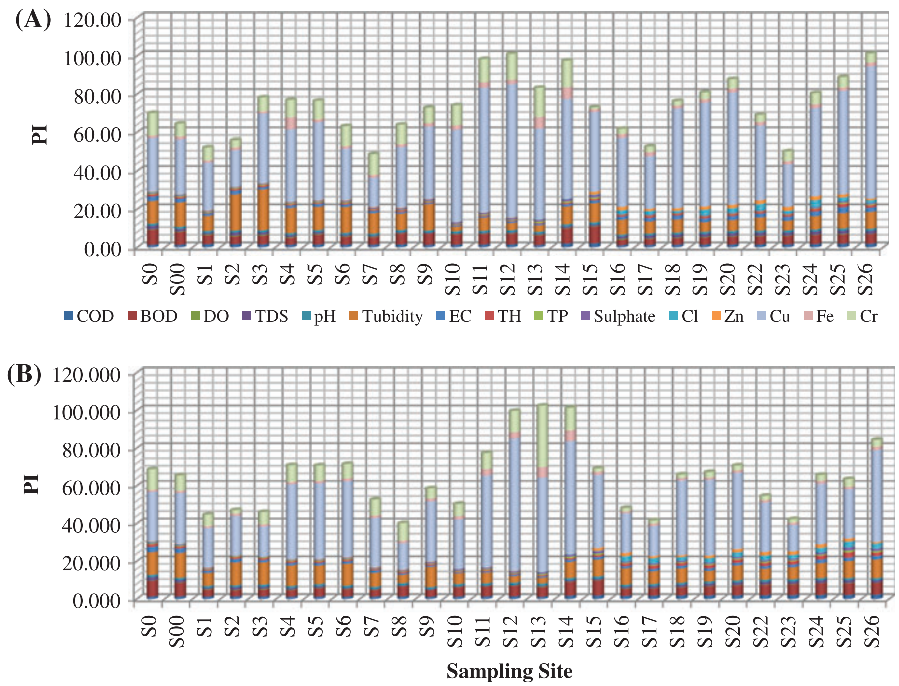


Fig. 2. PI of water quality parameters during pre- (A) and post-monsoon (B) (2013–14).

a class and dissimilarities between different classes [21]. In this paper, the Hierarchical Cluster Analysis (HCA) on basis of Ward method is performed to determine the similarities among the sampling stations. The most similar sampling stations are grouped in one cluster and the process repeated until all points belong to one cluster [22,23]. The results gained are being presented in a two-dimensional dendrogram plot. HCA involves the evaluation of proximity matrix of squared Euclidean distance along with an agglomeration schedule for clustering similar locations.

3. Results and discussions

3.1. Water pollution assessment

The water quality assessment of river Hindon has been done during pre- and the post-monsoon season (2013–14). The CPI clearly indicates that the river Hindon was severely polluted i.e. CPI: 2.68–7.12. The CPI calculated for each sampling location falls beyond the range, i.e. ≥2.01 which represents that water quality of the ricer is severely polluted in both the seasons (Table 1). Overall, the results of this study are in agreement with other studies conducted by many researchers [6,7] on the same river. To know the variation in water quality due to dilution in monsoon month, a CPI plot has been shown in Fig. 3.

Fig. 3 shows that, there has been very minute improvement in water quality in the post-monsoon as compared to pre-monsoon season, even though the water quality of the river is severely polluted. This result indicates that there is high anthropogenic pressure on the river which is beyond its assimilative capacity or tolerance capability.

3.2. Clustering of sample locations

To make out the clusters of sampling locations and to derive similar and dissimilar polluted sites, HCA was performed using the datasets of water quality parameters considered in study for both pre- and post-monsoon season as shown as a dendrogram plot in Fig. 4. Many applications of CA to assess water quality have been reported [8,21,24,25]. The agglomeration schedule in the pre-monsoon season gained two clusters; Cluster one may be featured to the anthropogenic sources while cluster two shows both anthropogenic and natural sources. The first cluster comprises S0, S00, S1, S3, S6, S8, S9, S12, S14, S16, S18, S19, and S24 locations while rest other sampling locations are constituted in the second cluster. Similarly, post-monsoon also gained two clusters, in which the first cluster comprises S0, S1, S3, S4, S8, S12, S14, S16, S18, S19, S20, S23, and S25 locations and second cluster constitutes rest other sampling locations. The result reveals that the locations S0, S1, S3, S8, S12, S14, S16, S18, and S19, in the first cluster have similar pollution level while the rest of the sites in the second cluster

Table 1
Water pollution at each sampling location

Sampling sites	CPI (Pre-monsoon)	CPI (Post-monsoon)	Polluted
S0	4.664	4.583	Severely
S00	4.296	4.367	Severely
S1	3.485	2.983	Severely
S2	3.738	3.142	Severely
S3	5.208	3.072	Severely
S4	5.123	4.729	Severely
S5	5.096	4.721	Severely
S6	4.209	4.771	Severely
S7	3.253	3.517	Severely
S8	4.260	2.682	Severely
S9	4.856	3.908	Severely
S10	4.936	3.360	Severely
S11	6.550	5.162	Severely
S12	6.730	6.648	Severely
S13	5.548	6.832	Severely
S14	6.493	6.757	Severely
S15	4.867	4.617	Severely
S16	4.114	3.217	Severely
S17	3.518	2.778	Severely
S18	5.087	4.401	Severely
S19	5.386	4.486	Severely
S20	5.851	4.719	Severely
S21	4.604	3.646	Severely
S22	3.349	2.821	Severely
S23	5.361	4.385	Severely
S24	5.923	4.239	Severely
S25	6.747	5.627	Severely
S26	8.654	7.140	Severely
S27	10.365	5.770	Severely

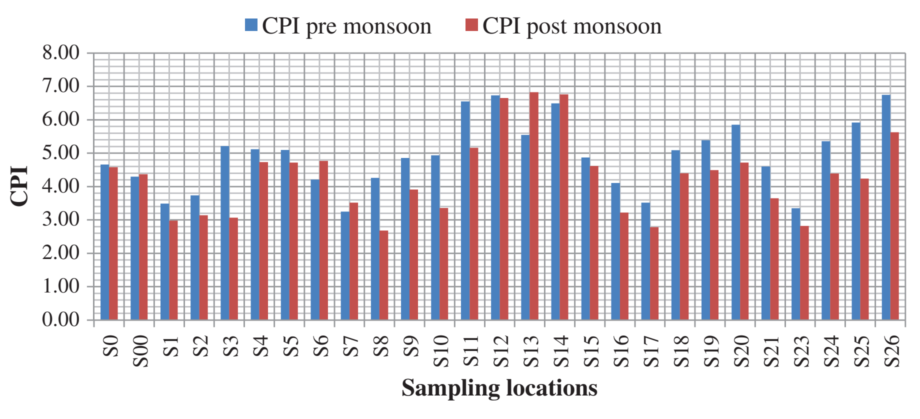


Fig. 3. Variation of CPI during pre- and post-monsoon.

have parallel results as above. However, the major variation in water pollution is observed in location S00, S4, S6, S9 S20, S23, S24, and S25 during pre- and post-monsoon, which is mainly due to geographical location of the sites as it acts as a support to dilute the river during rainy season.

3.3. Relationships between the water quality parameters

The inter-metal interactions may signify the pathways and input sources of the type of effluents that alter the concentration of different water quality parameters and heavy metals present in the particular

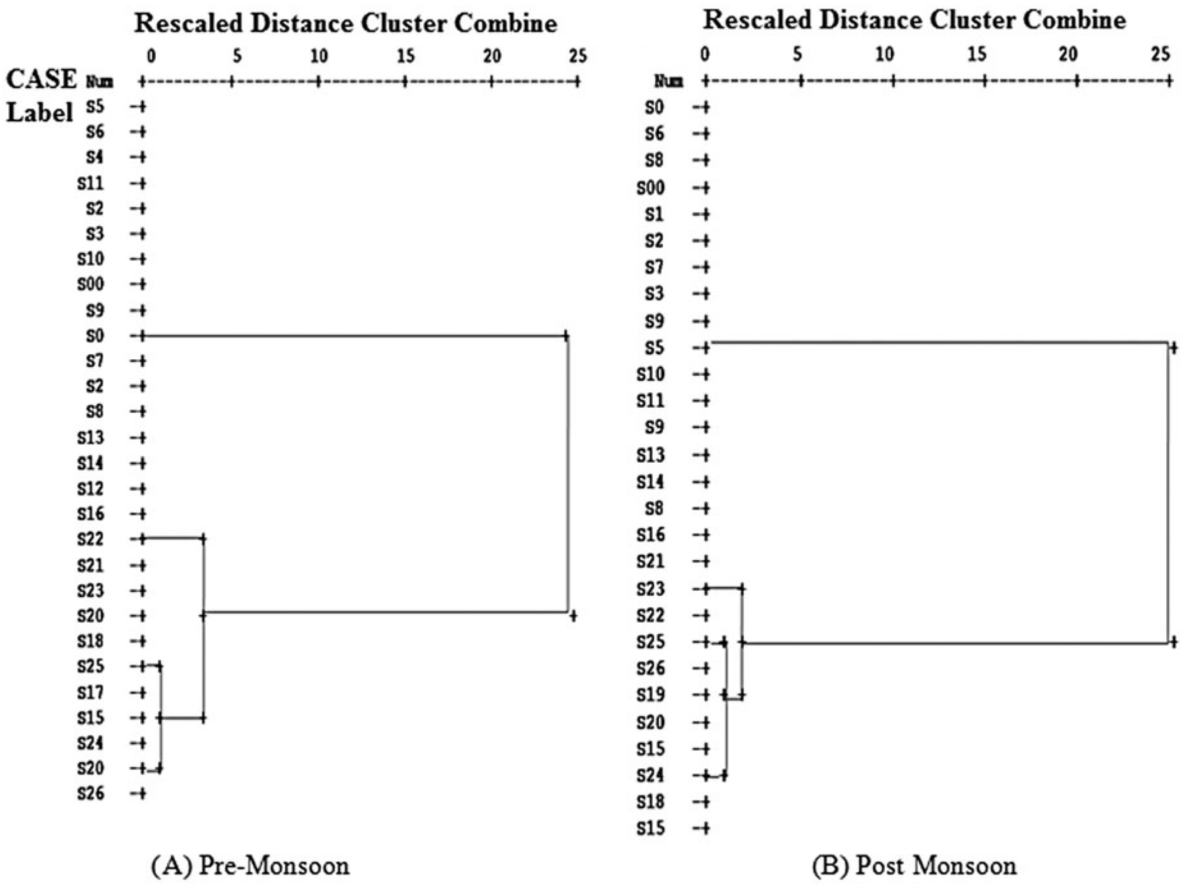


Fig. 4. Dendrogram using Ward Method.

media [7,26]. Pearson's correlation coefficient analysis was performed from the mean value of pre- and post-monsoon analysed water quality parameters; using SPSS 17.0 software (Table 2). It can be clearly observed that except DO and Cr, all water quality parameters have strong relationship in COD, which indicates natural input source i.e. from parental rocks. The higher correlation coefficient of BOD to COD and lower with DO is significance of local anthropogenic pollution like industrial and domestic wastes. The negative correlation of DO with pH signifies that water is not suitable for life, while the positive correlation of pH with TDS, chloride and TP is an indication of significant contribution of more organic and inorganic salts in the river Hindon [27]. The correlation between TDS and pH explains the fact that TDS are composed of algae biomass which affects the photosynthesis [28].

Among the heavy metals, Cr-Fe, Cu-Fe, and Cu-Cr show a strong positive relationship, while Zn shows positive relationship only with Cr and negative relationship with Fe and Cu. The strong relationship of COD with Cu, Zn and Fe clearly reflects that the river receives huge amount of discharge from chemical industries. These strong correlations among metal–metal pair may be an indication of common input sources of these metals as well as similar geochemical characteristics. The positive correlation coefficients among water quality parameter clearly indicate their actual characteristics, a mutual dependency and common input source of these heavy metals.

3.4. Source identifications

In order to further validate the relationship among the water quality parameters and to identify the input source to obtain more reliable information, PCA was performed [17,18,20,29–31], with Varimax normalized rotation (VNR) using SPSS 17.0. The Kaiser–Meyer–Olkin (KMO) and Bartlett's tests [19,25,26,30,32] were performed before performing the factor analysis and are shown in Table 3. The KMO were found as 0.689 and 0.683 (i.e. KMO > 0.5) for both pre- and post-monsoon respectively. In order to have clear idea of the data trends, PCA is represented by loadings and score

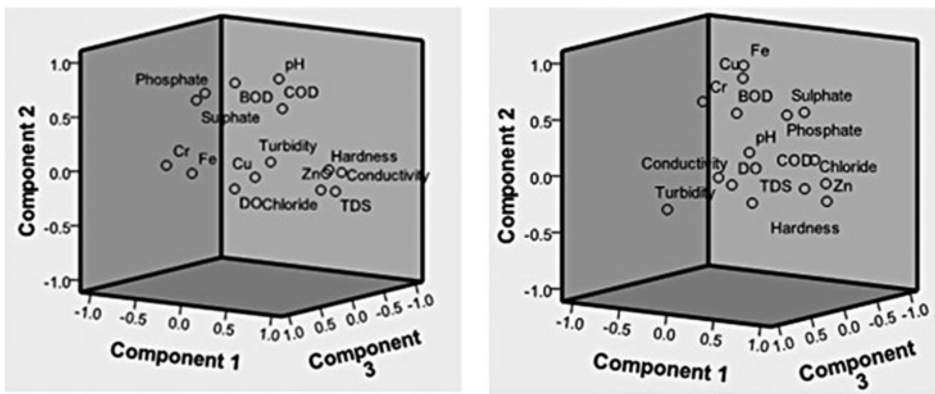
Table 2
Pearson's correlation coefficients of the parameters using mean values during 2013–14

		COD	BOD	DO	TDS	pH	Turbidity	EC	TH	TP	SO_4	Cl	Zn	Cu	Fe	Cr
Correlations	COD	1.000														
	BOD	0.421	1.000													
	DO	−0.396	−0.416	1.000												
	TDS	0.403	−0.139	−0.274	1.000											
	pH	0.348	0.430	−0.233	0.036	1.000										
	Turbidity	0.054	0.084	0.329	0.027	−0.115	1.000									
	Cond.	0.431	−0.113	−0.218	0.929	0.211	0.003	1.000								
	TH	0.538	−0.049	−0.395	0.872	0.159	−0.018	0.901	1.000							
	TP	0.496	0.661	−0.040	−0.248	0.290	0.215	−0.163	−0.059	1.000						
	SO_4	0.454	0.638	−0.415	−0.332	0.220	−0.226	−0.296	−0.048	0.725	1.000					
	Cl	0.203	−0.348	−0.255	0.670	0.126	−0.397	0.682	0.665	−0.468	−0.277	1.000				
	Zn	0.224	−0.291	−0.171	0.608	0.188	−0.399	0.637	0.584	−0.450	−0.238	0.869	1.000			
	Cu	0.518	0.119	−0.561	0.473	−0.054	−0.351	0.341	0.509	0.154	0.321	0.370	0.238	1.000		
	Fe	0.202	0.082	−0.152	0.035	−0.057	−0.216	−0.069	0.048	0.394	0.407	−0.013	−0.139	0.452	1.000	
	Cr	−0.194	0.331	−0.117	−0.475	−0.127	−0.058	−0.510	−0.379	0.415	0.439	−0.536	−0.704	0.063	0.435	1.000

Note: Determinant = 8.25E-009 and Sig. (1-tailed).

Table 3
KMO and Bartlett's test

		Pre-monsoon	Post-monsoon
Kaiser–Meyer–Olkin Measure of Sampling Adequacy		0.683	0.689
Bartlett's test of sphericity	Approx. Chi-Square	357.939	412.583
	Degree of freedom	105	105
	Significance	0.000	0.000



Pre monsoon Post monsoon

Fig. 5. PCA loadings and score plot of water quality parameters.

Table 4
PCA Components values and Communalities of water quality parameters

Parameters	PCs gained from pre-monsoon analysis				Communalities extraction	PCs gained from post-monsoon analysis				Communalities extraction
	1	2	3	4		1	2	3	4	
Initial Eigenvalues	5.150	3.725	1.782	1.384		6.105	3.122	1.684	1.231	
% of Variance	34.336	24.831	11.881	9.226		40.700	20.813	11.225	8.208	
Cumulative %	34.336	59.167	71.049	80.275		40.700	61.513	72.738	80.946	
EC	0.893	0.085	0.254	0.175	0.900	0.949	0.087	−0.172	−0.026	0.908
TDS	0.892	0.077	0.125	0.325	0.933	0.929	−0.203	−0.097	0.142	0.881
Cl	0.886	−0.083	−0.234	−0.154	0.884	0.865	−0.139	−0.354	0.150	0.934
TH	0.859	0.282	0.144	0.230	0.897	0.786	−0.205	−0.426	0.026	0.934
Zn	0.857	−0.129	−0.106	−0.319	0.902	0.773	−0.371	0.336	0.164	0.875
Cr	−0.657	0.376	−0.338	0.214	0.762	0.768	0.456	−0.130	0.077	0.836
SO_4	−0.311	0.831	−0.116	−0.168	0.837	0.750	0.489	0.064	0.120	0.886
TP	−0.397	0.749	0.323	0.141	0.930	0.640	−0.228	0.620	0.209	0.839
BOD	−0.267	0.735	0.341	−0.238	0.843	0.577	0.442	0.436	−0.130	0.737
COD	0.395	0.712	0.325	0.072	0.792	−0.060	0.918	0.053	0.171	0.939
DO	−0.319	−0.612	0.244	0.211	0.907	0.158	0.789	0.139	−0.158	0.915
Cu	0.452	0.595	−0.415	0.274	0.815	−0.519	0.600	0.183	0.415	0.720
Fe	−0.082	0.516	−0.472	0.394	0.836	0.103	−0.473	0.745	−0.116	0.888
Turbidity	−0.223	−0.158	0.741	0.501	0.891	−0.266	−0.113	0.016	0.859	0.806
pH	0.153	0.384	0.397	−0.622	0.757	0.317	0.342	0.132	−0.319	0.836

plot as shown in Fig. 5. The PCA results gained four PCs (Fig. 5.) with eigenvalues >1, cumulative variance of 80.275% (pre-monsoon) and 80.946% (post-monsoon). The PCs values obtained are shown in Table 4.

The PCA of pre-monsoon was analysed and results reveal that PC1 shows strong positive loadings on Zn, conductance, TDS, Chloride, TH and indicating common sources of pollution. PC2 has strong positive loadings on sulphate, phosphate, BOD, COD, Cr, Cu and Fe, whereas PC3 and PC4 have positive loading on pH and turbidity. A comparative analysis of PCA during pre- and post-monsoon has been shown in Fig. 5. It shows a variation in PCs loading for sulphate, phosphate, BOD, DO, Cr, and pH which may be an indication of the change in PCs loading due to monsoonal dilution. The extraction of water quality parameters gets reduced during post-monsoon, except Cl, TH, SO_4, Cr, COD and DO as shown in Table 4. The varying trend of extraction of the water quality parameters from pre- to post-monsoon also verifies the impact of dilution in the river water while increase in extraction of Cr indicates its major input sources from parental rocks and agricultural runoff. The water quality parameters whose loading were not altered by monsoonal variation were observed due to similar patterns seen in the river water samples in both the seasons (pre- and post-monsoon) and also due to mixed effluent sources of these parameters in the Hindon River. This analysis clearly indicates the influence of anthropogenic activities on the water with respect to described water quality parameters and heavy metals. These clusters of water quality parameters also reflect the extent of organic pollution and eutrophication in the river, indicating the main stem of anthropogenic pollution from the discharge of untreated industrial and domestic sewage. The water quality of river Hindon at all sites in both season was found to be severely polluted, and it has been verified by PCA. It says that—severe pollution of Hindon is due to direct discharge of untreated wastewater from different industries and domestic sector joining the river. The management of water quality in Hindon River is required to control the entrance of external contaminant.

4. Conclusions

In the present study, the CPI, PCA and CA are evaluated for 28 sampling locations at Hindon River using water quality parameters during 2013–14. CPI clearly indicates that the river Hindon was severely polluted (CPI >2 i.e. 2.68–7.12). The CA result was obtained based on the similarity and dissimilarity in water quality characteristics and after grouping all sampling sites into two clusters. As per Pearson's correlation matrix and PCA, the major source of river water pollution is the direct discharge of untreated wastewater from nearby industries containing toxic waste and domestic sector. The study clearly shows that the CPI, PCA and CA are useful tools for evaluating pollutants in human-affected water bodies and river water classification. It is further recommended that to maintain the aesthetic value of Hindon River, conservation plan should be taken in advance.

Acknowledgement

The author (PS) is thankful to MHRD, Government of India for financial assistance in the form of academic scholarship during his M.Tech (EMRL, IIT Roorkee) and also thankful to Mr Samrath Sharma (EMRL) for their help in sampling and laboratory testing. Authors are thankful to the reviewers for their fruitful comments.

References

[1] F.A. Khan, A.A. Ansari, Eutrophication: An ecological vision, Bot. Rev. 71 (2005) 449–482.
[2] T.G. Kazi, M.B. Arain, M.K. Jamali, N. Jalbani, H.I. Afridi, R.A. Sarfraz, J.A. Baig, A.Q. Shah, Assessment of water quality of polluted lake using multivariate statistical techniques: A case study, Ecotoxicol. Environ. Saf. 72 (2009) 301–309.
[3] G.J. Niemi, P. DeVore, N. Detenbeck, D. Taylor, A. Lima, Overview of case studies on recovery of aquatic systems from disturbance, Environ. Manage. 14 (1990) 571–587.
[4] W. Duan, K. Takara, B. He, P. Luo, D. Nover, Y. Yamashiki, Spatial and temporal trends in estimates of nutrient and suspended sediment loads in the Ishikari River, Japan, 1985 to 2010, Sci. Total Environ. 461 (2013) 499–508.
[5] W. Duan, B. He, K. Takara, P. Luo, D. Nover, N. Sahu, Y. Yamashiki, Spatiotemporal evaluation of water quality incidents in Japan between 1996 and 2007, Chemosphere 93 (2013) 946–953.
[6] S. Suthar, J. Sharma, M. Chabukdhara, A.K. Nema, Water quality assessment of river Hindon at Ghaziabad, India: impact of industrial and urban wastewater, Environ. Monit. Assess. 165 (2010) 103–112.
[7] M.K. Sharma, C.K. Jain, O. Singh, Characterization of point sources and water quality assessment of river Hindon using water quality index, J. Indian Water Res. Soc. 34 (2014) 53–64.
[8] Y. Zhao, X.H. Xia, Z.F. Yang, F. Wang, Assessment of water quality in Baiyangdian Lake using multivariate statistical techniques, Procedia Environ. Sci. 13 (2012) 1213–1226.
[9] C. Sarbu, H.F. Pop, Principal component analysis versus fuzzy principal component analysis a case study: The quality of danube water (1985–1996), Talanta 65 (2005) 1215–1220.

[10] R. Reghunath, T.R.S. Murthy, B.R. Raghavan, The utility of multivariate statistical techniques in hydrogeochemical studies: An example from Karnataka, India, Water Res. 36 (2002) 2437–2442.
[11] V. Simeonov, P. Simeonova, R. Tsitouridou, Chemometric quality assessment of surface waters: Two case studies, Chem. Eng. Ecol. 11 (2004) 449–469.
[12] American Public Health Association (APHA), Standard Methods for the Examination of Water and Waste Water, 20th ed., Washington, DC, 1998.
[13] Central Pollution Control Board (CPCB), Report on Status of Quality in India. Central Pollution Control Board, Monitoring of Indian National Aquatic, Resources, 2011.
[14] The Environment (Protection) Rules 1986, Environment (Protection) Amendment Rules 1996, Notified by GSR, 176.
[15] Indian Standard Specification for Drinking Water, Bureau of Indian Standards, BIS: 10500, 1991.
[16] World Health Organization, Guidelines for Drinking Water Quality, fourth ed., 2011.
[17] P. Villegas, V. Paredes, T. Betancur, L. Ribeiro, Assessing the hydrochemistry of the Urabá Aquifer, Colombia by principal component analysis, J. Geochem. Explor. 134 (2013) 120–129.
[18] R.L. Olsen, Rick W. Chappell, J.C. Loftis, Water quality sample collection, data treatment and results presentation for principal components analysis—Literature review and Illinois River watershed case study, Water Res. 46 (2012) 3110–3122.
[19] W. Petersen, L. Bertino, U. Callies, E. Zorita, Process identification by principal component analysis of river water-quality data, Ecol. Modell. 138 (2001) 193–213.
[20] K. Bengraïne, T.F. Marhaba, Using principal component analysis to monitor spatial and temporal changes in water quality, J. Hazard. Mater. 100 (2003) 179–195.
[21] P.R. Kannel, S. Lee, S.R. Kanel, S.P. Khan, Chemometric application in classification and assessment of monitoring locations of an urban river system, Anal. Chim. Acta 582 (2007) 390–399.
[22] G. Birth, A scheme for assessing human impacts on coastal aquatic environments using sediments, in: C.D. Woodcoffe, R.A. Furness, Coastal GIS, 2003.
[23] Å. Danielsson, I. Cato, R. Carman, L. Rahm, Spatial clustering of metals in the sediments of Skagerrak/Kattegat, Appl. Geochem. 14 (1999) 689–706.
[24] S. Li, J. Li, Q. Zhang, Water quality assessment in the rivers along the water conveyance system of the Middle Route of the South to North Water Transfer Project (China) using multivariate statistical techniques and receptor modeling, J. Hazard. Mater. 195 (2011) 306–317.
[25] K.P. Singh, A. Malik, S. Sinha, Water quality assessment and apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques—A case study, Anal. Chim. Acta 538 (2005) 355–374.
[26] B. Parinet, A. Lhote, B. Legube, M.A. Gbongue, Etude analytique et statistique d'un systeme lacustre soumis à divers processus d'eutrophisation (Study Analytical and Statistical Subject of a Lacustrine System to Variety Eutrophication), Rev. Sci. Eau. 13 (2001) 237–267.
[27] G. Muyzer, A.J.M. Stams, The ecology and biotechnology of sulphate-reducing bacteria, Nat. Rev. Microbiol. 6 (2008) 441–454.
[28] Y. Ouyang, Evaluation of river water quality monitoring stations by principal component analysis, Water Res. 39 (2005) 2621–2635.
[29] B. Selle, M. Schwientek, G. Lischeid, Understanding processes governing water quality in catchments using principal component scores, J. Hydrol. 486 (2013) 31–38.
[30] R.M. Page, G. Lischeid, J. Epting, P. Huggenberger, Principal component analysis of time series for identifying indicator variables for riverine groundwater extraction management, J. Hydrol. 432–433 (2012) 137–144.
[31] Y. Xu, C. Ma, S. Huo, B. Xi, G. Qian, Performance assessment of water quality monitoring system and identification of pollution source using pattern recognition techniques: A case study of Chaohu Lake, China, Desalin. Water Treat. 47 (2012) 182–197.
[32] I. Triki, N. Trabelsi, M. Zairi, H.B. Dhia, Multivariate statistical and geostatistical techniques for assessing groundwater salinization in Sfax, a coastal region of eastern Tunisia, Desalin. Water Treat. 52 (2014) 1980–1989.