Pollution, 3(3): 349-362, Summer 2017
DOI: 10.7508/pj.2017.03. 001
Print ISSN: 2383-451X Online ISSN: 2383-4501
Web Page: https://jpoll.ut.ac.ir, Email: jpoll@ut.ac.ir

Evaluation of seasonal variability in surface water quality of Shallow Valley Lake, Kashmir, India, using multivariate statistical techniques

Ishtiyaq, A.N.[1*], Anisa, B.K.[2] and Abdul, H.[3]

1. P.G. Department of Environmental Sciences, S.P. College, Kashmir (J&K), India-190001
2. Department of Ecology and Environmental Sciences, Pondicherry Central University, Puducherry, India-605014
3. Department of Zoology, S.P. College, Kashmir-190001, India

Received: 2 Oct. 2016 Accepted: 21 Feb. 2017

ABSTRACT: Seasonal variation in water quality of Anchar Lake has been evaluated, using two multivariate statistical techniques, namely Principal Component Analysis (PCA) and Cluster Analysis (CA). Water quality data, collected during four seasons, have been analyzed for 13 parameters and ANOVA has shown that pH (F_3= 10.86, P < 0.05), temperature (F_3 = 65, P < 0.05), electrical conductivity (F_3= 32.72, P < 0.05), Calcium (F_3= 36.84, P < 0.05), Magnesium (F_3= 16.52, P < 0.05), nitrate-nitrogen (F_3= 48.06, P < 0.05), ammonical nitrogen (F_3 =198.75, P < 0.05), and dissolved oxygen (F_3= 4.96, P < 0.05) varied by season, whereas the substantial variations of sodium (F_2= 7.18, P <0.05), phosphate-phosphorous (F_2= 25.31, P < 0.05), biological oxygen demand (F_2= 11.02, P < 0.05), and chemical oxygen demand (F_2=37.73, P < 0.05) were based on different sites. CA has grouped the three sampling sites throughout the four seasons into three clusters of similar water quality as relatively Less-Polluted (LP), Medium-Polluted (MP), and Highly-Polluted (HP). In addition, PCA has been applied on the extract to recognize the factors, responsible for water quality variations in four seasons of the year, resulting in four principal components for winter, summer, and autumn, five ones for spring, accounting for 79.58%, 89.07%, 83.34%, and 93.13% of total variance respectively. Thus the factors, responsible for water quality variation, are mainly related to domestic wastewaters, seasonal variation, agricultural runoff, and catchment geology. These results will help decision-makers better understand the influence of various factors on water quality and manage pollution/eutrophication adaptively in Anchar Lake.

Keywords: Anchar Lake, cluster analysis, PCA, pollution, water quality.

INTRODUCTION

Surface waters such as shallow lakes are dynamic systems, characterized by a high degree of heterogeneity in space and time (Papatheodorou et al., 2006). The difference of dissolved ions concentration in surface water is generally governed by lithology, quantity of water flow, nature of geochemical reactions, solubility of salts, and human activities (Takaijudin et al., 2016; Parmar & Bhardwaj, 2013). At present, one of the most common ecological problems of

* Corresponding author Email: ishtiyaq.env@gmail.com

inland water bodies is eutrophication, where water quality is impaired by spurring the excessive algae growth while the concentration of suspended organic material as well as heavy metal is increased (Wong et al., 2017; Noori et al., 2012; Ali et al., 2017). Eutrophication is most often the result of an elevated supply of nutrients, particularly nitrogen and phosphorus, which in turn enhances primary productivity (Najar & Khan 2013, 2012a, 2012b). Catchment area development, urbanization, and changes in hydrology affect the structure and function of these ecosystems (Mallick et al., 2016; Loganathan et al., 2015; Tian et al., 2012; Najar & Khan 2011). As human populates the watershed, deterioration of such environments has become a critical issue, in which excessive use of fertilizers in agricultural activities along with the inflow of domestic waste water greatly threatens surface water (Shin et al., 2013; Najar 2012; Ramachandra et al., 2014; Noori et al., 2015), diminishing its usefulness for drinking, industrial, agriculture, and recreation purposes. Further, dumping wastes into the lakes also poses a threat, as decaying waste influences phosphates, nitrates, ammonia, and total solids (Yidanaa et al., 2008), thus affecting their functions and services. Therefore, it is essential to monitor water quality of the lakes for sustainable use (Virkutyte & Sillanpää, 2006). Long-term monitoring, however, generates a large and complex database that needs a good approach for interpretation (Zhang et al., 2009). Thus multidimensional scaling analysis helps interpreting complex datasets, allowing a better understanding of spatial variations in water quality. These techniques are valuable tools to develop appropriate strategies for effective management of the water resources (Rajbira & Anishb, 2016). In the present study, water quality data matrix is subjected to different multivariate statistical techniques in order to extract some information about the similarities or dissimilarities of sampling sites during different seasons and to identify variables, responsible for any alteration and its sources.

MATERIALS AND METHODS

The Valley of Kashmir is a lacustrine basin of the intermountain depression, located between the Lesser and Greater Himalayas, which is characterized by numerous aquatic ecosystems of great ecological and economic importance. Freshwater lakes of Kashmir Himalayas have multiple important usages, such as being a source of drinking water, irrigation, navigation, fishery, agriculture, socioeconomic development, and recreation. However, in recent decades, the lake's ecosystem has changed drastically, having developed an exacerbated trend due to the disturbances in the catchment areas. As a result of anthropogenic pressures, the lake surface area is shrinking as the water quality deteriorates. The main problem of these lakes is nutrient enrichment from the catchment area in the form of domestic wastewaters and runoff from agricultural fields (Najar & Khan, 2012a).

Anchar Lake is a shallow basin lake within the geographical coordinates of 34°07′ to 34°10´ N latitude and 74°46′ to 74°48′ E longitude (Fig. 1). It is situated 14 km to the North-west of Srinagar city at an altitude of 1583 m above m.s.l, covering an area of 0.73 km^2. The lake is fed by Sindh Nallah as well as a number of springs, present in and along the periphery of the basin. The lake also gets water from the Khushalsar Lake via Achan Nallah. The catchment of the lake is comprised of arable land under paddy cultivation, vegetable gardens with multiple crops, and residential areas. The main threats to the lake are encroachment, sedimentation, agricultural runoff, dumping of domestic/municipal wastewaters, and effluents from Sher-i-Kashmir Institute of Medical Sciences (SKIMS).

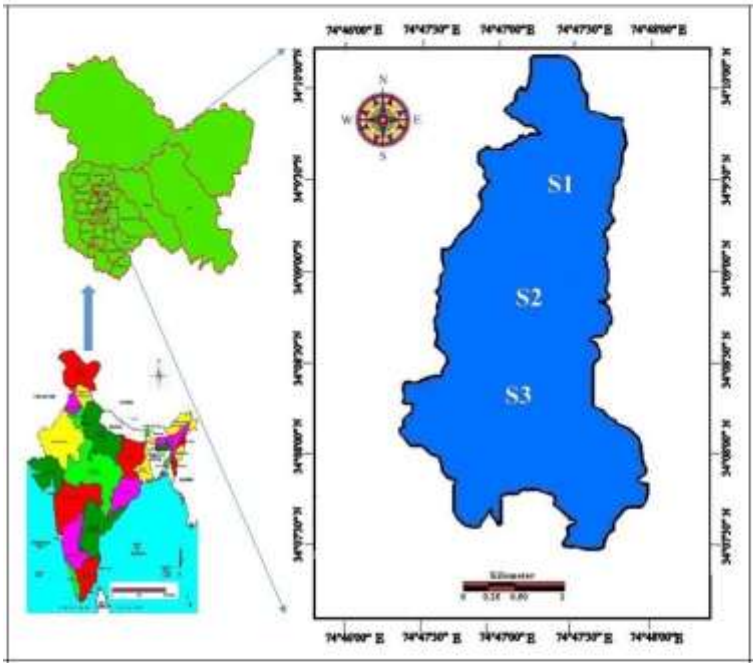

Fig. 1. Outline map of Anchar Lake, showing the sampling sites

Water samples were collected monthly from three sites of the lakes. They were kept in 1-liter polyethylene plastic bottles, which were cleaned before with metal-free soap, rinsed repeatedly with distilled water, and soaked in 10% nitric acid for 24 h, eventually to be rinsed with ultrapure water. All water samples were stored in insulated coolers, containing ice, and were taken on the same day to the laboratory to be stored at 4°C until processing and analysis (APHA, 2005).

Temperature (T) of water was measured in situ, using mercury centigrade thermometer (Ree, 1953). To measure the pH and electrical conductivity (EC), pH meter (Bates, 1978) and conductivity meter (Jasper, 1988) had been employed respectively. Calcium (Ca) and magnesium (Mg) concentrations were determined by versenate method (Katz & Navone, 1964), while Ammonium nitrogen (NH_4-N) and nitrate nitrogen (NO_3-N) were determined by phenate (Solorzano, 1969) and phenyldisulfonic acid method (Brown & Bellinger, 1978), respectively, using spectrophotometer. Phosphate phosphorous (PO_4-P) was determined by molybdate method (Edwards et al., 1965). Dissolved Oxygen content (DO) and Biochemical Oxygen Demand (BOD_5) were determined, using Winkler's method (Mancy & Jaffe, 1966). Chemical Oxygen Demand (COD) was estimated by dichromate method (Pitwell, 1983), while Sodium (Na) and potassium (K) were analyzed, using flame photometer (Thompson & Reynolds, 1978).

Aiming to evaluate significant differences within and among the sites for all water quality variables, the data was analyzed, using multivariate statistical techniques (Zar, 2009): two-way analysis of variance (ANOVA) at 0.05% level of significance, Cluster Analysis (CA), and Principal Component Analysis (PCA). All statistical analyses were performed using the SPSS statistical software (Version 16) and PAST statistical software (Version 1.93). Multivariate statistical methods have been applied widely to investigate water quality (Boyacioglu & Boyacioglu, 2008; Noori et al., 2010; Najar & Khan, 2012a; Yidanaa et al., 2008; Simeonova et al., 2010; Shrestha & Kazama, 2007). The combined use of principal component analysis (PCA) and cluster analysis enabled the classification of water samples into distinct groups on the basis of their physicochemical characteristics.

RESULTS AND DISCUSSION

Figure 2 gives water quality parameters, measured from different sampling sites. There was a significant variation ($P < 0.05$) in physicochemical characteristics within and among the sampling sites during the study. Due to its influence on nutrients' solubility and availability as well as their utilization by aquatic organisms, pH becomes an important factor. It varied significantly throughout the seasons (F_3= 10.86, $P < 0.05$), having no significant variation within the sites (F_2= 1.68, $P < 0.05$), ranging between 7.13±0.07 and 7.52±0.17 (Fig. 2a). The pH range from 6.0 to 8.5 indicates productive nature of the water body (Garg et al., 2010). Temperature plays a vital role in controlling the chemical and biological composition of a freshwater body. In the present study, it ranged between 6.5±1.31°C and 19.3±1.38°C, showing a significant variation among the seasons (F_3= 265, $P < 0.05$), but no substantial change among the sites (F_2= 4.48, $P < 0.05$). EC showed a major variation among the sites (F_2= 8.45, $P < 0.05$) as well as the seasons (F_3= 32.72, $P < 0.05$), having a maximum value of 0.37±0.04 mS/m at Site-I during spring. It accounts for the nutrient load of the lake as it is subjected to high degree of anthropogenic activities such as wastewater discharges and agricultural runoff. Figure 2b illustrates the concentration of different cations. The variations of Ca was significant among the seasons (F_3= 36.84, $P < 0.05$), but not so among the sites (F_2= 4.38, $P < 0.05$); it ranged between 19.73±1.38 and 50.26±3.01 mg/l. As for Mg, it ranged from 9.67±0.66 mg/l to 20.47±1.55 mg/l, showing a substantial variation among the seasons (F_3= 16.52, $P < 0.05$) and an insubstantial one among the sites (F_2= 2.48, $P < 0.05$). Na exhibited no significant change among the seasons (F_3= 2.66, $P < 0.05$) but varied significantly within the sites (F_2= 7.18, $P < 0.05$) and recorded a value between 10.74±0.55 mg/l and 17.73±2.33 mg/l. As for K, there was no major change either among the seasons (F_3= 3.04, $P < 0.05$) or within the sites (F_2= 3.30, $P < 0.05$); it ranged between 3.33±2.33 mg/l and 12.75±3.75 mg/l. Among the cations (Ca, Mg, Na, and K), the former is the most dominant one, which is attributed to the predominance of lime rich rocks in the catchment area (Najar & Khan, 2012b, 2012c). PO_4-P differs significantly within the sites (F_2= 25.31, $P < 0.05$) but not among the seasons (F_3= 3.03, $P < 0.05$), reaching a maximum value of 352.30±39.45 µg/l (Fig. 2c). Phosphorous is an essential plant nutrient that stimulates the growth of algae and macrophytes in lakes. It is a proxy indicator of lake productivity (Najar & Khan, 2013; Najar, 2012). PO_4-P enters the lakes through domestic wastewater, accounting for the accelerated eutrophication (Vyas et al., 2006; Najar & Khan 2012c). NO_3-N showed a significant variation among the seasons (F_3= 48.06, $P < 0.05$) but no substantial change within the sites (F_2= 1.41, $P < 0.05$), having a range of 188.82±1.24 µg/l to 236.56±4.90 µg/l. Increased concentration of PO_4-P and NO_3-N in the lakes results in enhanced productivity (Najar et al., 2014). NH_4-N had a value between 262.63±24.14 µg/l and 393.90±5.54 µg/l, differing significantly among the seasons (F_3= 198.75, $P < 0.05$) as well as the sites (F_2= 14.90, $P < 0.05$). Ammoniacal nitrogen is usually high in organically-polluted waters and is also formed by the hydrolysis of urea, released from agricultural fields. Readily available as a nutrient for plant uptake, it may contribute to biological productivity (Sheela et al., 2011). DO showed significant variations among the seasons (F_3= 4.96, P < 0.05) and within the sites (F_2= 135.33, P < 0.05), with a minimum value of 1.4±0.5 mg/l at Site-III during summer and a maximum value of 3.47±0.24 mg/l at Site-I during winter (Fig. 2d). DO is an essential factor for maintaining aquatic life. Its level in lakes varies according to the lake trophic levels. Dissolved oxygen content depends on photosynthetic activity and microbial decomposition of autochthonous and allochthonous organic matter. The overall low dissolved oxygen content in the lake indicates eutrophic condition. Depletion of DO in water probably is the most frequent result of certain forms of water pollution (Najar, 2012; Srivastava et al., 2009). BOD indicates the amount of biologically-active organic matter, present in water (Sheela et al., 2011). It ranged between 7.23±1.5 mg/l and 12±2.2 mg/l, showing no significant variation among the seasons (F_3= 1.48, P < 0.05), though it varied substantially within the sites (F_2= 11.02, P < 0.05). COD differed significantly within the sites (F_2= 37.73, P < 0.05); however, no significant variation was recorded among the seasons (F_3= 1.25, P < 0.05) with a value between 24.66±2 mg/l and 66±6 mg/l. BOD_5 and COD are important parameters that indicate contamination with organic and inorganic wastes (Noori et al., 2011; Najar & Khan 2012b; Najar et al., 2014). Khuhawari et al. (2009) associated higher value of COD with increased anthropogenic pressures on lakes.

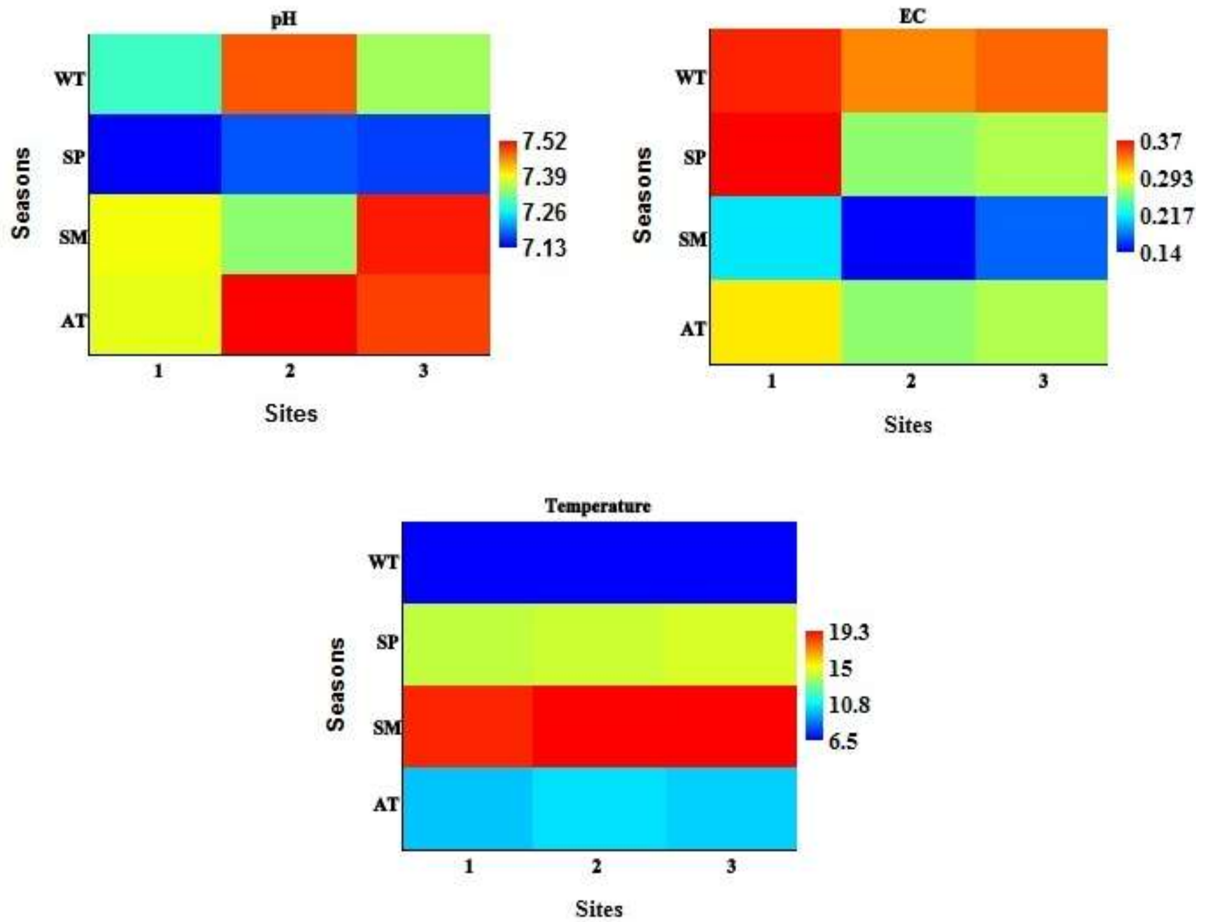

Fig. 2a. pH, electrical conductivity, and temperature, recorded at different sites

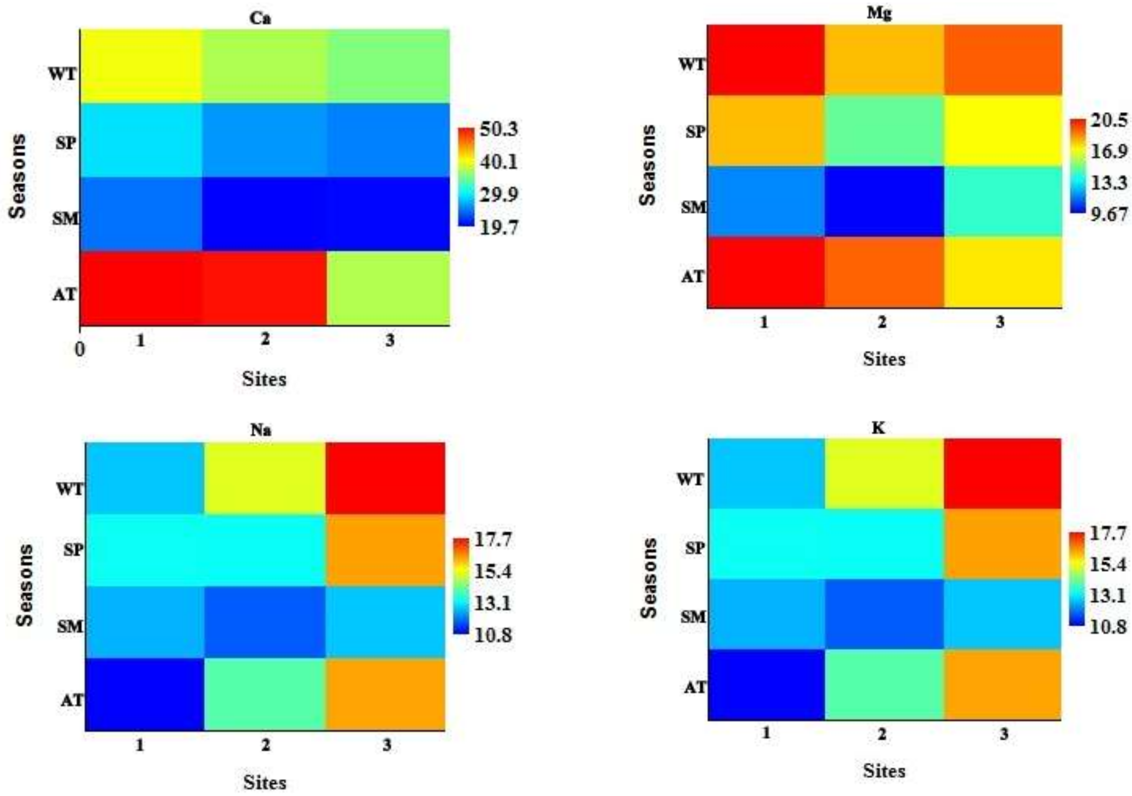

Fig. 2b. Cation concentration at different sites

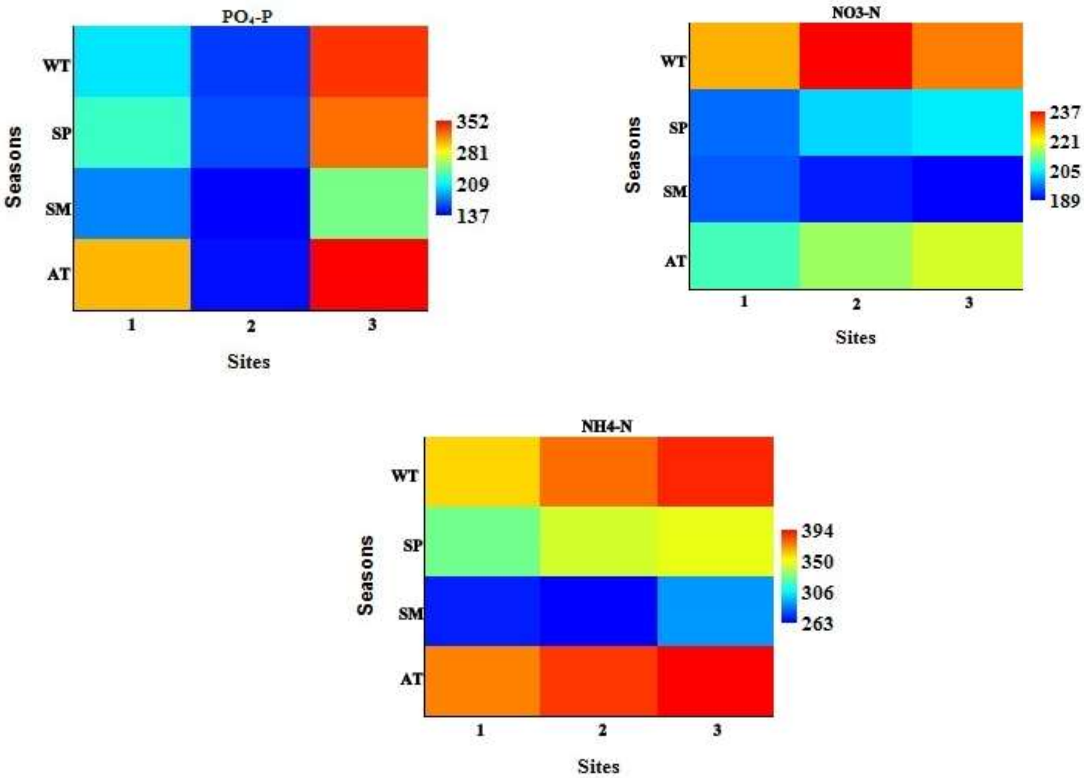

Fig. 2c. Concentration of phosphorous, nitrate-nitrogen, and ammonical-nitrogen at different sites

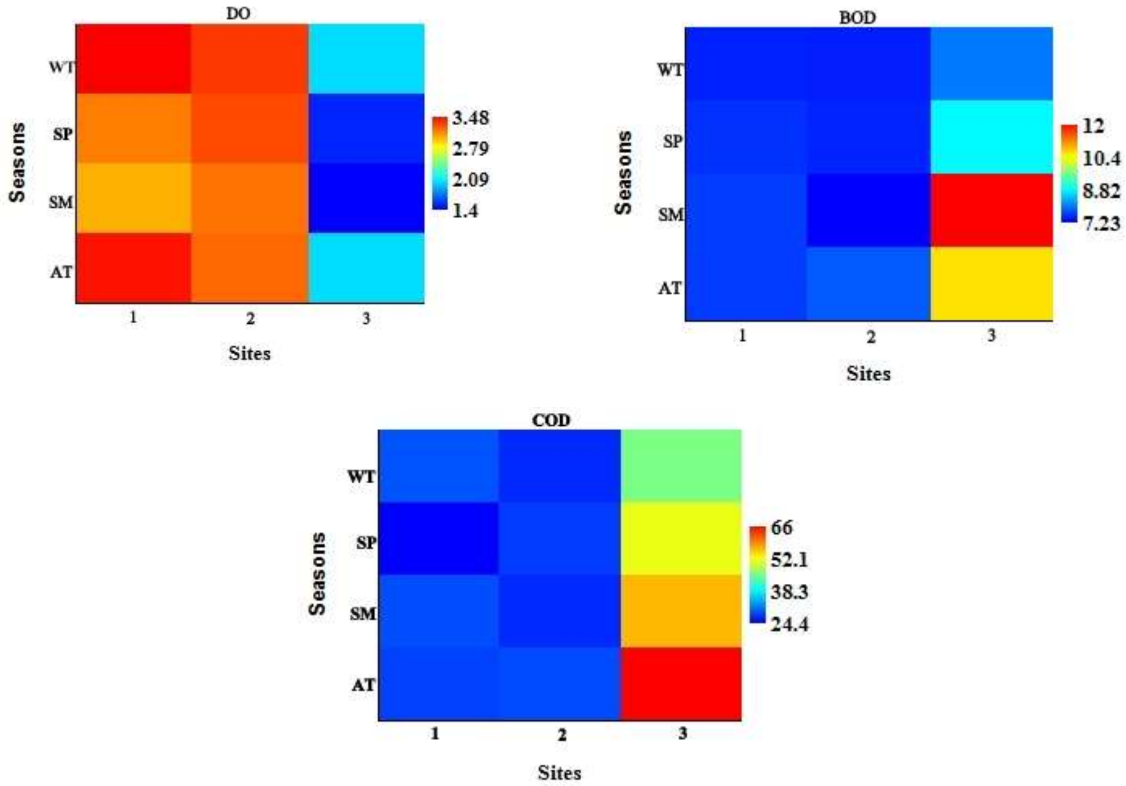

Fig. 2d. Dissolved oxygen, biological oxygen demand, and chemical oxygen demand at different sites

With the help of cluster analysis, similarity among the sampling sites during different seasons has been found out, resulting in a dendrogram (Fig. 3), in which all sampling sites have been grouped into three statistically-marked clusters. Since the present research has employed hierarchical agglomerative cluster analysis, the number of clusters is decided by water quality. Sites WTS2, ATS2, WTS1, and SPS2 form Cluster 1 which comprises low polluted sites (LP) that receive pollutants from non-point sources, mostly from agricultural and catchment runoff. Sites SMS1, SMS2, SPS1, and SMS3 that form Cluster 2 correspond to moderately polluted sites (MP), which receive pollutants mostly from point and non-point sources. The former includes domestic wastewaters while the latter consists agricultural and catchment runoff. Cluster 3, i.e. sites ATSI, SPS3, WTS3, and ATS3, corresponds to highly polluted sites (HP) which receive huge quantities of domestic wastewater. Cluster results revealed different physicochemical characteristics of water at each site, though Site-III remained highly polluted throughout the year, regardless of the season, as the site receives huge amount of wastewater mainly from municipal drains.

Principal Component Analysis (PCA) has been applied to 13 variables for three sampling sites in order to identify variations in water quality. An eigenvalue greater than 1 considered significant (Shrestha & Kazama, 2007) has been regarded as the main criterion for extracting principal components, required to explain the variance in the data. PCA application in order to extract and recognize the factors, responsible for water quality variations in four seasons of the year, resulted in four principal components for winter, summer, and autumn, and five principal components for spring, accounting to 79.58%, 89.07%, 83.34%, and 93.13% of the total variance, respectively. Table 1 presents the different factors, total variance (%), cumulative variance (%), and component loadings for the components of the principal components (PCs) analysis for different seasons. Liu et al., (2003) classified the factor loadings as "strong," "moderate," and "weak," corresponding to absolute loading values of > 0.75, 0.75 - 0.50, and 0.50 - 0.30, respectively. Fig. 4 demonstrates Biplots (1+2 components) of factor loading during different seasons.

Considering the dataset, related to winter season, among the four PCs, the PC1, explaining 23.97% of the total variance, has strong positive loading on Ca and Mg, and strong negative loading on EC (Table 1a). Najar and Khan (2012a) associated positive loading of Ca and Mg with parent rock materials in the catchment area. Negative loading of EC has been associated with lower temperature, as the solubility of salts decreases at lower temperature (Jyoti & Akhtar, 2007). PC2, explaining 22.93% of total variance, has a strong positive loading on Na, moderate positive loading on BOD_5, K, and PO_4-P, yet strong negative loading on DO. Positive loading on Na, K, and PO_4-P has been associated with agricultural runoff (Juahir et al., 2011). PC3, explaining 20.97%, of total variance has strong positive loading on COD and moderate positive loading on BOD_5, K, NH_4-N, and PO_4-P. Positive loading on NH4-N, BOD_5, and COD is associated with the influence of organic pollution from domestic wastewaters (Zhou et al., 2007). PC2 and PC3 represent pollution from domestic wastewaters and agricultural runoff. PC4, explaining 11.70 of total variance, has moderate positive loading on pH and strong negative loading on T. Negative loading of T has been associated with seasonal variation (Garg et al., 2010) and- at lower temperature- acid production is decreased, due to the decomposition of organic matter, hence PC1 and PC4 represent seasonal variation.

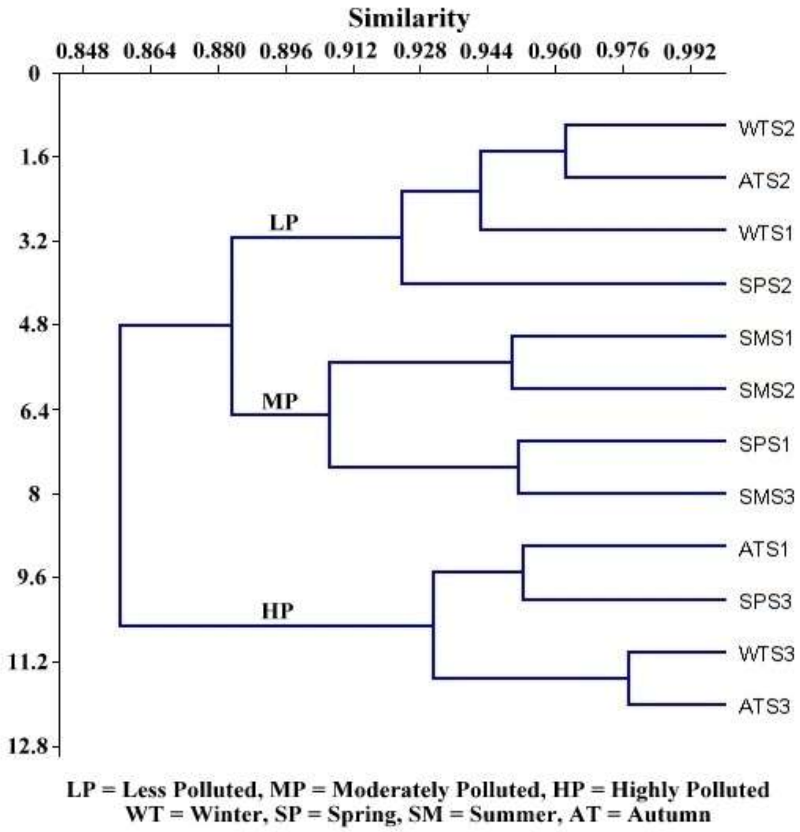

Fig. 3. Dendrogram of cluster analysis for sampling stations during different seasons, based on the surface water quality of Anchar Lake

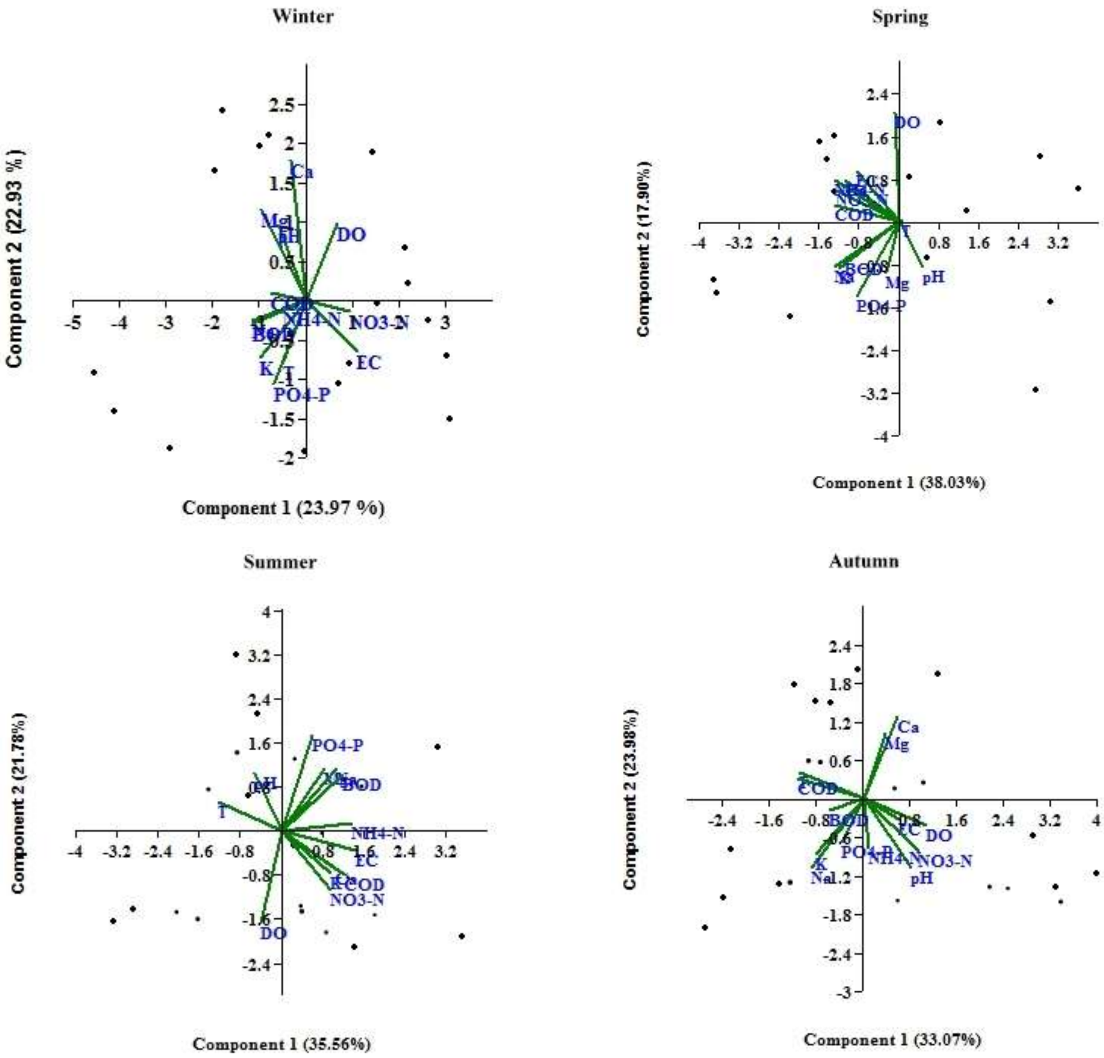

Fig. 4. Biplots of factor loadings for each variable during different seasons (1+2 component)

Table 1a. Factor loading values and explained variance of water quality during winter

Parameter	PC1	PC2	PC3	PC4
BOD_5	0.429	0.575	0.533	-0.260
Ca	0.881	-0.177	-0.165	0.183
COD	0.220	-0.070	0.900	-0.067
DO	-0.081	-0.935	0.198	0.216
EC	-0.779	-0.339	-0.322	0.172
K	0.077	0.695	0.594	0.100
Mg	0.889	0.200	0.256	0.029
Na	0.427	0.757	0.379	-0.024
NH_4-N	0.086	0.105	0.501	0.046
NO_3-N	-0.494	-0.294	-0.441	0.253
pH	0.446	0.194	0.288	0.679
PO_4-P	-0.212	0.578	0.596	0.098
Temperature	0.143	0.245	0.128	-0.889
Eigenvalues	3.117	2.981	2.727	1.521
Total variance (%)	23.975	22.933	20.976	11.701
Cumulative variance (%)	23.975	46.908	67.884	79.585

In case of spring, among the five PCs, PC1, explaining 38.03% of the total variance, has strong positive loading on BOD_5, COD, Na, NH_4-N, and NO_3-N, as well as moderate positive loading on Ca and K (Table 1b). Strong positive loading of BOD_5, COD, Na, NH_4-N, and NO_3-N has been linked with domestic wastewater (Iscen et al., 2008). PC1 represents organic pollution from domestic wastewaters. PC2, explaining 17.90% of total variance, has strong positive loading on PO_4-P, moderate positive loading on Na and K, but strong negative loading on DO. PC3, explaining 17.19% of the total variance, has strong positive loading on EC and strong negative loading on pH. PC2 and PC3 represent agricultural runoff factor as loading of PO_4-P, Na, K, and EC are associated with agricultural runoff (Juahir et al., 2011; Najar, 2012). PC4, explaining 10.66% of total variance, has strong positive loading on Mg, being linked with parent rock materials in the catchment area (Singh et al., 2006). It represents catchment geology. Finally, PC5, explaining 9.32% of total variance, has strong positive loading on T and represents seasonal variation (Shrestha & Kazama, 2007).

As for summer, among the four PCs, PC1, explaining 35.56% of the total variance, has a strong positive loading on BOD_5, Mg, Na, and PO_4-P, moderate positive loading on EC and NH_4-N, and strong negative loading on DO (Table 1c). PC2, explaining 21.78% of total variance, has strong positive loading on K, moderate positive loading on COD and NH_4-N, yet strong negative loading on T. Both PC1 and PC2 represent domestic wastewater and agricultural runoff factor (Zhou et al., 2007). PC3, explaining 19.87% of the total variance, has strong positive loading on COD, moderate positive loading on EC, and NO_3-N, but strong negative loading on pH. Strong positive loading on COD, EC, and NO_3-N has been associated with agricultural runoff (Buck, 2003). Thus PC3 represents agricultural runoff factor. PC4, explaining 11.85% of the total variance, has strong positive loading on Ca, moderate positive loading of NH_4-N, yet moderate negative loading on pH. Positive loading of Ca has been associated with catchment geology (Najar & Khan, 2012b). Thus PC2 represent organic pollution and catchment geology.

Table 1b. Factor loading values and explained variance of water quality during spring

Parameter	PC1	PC2	PC3	PC4	PC5
BOD_5	0.836	0.202	-0.303	0.341	0.079
Ca	0.675	-0.198	0.421	0.401	0.130
COD	0.946	0.096	0.092	-0.152	0.001
DO	0.289	-0.860	0.170	-0.189	0.206
EC	0.296	-0.001	0.905	0.219	-0.131
K	0.626	0.663	0.205	-0.014	0.265
Mg	0.006	0.190	0.038	0.947	0.064
Na	0.782	0.526	0.041	0.144	0.136
NH_4-N	0.885	0.034	0.367	-0.228	-0.127
NO_3-N	0.914	-0.060	0.202	0.085	-0.217
pH	-0.007	-0.122	-0.923	0.124	-0.125
PO_4-P	0.308	0.850	0.193	0.063	-0.017
Temperature	-0.061	-0.065	0.015	0.075	0.979
Eigenvalues	4.944	2.328	2.236	1.387	1.213
Total variance (%)	38.033	17.907	17.196	10.666	9.328
Cumulative variance (%)	38.033	55.940	73.136	83.803	93.130

Table 1c. Factor loading values and explained variance of water quality during summer

Parameter	PC1	PC2	PC3	PC4
BOD_5	0.897	0.173	0.232	-0.085
Ca	0.094	0.233	0.100	0.892
COD	0.101	0.529	0.799	-0.019
DO	-0.953	0.191	0.025	-0.233
EC	0.537	0.379	0.735	-0.081
K	-0.106	0.864	0.277	0.333
Mg	0.795	0.031	-0.357	0.130
Na	0.819	0.441	0.173	-0.146
NH_4-N	0.508	0.638	0.053	0.505
NO_3-N	-0.249	0.242	0.650	0.068
pH	0.172	0.135	-0.765	-0.516
PO_4-P	0.961	0.018	-0.221	0.034
Temperature	-0.124	-0.929	-0.218	-0.011
Eigenvalues	4.623	2.832	2.583	1.541
Total variance (%)	35.562	21.786	19.870	11.852
Cumulative variance (%)	35.562	57.348	77.219	89.071

For autumn, among the four PCs, PC1, explaining 33.07% of the total variance, has a strong positive loading on DO, NO_3-N, and pH, but moderate positive loading on EC and strong negative loading on COD and temperature (Table 1d), which has been associated with seasonal variation (Najar et al., 2014; Shrestha & Kazama, 2007), thus PC1 represents seasonal variation factor. PC2, explaining 23.98% of total variance, has strong positive loading on Na, moderate positive loading on K, PO_4-P, and Mg, but strong negative loading on Ca. PC3, explaining 13.51% of total variance, has strong positive loading on NH_4-N and strong negative loading on EC. Positive loading on Na, K, PO_4-P, and Mg is linked with agricultural runoff, whereas negative loading on EC has been associated with lower temperature as salt solubility is decreased at lower temperature (Najar & Khan, 2012a). PC2 and PC3 represent agricultural runoff factor with seasonal variation factor. PC4, explaining 12.76% of the total variance, has strong positive loading on BOD_5 and moderate negative loading on DO. Both positive loading on BOD_5 and negative loading on DO reveal discharge of domestic wastewaters (Iscen et al., 2008), hence PC4 represents organic pollution. As a result, from the principal component/factor analysis it is clear that the organic pollution from domestic wastewaters, seasonal variation, agricultural runoff, and catchment geology and flow are significant factors contributing to water quality variations during different seasons.

Table 1d. Factor loading values and explained variance of water quality during autumn

Parameter	PC1	PC2	PC3	PC4
BOD_5	-0.172	0.165	0.034	0.865
Ca	0.024	-0.904	0.011	-0.059
COD	-0.843	0.319	0.107	0.234
DO	0.754	-0.183	0.015	-0.610
EC	0.507	0.046	-0.805	-0.033
K	-0.296	0.702	0.404	0.078
Mg	-0.120	-0.615	0.062	-0.349
Na	-0.262	0.851	0.209	0.257
NH_4-N	0.308	0.127	0.900	0.012
NO_3-N	0.941	-0.075	-0.053	0.065
pH	0.923	0.112	-0.042	0.061
PO_4-P	-0.165	0.652	-0.190	-0.410
Temperature	-0.839	0.288	-0.184	0.329
Eigenvalues	4.300	3.118	1.757	1.660
Total variance (%)	33.073	23.988	13.513	12.766
Cumulative variance (%)	33.073	57.062	70.574	83.340

CONCLUSIONS

Hierarchical cluster analysis has grouped three sampling sites during four seasons into three clusters (LP, MP, and HP) based on water quality characteristics. Site-III remained highly polluted throughout the year, with the exception of summer, as the site receives huge amount of domestic wastewaters from immediate catchment. PCA application helped extracting and identifying the factors/sources, responsible for variation in water quality, during different seasons in the lake, which is mainly related to catchment geology, domestic wastewaters, agricultural runoff, and seasonal variation. These results may be valuable for lake-management authorities so that they can take strong actions for effective management of the lake.

REFERENCES

Ali, J., Tuzen, M. and Kazi, T.G. (2017). Determination of Arsenic in Water Samples by Using a Green Hydrophobic-Hydrophilic Switchable Liquid-Solid Dispersive Microextraction Method. Water Air Soil Pollut., 228, 34. DOI 10.1007/s11270-016-3211-6.

APHA (2005). Standard methods for the examination of water and wastewater. American Public Health Association, 21th edition, Washington DC.

Bates, R.G. (1978). Concept and determination of pH. In: Kolthoff I M, Elving PJ (eds) Treatise on analytical chemistry (Part 1, Vol. 1. pp. 821). New York: Wiley-Interscience.

Boyacioglu, H. and Boyacioglu, H. (2008). Water pollution sources assessment by multivariate statistical methods in the Tahtali Basin, Turkey. Environ. Geol., 54, 275-282.

Brown, L. and Bellinger, E.G. (1978). Nitrate determination in fresh and some estuarine waters by ultraviolet light absorption: a new proposed method. Water Res., 12(4), 223-229.

Buck, O., Niyogi, D.K. and Townsend, C.R. (2003). Scale-dependence of land use effects on water quality of streams in agricultural catchments. Environ. Poll., 130, 287-299.

Edwards, G.P., Molof, A.H. and Schneeman, R.W. (1965). Determination of orthophosphate in fresh and saline waters. J. Am. Water Works Assoc., 57, 917.

Garg, R.K., Rao, R.J., Uchchariya, D., Shukla, G. and Saksena, D.N. (2010). Seasonal variations in water quality and major threats to Ramsagar reservoir, India. Afr. J. Environ. Sci. Technol., 4(2), 061-076.

Iscen, C.F., Emiroglu, O., Ilhan, S., Arslan, N., Yilmaz, V. and Ahiska, S. (2008). Application of multivariate statistical techniques in the assessment of surface water quality in Uluabat Lake, Turkey. Environ. Monit. Assess., 144, 269-276.

Jasper, W.S. (1988). Secondary standard potassium chloride conductivity solutions at 25°C. Corporate Metrology Laboratory, YSI Inc: Yellow Springs, Ohio.

Juahir, H., Zain, S.M., Yusoff, M.K., Hanidza, T.I.T., Armi, A.S.M., Toriman, M.E., Mokhtar, M. (2011). Spatial water quality assessment of Langat River Basin (Malaysia) using environmetric techniques. Environ. Monit. Assess. 173, 625-641.

Jyoti, M.K., Akhtar, R. (2007). Some limnological investigations of Sarkoot pond located in Kishtwar, district Doda, J&K State. J. Res. Dev., 7, 27-34.

Katz, H., Navone, R. (1964). Methods for simultaneous determination of calcium and magnesium. J. Am. Water Works Assoc., 5, 121.

Khuhawari, M.Y., Mirza, M.A., Leghari, S.M. and Arain, R. (2009). Limnological study of Baghsar Lake district Bhimber, Azad Kashmir. Pak. J. Bot., 41(4), 1903-1915.

Liu, C.W., Lin, K.H. and Kuo Y.M. (2003). Application of factor analysis in the assessment of groundwater quality in a blackfoot disease area in Taiwan. Sci. Total Environ., 313, 77-89.

Loganathan, G., Krishnarajb, S., Muthumanickamb, J. and Ravichandran, K. (2015). Chemometric and trend analysis of water quality of the South Chennai lakes: an integrated environmental study. J. Chemometr., 29, 59-68.

Mallick, D., Shafiqul, I.M., Talukder, A., Mandol, S., Imran, M.A. and Biswas, S. (2016). Seasonal variability in water chemistry and sediment characteristics of intertidal zone at Karnafully estuary, Bangladesh. Pollut., 2(4), 411-423.

Mancy, K.H. and Jaffe, T. (1966). Analysis of dissolved oxygen in natural and waste waters. Publ. No. 99-WP-37. U.S. Public Health Service: Washington, D.C.

Najar, I.A. (2012). Studies on earthworm communities of Kashmir Valley, their application in management of fresh water weeds (macrophytes) and use of vermicompost in horticulture. Ph.D thesis, Pondicherry University.

Najar, I.A., Khan, A. B. and Hai, A. (2014). Changing climatic conditions and seasonal variability in surface water quality of a shallow valley lake, Kashmir, India. Proceeding of the international conference on Green India: Strategic knowledge for compacting climate change: prospects and challenges, Excel India Publishers, 87-97.

Najar, I.A., and Khan, A.B. (2013) Management of fresh water weeds (macrophytes) by vermicomposting using *Eisenia fetida*. Environ. Sci. Pollut. Res., 20:6406-6417.

Najar, I.A., and Khan, A.B. (2012a). Vermicomposting of fresh water weeds (macrophytes by *Eisenia fetida* (Savigny, 1826), *Aporrectodea caliginosa trapezoides* (Duges, 1828) and *Aporrectodea rosea rosea* (Savigny, 1826). Dynamic Soil. Dynamic Plant., 6 (S1),73-77.

Najar, I.A. and Khan, A.B. (2012b). Assessment of water quality and identification of pollution sources of three lakes in Kashmir, India, using multivariate analysis. Environ. Earth Sci., 66(8), 2367-2378.

Najar, I.A. and Khan, A.B. (2012c). Assessment of seasonal variation in water quality of Dal Lake (Kashmir, India) using multivariate statistical techniques. Conference on Water Pollution-XI: Modeling, Monitoring and Management, WIT Trans. Ecol. Environ., 164, 123-134.

Najar, I.A. and Khan, A.B. (2011). Assessment of pollution status of Khushalsar Lake, Kashmir, India using multivariate statistical techniques. Pollut. Res., 30(2), 131-136.

Noori, R., Yeh, H., Ashrafi, K., Rezazadeh, N., Bateni, S.M., Karbassi, A., Kachoosangi, F. T. and Moazami, S. A. (2015). Reduced-order based CE-QUAL-W2 model for simulation of nitrate concentration in dam reservoirs. J. Hydrol., 530, 645-656.

Noori, R., Karbassi, A., Khakpour A, Shahbazbegian M, Badam H.M.K. and Vesali-Naseh, M. (2012). Chemometric Analysis of Surface Water Quality Data: Case Study of the Gorganrud River Basin, Iran. Environ. Model. Assess., 17, 411-420.

Noori, R., Karbassi, A.R., Ashrafi, K., Ardestani, M. and Mehrdadi, N. (2011). Development and Application of Reduced-Orde Neural Network Model Based on Proper Orthogonal Decomposition for BOD5 Monitoring: Active and Online Prediction. Environ. Progr. Sust. Energy., 32(1), 120-127.

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

Papatheodorou, G., Demopoulou, G. and Lambrakis, N. (2006) A long-term study of temporal hydrochemical data in a shallow lake using multivariate statistical techniques. Ecol. Model., 193, 759-776.

Parmar, K.S. and Bhardwaj, R. (2013). Water quality index and fractal dimension analysis of water parameters. Int J Environ. Sci. Technol., 10(1), 151-164.

Pitwell, L.R. (1983). Standard COD. Chem. Brit., 19, 907.

Rajbira, K. and Anishb, D. (2016). Assessment of Water Quality of Tung Dhab Drain-An International Water Channel-Using Multivariate Statistical Techniques. Asian J. Water Environ. Pollut., 13(3), 85-93.

Ramachandra, T. V., Asulabha, K. S. and Lone, A. A. (2014). Nutrient Enrichment and Proliferation of Invasive Macrophytes in Urban Lakes. J Biodiversity, 5(1,2), 33-44.

Ree, W.R. (1953). Thermistors for depth thermometry. J. Am. Water Works Assoc. 45, 259.

Sheela, A.M., Letha, J. and Joseph, S. (2011). Environmental status of a tropical lake system. Environ. Monit. Assess., 180, 427-449.

Shin, M.H., Won, C.H., Jang, J.R., Choi, Y.H., Shin, Y.C., Lim, K.J. and Choi, J.D. (2013). Effect of surface cover on the reduction of runoff and agricultural NPS pollution from upland fields. Paddy Water Environ., 11, 493-501.

Shrestha, S. and Kazama, F. (2007). Assessment of surface water quality using multivariate statistical techniques: A case study of the Fuji river basin, Japan. Environ. Model. Softw., 22(4), 464-475.

Simeonova, P., Lovchinov, V., Dimitrov, D. and Radulov, L. (2010). Environmetric approaches for lake pollution assessment. Environ. Monit. Assess., 164, 233-248.

Singh, K.P., Malik, A., Singh, V.K., Basant, N. and Sinha, S. (2006). Multi-way modeling of hydro-chemical data of an alluvial river system- A case study. Anal. Chim. Acta., 571, 248-259.

Solorzano, L. (1969). Determination of ammonia in natural waters by the phenolhypochlorite method. Limnol Oceanogr., 14, 799.

Srivastava, N., Harit, G.H. and Srivastava, R. (2009). A study of physico-chemical characteristics of lakes around Jaipur. India J. Environ. Bio., 30(5), 889-894.

Takaijudin, H., Ghani, A.A. and Zakaria, N.A. (2016). Challenges and developments of bioretention facilities in treating urban stormwater runoff; A review. Pollut., 2(4), 489-508.

Thompson, K.C. and Reynolds, R.J. (1978). Atomic absorption, fluorescence, and flame spectroscopy-a practical approach, 2nd edn. John Wiley and Sons: New York.

Tian, P., Zhao, G., Li, J., Gao, J. and Zhang, Z. (2012). Integration of monthly water balance modeling and nutrient load estimation in an agricultural catchment. Int .J. Environ. Sci. Technol., 9(1), 163-172.

Virkutyte, J. and Sillanpää, M. (2006). Chemical evaluation of potable water in Qingshai province, China: Human Health Aspects. Environ. Int., 32(1), 80-86.

Vyas, A., Mishra, D.D., Bajapai, A., Dixit, S. and Verma, N. (2006). Environment Impact of Idol Immersion Activity Lakes of Bhopal, India. Asian J. Expl. Sci., 20(2), 289-296.

Wong, K.W., Yap, C.K., Nulit, R., Hamzah, M.S., Chen, S.K., Cheng, W.H., Karami, A. and Al-Shami, S.A. (2017). Effects of anthropogenic activities on the heavy metal levels in the clams and sediments in a tropical river. Environ. Sci. Pollut. Res., 24, 116-134.

Yidanaa, S.M., Ophoria, D. and Yakubo, B.B. (2008). A multivariate statistical analysis of surface water chemistry data-The Ankobra Basin, Ghana. J. Environ. Manage., 86, 80-87.

Zar, J.H. (2009). Biostatistical analysis, 5th. edition. Prentice Hall: Englewood Cliffs, New Jersey.

Zhang, Q., Li, Z., Zeng, G., Li, J., Fang, Y., Yuan, Q., Wang, Y. and Ye, F. (2009). Assessment of surface water quality using multivariate statistical techniques in red soil hilly region: a case study of Xiangjiang watershed, China. Environ. Monit. Assess., 152, 123-131.

Zhou, F., Guo, H.C. and Liu, L. (2007). Quantitative identification and source apportionment of anthropogenic heavy metals in marine sediment of Hong Kong. Environ. Geol., 53(2), 295-305.