Assessment of Surface Water Quality by using Multivariate Statistical Techniques of Various Lakes of Kancheepuram District in Tamil Nadu, India

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Abstract

Multivariate statistical methods such as Principal Component Analysis/Factor analysis (PCA/FA), and Cluster Analysis (CA) were used to characterize spatial and temporal variations and to find out the pollution source of 11 lakes of the Kancheepuram district, a northeast district of Tamilnadu in India. Sampling events were conducted during the northeast monsoon (Dec 2015 & 2016) and Pre-monsoon (Oct 2016). The 20 physicochemical water quality parameters were used to analyze the collected water samples. In PCA, four components were demonstrated up to 73.12% of the total variance in the data set. It clarifies that variations in water quality parameters concentration are mainly identified with agricultural, industrial, domestic wastes, and natural factors. The CA showed the formation of three clusters based on the water quality variation at different locations. From the CA data, sampling sites were classified into high, moderate, and least polluted. Among these sites, Kolavai, Nattapettai and Uthiramerur were highly polluted because of rapid urbanization and industrialization. Therefore, these areas need some effective measures to enhance the quality of water.

Keywords: Water quality, Physicochemical parameters, Statistical analysis, Lake water pollution.

1. Introduction:

Water pollution is a worldwide issue and it reduces the accessible water resources. Making surface water to be contaminated is very easy compare to groundwater. Because of human activities and natural factors surface water was progressively defenseless. Lake water quality change is constantly directed by natural processes including weathering, precipitation, soil erosion, etc., anthropogenic activities like agricultural, untreated urban sewage, industrial effluents, tourism, and the increased utilization of water resources[1] because of the multifaceted impacts noted previously, water purity degradation has become a difficult issue around the world. Remarkably in future freshwater resources may turn out to be rare, which would scare water resource use, particularly for drinking water and economic development. As indicated[2], roughly 1.1 billion people worldwide do not access a reliable source of drinking water. Lakes give the primary water resources for residential, industrial, and irrigational purposes; in any case, they are easily contaminated due to their critical roles in transporting from urban and industrial pollution and runoff from agricultural land. As a result of their critical roles in environmental and human health and monetary advancement, it is basic to prevent and control declining water quality in lakes. Therefore, solid data with regard to water quality parameter variations must be gathered for proper management; this has just been led in numerous nations and districts. Hence, research on lake water quality has become the exploration subject of numerous researchers over the world[3,4]. A few research works have been centered on the anthropogenic contamination of biological systems[5].

However, monitoring programs that provide representative and reliable information of the data are not effectively implemented because of both spatial and temporal variations in water quality including temperature, pH, substantial metals, harmful organic compounds, nutrients, and pesticides, etc. To secure water quality and to decrease the pressures on water resources, it is important to study elaborately on spatial-temporal variations in territorial water quality and identify the potential contamination sources. Recently, the multivariate statistical technique becomes suitable for a better understanding of water quality and environmental status, due to their capability to treat an enormous volume of spatial and temporal information from various monitoring sites[6-9].

In the research literature, different statistical techniques have been adopted which includes cluster analysis (CA)[10], PCA /factor analysis (FA)[11-12] and discriminate analysis (DA)[13] and were utilized for this kind of studies since they are capable to assess contaminations in water resources. Among these CA and PCA statistical techniques are fundamental tools to determine basic connections between the water quality parameters, predicting pollution sources, and group similar monitoring stations into clusters with similar characteristics[14]. Hence, in this work two statistical methods, PCA and CA were used to study the water quality in Kancheepuram district lakes, Tamilnadu. Kancheepuram is the first district in the country with the largest number of lakes. It has more than 200 big lakes and ponds. In this study eleven main lakes of Kancheepuram were selected. They are Maduranthakam, Kolavai, Nattapettai, Uthukadu, Vaiyavoor, Thenneri, Uthiramerur, Edamichi, Pon Vilaintha *Kalathur, Chettipunyam, and Salavakkam Lakes. The samples were collected during northeast monsoon periods of December 2015 and 2016 and the southwest monsoon period of October 2016. Global warming is an event of climate change indicated by a general increase in average temperatures of the Earth, and that reshapes the weather balances and ecosystems for a long time*[15].

The 2015 urban flood resulted from heavy rainfall achieved by the annual northeast monsoon in November-December 2015[16,17]. Among the districts of Tamil Nadu, Kancheepuram district registered the heaviest rainfall of 183 percent higher at 181.5 cm as against average rainfall of 64 cm (The Hindu). Almost all the lakes reached their full storage capacity and some of the lakes had overflowed. Alike, in December 2016 an extremely Severe Cyclonic Storm Vardah was the fourth big cyclonic storm, just as the most extraordinary tropical cyclone of the 2016 North Indian Ocean cyclone season[18]. Cyclone Vardah made landfall near Chennai and it brought heavy rainfall to Kancheepuram, Chennai and Thiruvallur districts. But it is approximately three times less than the normal expected rainfall. The regular rain diminishes and water levels in lakes and reservoirs drop and then it tends to affect ecosystems. Due to climate changes, in recent decades summer season has extended up to October and at the same time shortage in rainfall takes place. Thus, in this part of the country there will be rainfall only for a couple of months. The sampling was carried out during 2015-16 and this data is relevant till date as there has been no major climate changes and sources of contamination are still prevalent.

2. Materials and Methods

2.1 Description of Study Area

Maduranthakam Lake is an artificial lake and is the biggest lake in the district of Kancheepuram and the second biggest lake in the state of Tamil Nadu. This Lake has an annual storage capacity of 694 Mcft and with a depth of 23.5 feet. It is spread over 1151.7 hectares and presently more than 30 villages are benefitted by this lake. The Maduranthakam Lake also receives water from the Kiliyar River which originates from Vandavasi Taluk of Thiruvannamalai District and municipal wastewater of Thiruvannamalai, Vandavasi, and Cheyyar enter into this lake through this river[19]. Kolavai Lake is the second biggest lake in the Kancheepuram district and the tenth-biggest lake in the state of Tamil Nadu. Once a huge lake, Kolavai Lake has now decreased to a large portion of the size as a result of Mahindra World City which is built upon the bank of the lake. This Lake has an annual storage capacity of 476.69 Mcft and with a depth of 15.06 feet. It is spread over 894 hectares and presently above 12 villages are benefitted by this lake. It even supplies water to industries in Chennai when the lakes in Chennai go dry. The lake is currently being contaminated because of the rapid urbanization of Chengalpattu[20-21]. Nattapettai and Vaiyavoor were situated near to one another. Nattapettai Lake is a rain-fed freshwater lake used for irrigation and fishing. This lake also attracts a wide variety of migratory birds over the past few years. Nowadays, this lake gets contaminated because it receives municipal water from Thirukaalimedu and surrounding areas through Manjal neer kalvai. The main damages are caused by textile dyeing industries in Kancheepuram. Vaiyavoor lake water is utilized for household activities of Vaiyavoor and surrounding village people and both Nattapettai and Vaiyavoor lakes distribute water to farming fields. Uthukadu Lake is reduced to one-third part because this lake depends only on rainwater. Uthukadu Lake also distributes water to farming fields through irrigational canals. Thenneri Lake is one of the largest lakes in Kancheepuram. This lake provides water to surrounding villages[22]. Thenneri lake water joins with the Palar River at Chengalpattu through the Palar canal. Uthiramerur Lake is one of the famous lakes built during the Cholas period and is 1000 years old lake. This lake supplies water to farming fields and it is polluted by pharmaceutical, chemical, ceramic, fiberglass, and steel industries as well as domestic and agricultural waste. Edamichi, Pon Vilaintha *Kalathur, Chettipunyam, and Salavakkam are the small lakes situated in the village surrounded by farming fields. Edamichi, Pon Vilaintha Kalathur, Chettipunyam, and Salavakkam were the small lakes located in the town encompassed by cultivating fields and houses.*

2.2 Sample Collection and Analysis

Eleven sampling sites of different lakes were carefully selected to represent the nature of Kancheepuram district lakes and presented in Fig.1. Taking into account the variations of seasons two sampling events were conducted in a pre-monsoon (October 2016) and monsoon (December 2015 & December 2016) season. To estimate the effects of weather, some efforts were made to collect the samples in urban flood and vardah cyclone conditions. Water samples were manually collected approximately from the depth of 30 cm. The collected samples were stored in polyethylene bottles of previously soaked in 10% of HNO_3 for 24 h and rinsed several times with double distilled water and then they were rinsed with surface water before sampling. The collected samples were acidified with 0.05M H^+ with nitric acid and stored at 4°C. Conductivity and pH of water samples were measured in situ at field sampling sites itself using a portable water quality analyzer (ELICO Model: PE138). After sampling all bottles were brought immediately to the college chemistry laboratory and stored in a refrigerator. The Collected samples were mainly utilized for in situ measurement of physicochemical characteristics and Water quality aspects[1,11,12,19]. Various physicochemical water quality parameters were analyzed using the standard analytical procedure following the standard methods (APHA-2012). The analytical methods followed for analysis of different parameters are given below in Table 1.

2.3 Multivariate Statistical Methods

Under the study to interpret the degree of association between two variables the Pearson correlation coefficient was obtained. PCA is generally applied to simplify the data by the removal of data noise using a dimensionality reduction technique and make it simpler to visualize by finding a set of principal components (eigenvectors). Principal Components (PC) are the orthogonal variables that are calculated by multiplying a list of coefficients with the correlated variables. FA was used to extract a lower-dimensional linear structure from a set of data and with regard provide a powerful means for detecting similarities among samples. FA can lower the contribution of less significant variables attained from PCA and further, that minimized the number of variables that have high loading on each factor using varimax rotation it is an orthogonal rotation method. The extracted group of variables is known as Varifactors[23]. CA is used to study similarities and dissimilarities between water samples. The classification of similar sampling sites into groups is illustrated by a dendrogram (tree diagram) and the reduction in the linearity of the original data leads to their proximity. CA was operated on the normalized data according to the Ward's method, by using the Squared Euclidean distances as a measure of similarity[24-25].

3. Results and Discussion

3.1 Statistical Analysis Results

Correlation is the linear relationship between two variable parameters. The linear relationship exists when an increase or decrease in the value of one variable is correlated with a corresponding increase or decrease in the value of the other variable. The correlation is reported as positive when the increase in one variable causes the increase in other and it is negative when the increase in one variable causes a decrease in the other. The correlation coefficient has a value between +1 and -1 [26]. The correlation coefficient between various physicochemical water quality parameters was calculated and the values obtained were given in Table 2. The strong positive correlation occurred between Cl and Turb. (0.82), TH and Ca (0.91), SO_4 and Turb. (0.816), BOD (0.859). Pb and Cd (0.827) were found. The moderate positive correlation occurred between Turb. and Mg (0.774), K and Na (0.736), Turb. and EC (0.724), TDS (0.717). SO_4 and EC (0.781), TDS (0.776), Cl (0.785) were found. Other significant negative correlations occurred between pH and Turb. (-0.534), SO_4 (-0.539). Finally, Zn shows weakly negative correlations with variables except for pH (0.091) and DO (0.088) which shows weekly positive correlations.

3.2 Source identification of monitored parameters

The PCA/FA was dependent on the Pearson correlation matrix. It was used to understand the basic relationships between the various water quality parameters of all monitoring sites and to identify their unique properties. Principal components (PC) with Eigen values ≥ 1 considered as significant[27,28] so that four PCs with Eigen value greater than one only extracted as factor loadings. As indicated[29] factor loadings are classified as strong, moderate, and weak corresponding to >0.75, 0.75–0.5, and >0.5 respectively. The results given in Table3 which show that the four components of PCA analysis produced are explaining 73.12% of the total variance in the data set.

Among the four components, the first component (PC1) calculating that 29.71% of the total variance contained strong positive loadings of EC, TDS, Turb., BOD, Cl, and SO_4 corresponds to Group 1 in cluster analysis, moderate positive loadings of Na and K correspond to Group 2, strong negative loading of pH corresponds to Group 6 and other parameters show weakly positive and negative loadings. This strong positive loading is attributed to domestic sewage and agricultural waste[30]. Electrical conductivity is related to the concentration of conductive ions in the lake water. These conductive ions include dissolved salts and inorganic materials such as alkali metals, chlorides, sulfides, and carbonates. The strong positive loading of BOD representing organic pollution[31] is likely to arrive from dye industries in Kancheepuram. Na and K cations were originated from soil or rock structure by farming runoff.

The second component PC2, accounting for 19.96% of the total variance and it showed strong positive loading of Ca, Mg, TH, and TA corresponds to Group 4 and all other parameters show weakly positive to negative loadings. The concentration of Ca and Mg shaped by anthropogenic factors and surface runoff. A high concentration of these increases the concentration of TH and TA. Alkalinity is water's ability to oppose acidic changes in the pH of the water using calcium and magnesium carbonates. But higher levels in lake water will affect aquatic life, farming irrigations patterns and livestocks.

The third component PC3 showed 15.22% of the total variance had strong to moderate positive loadings of Cr, Cd, Pb, Cu, and Fe and moderate negative loading of Zn. Among these Cd, Pb, and Cu experience Group 3 in cluster analysis, Cr and Fe undergo Group 5, and Zn corresponds to Group 6. Sources of these heavy metals[32,33] are agricultural, domestic sewage, pharmaceutical, and aquatic sources. Fe and Cr heavy metals were derived from lithogenic sources[34]. Higher concentrations of Fe are generally associated with organic matter of natural origin and leaching of soil and rocks. The fourth component PC4 revealed that 8.24% of the total variance and showed weak positive and weak negative loadings except DO. It showed strong negative loading and correspond to Group 6.

3.3 Spatial and temporal variations in lake water quality

CA was used to classify spatial and temporal similarity groups of all sampling sites by reported water quality similarities. The water quality similarities were categorized using factor loadings of physicochemical parameters and their cluster analysis is shown in Figure 2. The dendrogram of various sites obtained by Ward's method [35] in the pre-monsoon and monsoon seasons are shown in Figure 3. Temporal variations were noted in water quality parameters of studied lake water samples. Different parameters like EC, Td, BOD, Cl, TH, and TA showed maximum value during pre-monsoon, while minimum values were recorded during monsoon. The detected trends could be attributed to the evaporation of water from studied lakes during pre-monsoon and consequent dilution due to precipitation and runoff from catchment area during monsoon season.

The Spatial CA result revealed that all 11 sampling sites were classified into three clusters and sites in each cluster group hold similar water contaminations. The first group contained sites 1, 6, 8, 9, 10, and 11. These sampling sites are situated in zones with the highest agricultural runoff and domestic sewage activities, especially the dispersed and unsettled wastewaters from surrounding villages. Samples collected from these lakes were moderately polluted. The second group comprised of sites 2[36], 3, and 7. These sites were demonstrated at the highest level of pollution with multiple anthropogenic activities like an untreated waste, industrial effluents, hospital waste, agricultural waste, domestic sewage, boating, and fishing activities. Group 3 contains 4 and 5 sampling sites respectively. These are the least contaminated sampling sites with agricultural activity.

4. Conclusion

This study enables us to identify the source of contamination effecting the water quality of Kancheepuram district lakes in Tamil Nadu, India. Multivariate statistical techniques were employed to characterize spatial and temporal variations of surface lake water quality data. The obtained values of some physicochemical water quality parameters at most sites showed that the average concentration exceeds the prescribed levels permitted by the Indian guidelines. Different parameters like EC, Turbidity, BOD, Cl, TH, and TA showed that maximum value during pre-monsoon, while minimum values were recorded during monsoon. The detected trends could be attributed to the evaporation of water from studied lakes during pre-monsoon and consequent dilution due to precipitation and runoff from catchment area during monsoon season. PCA for the four components indicates that 29.71%, 19.96%, 15.22% and 8.24% were obtained for PC1, PC2, PC3 and PC4 respectively for of the total variance which contained strong positive loadings. PCA/FA data has been used to bring out the relationship between various water quality parameters of all monitored sites. The results on factor loadings were classified as strong, moderate and weak respectively and based on this loadings water quality parameter classified into six groups in cluster analysis. The spatial cluster analysis result showed that 11 sampling sites were classified into three clusters with similar water contaminations. Among this, the second group contains highly polluted sites such as Kolavai, Nattapettai, and Uthiramerur lakes with multiple anthropogenic activities. The studies indicate that remedial measures have to be taken on a war footing to restore the water bodies from heavy metal contamination and prevent the sources of contaminants.

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Figures:

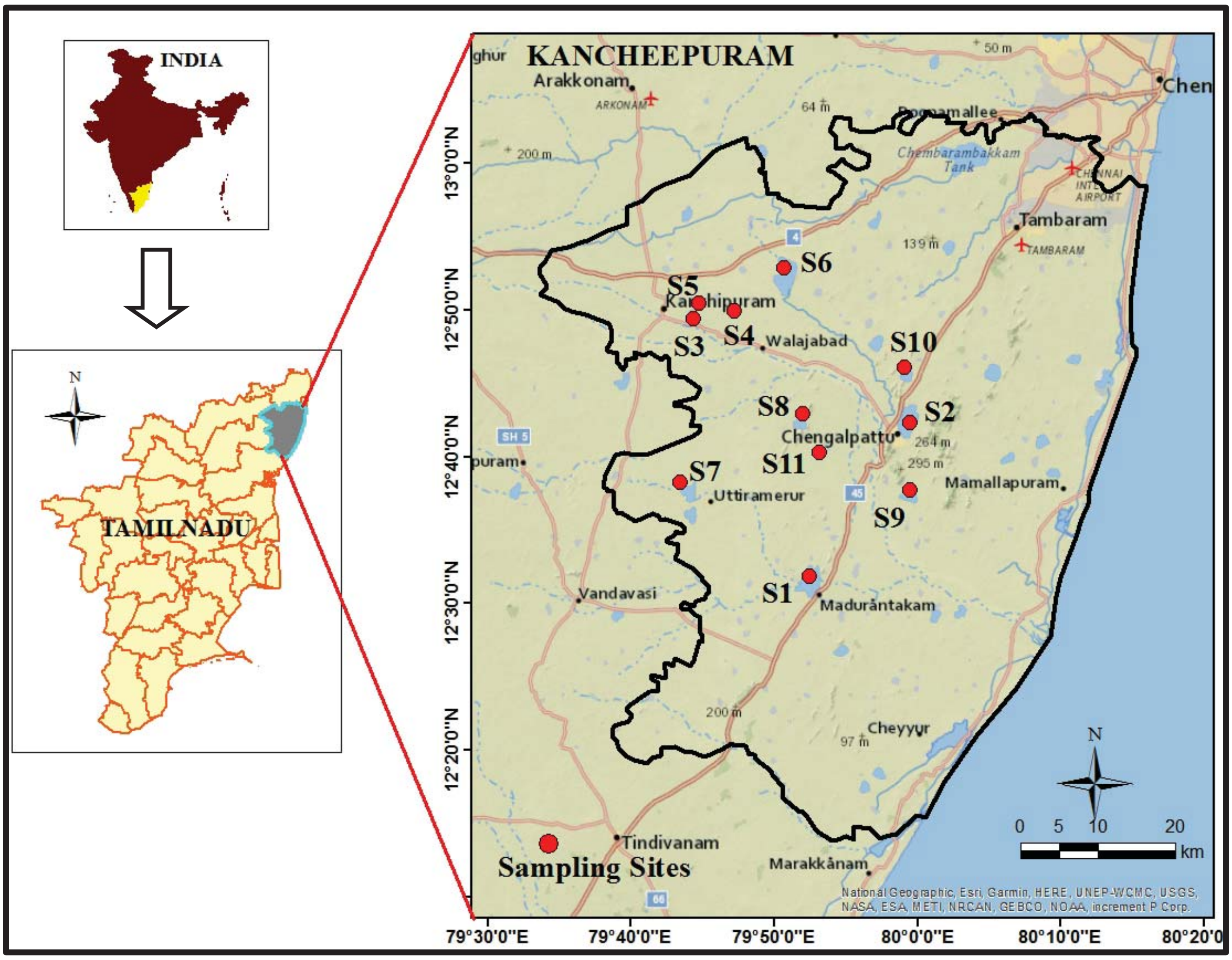

Figure 1: Location of sampling sites in Kancheepuram district lakes, India.

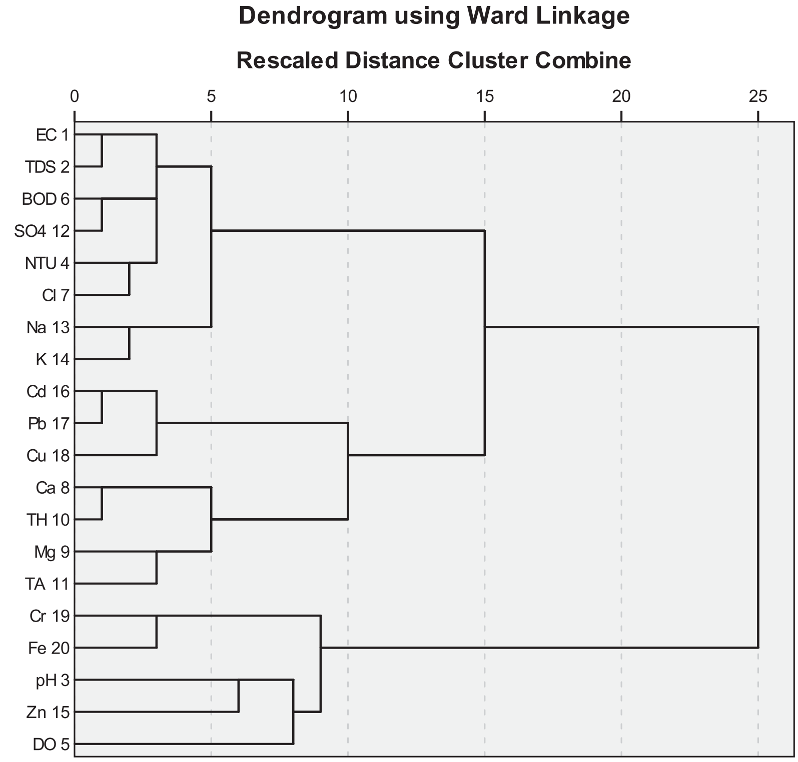

Figure 2: Dendrogram showing clustering of water quality parameters.

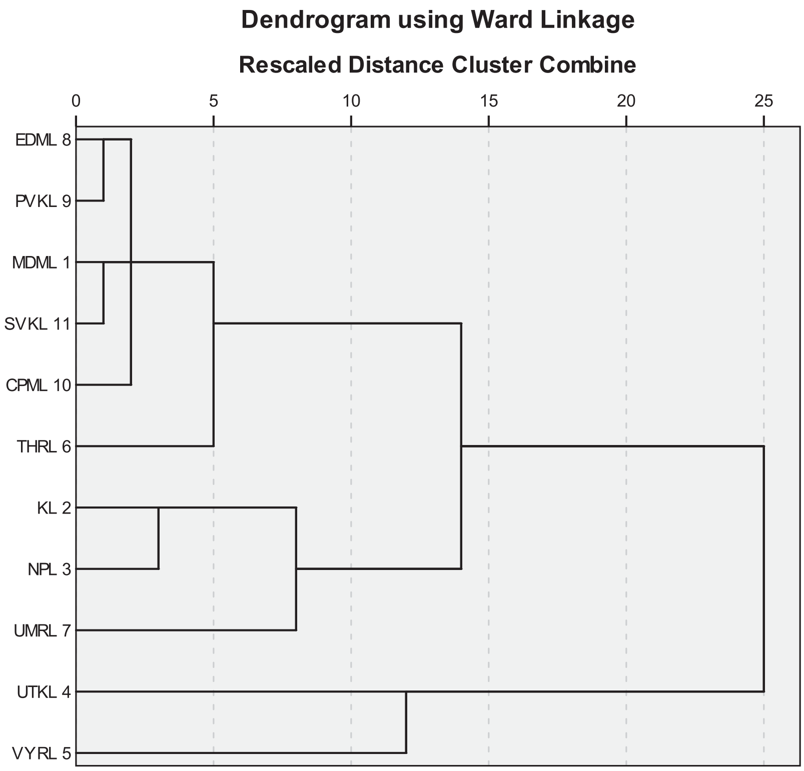

Figure 3: Dendrogram showing clustering of sampling sites.

Tables:

Table1 : The water quality parameters and analytical methods used in this study.

Water quality parameters	Abbreviations	Units	Analytical Methods
Electrical Conductivity	EC	µS/cm	Portable conductivity meter
Total Dissolved Salts	TDS	mg/L	Conductivity TDS meter
pH	pH	-	Potentiometry/pH electrode
Turbidity	Turb.	NTU	Turbidimetry
Dissolved Oxygen	DO	mg/L	Winkler method
Biological Oxygen Demand	BOD	mg/L	Winkler method
Chloride	Cl	mg/L	Argentometric titration
Calcium	Ca	mg/L	EDTA titrimetric
Magnesium	Mg	mg/L	EDTA titrimetric
Total Hardness	TH	mg/L	EDTA titrimetric method
Total Alkalinity	TA	mg/L	Titrimetric
Sulphates	SO_4	mg/L	Barium chloride
Sodium	Na	mg/L	Flame photometric
Potassium	K	mg/L	Flame photometric
Zinc	Zn	µg/L	ICP-AES
Cadmium	Cd	µg/L	ICP-AES
Lead	Pb	µg/L	ICP-AES
Copper	Cu	µg/L	ICP-AES
Chromium	Cr	µg/L	ICP-AES
Iron	Fe	µg/L	ICP-AES

Table 2: Pearson correlation coefficient matrix of physicochemical parameters for various lakes in Kancheepuram district.

	EC	TDS	pH	Turb.	DO	BOD	Cl	Ca	Mg	TH	TA	SO_4	Na	K	Zn	Cd	Pb	Cu	Cr	Fe
EC	1.000	1.000	-0.341	**0.724**	-0.379	0.680	**0.799**	0.671	0.335	0.628	0.495	**0.781**	0.491	0.486	-0.113	0.445	0.265	0.344	0.076	-0.122
TDS		1.000	-0.334	**0.717**	-0.379	0.678	**0.795**	0.668	0.337	0.627	0.495	**0.776**	0.488	0.481	-0.117	0.447	0.268	0.348	0.079	-0.120
pH			1.000	-0.534	-0.149	0.475	-0.406	0.097	0.213	0.025	0.162	-0.433	-0.328	-0.375	0.091	0.026	0.004	-0.134	0.191	0.214
Turb.				1.000	-0.185	0.631	**0.820**	0.495	0.229	0.455	0.240	**0.816**	0.629	0.606	-0.164	0.407	0.321	0.405	0.053	-0.075
DO					1.000	-0.51	-0.187	0.095	-0.224	-0.17	-0.426	-0.539	-0.275	-0.116	0.088	-0.361	-0.32	0.157	0.056	0.058
BOD						1.000	0.629	0.271	0.257	0.306	0.358	**0.859**	0.656	0.585	-0.146	0.306	0.226	0.120	0.073	-0.111
Cl							1.000	0.665	0.304	0.610	0.357	**0.785**	0.451	0.587	-0.067	0.353	0.233	0.271	0.021	-0.119
Ca								1.000	0.467	**0.921**	0.543	0.407	0.386	0.366	-0.063	0.508	0.320	0.475	0.132	-0.209
Mg									1.000	**0.774**	0.675	0.298	0.283	0.012	-0.022	0.358	0.182	0.285	0.059	-0.139
TH										1.000	0.685	0.422	0.400	0.268	-0.055	0.521	0.309	0.465	0.120	-0.211
TA											1.000	0.367	0.421	0.281	-0.119	0.486	0.381	0.129	0.112	-0.114
SO_4												1.000	0.528	0.505	-0.14	0.395	0.246	0.191	0.025	-0.066
Na													1.000	**0.736**	-0.259	0.556	0.602	0.518	0.106	-0.158
K														1.000	0.000	0.246	0.351	0.187	0.010	-0.029
Zn															1.000	-0.244	0.194	-0.276	0.187	-0.101
Cd																1.000	**0.827**	0.691	0.517	-0.071
Pb																	1.000	0.639	0.468	-0.132
Cu																		1.000	0.443	-0.105
Cr																			1.000	0.662
Fe																				1.000

Table 3: Factor loadings after varimax rotation of physicochemical parameters on four main components.

Parameters	PC 1	PC 2	PC 3	PC 4
EC	0.764	0.461	0.096	0.126
TDS	0.758	0.462	0.100	0.128
pH	-0.715	0.292	0.094	0.371
Turb.	0.855	0.179	0.196	-0.091
DO	-0.275	-0.221	-0.076	-0.784
BOD	0.843	0.115	0.030	0.326
Cl	0.795	0.376	0.038	-0.037
Ca	0.374	0.760	0.169	-0.219
Mg	0.027	0.826	0.045	0.151
TH	0.279	0.908	0.140	-0.091
TA	0.179	0.750	0.145	0.354
SO_4	0.857	0.217	0.071	0.317
Na	0.643	0.206	0.445	-0.042
K	0.724	0.025	0.179	-0.051
Zn	-0.132	0.067	-0.518	-0.050
Cd	0.236	0.455	0.744	0.048
Pb	0.199	0.261	0.766	-0.024
Cu	0.195	0.322	0.707	-0.473
Cr	-0.138	-0.013	0.836	0.200
Fe	-0.172	-0.355	0.585	0.410
Eigen Value	5.942	3.991	3.043	1.647
Percent of variance	29.709	19.955	15.217	8.235
Cumulative percentage	29.709	49.664	64.881	73.116

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