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STATISTICAL EVALUATION OF THE EFFECT OF SECONDARY MUNICIPAL WASTEWATER AND SOLID WASTE LEACHATE ON GROUND WATER QUALITY AT LAWSPET IN PUDUCHERRY, INDIA

At Lawspet area in Puducherry, India, a unique situation of co-disposal of solid waste dumping and secondary wastewater disposal on land, prevails simultaneously within the same campus. So an attempt is made to assess the combined effect of this co-disposal on the environmental quality and pollution effects on groundwater quality with a view to correctly monitor the situation. Multivariate statistical analysis like hierarchical cluster analysis (HCA) and discriminant analysis (DA) were employed. HCA was performed on borewells, physiochemical parameters and seasons. Borewell clustering identified four clusters illustrating varying degree of groundwater contamination. In parameter clustering, two major clusters were formed indicating hardness and anthropogenic components. Temporal clustering identified three major clusters indicating pre-monsoon, monsoon and post-monsoon. Discriminant analysis revealed nine significant parameters which discriminate four clusters qualitatively affording 86% correct assignation to discriminate among the clusters. Also three major components viz. anthropogenic, hardness and geogenic responsible for groundwater quality in the study area were identified. Conclusively the investigation revealed that the direction of the contaminant transport is towards the southeast direction of the study area, where all the borewells (100%) are affected.

1. INTRODUCTION

Groundwater is one of the major sources of drinking water in both urban and rural areas and is a limited resource across the globe. Rapid urbanization obstructed the global efforts to improve the quality and quantity of drinking water. There are several factors

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capable of deteriorating the groundwater quality not only the geogenic factor of the aquifer, the recharge water quality and the type of interaction between recharge water and water bearing strata but also human activities such as unplanned disposal of wastewater generated from domestic, industrial and husbandry sources with little or no treatment prior to discharge and indiscriminate, non-engineered solid waste dumping. Either one or two factors could contaminate the aquifers to such an extent that the use of groundwater becomes restricted and this leads to the subsequent leaching of the pollutant into the ground, thereby causing irreversible damage to groundwater quality.

1.1. SOLID WASTE LEACHATE

Landfilling of municipal solid waste (MSW) is one of the cheapest methods for organized waste management in many countries. India generates about 70 million tons of MSW every year from various cities and towns. Considering rapid expansion of the cities/towns with massive migration of population from rural to urban centers, considerable increase in generation of MSW with each passing day has continuously been increasing. In the next decade, urban India will generate a total of 920 million tons of municipal solid waste which should be properly managed else further deterioration of air, water and land resources will result in. More than 90% of the MSW generated in India is directly disposed of in open low-lying areas indiscriminately in an unscientific manner, posing a potential threat to the public health, environmental quality and aesthetics. Landfill leachate has been responsible for contaminating groundwater supplies and surface water ecosystems in communities all over the world. Consequently, the management of our environment and the control of discharge of waste products from anthropogenic activities are becoming a thrust area to researchers, government organizations, environmental monitoring agencies and decision-makers around the globe.

1.2. LAND APPLICATION OF SECONDARY WASTEWATER

Large amount of secondary wastewater (SWW) generated from sewage treatment facilities are potentially a valuable resource for irrigating crops, industrial cooling water, ground water recharge, etc. In the recent years, large increase in the quantity of SWW originating from partially treated process has resulted in significant disposal problems. Currently, the most prevalent method for SWW disposal is land application which is regarded an effective method to reduce the pressure on fresh water resources in the world especially in the arid and semi-arid areas. On the other hand, the application of SWW on land is questionable environmentally with a few risks in water quality standards due to excess chloride, sulfate, nitrate, carbonate, soil-salt accumulation, soil property degradation, etc. When large quantities of SWW are applied to the land for long periods, it may percolate through the soil layers and reach the ground water. Thus in order to minimize the health risks, it is important to know the total content of hazardous substances.

In Puducherry, India, a unique situation of co-disposal of MSW dumping and SWW disposal on land prevails simultaneously within the same campus. Against this backdrop, an attempt is made to assess the combined effect of co-disposal on the environmental quality and pollution effects resulting from indiscriminate dumping of MSW and SWW disposal on land with a view to correctly monitor the situation. Also to assess whether the groundwater is fit for domestic purposes in future or whether the land is fit for ground water recharge including the evaluation of physio-chemical characteristics of groundwater at Karuvadikuppam, Lawspet in Puducherry, India.

2. STUDY AREA AND PRESENT SCENARIO

Puducherry is a Union Territory in India with an extent of 293 km^2. The study area falls in Lawspet area, where STP and solid waste landfill are located in the same campus at 11°58′16″ N latitude and 79°48′11″ E longitude on the northern part of Puducherry, India. The terrain declines from North to South with the ground elevation ranging from 53 to 6m. The ground elevation of the study area is depicted in Fig. 1. The region is characterized by tropical climate with a mean annual precipitation of 1200 mm. 35% of the rainfall occurs during the South-West monsoon from June to September and the remaining 65% occurs during the North-East monsoon, i.e., from October to December.

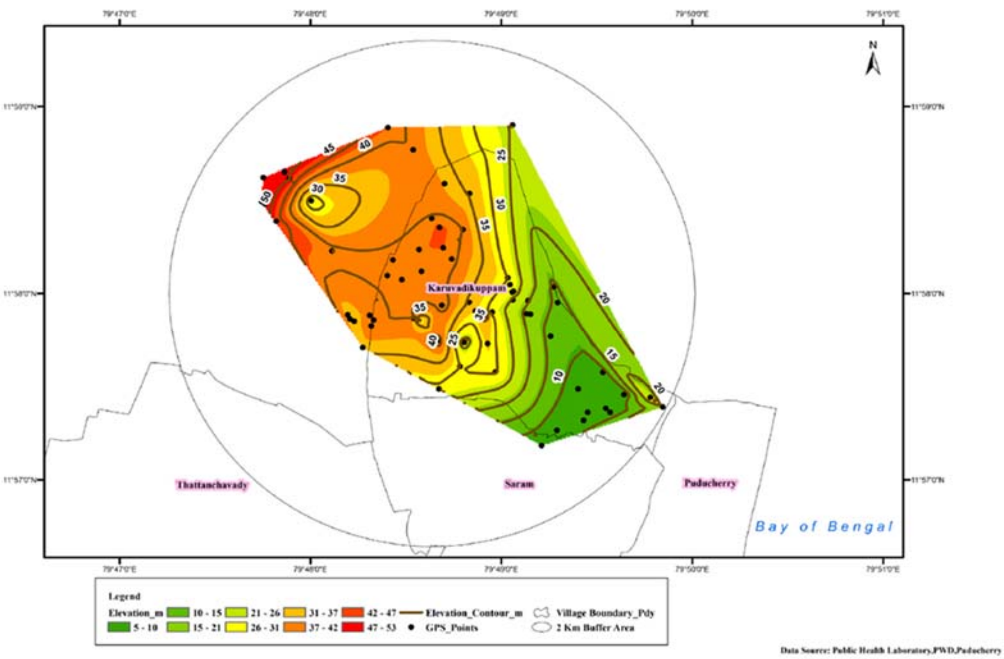

Fig. 1. Ground elevation contour map of study area

The present research was initiated with the aim to provide data on the groundwater quality due to MSW and SWW leachates, their variations and transformations over a period of time. Considering the above-mentioned facts, the specific objectives of this study are to evaluate the effectiveness of inorganic compound transport using multivariate statistical analysis including the interaction between biodegradation of contaminants in leachate during the landfilling operation and SWW land application.

3. SAMPLE COLLECTION AND FIELD MEASUREMENTS

3.1. MONITORING BOREWELLS

To accurately represent the groundwater quality, a sampling strategy was designed to cover a wide range of borewells at key locations. Totally, 68 borewells were identified in and around the study area.

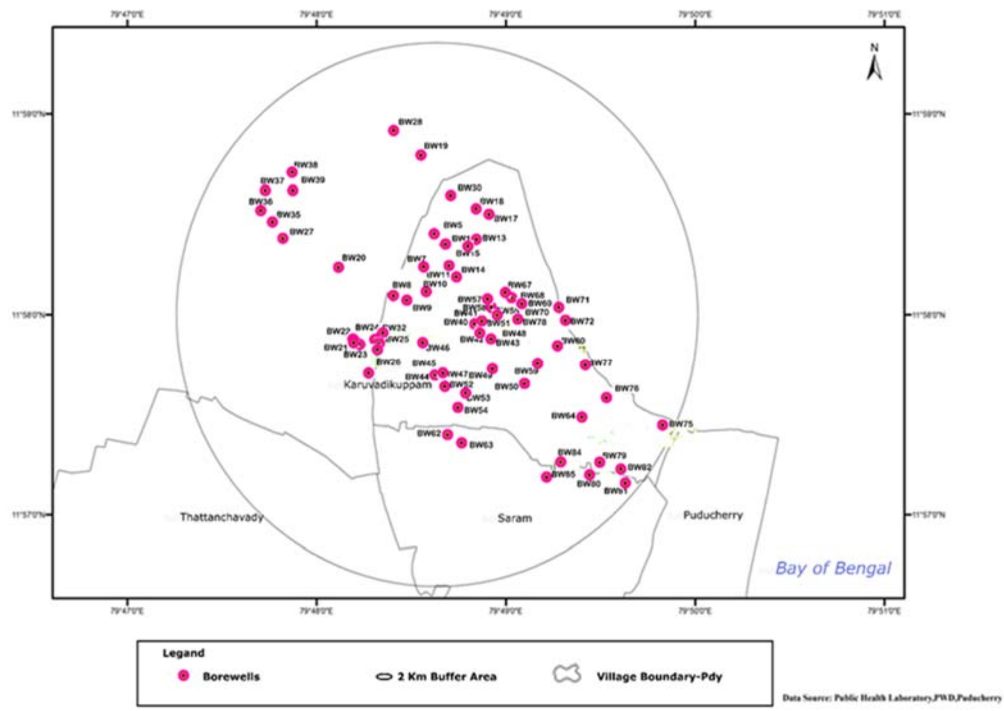

Fig. 2. Location of borewells in study area

The locations of these borewells are illustrated in Fig. 2. Out of which, in phase I, 43 borewells were considered for investigation and water samples were collected every month from Jan 2014–Dec 2014 (cycle I) from solid waste dump area, recharge pond area, sewage farm area (existing) and peripheral area (private and government) in order to study the seasonal and spatial variations.

3.2. PHYSICOCHEMICAL ANALYSIS OF GROUND WATER

Totally 249 water samples were collected from 43 borewells and tested for 17 physicochemical and bacteriological parameters viz. electrical conductivity (EC) pH, total dissolved solids (TDS), alkalinity, total hardness (TH), bicarbonate, calcium, magnesium, iron, chloride, sulfate, nitrate, sodium, fluoride, potassium, phosphate, silica, BOD, COD, total coliforms and fecal coliforms contents. The study was confined to the physicochemical parameters and their mean values for 43 borewells are given in Table 1.

Table 1

Mean results of the physicochemical analyses for 43 borewells (January–December 2014)

BW	EC	pH	TDS	Alk	HCO_3	TH	Ca	Mg	Fe	Cl	SO_4	NO_3	F	Na	K	PO_4	Si
	[µS/cm]		[mg/dm^3]														
Cluster 1																	
BW1	1250	6.4	789	203	248	360	86	31	1.9	207	130	5	0.2	107	5.4	0	1.3
BW5	1459	6.3	916	211	257	364	85	35	1.6	254	151	5	0.1	267	5.8	0	1
BW14	1192	6.8	752	332	405	373	82	43	1.1	177	62	5	0.1	172	3.6	0	1.5
BW15	1452	7.3	914	318	387	486	120	43	0.3	282	60	6	0.2	81	4.8	0	1
BW40	1532	6.6	960	247	302	293	74	31	0.4	303	61	6	0.1	185	0	0	1
BW41	1528	6.8	964	279	340	327	65	41	0.3	357	57	7	0.2	199	4.5	0	1.5
BW42	1360	6.8	850	273	333	298	84	22	0.1	309	40	6	0.2	170	1.5	0	2
BW43	1337	6.8	802	227	277	265	70	13	0.1	282	28	5	0.1	180	1	0	1.8
BW48	1248	6.5	786	216	264	249	62	24	2.4	298	44	5	0.2	170	2	0	1.5
BW49	1280	6.5	808	238	290	265	69	23	0.2	290	55	5	0.2	170	3	0	2.5
BW50	1243	6.6	783	208	254	270	66	26	0.1	316	48	5	0.2	160	3	0	2
BW51	1424	6.5	897	256	312	282	58	34	0.1	334	54	5	0.2	200	4	0	2.5
BW52	1312	6.3	827	222	271	272	51	36	0.1	295	42	6	0.2	183	2	0	2
BW53	1251	6.2	788	196	239	251	52	30	0.1	281	45	6	0.2	178	2	0	2
Cluster 2																	
BW7	1897	6.9	1195	392	479	369	71	36	1.7	421	88	5	0.1	281	8.6	0	1.7
BW8	1845	6.7	1165	274	334	397	84	39	2.4	411	80	5	0.1	266	11	0.4	2.4
BW9	1862	6.9	1171	318	388	383	89	41	1.3	400	79	6	0.1	248	8.8	0.1	1.5
BW10	2038	6.9	1284	368	448	421	72	51	2.6	439	102	6	0.2	241	12	0	2.3
BW11	1998	7.8	1259	463	565	298	56	39	1.8	343	130	6	0.1	242	12	0	2
BW13	1774	6.6	1118	317	387	373	80	37	0.3	417	60	5	0.1	273	10	0	2.1
BW44	1902	6.2	1198	212	259	439	99	48	0.9	452	86	22	0.2	230	4	0	2
BW45	2230	6.6	1405	328	400	422	85	52	2.8	516	88	5	0.2	330	3	0	2.5

Table 1

Mean results of the physicochemical analyses for 43 borewells (January–December 2014)

Cluster 3																
BW19	768	6.9	479	373	455	355	71	41	0.3	60	25	5	0.2	45	5	0	1.5
BW20	583	6.9	368	269	328	259	55	29	0.2	35	14	5	0.1	39	0.8	0	1
BW32	861	6.8	542	312	381	205	43	26	0.2	98	72	13	0.1	103	2.8	0	1.9
BW38	589	6.9	371	254	310	223	55	21	0.2	39	18	11	0.1	48	1	0	1
BW46	742	6.8	460	308	376	286	64	32	0.2	41	32	5	0.1	57	1	0	1.5
Cluster 4																
BW17	307	6.1	192	110	135	123	34	12	0.4	34	6	5	0.1	24	1.6	0	1
BW18	197	5.8	124	64	77	73	18	7	0.2	24	3	6	0.1	27	1.8	0	1.2
BW21	269	5.9	163	85	104	89	22	8	0.3	16	26	7	0.1	19	2.7	0	1.2
BW22	339	6.5	213	91	112	112	29	12	0.3	48	12	7	0.1	36	1.8	0	0.8
BW23	253	6.4	160	86	105	96	31	5	0.2	28	9	9	0.1	16	1	0	1
BW24	243	6.2	152	58	71	90	29	4	0.2	38	3	18	0.1	19	1.4	0	1
BW25	245	6.3	157	81	99	94	28	4	0.1	35	5	5	0.1	19	1.4	0	1
BW26	328	6.3	202	73	89	111	35	6	0.3	39	11	23	0.1	25	0	0	1.1
BW27	425	6.8	268	183	223	178	38	18	0.2	32	21	5	0.1	24	1.2	0	1.5
BW28	449	6.6	282	205	250	208	55	13	0.2	31	15	6	0.1	23	1	0	1.5
BW30	216	6.0	138	83	102	88	24	6	0.3	20	3	7	0.1	16	0.6	0	1.5
BW35	346	7.1	218	154	187	160	36	16	0.2	22	11	10	0.1	25	3	0	1
BW36	531	7.1	336	239	292	163	44	14	0.3	27	15	5	0.1	42	0.8	0	1.5
BW37	378	7.0	238	141	172	139	42	8	0.2	29	7	9	0.1	29	0.9	0	1
BW39	202	6.8	132	76	93	85	17	5	0.3	18	7	8	0.1	30	0.2	0	1
BW47	793	6.6	500	85	104	159	43	13	3.5	187	33	22	0.2	108	2	0	1.5

4. METHODOLOGY

4.1. MULTIVARIATE STATISTICS

In this work, multivariate statistical analyses like cluster analysis (CA) and discriminant analysis (DA) were employed to examine the spatial groupings of the sampling wells [1–3]. CA is a common method used to classify variables into clusters. CA is supported by DA as a confirmation for CA. Therefore the main objectives of this research work are to determine the spatial variability of groundwater and to identify the root cause of the contamination that presently affects the groundwater. The statistical software package SPSS Version 21 was used for the multivariate statistical analysis of the data [4–7].

4.2. CLUSTER ANALYSIS

CA is one of the most popular statistical tools for analyzing hydrochemical composition of groundwater [8, 9]. In order to recognize the existence of different groups of groundwater, CA is employed to split the standardized physicochemical data into various clusters with similar hydrochemical variable characteristics so that each group represents a specific hydrochemistry process in the study area. In other words clusters are formed with high homogeneity level within the class and high heterogeneity level among the classes.

The hierarchical cluster analysis (HCA) is used which wherein the objects are grouped in such a way that similar objects fall into the same class and join the most analogous observations and successively the next most analogous observations. The similarity levels at which observations are agglomerated into a configuration of a tree with different branches (dendrogram), provide a visual summary of the clustering process, thereby depicting a picture of the group and their proximity. Branches that have linkage closer to each other indicate a stronger relationship among samples/variables. Thus the dendrogram can be broken at different levels to yield different clusters of the data set.

To perform HCA, it is most common to calculate the dissimilarity between two patterns using a distance measure. The most commonly used is the Euclidean distance. The HCA with Ward's method of linkages with squared Euclidean distance as dissimilarity measure was applied to detect multivariate similarities and depending on their similarities to group parameters into clusters. The Ward's method of linkage uses the minimum variance approach to evaluate distance between the clusters.

In the current study, HCA was applied for the grouping of 43 different borewells using squared Euclidean distance measurement together with Ward's method for linkage which produced the most distinctive groups where each member within groups is more similar to its fellow member than any member outside the group.

4.3. DISCRIMINANT ANALYSIS

Discriminant analysis (DA) is a technique for classifying a set of observations into predefined classes. It operates on raw data and the technique constructs a discriminant function for each group. A simple linear discriminant function transforms the original set of observations on a sample into a single discriminant score. DA involves the determination of a linear equation that will forecast which group the occurrence belongs to.

The main objective of DA is to discriminate between two or more groups in terms of the discriminating variables. Out of three different modes available, a standard mode was used in the present study to construct the best discriminant functions (DFs) in order to confirm the clusters developed by HCA and to evaluate spatial variation in groundwater quality at Lawspet in Puducherry, India. The membership of a borewell in a cluster was the dependent variable whereas all the measured parameters constituted the independent variables.

5. RESULTS AND DISCUSSION

5.1. CLUSTER ANALYSIS

In the current study, with the available hydro-chemical dataset, Ward's method of HCA with squared Euclidean distance as the distance measure was found to be more successful to form clusters that are more or less homogenous and hydro chemically distinct from other clusters. With this approach three types of HCA viz. borewell clustering, parameter clustering and temporal clustering were performed in order to have a distinct and clear vision of groundwater qualitatively, spatially and seasonally [10–14].

The HCA was performed on 249 groundwater samples and the cluster classification is depicted in Fig.3. Also the dendrogram in Fig. 4 shows the results of HCA for water quality of the borewells in the study area. Four clusters were obtained from this analysis as detailed below:.

Cluster 1. 14 borewells were represented by cluster 1 which constituted 32.6% of the total 43 borewells viz., BW1, BW5, BW14, BW15, BW40–BW43, BW48–BW53.

The subclusters were:

- subcluster 1.1: BW1 and BW5,
- subcluster 1.2: BW48–BW50, BW52 and BW53,
- subcluster 1.3: BW40, BW41 and BW51,
- subcluster 1.4: BW42 and BW43,
- sub cluster 1.5: BW14 and BW15.

The borewells in cluster 1 are located in the solid waste dumpsite area and in the south-eastern part of the study area. The ground level difference between the BW1 (44.065) in the solid waste dump area and the farthest borewell BW49 (21.966) is 22.10 m. In other words, the contaminant movement follows the ground elevation. Here, the most contributing parameters to groundwater quality are EC, TDS, alkalinity, bicarbonates, TH, iron and chloride content. Table 1 (for 14 borewells pertaining to cluster 1) demonstrates that the EC values in groundwater samples ranged from 1192 to 1532 μS/cm with a mean value of 1348 μS/cm in this group; the TDS values of samples ranged from 752 to 964 mg/dm^3 with an average of 845 mg/dm^3; the alkalinity varied from 196 to 332 mg $CaCO_3$/dm^3 with a mean value of 245 mg $CaCO_3$/dm$^{3;}$ TH varied from 249 to 486 mg $CaCO_3$/dm^3 with a mean value of 311 mg $CaCO_3$/dm^3; the bicarbonate concentration varied from 239 to 405 mg/dm^3 with a mean value of 299 mg/dm^3; iron concentration varied from 0.1 to 2.4 mg/dm^3 with a mean value of 0.62 mg/dm^3; chloride concentration ranged from 177 to 357 mg/dm^3 with a mean value of 285 mg/dm^3. All these parameters exceeded their acceptable threshold limits for drinking water.

It is found that high increased concentrations of these elements are associated with natural process and anthropogenic activity like solid waste dumping. The results reflect that groundwater in this group is unsuitable for human consumption as the aforementioned values exceeded the allowable threshold limits.

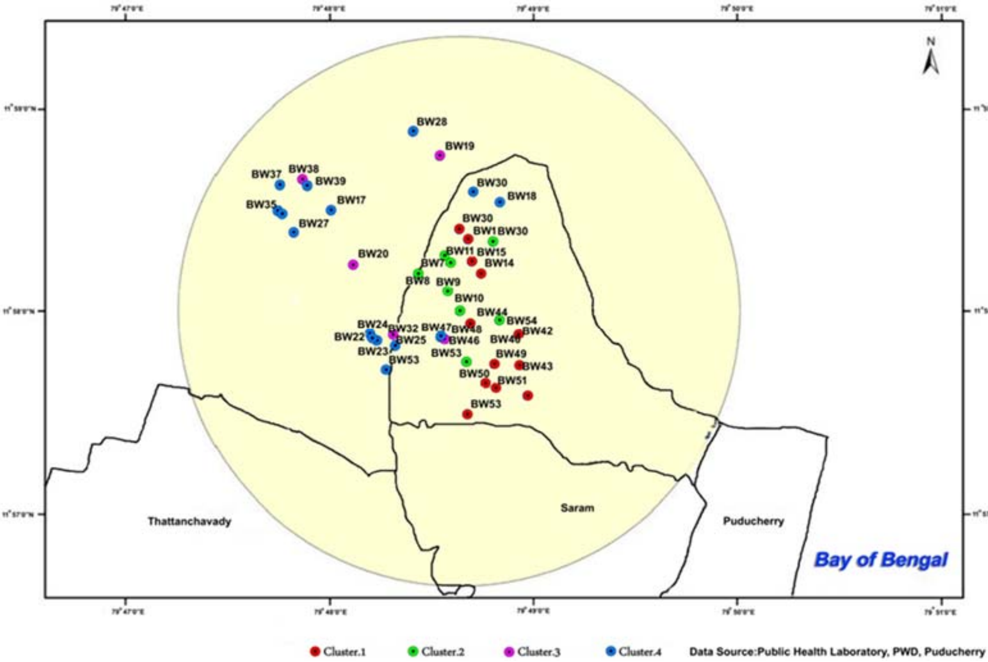

Fig. 3. Regional distribution of four clusters

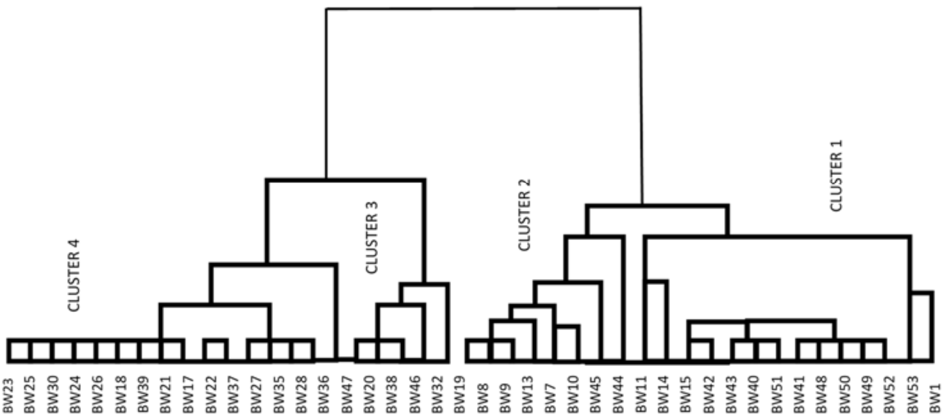

Fig. 4. Borewell dendrogram

Cluster 2. 8 borewells were identified in cluster 2 which formed 18.6% of the 43 studied borewells viz., BW7–BW11, BW13, BW44 and BW45. It included five subclusters:

- subcluster 2.1: BW11,
- subcluster 2.2: BW44,
- subcluster 2.3: BW10 and BW45,
- subcluster 2.4: BW7,
- subcluster 2.5: BW8, BW9 and BW13.

In cluster 2, the borewells are located in the recharge pond area and south-eastern part of the study area. Here, the most contributing parameters to groundwater quality are EC, TDS, alkalinity, bicarbonates, TH, iron, chloride, calcium and magnesium content. Table 1 for 8 borewells belonging to cluster 2) demonstrates that the EC values in groundwater samples ranged from 1774 to 2230 μS/cm with a mean value of 1943.3 μS/cm in this group; the TDS values of samples ranged from 1118 to 1405 mg/dm^3 with an average of 1224.4 mg/dm^3; the alkalinity varied from 212 to 463 mg $CaCO_3$/dm^3 with a mean value of 334 mg $CaCO_3$/dm^3; TH varied from 298 to 439 mg $CaCO_3$/dm^3 with a mean value of 387.8 mg $CaCO_3$/dm^3; the bicarbonate concentration varied from 259 to 565 mg/dm^3 with a mean value of 407.5 mg/dm^3; iron concentration varied from 0.3 to 2.8 mg/dm^3 with a mean value of 1.72 mg/dm^3, which even exceeded the maximum permissible limit. Also chloride concentration ranged from 343 to 516 mg/dm^3 with a mean value of 424.9 mg/dm^3. Calcium concentration ranged from 56 to 99 mg/dm^3 with a mean value of 79.5 mg/dm^3. Magnesium concentration ranged from 36 to 52 mg/dm^3 with a mean value of 42.9 mg/dm^3. All these parameters have exceeded their acceptable threshold limits.

The elevated concentrations of these polluting elements are due to natural process and anthropogenic activity like SWW land application. These effects reveal that the groundwater in cluster 2 is unfit for domestic purposes due to the aforesaid reasons.

Cluster 3. The smallest cluster 3 included only five wells and represented 11.6% of the total 43 borewells viz., BW19, BW20, BW32, BW38 and BW46 with three subclusters:

- subcluster 3.1: BW19,
- subcluster 3.2: BW32,
- subcluster 3.3: BW20, BW38 and BW46,

The borewells in cluster 3 are located in the peripheral area and in the north-western and south-western parts of the study area. In cluster 3, the most contributing parameters to groundwater quality are EC, alkalinity and bicarbonates. Table 1 (for 5 borewells related to cluster 3) demonstrates that the EC values in groundwater samples ranged from 583 to 861 μS/cm with a mean value of 708.6 μS/cm in this group; the alkalinity varied from 254 to 373 mg $CaCO_3$/dm^3 with a mean value of 303.2 mg/dm^3; the bicarbonate concentration varied from 310 to 455 mg/dm^3 with a mean value of 370 mg/dm^3, All these parameters have exceeded their minimum permissible limits for drinking water. All other parameters were within the acceptable limits.

It may be concluded that higher concentrations of these elements are associated with natural process. Fortunately, the contamination situation in cluster 3 is not serious as most of the hydro chemical element contents fall within the drinking water standards, which are basically suitable for human utilization.

Cluster 4. The largest cluster was identified as cluster 4 with 16 borewells which constituted 37.2% of the 43 borewells under study viz., BW17, BW18, BW21–BW28, BW30, BW35–BW37, BW39 and BW47.

It included three subclusters:

- subcluster 4.1: BW47,
- subcluster 4.2: BW27, BW28, BW35 and BW36,
- subcluster 4.3: BW17, BW18, BW21–BW26, BW37 and BW39.

The borewells in cluster 4 are located in the peripheral area and in the north-western and south-western parts of the study area beyond cluster 3. In cluster 4, the most contributing parameter to groundwater quality is iron as all other parameters fall within the minimum permissible limits of the drinking water standards. Table 1 demonstrates that for 16 borewells pertaining to cluster 4, the iron concentration in groundwater samples ranged from 0.12 to 3.5 mg/dm^3 with a mean concentration of 0.43 mg/dm^3 in this group which exceeded its acceptable threshold limit. It is found that higher concentration of iron in this cluster is due to natural occurrence. The contamination here is not severe and with aeration/iron removal plants the groundwater can be made potable for domestic consumption.

The conclusion from the above analyses is that clusters 1 and 2 have relatively higher pollution levels than clusters 3 and 4. The characteristic of clusters 3 and 4 if judged based on water pollution may be considered to be non-polluted or slightly polluted category. Further all water quality parameters except few do not tend to have increased concentration which indicates that clusters 3 and 4 belong to good water quality category. The analyses further reveal that the water quality parameters in these clusters have small ranges of variations and evenly distributed over the various seasons of the year. Hence clusters 3 and 4 may be termed as unpolluted, indicating that the groundwater quality is relatively good and fit for human consumption better than clusters 1 and 2 whose contamination is due to MSW dumping and SWW land application which are anthropogenic in nature.

The levels of similarity of the hydrochemical parameters were used to construct a parameter dendrogram, using the squared Euclidean distance for similarity measures. The 10 most contributing water quality parameters out of 17 indices were considered for parameter cluster analysis. They are depicted in Fig. 5 which shows the dendrogram tree for the studied parameters of all samples in the data set. The dendrogram shows four main clusters, which are divided into subclusters as follows:

Cluster 5: EC, TDS, Na and Cl, Subcluster 5.1: EC and TDS, Subcluster 5.2: Na and Cl.
Cluster 6: TH, Ca and Mg, Subcluster 6.1: TH and Ca, Subcluster 6.2: Mg.
Cluster 7: ALK and HCO_3, Cluster 8: SO_4.

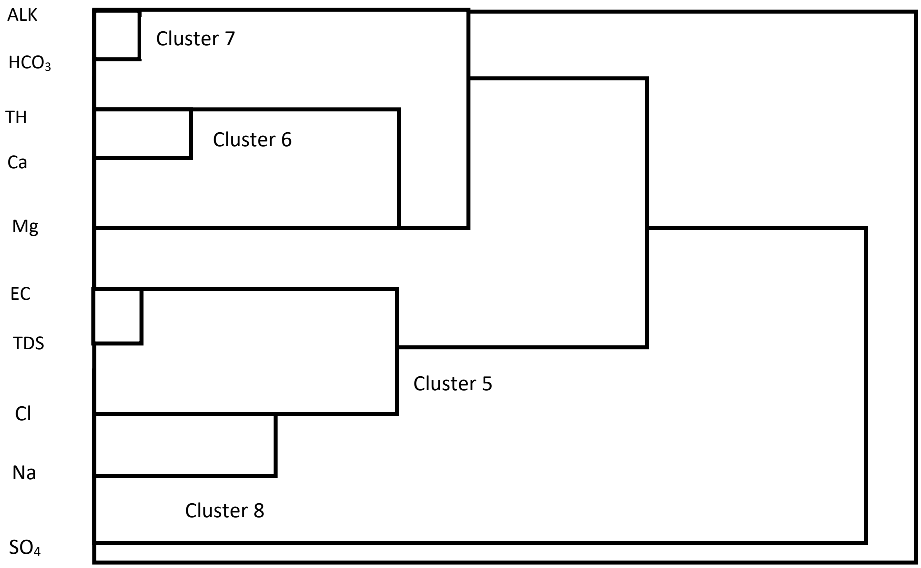

Fig. 5. Parameter dendrogram

This data analysis gives an idea of how a single water quality parameter should be compared and related to another, if the sample is treated with all parameter values simultaneously and not separately. Careful observation of cluster 5 seems to follow specific water quality parameters classification rule, which indicates the presence of EC, TDS, Na and Cl. Two subclusters were formed, namely subcluster 5.1 – EC and TDS and subcluster 5.2 – Na and Cl. A stronger relation between the parameters EC and TDS was observed with parameters like Na and Cl than to Mg and the other studied quality parameters.

The enrichment of groundwater with Na and Cl ions is due to the interaction of water with rocks. The association of TDS with high concentration of Na and Cl ions, indicated that anthropogenic activities (such as discharge of SWW and solid waste leachate) worsen the contamination of groundwater.

Cluster 6 indicates the presence of TH, Ca and Mg. Two subclusters were formed, namely subcluster 6.1 – TH and Ca and subcluster 6.2 – Mg. This cluster indicates the hardness component of the water quality. Cluster 7 identifies the presence of alkalinity and bicarbonates. Cluster 8 identifies the presence of sulfates. This may be due to weathering of bedrock and subsequent leaching, which contribute to groundwater quality deterioration. Further it is confirmed that physicochemical water quality parameters are to be group specific.

An initial exploratory approach was involved in the use of HCA on hydro-chemical data sorted by seasons [15–17]. Temporal variation in groundwater quality is absolutely not determined by seasonal effects but the nature and frequency of discharge of SWW and solid waste leachate play a crucial role in groundwater quality.

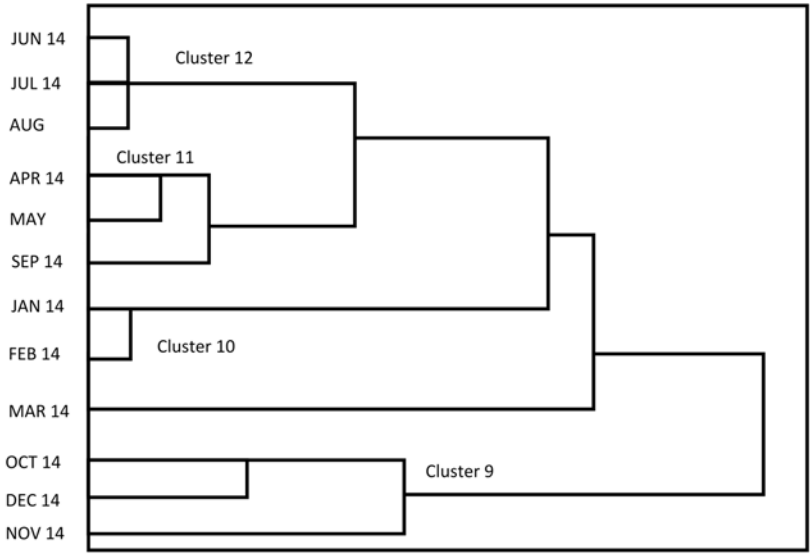

Fig. 6. Temporal dendrogram of BW9

For instance, temporal HCA was applied to BW9 in recharge pond area and it generated a dendrogram as shown in Fig. 6 grouping the 12 months into four clusters. Cluster 9 identifies North-East monsoon period in South-India comprising of October, November and December representing the rainy season. Cluster 10 comprises of post-monsoon season, i.e., January and February. Cluster 11 formed the summer season, i.e., April and May. June, July and August representing the pre-monsoon season are identified as Cluster 12. The temporal pattern of groundwater quality was to a large extent consistent with the four seasons with the exception of September getting clustered with the summer months which is transitional in nature. Another exception is March which is also transitional in nature as the same do not couple with any other month.

5.2 DISCRIMINANT ANALYSIS

Discriminant analysis was used to find one or more functions of the observed data (called discriminant functions) that separate water quality into four clusters. Standard mode discriminant analysis was applied on raw data in the present study. According to this method, 15 parameters: EC, pH, TDS, alkalinity, TH, Ca, Mg, Fe, Cl, SO_4, NO_3, F, Na, K and Si were extracted to divide groundwater samples into 4 clusters.

Table 2

Summary of canonical discriminant functions

Function	Eigen value[a]	Percent of variance	Cumulative percent	Canonical correlation
1	45.320	91.5	91.5	0.989
2	2.381	4.8	96.3	0.839
3	1.810	3.7	100	0.803

[a]First three canonical discriminant functions were used in the analysis.

Three discriminate functions (DFs) were found to discriminate the four clusters as shown in Table 2. Wilk's Lambda Test showed that all the three functions were statistically significant as the values are less than 0.05 (Table 3).

Table 3

Wilks' lambda test values

Test of function(s)	Wilks' λ	χ^2	*df*	Sig
1 through 3	0.002	197.823	45	0
2 through 3	0.105	73.167	28	0
3	0.356	33.58	13	0.001

Further, 100 % of the total variance among the four clusters was explained by the three DFs. The relative contribution of each parameter to all the three functions is given in Table 4. The first function DF1 explained 91.5% of the total spatial variance with high canonical correlation of 0.989. This function is positively correlated with EC (3.6), Mg (0.821) and pH (0.59) and negatively correlated with TDS (–5.53), TH (–0.93) and K (–0.64).

Table 4

Coefficients of the standardized canonical discriminant function

Parameter	Function			Parameter	Function		
	1	2	3		1	2	3
pH	0.594	0.263	–0.572	SO_4	0.483	1.011	0.125
TDS	–5.533	–5.159	–3.479	NO_3	0.214	–0.527	0.51
ALK	0.325	0.35	1.468	F	0.264	0.832	–0.119
TH	–0.928	–0.505	0.118	Na	0.03	0.321	0.084
Ca	0.455	0.711	–0.043	K	–0.639	–0.898	–0.25
Mg	0.821	0.117	0.453	Si	0.14	–0.103	0.017
Fe	0.452	–0.525	0.083	EC	3.604	4.136	2.82
Cl	0.282	0.705	0.087				

The second function DF2 explained 4.8% of the variance with canonical correlation of 0.839. This function is positively correlated with EC (4.14), SO_4 (1.01), F (0.83), Ca (0.71) and Cl (0.71). Also it is negatively correlated with TDS (–5.16). The third function DF3 explained 3.7% of the variance with canonical correlation of 0.803. This function is positively correlated with EC (2.82), Alkalinity (1.47) and NO_3 (0.51). It is also negatively correlated with TDS (–3.48).

Parameters were grouped based on function coefficients and are indicated as below:

DF 1: EC, Mg and pH,

DF 2: EC, SO_4, F, Ca and Cl,

DF 3: EC, alkalinity and NO_3.

In the first function EC, Mg and pH exhibited strong contribution in discriminating the four clusters and account for most of the expected spatial variations in the quality of water of four clusters, while less contribution was exhibited by other parameters. In the second function, contributions of EC, SO_4, F, Ca and Cl are significant in discriminating the four clusters. In the third function, EC, alkalinity and NO_3 are the most contributing parameters in discriminating the clusters.

Table 5

Classification matrix results

Cluster			Predicted group membership				Total
			1	2	3	4	
Original	count	1	14	0	0	0	14
		2	0	8	0	0	8
		3	0	0	5	0	5
		4	0	0	0	16	16
	%	1	100[a]	0	0	0	100
		2	0	100[a]	0	0	100
		3	0	0	100[a]	0	100
		4	0	0	0	100[a]	100
Cross-validated[b]	count	1	10	2	1	1	14
		2	1	7	0	0	8
		3	0	0	5	0	5
		4	0	0	1	15	16
	%	1	71.4[c]	14.3	7.1	7.1	100
		2	12.5	87.5[c]	0	0	100
		3	0	0	100[c]	0	100
		4	0	0	6.3	93.8[b]	100

[a]100 % of original grouped cases correctly classified.

[b]Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

[c]88.0% (mean) of cross-validated grouped cases correctly classified.

The cross-validation of the formation of clusters is given in classification matrix (Table 5). The discriminant analysis gave the classification matrix with 71.4% of correct assignation in the formation of cluster 1. Originally 14 borewells were grouped in cluster 1. But according to the discriminant analysis these 14 borewells were distributed as 10 borewells in cluster 1, 2 borewells in cluster 2, 1 borewell in clusters 3 and 4 each.

Similarly, the classification matrix explained 87.5% of correct assignation in the formation of cluster 2. 8 borewells were originally classified in cluster 2. But according to the discriminant analysis, these 8 borewells were distributed as 7 borewells in cluster 2 and 1 borewell in cluster 1. The discriminant analysis gave the classification matrix with 100% correct assignation in the formation of cluster 3 which means the discriminant function endorsed the original grouping of 5 borewells.

The discriminant analysis gave the classification matrix with 93.8% correct assignation in the formation of cluster 4. Originally 16 borewells were grouped in cluster 4. But according to the discriminant analysis these 16 borewells were distributed as 15 borewells in cluster 4 and 1 borewell in cluster 3. In DA 100% of original grouped cases are correctly classified. Also cross validation based on discriminant functions gave 86% of cross validated classified groups cases correctly.

Therefore, as per the classification matrix, and according to the DA theory, only 9 hydrochemical variables were required to discriminate the 249 samples in four clusters with 86% correct classification of clusters.

6. CONCLUSIONS

A field investigation was carried out and 249 groundwater samples were collected from 43 borewells for a period of 12 months. The statistical analyses performed on 17 physicochemical parameters have revealed the following:

- Borewell clustering identified four clusters viz., cluster 1 (14 borewells) located at the solid waste dumpsite area in the south-eastern direction, cluster 2 (8 borewells) located at the recharge pond area in the south-eastern direction, cluster 3 (5 borewells) located in the north-west and south-west directions and cluster 4 (16 borewells) located in the north-west and south-west directions beyond cluster 3. Here, clusters 1 and 2 are highly polluted. Cluster 3 is less polluted and cluster 4 is not polluted.
- The groundwater contaminant movement is towards south-eastern direction and follows the ground profile. The level difference between the borewell BW1 (solid waste dump area) and further borewell BW49 (south-eastern part) is around 22.10 m.
- In parameter clustering, two major clusters were formed: cluster 5 and cluster 6 indicating hardness and anthropogenic components (discharge SWW and solid waste leachate,) respectively.
- Temporal clustering identified three major clusters cluster 12, cluster 9 and cluster 10 indicating pre-monsoon, monsoon and post-monsoon, respectively.

• Discriminant analysis indicated nine significant parameters such as EC, Mg, pH, SO_4, F, Ca, Cl, alkalinity and NO_3 which discriminate the groundwater quality of the four clusters affording 86% correct assignation to discriminate among the clusters using standard mode from the original 17 parameters. Therefore, DA allowed a reduction in the dimensionality of the large data set and determined a few important parameters responsible for large fluctuations in water quality that could curtail the number of sampling parameters.

• The investigation revealed that the contaminant movement is in the south-eastern direction of the study area and the boundary up to which contamination exists has been identified. All the borewells (100%) in the south-eastern part of the study area are affected.

• Three major components, anthropogenic, hardness and geogenic, responsible for groundwater quality in the study area were identified. Anthropogenic activities are mainly due to MSW dumping and SWW disposal on land. Indiscriminate dumping of municipal solid waste without proper solid waste practices should be stopped. If possible, controlled solid waste dumping combined with some remedial measures like proper segregation, recycling and lining are required to be adapted to prevent further contamination due to already dumped solid waste in a scientific way.

• The old treatment method using oxidation ponds shall be dispensed with in future. The latest wastewater disposal method using SBR technology is already underway. Thus controlled wastewater disposal on land after proper treatment can minimize the groundwater quality degradation in the affected area. Proper water treatment for hardness removal should be carried out before domestic usage. Iron which is geogenic in nature is prevalent almost in the entire study area and the same shall be removed with aeration and iron removal plant (IRP) before domestic supply.

• The result of this study illustrates that multivariate statistical methods are excellent inductive tools for analyzing complex water quality data sets and for understanding spatial variations, which are fruitful and emphatic for water quality management. Additionally this result may be used to reduce the number of samples analyzed both spatially and temporally without much loss of information. This will assist the decision makers to identify priorities to improve water quality that has deteriorated due to pollution from various anthropogenic activities.

• Further studies will utilize the artificial neural network (ANN) and 3D contaminant transport models to predict the movement of groundwater contaminants and to understand the characteristics of groundwater quality in northern part of Puducherry, India.

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