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Spatial Analysis of Groundwater Quality of Malwa Region of Punjab using Multivariate Statstical Techniques

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Abstract: The Multivariate platform examines multiple variables to see how they relate and more than one dependent variable is analyzed simultaneously with other. This research explored the quality of groundwater of 43 wells during 5 years (2011-2015), in 12 districts of Malwa region, Punjab, to survey spatial variation of groundwater quality and also major sources of physico-chemical components for drinking and agricultural uses. Multivariate statistical techniques, cluster analysis (CA) and principal component analysis (PCA) had been integrated to assess and interpret spatial variations of water quality of wells. Hierarchical cluster analysis revealed all sites could be grouped into three clusters representing different levels of pollution: 16 relatively less polluted (LP) sites, 19 moderate polluted (MP) sites, and 8 highly polluted lower (HP) sites. Principal component analysis was used to explore the most important factors determining the spatial dynamics of water quality in Malwa region of Punjab. Principal component analysis is applied to each cluster to calculate optimum number of principal components required for describing the water quality variation using IBM SPSS 22. Principal components obtained from the analysis indicated the parameters responsible for water quality variation were mainly related to CO_3^{2-} and SiO_2 in less polluted areas mainly due to natural cause, high salinity due to high EC, Cl^- and Na^+ due to use of fertilizers and sewage in moderately polluted areas and high concentration of Mg^+, Ca^+, NO_3^-, SO_4^{2-} and TH due to high use of fertilizers, agricultures(non-point sources) and sewage, industries of pulp-paper, textiles and fertilizers (point sources). This study suggested that multivariate statistical techniques are useful tools for identification of important water quality monitoring sites parameters and interpretation of complex data matrix, and in water quality assessment, identification of pollution sources/factors and understanding spatial variations.
Keywords: Malwa region, Punjab; Groundwater quality; Multivariate statistical techniques; Cluster analysis; Principal component analysis

I. INTRODUCTION

Groundwater resources are essential and main source of drinking water around the world, because they are often free from contamination, difficult to pollute, widely dispensed, and adjust throughout the year. Groundwater pollution occurs when pollutants make their way down into groundwater and exploit the quality. Groundwater is polluted due to pollution associated with the human activities as well as natural sources. Groundwater chemistry depends on a number of factors, such as general geology, degree of chemical weathering of the various rock types, quality of recharge water and inputs from sources other than water rock interaction. Such factors and their interactions result in a complex groundwater quality (Carrera et. al. 2005). Groundwater is an important water resource for drinking, agriculture and industrial uses in Punjab. Multivariate statistical techniques are used by many researchers for the assessment and interpretation of groundwater quality and interpretation of factors influencing the groundwater quality of the area. Multivariate statistical techniques, cluster analysis (CA) and principal component analysis (PCA) used for the analysis of temporal and spatial variation of Fuji river basin in Japan consisted of large data set water quality parameters generated during 8 years (1995-2002). The data set consist of 12 parameter monitored at 13 different sites with 14,976 observations (Shrestha et al. 2006). (Singh et al. 2004) presented the functionality of multivariate statistical techniques for the assessment and explanation of complex data set of water quality parameters to get better information about water quality of Gomti River.Cluster analysis and PCA applied on about 18000 observations of 24 parameters over the period of five years at eight sampling sites. PCs explained that the soluble salts (natural) and organic pollution loads (anthropogenic) are responsible for water quality variation. PCA and cluster analysis for the evaluation of water quality of Baiyangdian Lake in China in which area is divided into five clusters and five principal component helped to identify the factor responsible for water quality variation. According to factors they have explained the different sources responsible for pollution (Zhao et al. 2012). Most applications of this analysis have involved a correlation matrix rather than a covariance matrix. If the parameter variables are in wildly different units (concentrations in mg/L, pH, and temp in ^{o}C) then standard variates and correlation matrix should be used and if the variables are not to be considered of equal importance, then the analysis of the correlation matrix is not recommended (Karpuzcu et al. 1987).

In the present study, two different multivariate statistical techniques (CA, FA/PCA) were applied to evaluate the spatial variations in water-quality data set of the Groundwater of Malwa region of Punjab by data reduction without losing much information, which were generated during the 5-years (2011-15) and about 3000 observations.

II. METHODS

A. Study Area

The study area is the southern region of Punjab state of India. The geographical location of the study region of South Punjab is between latitude 29^{o}20' – 31^{o}10'N and longitude 73^{o}75' to 76^{o}50'E at an average elevation of 200 m from the mean sea level. It comprises 12 districts (Bhathinda, Faridkot, Fatehgarh, Firozpur, Fazilka, Ludhiana, Mansa, Moga, Muktsar, Nawanshar, Patiala and Barnala) with 43 sampling sites. The total study area is about 31500 sq. km with mean elevation of about 200 m from M.S.L. Average rainfall in this region is 750 mm and Sutlej is main river flows through some of the districts. Punjab state occupies only 1.5 per cent of the geographical area of the country and being most fertile regions in India produce around two-third of the food grains annually in the country. By the excessive use of pesticides, fertilizer and other chemicals Punjab took the lead in the Green Revolution and became the country's no. 1 state in food grain production and also for the contaminated groundwater. Industrial units including food & food products, beverages, paper, textile, tanning, electroplating & machinery units which discharge their industrial wastes into drains which are responsible for the contamination of groundwater quality.

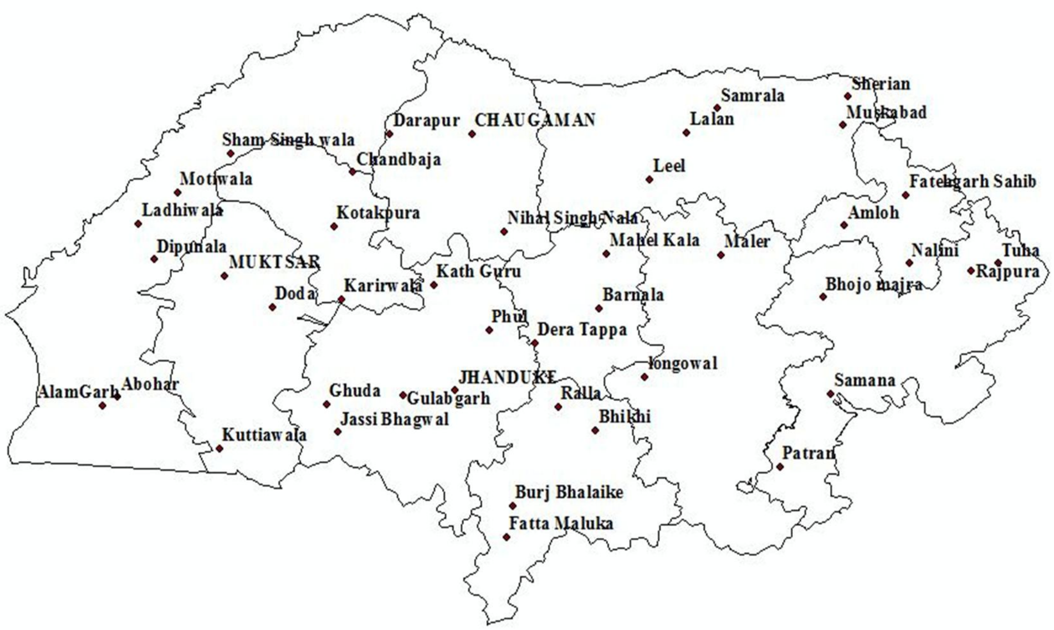

Fig 1. Study Area

B. Data Collection

The water quality parameters data for the groundwater is obtained from Central Ground Water Board (CGWB), Chandigarh the regulatory body accountable for collecting and storing the data. The data set included 15 water quality parameters including pH, carbonate (CO_3^{2-}), bicarbonate (HCO_3^{-}), calcium (Ca^{2+}), chloride (Cl^{-}), fluoride (F^{-}), total hardness (TH), magnesium (Mg^{2+}), potassium (K^{+}), sodium (Na^{+}), electrical conductivity(EC), sulfate (SO_4^{2-}), nitrate(NO_3^{-}), phosphate (PO_4^{3-}) and Silicate (SiO_2) monitored annually over the period of 5 years (2011-15). Only 15 parameters were selected due to their continuity and availability in measurement at all selected water quality monitoring stations.The C.G.W.B., Chandigarh annually monitors the groundwater quality through allocated groundwater monitoring stations consisting of dug well and hand pumps of shallow depths. Samples were analyzed in Regional Chemical Laboratory by following 'Standard analytical procedures' as given in APHA 1998 and 2012. The basic statistics of the annually measured, 5-year data set groundwater quality is summarized in Table 1.

C. Data Pretreatment and Multivariate Statistical Analysis

The Kaiser-Meyer-Olkin is the measure of sampling adequacy, which varies between 0 and 1. It indicates the proportion of variance which is common variance, The values closer to 1 are better and the value of 0.6 is the suggested minimum and in this case study KMO = 0.633 which indicates that the sample is adequate and may proceed with the Principal Component Analysis. The Bartlett's Test of Sphericity is the test for the correlation matrix has an identity matrix. It checks if there is a certain redundancy between the variables that we can summarize with a few number of factors. The significance level which is 0 in this study (less than 0.05) indicates that there are significant relationships among variables. Taking this into consideration, these tests shown in Figure 3 provide the minimum standard to proceed for PCA.

Multivariate statistical analysis of the river water-quality data set was analyzed through CA and PCA techniques (Wunderlin et al., 2001; Simeonova et al., 2003). Cluster analysis and FA/PCA were applied on z-scale standardized data to avoid misclassification due to large dissimilarity and variability in data dimensionality (Liu et al., 2003; Shrestha et. al. 2007). All statistical computations were made using MS Office Excel 2013 and SPSS 22.0

1) *Cluster Analysis:* Cluster analysis is an investigative data analysis tool for assembling observed data into meaningful clusters (groups) based on combinations of variables. Cluster analysis can perform the data reduction procedure objectively by reducing the information from the entire population of sample into the information about specific group. Clustering is a standard procedure in multivariate data analysis and the natural grouping of similar objects based upon input parameters. Cluster analysis is a grouping based upon distances proximity. The similarity, or dissimilarity, between two data objects is typically measured as the distance between the multi-dimensional feature vectors that represent the objects. It means the cluster formed are homogeneous within and heterogeneous across. The larger the distance between two data points, the less similar they are to each other. Hierarchical cluster analysis is a stepwise procedure that to identifies relative homogeneous groups of cases based on selected characteristics using an algorithm either agglomerative or divisive, resulting to a construction of hierarchy or tree like structure called dendogram diagram depicting the formation of clusters. CA was applied on the standrdized data set by means of the Ward’s method, using squared Euclidean distances.
2) *Principal Component Analysis:* Principal component is a technique used to emphasize variation and bring out strong patterns in a data set. (Wunderlin et al., 2001) PCA is a method which is applied to reduce the dimensionality of large set of correlated variables without losing much information and variability present in data set. The data reduction is attained by transforming the data set of original variable into new set of uncorrelated or orthogonal variables sets (called Principal Components) in the decreasing order of importance. Principal components are linear combination of original variables. In this research work Cluster analysis was applied to detect spatial representation for grouping of sites under the monitoring stations. PCA was applied to summarize the statistical relation among parameters in the water quality data set. Concentration order among all physico-chemical parameters differ greatly and the statistical outcomes should be highly biased by any parameter with high concentration. The calculation was performed based on the correlation matrix of parameters and the PCA scores were obtained from the standardized analytical data

III. RESULTS AND DISCUSSION

Water-quality monitoring of the groundwater was regularly conducted over a period of 5-years (2011-16) at 43 different sites. All the samples were analysed for 15 parameters and their station wise annual mean values are summarized in Table 1.

A. The Physical-Chemical Characteristics of Groundwater

The pH values of collected water samples ranged from 7.9-9.2, in some places beyond the limit range of 6.5-8.5 allowed by the CPCB for drinking purpose showing strong basic characteristic. EC cycle showed significant variations ranging from 411 – 7071 µS/cm, high salinity in some regions. The major cations Na (17.67 – 1397 mg/L), Ca (9.7-262.4 mg/L), Mg (17.49-164.7 mg/L), and K (2.33-313 mg/L) were found to be present in lower to very high concentrations throughout the region. The anions Cl (10-1177 mg/L), SO_4 (4.07-1704 mg/L), F (0.11-2.97 mg/L) were high in some regions. Total hardness was in the range of 104.4-1090 mg/L. It was found that the average nutrient concentrations (NO_3 and PO_4) were in higher concentrations, values measured at 3.37-295.7 mg/L and 0-1.18 mg/L respectively.

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Table 1 Mean and Standard Deviation of Groundwater Quality Parameters

Variables	Min	Max	Mean	SD
pH	7.94	9.21	8.5714	0.34388
EC (µS/cm)	411	7071	1889.13	1553.51
CO_3^{2-} (mg/L)	4	136.89	47.6426	34.1701
HCO_3^- (mg/L)	121.33	653.67	312.389	119.71
Cl^- (mg/L)	10	1177.12	211.763	268.249
SO_4^{2-} (mg/L)	4.07	1706.67	321.922	401.696
NO_3^- (mg/L)	3.37	295.67	70.4274	64.4416
F^- (mg/L)	0.11	2.97	0.82279	0.65798
PO_4^{2-} (mg/L)	0	1.18	0.05775	0.18037
Ca^{2+} (mg/L))	9.7	262.43	39.8652	41.8707
Mg^{2+} (mg/L)	17.49	164.67	57.5812	36.0091
Na^+ (mg/L)	17.67	1397.33	293.423	317.34
K^+ (mg/L)	2.33	313	46.1574	68.0112
SiO_2 (mg/L)	8.5	28.67	20.2684	3.80386
T.H (mg/L)	101.35	1089.6	335.622	212.32

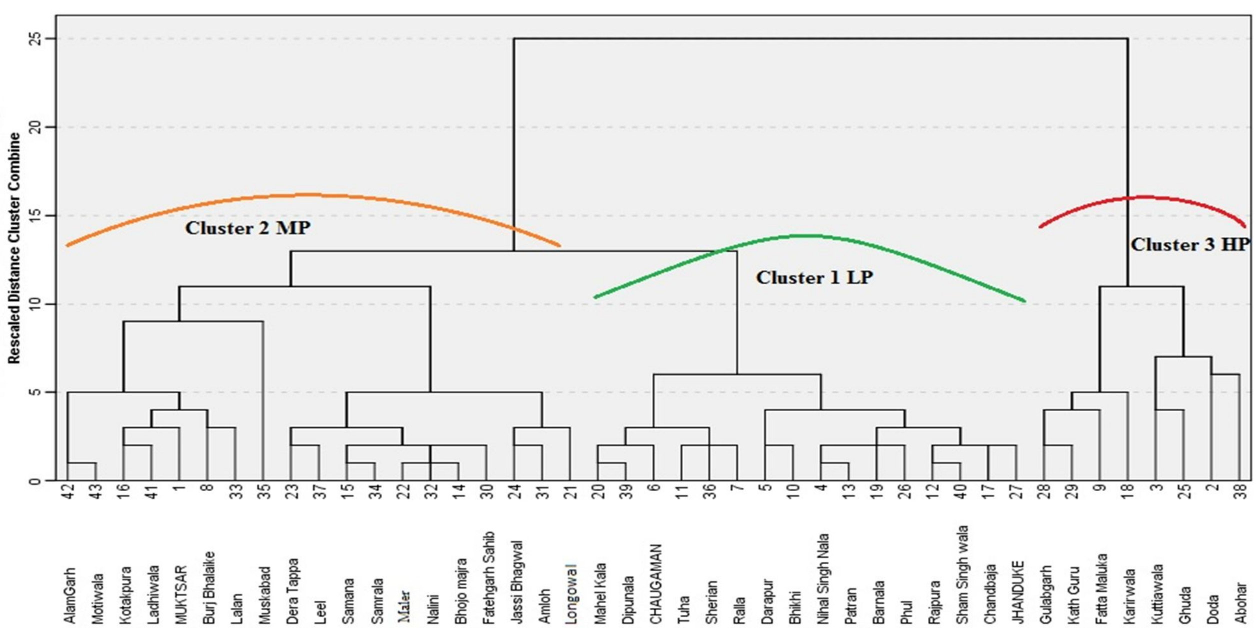

Fig 2. A Dendogram showing the three regions of the cluster

B. Cluster Analysis

From results of cluster analysis, the water quality could be divided into three polluted areas. Cluster 1 corresponds to Rajpura, Patran, Chandbaja, Barnala, Mahel Kala, Phul, Jhanduke, Sherian, Dipunala, Sham Singh wala, Chaugaman, Ralla, Bhikhi, Tuha, Nihal Singh Nala, Darapur, the less polluted (LP) areas. Cluster 2 corresponds to Muktsar, Burj Bhalaike, Bhojo Majra, Samana, Kotakpura, Longowal, Maler, Dera Tappa, Jassi Bhagwal, Fatehgarh Sahib, Amloh, Nalini, Lalan, Samrala, Muskabad, Leel, Ladhiwala, Alamgarh and Motiwala, moderately polluted (MP) ares. Cluster 3 corresponds to Doda, Kuttiawala, Fatta Maluka, Karirwala, Ghuda, Gulabgarh, Kath Guru and Abohar, the highly polluted (HP) regions. A dendrogram of sampling sites obtained by Ward's method is shown in Figure 2.

C. Principal Component Analysis

PCA is a robust pattern identification technique that explain the variance of a large set of data of inter correlated variables with a smaller set independent variables (Principal component) (J.A. Simeonova et. al. 2003). Principal component analysis was applied on the normalized dataset of 15 variables for 3 different grouped regions clustered by hierarchical cluster analysis, in order to identified important water quality parameters. An eigenvalue gives a measure of the significance of the factor: the factors with the highest eigenvalues are the most significant. Eigenvalues of 1.0 or greater are considered significant (S. Shrestha et. al. 2007). Factors loading can be classified as 'strong', 'moderate' and 'weak', according to definite loading values of >= 0.75, 0.75-0.5 and 0.5-0.3 respectively (Liu et. al. 2003). These factors with eigenvalue greater than 1 explain about 82.489 % of total sample variance in less polluted (LP) regions, 88.07% of total sample variance in moderately polluted (MP) regions and 91.87% of the total sample variance in highly polluted (HP) regions.

1) *Principal Component Analysis in Less Polluted Region:* In less polluted regions five components of PCA analysis showed 87.48 % of the variance in the data set, as the eigenvectors classified the 15 parameters of 16 monitoring stations into five groups shown in Table 2. Among five PCs, PC1, explaining 23.42% of total variance, has strong positive loading on pH, CO_3^{2-} and SiO_2 and strong negative loading of Ca^{2+} shows the alkalinity of groundwater in the regions due to natural causes. Silica released due to chemical breakdown of silicate minerals in rocks and sediments by chemical weathering is acquired by circulating groundwater. PC2, PC3 and PC4 explaining 22.46%, 15.27% and 14.289% of the total variance respectively, has strong positive loadings on EC, Na^+, nitrate and chloride ions . This explains the salinity of groundwater due to presence of ions. These represent the seasonal and natural impact of discharge and temperature. PC5 showed the 12.01% variance due to strong loading of K^+ and F^- ions in the groundwater due to natural occurrence of fluoride in rocks and fertilizers leads to its infiltration in groundwater.
2) *Principal Component Analysis in Moderately Polluted Region:* In moderately polluted regions four components of PCA analysis showed 85.07 % of the variance in the data set, as the eigenvectors classified the 15 parameters of 19 monitoring stations into four groups shown in Table 3. Among four PCs, PC1, explaining 44.79% of total variance, has strong positive loading of EC, NO_3^-, SO_4^{2-}, Mg^+, Na^+ and TH. This shows the infiltration of agricultural sub waste like fertilizers and domestic sewage wastewater through drains in groundwater. PC2 and PC3 shows 16.77% and 15.96% variance respectively due to strong loading of pH and PO_4^{3-} caused by an increase of mineral and organic nutrients, intensified by human activities due to use of excessive phosphatic fertilizers
3) *Principal Component Analysis in Highly Polluted Region:* In highly polluted regions four components of PCA analysis showed 91.87 % of the variance in the data set, as the eigenvectors classified the 15 parameters of 8 monitoring stations into four groups shown in Table 4. Among four PCs, PC1, explaining 34.87% of the total variance strong negative loading of pH, CO_3^{2-}, with strong positive loading Mg+, TH and moderate positive loading of NO_3^-, Ca^{2+} and K^+. This shows the excessive use of fertilizers in these regions and also wastewater from the sewage drains infiltrate into the groundwater. PC2 explains 31.36% variance in the data due to strong positive loading of EC, Cl^-, SO_4^{2-} and Na^+. This indicates the high salinity of groundwater due to high concentration of ions present in the ground water due to waste from industries, excessive use of fertilizers and make water unfit for drinking and agricultural purposes. PC3 and PC4 accountable for 16.45% and 19.23% variability show negative loading of fluoride and positive loading of silica and phosphate respectively. Silica is mainly due to water rock interaction in groundwater and phosphate is due to waste released by chemical industries of fertilizers and their use in fields.

Kaiser-Meyer-Olkin of Sampling Adequecy.		0.633
Bartlett's Test of Sphericity	Approx. Chi-Square	944.147
	df	78
	Sig.	.000

Fig 3**.** The Kaiser-Meyer-Olkin is the measure of sampling adequacy, KMO = 0.633 which indicates that the sample is adequate and may proceed with the Principal Component Analysis. The Bartlett's Test of Sphericity checks if there is a certain redundancy between the variables that we can summarize with a few number of factors. The significance level which is 0 in this study (less than 0.05) indicates that there are significant relationships among variable and provide the minimum standard to proceed for PCA.

Table 2 Principle component analysis and the rotation method is varimax with Kaiser for less polluted areas.

Less Polluted areas					
Variables	PC1	PC2	PC3	PC4	PC5
pH	0.873	0.15	0.056	-0.124	-0.062
EC	0.263	0.82	0.302	0.347	0.191
CO_3^{2-}	0.781	0.458	-0.068	-0.113	0.095
HCO_3^-	0.055	0.732	-0.338	-0.16	-0.246
Cl^-	0.072	0.2	0.133	0.922	0.104
SO_4^{2-}	0.133	0.731	0.495	-0.199	0.113
NO_3^-	0.061	-0.044	0.845	0.265	0.208
F^-	0.141	0.531	-0.1	0.04	0.776
PO_4^{2-}	0.06	0.238	0.873	0.114	-0.167
Ca^{2+}	-0.861	-0.099	-0.246	-0.01	-0.091
Mg^{2+}	-0.401	-0.342	0.381	0.671	-0.001
Na^+	0.47	0.847	0.195	0.067	-0.067
K^+	-0.09	-0.236	0.095	0.076	0.885
SiO2	0.703	-0.01	0.082	0.425	-0.445
T.H	-0.631	-0.336	0.263	0.594	-0.033
Eigen Values	3.516	3.369	2.291	2.143	1.803
% total Variance	23.442	22.46	15.27	14.289	12.018
% Cummulative Variance	23.442	45.902	61.173	75.461	87.479

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Table 3 Principle component analysis for moderately polluted areas

Moderately Polluted areas				
Variables	PC1	PC2	PC3	PC4
pH	0.192	0.858	-0.239	0.136
EC	0.966	0.19	0.071	-0.043
CO_3^{2-}	0.367	0.697	-0.347	-0.235
HCO_3^-	0.26	-0.522	0.608	0.027
Cl^-	0.96	0.106	0.054	-0.064
SO_4^{2-}	0.755	0.552	0.015	-0.043
NO_3^-	0.716	-0.595	0.1	-0.019
F^-	0.542	0.106	-0.038	0.731
PO_4^{2-}	-0.062	0.14	0.926	-0.067
Ca^{2+}	0.104	-0.083	0.86	0.061
Mg^{2+}	0.948	-0.077	0.052	0.046
Na^+	0.833	0.397	-0.008	0.133
K^+	0.58	0.1	0.06	-0.726
SiO2	-0.672	-0.309	0.332	0.062
T.H	0.897	-0.095	0.335	0.063
Eigen Values	6.672	2.516	2.393	1.181
% total Variance	44.479	16.77	15.956	7.87
% Cummulative Variance	44.479	61.249	77.205	85.075

Table 4 Principle component analysis for highly polluted areas

Highly Polluted areas				
Variables	PC1	PC2	PC3	PC4
pH	-0.921	-0.196	-0.181	0.217
EC	0.242	0.925	0.169	-0.189
CO_3^{2-}	-0.985	-0.095	-0.081	0.015
HCO_3^-	-0.358	-0.865	0.272	-0.106
Cl^-	0.482	0.735	0.391	-0.228
SO_4^{2-}	0.038	0.961	-0.218	-0.051
NO_3^-	0.639	0.564	0.218	0.157
F^-	0.078	-0.082	-0.953	-0.15
PO_4^{2-}	-0.076	-0.235	-0.045	0.855
Ca^{2+}	0.618	0.138	0.61	-0.313
Mg^{2+}	0.819	0.187	-0.103	0.502
Na^+	0.217	0.956	0.085	-0.145
K^+	0.742	-0.278	-0.266	-0.326
SiO2	0.392	-0.339	0.743	-0.035
T.H	0.874	0.22	0.391	0.046
Eigen Values	5.227	4.703	2.466	1.385
% total Variance	34.847	31.356	16.438	9.237
% Cummulative	34.847	66.202	82.64	91.87

Variance				

IV. CONCLUSION

In this case study, multivariate statistical techniques, cluster analysis and principal component analysis were used to evaluate spatial variations of the groundwater quality of the Malwa region. This show the applicability of the use of multivariate statistical analysis for the pollution studies of groundwater. CA shows the significant three clusters in which region can be divided and classified as the less polluted (LP), moderately polluted (MP) and highly polluted (HP). Groundwater pollution is a major concern from the past few years in Punjab. Malwa region is worst hit due to agricultural revolution with the use of wide varieties of fertilizers and pesticides. PCA study shows that most of the groundwater in the moderately polluted area is not fit for drinking and other household purposes due to moderate to high concentration of electrical conductivity, fluoride, magnesium and potassium. But in the highly polluted region the water is not even useful for the agricultural purposes too due to high salinity and high concentration of ions. The groundwater of Malwa region of Punjab in mainly polluted due to excessive use fertilizers and pesticides in agricultural activities and due to industrial units disposing their waste into drains and landfills without proper treatment.

V. ACKNOWLEDGEMENTS

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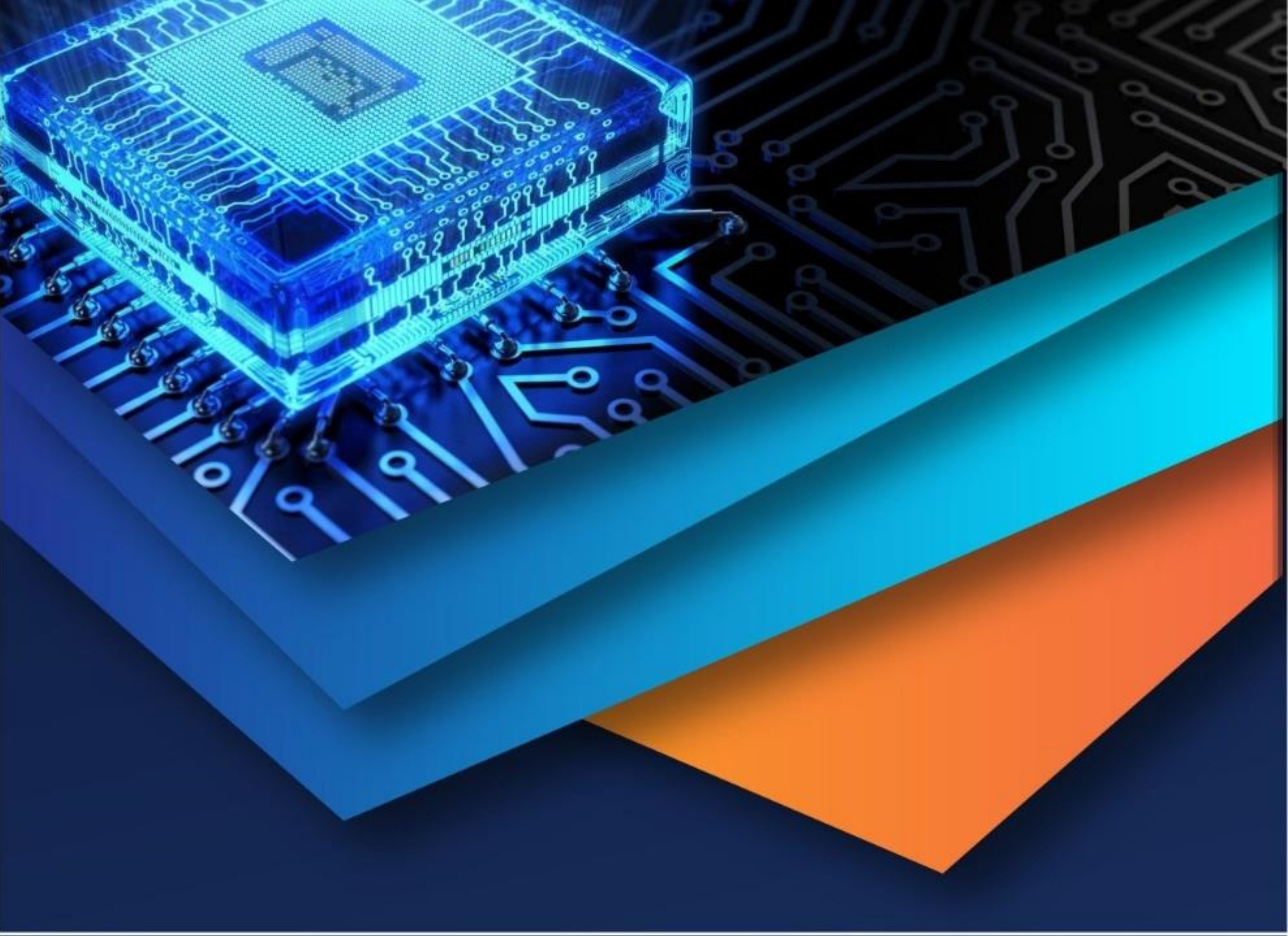

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