

FACTOR ANALYSIS OF GROUND WATER QUALITY PARAMETERS FROM POLLACHI DISTRICT, TAMILNADU, INDIA

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MSC 2010 Classifications: Primary 62H25; Secondary 62H20;

Keywords and phrases: Factor Analysis, Water Quality Parameters, Ground Water and Pollachi district.

The authors would like to thank the reviewers and editor for their constructive comments and valuable suggestions that improved the quality of our paper

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Abstract: In this study, an investigation was conducted into the Factor Analysis of Physico-chemical parameters of groundwater samples sourced from different areas within Pollachi District, Tamil Nadu, India. The samples included Bore well water, Open well water, and Municipal water (drinking water). Each category of water samples was analyzed for ten parameters: Electric conductivity, pH value, Calcium, Magnesium, Sodium, Potassium, Bicarbonate, Chloride, Total Dissolved Solids, and Alkalinity. Factor Analysis techniques were applied to these parameters to discern their significant characteristics and their impact on the three types of water samples was thoroughly explored. Furthermore, comparisons were drawn between the findings of this study and existing literature. This methodological approach aids in pinpointing the most influential water quality parameter for further investigations, thereby streamlining the complexity of the analysis process.

1 Introduction

Whilst seventy-five percent of the Earth's surface is submerged in water, the availability of freshwater has been steadily declining due to excessive contamination and usage. Groundwater, serving as the primary source of portable water in both rural and urban areas regions, stands out as a significant and renewable energy source of the planet. Freshwater constitutes just 2.5% of Earth's total water; the remaining water is saline or marine. From 88% of groundwater, only 1% of the freshwater is easily accessible and portable, underscoring its vital significance in human civilization. Recently, the evaluation of parameters determining water quality in samples gathered from diverse water collection areas has grown crucial for implementing scientific procedures in water administration. Both surface and subterranean water sources in Coimbatore are increasingly facing contamination due to industrial expansion and urbanization.

Many Research Papers like, Investigating spatial water quality variation is crucial for effective river management. Aminu Ibrahim *et al.*[1] employ Artificial Neural Networks and Principal Component Analysis to develop precise models, enhancing river management strategies. Groundwater contamination necessitates water quality assessment. This study classifies samples based on ten parameters using Q-mode PCA, aiding in contamination prevention. Model estimates water quality index, but accuracy relies on parameter selection. Himanshu Sahu *et al.* [2] and Kamaran Zeinalzadch and Elnaz Rezaei[3] applied PCA to assess environmental effects in Shahr Chai River, Iran, shedding light on water quality dynamics. Aminu Ibrahim *et al.*[1] also discussed the same situation using PCA. They continue to refine models for water quality prediction, contributing to ongoing river management efforts. Furthering the research, Jothi Venkatachalam *et al.* [4] analyze Noyyal River's water quality parameters in India, providing insights into local water quality variations. Mohamed Sheriff and Zahir Hussain [5] conduct statistical correlation analysis on groundwater quality along Noyyal River bank in India, identifying

critical factors affecting water quality. The study applies PCA to interpret complex data from Ganges River monitoring, identifying key factors contributing to water quality variation. PCA extracts four principal factors explaining 90% of variance. Mishra [6] and Nguyen Thanh Giao *et al.* [7] assess Bung Binh Thien reservoir in Vietnam, highlighting seasonal variations and suggesting improvements for water quality management. Kamal Jyoti Maji and Ramjee Choudhary [8] investigate human and industrial impacts on Ganga River water quality in Uttar Pradesh, offering valuable insights for improved management strategies. Ramakrishnan and Gowrisankar [9] explore physico-chemical parameters in Bhavani River, Coimbatore, emphasizing the significant impact of human activities on water quality in the region. One can find numerous literature in analyzing water quality parameters at various configurations with and without using PCA (Rose Mary George [10]; Rajasekhar Pullabhotla and Ntsako Dellas Baloyi [11]; Shahjad Ali *et al.* [12]; Galal Uddin Md *et al.* [13]; Shuang Gan *et al.* [14]; Shyamala *et al.* [15]; Sarbu and Pop [16]; Ivan Benkov *et al.* [17]; Nguyen Thanh Gao *et al.* [18]; Anh Thi Lan Nguyen *et al.* [19]; Toshinori Tabata *et al.* [20]; Mohab Amin [21]; Ying Ouyang [22]; Yilma *et al.* [23]). Recently, Ramakrishnan and Sudharson [24] utilized multivariate statistical methods to analyze the quality parameter of drinking water samples collected from various locations in Pollachi, Tamil Nadu, India.

In this study, we adopt a comprehensive approach by conducting factor analysis on samples of groundwater quality parameters obtained from Pollachi district. Various parameters pertaining to water quality have been examined, and factor analysis techniques have been employed to gain insights.

2 Materials and Methods

2.1 Study Area

Pollachi is situated at 10.662° N, 77.0065° E near the center of the South Indian Peninsula, surrounded by Western Ghats. On the banks of Aliyar river it has an average elevation of 293 meters (961 ft). The region is characterized by its rugged terrain, traversed by multiple rivers, and adorned with dense forests, marshlands, and sporadic grassy patches. The town receives majority of the rainfall from Southwest monsoon arriving through the Palghat gap and receives an average annual rainfall of around 1,274 mm. Pollachi Town is known as a 'Town of Export Excellence'.



Fig.1 Map of Pollachi District

Water samples for the current study were gathered from various sites across the Pollachi district. The investigation focused on physiochemical parameters, including electrical conductivity, magnesium, alkalinity, total dissolved solids, chloride, bicarbonate, sodium, potassium, pH levels.

2.2 Methods

In Principal Component Analysis (PCA) offers flexibility in utilizing either correlation or covariance matrices. When deriving principal components from the correlation matrix R, This suggest that the variables have been adjusted to have uniform variance, resulting in the components being Eigenvectors of R. In cases where parameters (variables) exhibit significantly different units (e.g., pH, ,m/min C, mg/L, etc.), it's advisable to employ standard variates and the correlation matrix.

After calculating the variances (Latent root or Eigenvalues) and Principal Components (Eigenvectors) of a correlation matrix, the typical procedure involves examining the first few components that ideally explain a substantial portion of the total variance. Variables in PCA are often rotated to derive new variables (principal components or principal axes), and subsequently, the number of principal components is reduced by discarding less significant components. At times, I initial principal components are rotated to get a new set of components that are easier to interpret This aim is to ensure that each variable contributes significantly to a small number of components.

A common method for achieving this transformation is Varimax rotation, which aims to minimize medium-range correlations between the components and the original variables.

3 Results and Discussion

The study considers groundwater parameters to check quality, specifically Electric Conductivity (EC), pH value (pH), Calcium (CA), Magnesium (MG), Sodium (NA), Potassium (K), Bicarbonate (HCO_3), Chloride (Cl), Total Dissolved Solids (TDS) and Alkalinity (AL), for water samples collected from bore wells, open wells, and municipal water sources.

Table 1 presents the Eigenvalues and their cumulative contribution rates for various parameters for checking quality of bore well water samples. Notably, the physical parameters such as EC, pH, and CA exhibit higher loadings (Eigenvalues). Upon cumulative assessment of the percentages of total variances across the three extracted components, it's evident that three principal components collectively account for hundred percentage of the variance in the data. Subsequently, these components undergo rotation and are detailed in Table 2.

Moreover, the communalities displayed in Table 2 suggest that the variances of variables are nearly equal in value, indicating comprehensive representation of all parameters by these three principal components. This also suggests that further rotation is unnecessary.

Table 3 shows that the accumulated contribution rates for various water quality parameters of water samples collected from open well It can we well observed that the physical parameters EC, pH and CA have larger loadings (Eigenvalues) when compared with other parameters. It is also noted that these contribution is little lesser than as it is observed in the case of Bore Well Water. When the percentages of total variance of the three extracted principal components are accumulated, it may be noticed that the three Principal components accounts hundred percentage of the variance of the original data. Further, using varimax rotation the components were rotated and show in Table 4. Further, the communalities have almost equal values, indicates that the parameters are well described by the principal components.

For the samples drawn from municipal water, the accumulated contribution rates are shown in Table 5. Once again, it is noticed that the loadings of EC, pH and CA have larger values, but lesser when compared with Bore well and Open well water samples. The three principal components collectively explain the variance of the original dataset. The values obtained by Varimax rotation shown in Table 6. Here again, the communalities of the ariables have equal values, shown that all the parameters have been described well by the three principal components.

The significance of variables indicated by significant i.e high loadings has been considered in evaluating the components . Additionally, the variance of components plays a crucial role, with components exhibiting larger variances being more informative on data. Examination of the variances (Eigenvalues) of the components reveals that the principal components are ranked in decreasing order of significance according on their variances.

Interpretation of the rotated three principal components in Table 2 involves seeing the component loadings and their relationship with the original variables. The first principal component reflects variations in EC, pH, and CH, highlighting their importance. The second principal com-

ponent indicates variations in CA, SO, PO, and AL, while the third principal component pertains to variations in SU and NI.

Similarly, in Table 4 and 5, the variation of parameters represented by the principal components for open well and municipal water samples, respectively, is highlighted. Notably, the variation of parameters shown by the principal components for all three categories of water samples differs. The results of principal component analysis underscore its reliability in providing insights into scientific research fields.

TABLE 1: Bore well - Eigenvalues, Contribution rates and Accumulated contribution rates of Principal Components

<i>Component</i>	Initial Eigenvalues			Extraction Sums of Squares of Loadings		
	<i>Total</i>	<i>Variation(%)</i>	<i>Cumulative(%)</i>	<i>Total</i>	<i>Varation(%)</i>	<i>Cumulative(%)</i>
EC	589.64	81.74	81.74	589.64	81.74	81.74
pH	97.39	13.50	95.24	97.39	13.50	95.24
CA	34.31	4.76	100.00	34.31	4.76	100.00
MG	0.00	0.00	100.00			
SO	0.00	0.00	100.00			
PO	0.00	0.00	100.00			
BIC	0.00	0.00	100.00			
SU	0.00	0.00	100.00			
CH	0.00	0.00	100.00			
NI	0.00	0.00	100.00			
TDS	0.00	0.00	100.00			
AL	0.00	0.00	100.00			

TABLE 2: Bore well - Principal Components

<i>Component</i>	Component Loadings			Rotated Loadings			<i>Communalities</i>
	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	
EC	-1.04935	-0.6171	0.9229	0.88	-0.15	0.44	0.99
pH	1.3744	0.9704	0.5078	-0.93	0.26	0.27	1.00
CA	-1.6267	0.8204	0.5158	0.49	-0.87	0.01	0.99
MG	-1.5965	-0.5160	-0.9397	0.75	0.01	-0.66	0.99
SO	0.0030	-1.3602	-0.8341	0.46	0.88	-0.15	1.00
PO	1.2007	-0.7126	-0.5694	-0.22	0.94	0.27	1.00
BIC	1.3803	0.2291	0.4215	-0.49	0.39	0.78	1.00
SU	0.3156	0.0123	1.3402	0.17	-0.06	0.98	0.99
CH	0.8116	1.6171	-0.7147	-0.99	-0.16	-0.01	1.00
NI	0.8331	-0.3700	0.9416	0.05	0.36	0.93	0.99
TDS	-0.1207	-1.4572	-0.2824	0.64	0.76	0.11	0.99
AL	-1.5255	1.3839	-0.2938	0.1	-0.91	-0.4	0.99

TABLE 3: Open well - Eigenvalues, Contribution rates and Accumulated contribution rates of Principal Components

<i>Component</i>	Initial Eigenvalues			Extraction Sums of Squares of Loadings		
	<i>Total</i>	<i>Variation(%)</i>	<i>Cumulative(%)</i>	<i>Total</i>	<i>Varation(%)</i>	<i>Cumulative(%)</i>
EC	237.76	84.09	84.09	237.76	84.09	84.09
pH	24.59	8.69	92.78	24.59	8.69	92.78
CA	20.40	7.21	100.00	20.40	7.21	100.00
MG	0.00	0.00	100.00			
SO	0.00	0.00	100.00			
PO	0.00	0.00	100.00			
BIC	0.00	0.00	100.00			
SU	0.00	0.00	100.00			
CH	0.00	0.00	100.00			
NI	0.00	0.00	100.00			
TDS	0.00	0.00	100.00			
AL	0.00	0.00	100.00			

TABLE 4: Open well - Principal Components

<i>Component</i>	Component Loadings			Rotated Loadings			<i>Communalities</i>
	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	
EC	0.8813	1.1874	0.6943	0.69	-0.55	0.48	1.00
pH	-1.9089	0.3355	0.6023	-0.93	-0.09	0.35	0.99
CA	1.4068	0.2724	-0.2211	1.00	-0.03	-0.06	1.00
MG	-0.0629	-0.1167	-1.7474	0.18	0.14	-0.97	0.99
SO	1.2094	0.8700	-0.5201	0.9	-0.38	-0.22	1.00
PO	-0.2589	-1.5197	-0.3357	0.02	0.98	-0.19	0.99
BIC	-0.4375	-1.2763	0.8531	-0.1	0.86	0.49	0.98
SU	-0.2589	-1.5197	-0.3357	0.02	0.98	-0.19	0.99
CH	-0.8779	1.8213	-0.2066	-0.3	-0.95	-0.06	0.99
NI	1.2934	-0.3530	0.2785	0.92	0.34	3.22	1.00
TDS	-2.0239	0.4730	-0.0169	-0.98	-0.18	0.00	0.99
AL	1.0383	-0.1742	0.9552	0.76	0.25	0.61	1.00

TABLE 5: Municipal Water - Eigenvalues, Contribution rates and Accumulated contribution rates of Principal Components

<i>Component</i>	Initial Eigenvalues			Extraction Sums of Squares of Loadings		
	<i>Total</i>	<i>Variation(%)</i>	<i>Cumulative(%)</i>	<i>Total</i>	<i>Varation(%)</i>	<i>Cumulative(%)</i>
EC	7.53	52.22	52.22	7.53	52.22	52.22
pH	4.42	30.65	82.87	4.42	30.65	82.87
CA	2.47	17.13	100.00	2.47	17.13	100.00
MG	0.00	0.00	100.00			
SO	0.00	0.00	100.00			
PO	0.00	0.00	100.00			
BIC	0.00	0.00	100.00			
SU	0.00	0.00	100.00			
CH	0.00	0.00	100.00			
NI	0.00	0.00	100.00			
TDS	0.00	0.00	100.00			
AL	0.00	0.00	100.00			

TABLE 6: Municipal Water - Principal Components

<i>Component</i>	Component Loadings			Rotated Loadings			<i>Communalities</i>
	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	<i>PC1</i>	<i>PC2</i>	<i>PC3</i>	
EC	0.1870	1.4517	1.3249	-0.11	-0.99	0.12	1.00
pH	-0.2384	-1.4259	1.0818	0.34	0.28	-0.90	1.00
CA	-1.7212	0.5871	-0.2408	-0.96	0.25	0.09	0.99
MG	-0.7698	-1.0760	-0.8143	-0.09	0.99	-0.09	0.99
SO	0.9072	-0.0217	-1.0898	0.53	0.45	0.72	1.00
PO	-1.5936	-0.8053	0.5213	-0.54	0.47	-0.70	1.00
BIC	1.4683	-0.2650	-0.2371	0.91	0.12	0.39	0.99
SU	1.1807	-1.011	0.2567	0.96	0.25	-0.14	1.00
CH	-1.7212	0.5871	-0.2408	-0.96	0.25	0.09	0.99
NI	0.9072	-0.0217	-1.0898	0.53	0.45	0.72	1.00
TDS	0.1828	1.4619	-0.7447	-0.19	-0.15	0.97	0.99
AL	1.211	0.5391	1.2752	0.65	-0.76	0.00	1.00

4 Conclusion remarks

- This study investigates various groundwater quality parameters across the samples of water obtained from bore wells, open wells, and municipal water sources.
- Factor analysis have been utilized to discern the variance among these parameters.
- The correlation matrix was employed, and the principal components were rotated using Varimax rotation Consistently, physical parameters such as EC, pH, and CA exhibit substantial loadings (Eigenvalues) across all three categories of water samples.
- Each category of water samples reveals three principal components. Notably, further rotation is deemed unnecessary based on communalities. Moreover, the variation of parameters represented by the principal components differs among the three categories of water samples, implying distinct significance of physical parameters in bore well, open well, and municipal water samples.
- This underscores the importance of employing tailored methodologies to effectively manage water systems.

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