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Application of Principal Component Analysis (PCA) in Groundwater Quality Evaluation: A Case Study of Arid Region

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Abstract. Principal component analysis (PCA) is a commanding tool for assessing groundwater quality. It has potential to reduce data complexity, identify substantial variables, and disclose patterns. Groundwater quality dynamics could be understood well by using PCA which would advance the management and protection strategies of groundwater resources. The study aims to evaluate groundwater quality of an arid region of India. Principal component analysis was done for two seasons for two consecutive years by utilizing Minitab software. Groundwater samples of pre-monsoon 2019 shows that parameters like EC, TDS, TH, sodium, potassium, calcium, magnesium, chloride, fluoride, sulfate, bicarbonate, uranium, and zinc have major contribution in groundwater quality. All parameters come under first principal component (except carbonate and nitrate) in pre-monsoon 2020. While, the principal component analysis of monsoon season of 2019 and 2020 display that all the parameters fall under first principal component with exception of manganese and nitrate for monsoon 2019 and bicarbonate, carbonate, nitrate, EC, TDS, and chromium in monsoon 2020. Henceforth, PCA provides a comprehensive and insightful analysis that aids in effective groundwater quality assessment and management.

Keywords: Principal Component Analysis; Eigenvalues; Groundwater Quality; Arid Region

1. Introduction

Water quality assessment is a crucial component of sustainable water resource management, particularly in regions experiencing rapid population growth and increasing demand for clean water. Ensuring that water is safe for drinking, agriculture, and industrial applications, it requires systematic monitoring and effective analytical techniques. Among the various statistical methods available, Principal Component Analysis (PCA) has emerged as a valuable tool for simplifying complex datasets while preserving key patterns and trends. Several physicochemical parameters of groundwater like pH, electrical conductivity (EC), total dissolved solids (TDS), various cations, anions and metals play crucial role in its chemistry which demands utilization of PCA in groundwater quality valuation. The key parameters contributing to groundwater quality change are recognized with the help of PCA which can further reduce the number of variables to be monitored. Groundwater quality is detected with respect to time and place too by utilizing PCA, aiding researchers spot contamination sources and concern areas [1]. Additionally, groundwater samples are classified and grouped based on water quality by utilizing PCA which delivers an apparent understanding of the groundwater quality controlling factors [2,3].

Principal Component Analysis (PCA) is one of several multivariate statistical methods. It complements other statistical methods like hierarchical cluster analysis (HCA), factor analysis (FA), multivariate analysis of variance (MANOVA) and discriminant analysis (DA) by providing a different

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perspective on the data [4]. Such as: 1) Hierarchical Cluster Analysis (HCA) groups similar objects into clusters based on their characteristics. HCA focuses on grouping similar samples. While PCA reduces the dimensionality of the data and identifies the most significant variables, PCA is more useful for identifying patterns and trends, whereas HCA is better for classification and grouping. 2) Factor Analysis (FA) identifies underlying relationships between variables by grouping them into factors. PCA and FA are similar in that they both reduce data dimensionality. However, PCA transforms the original variables into principal components, while FA identifies latent factors that explain the observed correlations among variables. PCA is often preferred for its simplicity and ease of interpretation. 3) Multivariate Analysis of Variance (MANOVA) assesses the differences between groups on multiple dependent variables simultaneously. MANOVA is used to test hypotheses about group differences, whereas PCA is used to explore data structure and identify key variables. PCA is more exploratory, while MANOVA is more confirmatory. 4) Discriminant Analysis (DA) classifies samples into predefined groups based on their characteristics. PCA is used to reduce data complexity and identify patterns, while DA is used for classification and prediction. PCA can be a preliminary step before DA to reduce the number of variables.

Principal Component Analysis (PCA) is most useful in groundwater studies in the following situations:

•Data Reduction - When dealing with large datasets that include numerous physicochemical parameters, PCA helps reduce the number of variables by identifying the most significant ones. This makes the analysis more manageable and efficient without losing valuable information.

•Identifying Key Parameters - PCA is useful in pinpointing the key parameters that influence groundwater quality. By understanding which variables contribute the most to variations in the data, researchers can focus their monitoring and remediation efforts on these critical factors.

•Pattern Recognition - PCA helps in recognizing patterns and trends in groundwater quality data. This is particularly useful for detecting spatial and temporal variations, identifying areas of contamination, and understanding the underlying processes affecting groundwater quality.

•Source Identification - When trying to identify the sources of contamination, PCA can be used to distinguish between natural and anthropogenic influences. By analyzing the principal components, researchers can infer the likely sources of pollutants and their contribution to overall groundwater quality.

•Classification and Grouping - PCA aids in the classification and grouping of groundwater samples based on their quality characteristics. This helps in distinguishing between different groundwater regimes and understanding the factors that differentiate them.

•Trend Analysis - PCA can be used to analyze long-term trends in groundwater quality. By examining changes in the principal components over time, researchers can assess the effectiveness of management strategies and predict future changes in groundwater quality.

•Multivariate Relationships - When dealing with complex interactions among multiple variables, PCA simplifies the dataset and reveals the underlying multivariate relationships. This enhances the understanding of how different parameters interact and influence each other.

Table 1 represents some examples of research work that utilize PCA in groundwater quality analysis. The present study also utilizes PCA in analysis of groundwater quality of Bikaner city of Rajasthan (India).

Table 1. Recent groundwater studies at various settings using principal component analysis (PCA).

Location of the study	Purpose of applied PCA	PCA findings	Reference
Bhaskar Rao Kunta Watershed, Andhra Pradesh, India	Analyzed groundwater samples from deep aquifers during pre-monsoon and post-monsoon seasons using PCA	Identified two main components: PC-I for total variance in groundwater, PC-II capturing remaining variance related to various factors	Reddy & Kumar [5]

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Srikakulam District, Andhra Pradesh, India	Applied PCA to identify representative sampling sites for groundwater quality monitoring	PC1 influenced by multiple factors including alkalinity and pollution, PC2 by hardness-related processes	Chandrasekhar & Rao [6]
Achnera block, Agra district, UP, India	Analyzed multiple physico-chemical parameters and identified three principal components influencing groundwater quality	PC1 explained variance related to natural geological factors, PC2 related to water hardness, PC3 linked to salinity	Ali et al. [7]
North-Eastern Rajasthan, India	Applied Monte Carlo simulation approach using PCA for groundwater quality assessment and fluoride exposure risk	Identified higher central tendencies and upper limits of fluoride exposure risk compared to deterministic estimates	Gautam et al. [8]
River Ganga, Varanasi, India	PCA used for calculating Water Quality Index over three years across different seasons	Major ions identified, hydrochemical processes dominated by Ca-Mg-HCO3 and mixed SO4-Cl facies	Singh et al. [9]
Alaçam, Turkey	Analyzed pre-irrigation and post-irrigation groundwater samples using PCA	PC1 influenced by salinity factors, PC2 by agricultural runoff and urban wastewater, PC3 indicating pollution from agricultural activities	Taşan et al. [10]
Assiut Governorate, Egypt	PCA on 12 parameters from 217 wells to identify main factors affecting groundwater	PC1 influenced by salinity and mineral dissolution, PC2 by alkalinity and anthropogenic activities	Abdelgawad & El-Sheikh [11]
Kızılırmak Delta, Turkey	Utilized PCA on 11 water quality parameters to reduce dataset dimensionality	PC1 related to mineral dissolution and anthropogenic activities, PC2 associated with alkalinity and pollution processes	Ariman et al. [12]
Dhaka, Bangladesh	Used PCA to develop a water quality index model for rivers	Identified key parameters influencing river water quality, emphasizing anthropogenic pollute	Roy et al. [13]

2. Methodology

2.1. Study Area

The study area of the present study is Bikaner district which is situated in the north-western part of Rajasthan, India. Bikaner is geographically positioned between latitudes 27°11’ to 29°03’ North and longitudes 71°52’ to 74°15’ East, covering an area of approximately 30247.90 Km^2.

Bikaner experiences an arid climate characterized by extreme temperature variations and low annual precipitation. The district receives an annual rainfall ranging from 260 to 440 millimeters, with nearly 90% of this precipitation occurring during the southwest monsoon season, which typically begins in the first week of July and withdraws by mid-September. The hottest month is June, with average temperatures around 36°C, while January is the coldest month, with average temperatures around 16°C. Temperature extremes are significant, with summer temperatures reaching up to 48°C and winter temperatures dropping to around 1°C.

2.2. Sampling and Analysis

Groundwater samples were collected from 20 tube wells of Bikaner (Rajasthan). These sampling sites are Raisar, Naurangdesar, Sagar, Ridmalsar, Gadhwala, Sinthal, Napasar, Udasar, Naal, Gajner, Deshnokh, Palana, Udairamsar, Gangasahar, Patel nagar, Khara, Jamsar, Antyodaya nagar, Bicchwal,

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and Karmisar. Samplings were done in pre-monsoon and monsoon seasons for two consecutive years (2019 and 2020). The sampling of the post-monsoon season could not be conducted due to the outbreak of the coronavirus pandemic, which was at its peak during this period in both years.

In the laboratory, various physicochemical parameters were measured. The pH and electrical conductivity (EC) of the groundwater were determined using a pH meter and an electro-conductivity meter, respectively. Major cations and anions were analyzed using established methods such as sodium (Na) and potassium (K) concentrations were measured with a flame photometer, while magnesium (Mg) and calcium (Ca), along with total hardness (TH), were assessed using the EDTA titration method. Anions such as bicarbonate (HCO_3^-) was quantified via titration, and chloride (Cl^-) content was determined using the silver nitrate titration method. Fluoride (F^-) and nitrate (NO_3^-) concentrations were estimated using a UV-spectrophotometer, with fluoride measured by the SPADNS method. Heavy metals including manganese (Mn), copper (Cu), zinc (Zn), lead (Pb), chromium (Cr), uranium (U), and arsenic (As) were analyzed using an Inductively Coupled Plasma Optical Emission Spectrometer (ICP-OES), following the standard methods [14].

Principal component analysis (PCA) is done by Minitab Software 2022. Multivariant principal component analysis and factor analysis (varimax rotation) methods are applied to find out the main factors in PCA.

3. Results and Discussion

Principal component analysis of pre-monsoon 2019 groundwater samples of sampling sites is shown in Figure 1 to Figure 3. The score plot (Figure 1) depicts the distribution of groundwater samples from various locations. Samples from different sites cluster together, indicating similarities in their water quality parameters. It is found that Jamsar, Bichwal, Gajner, Raisar, Patel nagar and Khara area have positive correlation for first component. However, Sinthal, Napasar, Ghardwala, Udasar, Palana, Udayramsar and Deshnokh area have positive correlation for second component. While other have negatively related with both components. The loading plot (Figure 2) shows the relationship between different water quality parameters and the principal components. The first component (48.1%) is strongly influenced by total dissolved solids, electrical conductivity, chloride, sodium, and calcium. The second component (11.9%) has a moderate influence from pH, magnesium, and sulfate. The scree plot (Figure 3) displays the eigenvalues of the principal components. The first few components explain a significant amount of the total variance, with the first component contributing the most. The high loading of TDS, EC, chloride, sodium, and calcium on the first component suggests that these parameters are key contributors to groundwater quality variation in the study area. The influence of pH, magnesium, and sulfate on the second component indicates additional geochemical processes affecting groundwater quality.

The principal component analysis of monsoon 2019 groundwater samples of the study sites as the score plot (Figure 4) shows the clustering of groundwater samples, with some overlap between pre-monsoon and monsoon samples, indicating seasonal changes in water quality. It shows 46.2% contribution of first component and 11.5% contribution of second component which defines that Jamsar, Khara, Raisar, Patel nagar, Gangasahar, Bichhwal and Gajner sampling sites have positive correlation for first component. However, Palana, Naurangdesar, Naal, Ridmalsar, Udairamsar and Ghardwala sampling sites have positive correlation for second component. Sinthal, Karmisar, Sagar, Napasar, Deshnokh, Udasar and Antoday nagar sites are negatively related with both components. Figure 5 is the loading plot which shows that all the parameters fall under first component except manganese and nitrate. The loading plot for the monsoon season highlights the significant influence of magnesium, carbonate, and potassium on the first component (46.2%). The second component (11.5%) is moderately influenced by nitrate, sulfate, and uranium. The scree plot (Figure 6) shows the eigenvalues, with the first component explaining a substantial portion of the variance. The difference between component 1 and 2 is significant. Eigen values more than 1 is found in PC1, PC2, PC3, PC 4 and PC5. Eigen values of principal components of monsoon 2019 groundwater samples are added as Table 3. The seasonal changes in water quality are evident, with magnesium, carbonate, and potassium being prominent in the

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monsoon season. The influence of nitrate, sulfate, and uranium on the second component highlights potential sources of contamination during monsoon 2019 period.

Figure 7 is the score plot of principal component analysis of pre-monsoon 2020 groundwater samples of the study sites. It depicts the distribution of groundwater samples, showing a distinct separation of samples based on their water quality with 28.2% contribution of first component and 14.2% contribution of second component. It is found that Jamsar, Bichhwal, Naurangdesar, Patel nagar, Raisar, Gangasahar and Khara area have positive correlation for first component. However, Sagar, Ghardwala, Palana, Ridmalsar, Napasar, Udasar area have positive correlation for second component. While other have negatively related with both components. Figure 8 is the loading plot which shows that all parameters are under first component except carbonate and nitrate. The loading plot indicates that the first component (28.2%) is strongly influenced by total hardness, calcium, and magnesium. The second component (14.2%) is influenced by Pb, Cu, and bicarbonate. The scree plot (Figure 9) shows the eigenvalues, with the first two components explaining a significant portion of the variance. The difference between component 1 and 2 is significant. Eigen values more than 1 is found in PC1, PC2, PC3, PC4, PC5 and PC6. Eigen values of principal components of pre-monsoon 2020 groundwater samples are shown in Table 4.

The dominance of total hardness, calcium, and magnesium in the first component suggests the importance of these parameters in determining groundwater quality during the pre-monsoon season. The influence of Pb and Cu on the second component indicates potential contamination sources that need further investigation.

Figure 10 demonstrates the score plot of principal component analysis of monsoon 2020 groundwater samples of the study sites. The score plot reveals the distribution of groundwater samples, with some clustering indicating similarities in water quality parameters during the monsoon season of 2020. It shows 18.3% contribution of first component and 16.6% contribution of second component. Sampling sites Jamsar, Naal, Patel nagar, Khara, Karmisar, Udasar, Udairamsar, Bichhwal, and Sagar have positive correlation for first component. However, Sinthal, Napasar, Ghardwala, Gajner, Raisar and Deshnokh sites have positive correlation for second component. While other sites have negatively related with both components. The loading plot (Figure 11) exhibits that most of the parameters come under first component except bicarbonate, carbonate, nitrate, EC, TDS, and chromium. The loading plot shows that the first component (18.3%) is influenced by pH, arsenic, and copper. The second component (16.6%) has significant contributions from nitrate, sulfate, and zinc. The scree plot (Figure 12) displays the eigenvalues, indicating that the first two components explain a considerable amount of the total variance as the difference between component 1 and 2 is significant. Eigen values of more than 1 is found in in PC1, PC2, PC3, PC 4, PC5, PC6 and PC7. Eigen values of principal components of monsoon 2020 groundwater samples are included in Table 5. The presence of pH, As, and Cu as key parameters in the first component suggests potential sources of contamination affecting groundwater quality during the monsoon season of 2020. The influence of nitrate, sulfate, and zinc on the second component indicates the need for further investigation into the sources and processes affecting these parameters.

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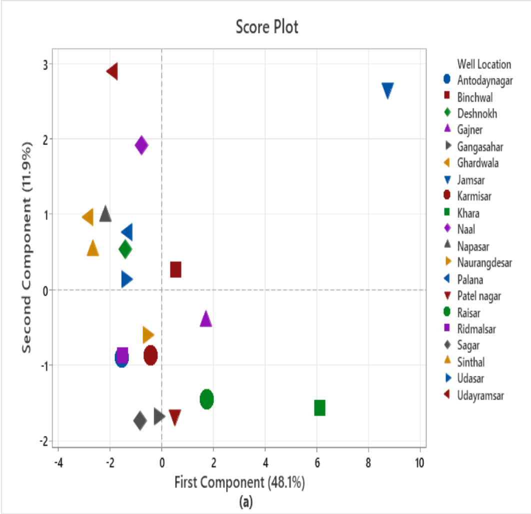

Figure 1. Score plot of groundwater of pre-monsoon season of 2019.

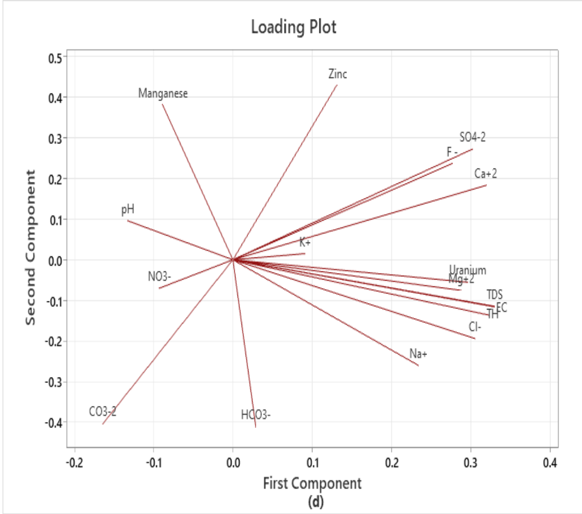

Figure 2. Loading plot of groundwater of pre-monsoon season of 2019.

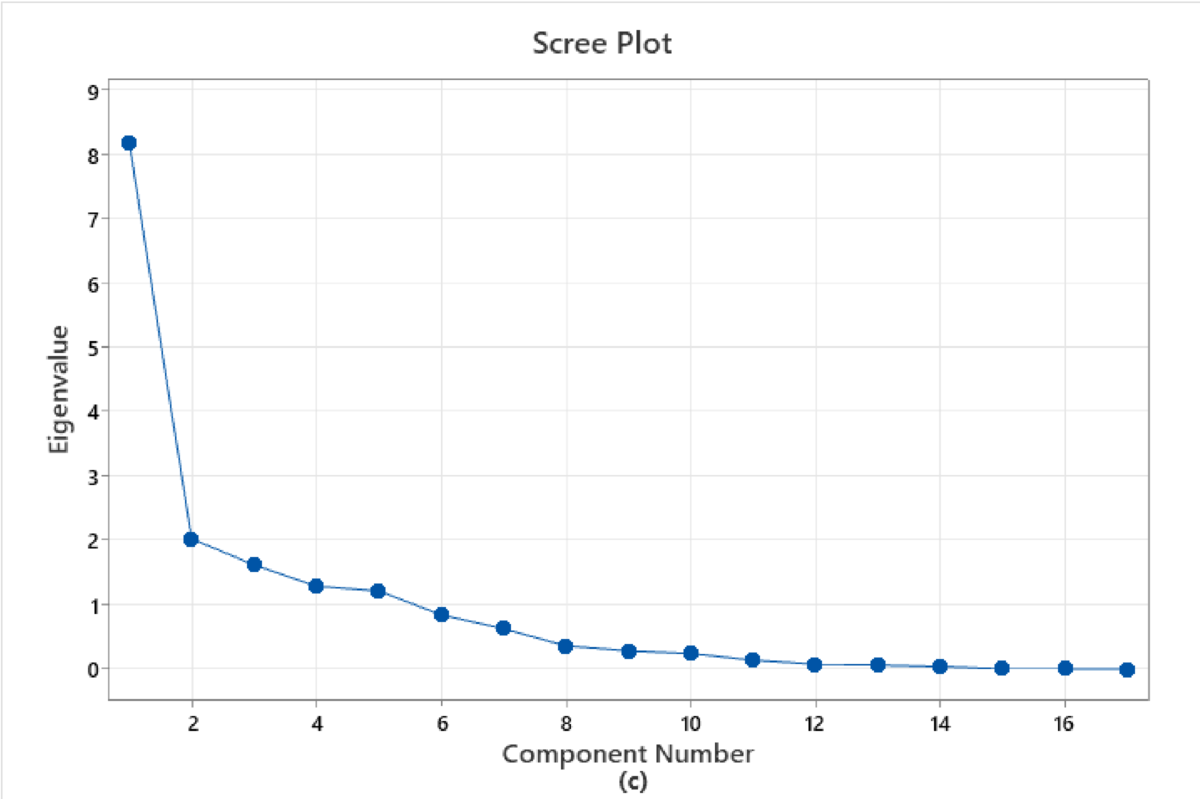

Figure 3. Scree plot of groundwater of pre-monsoon season of 2019.

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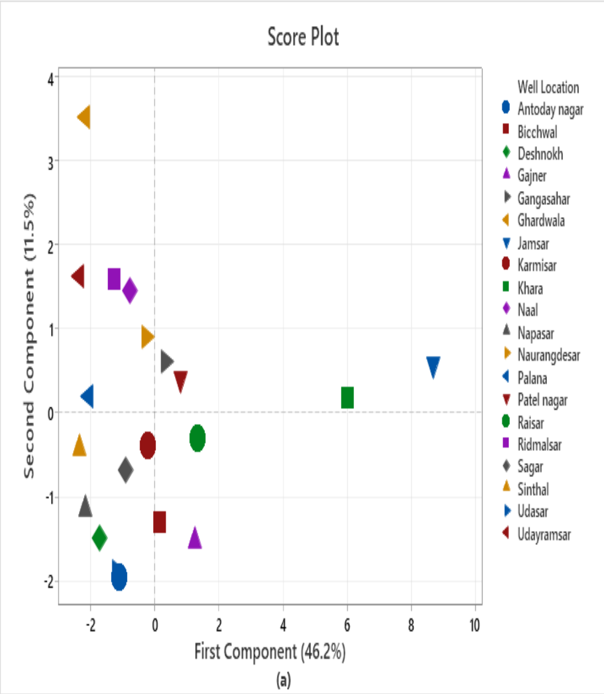

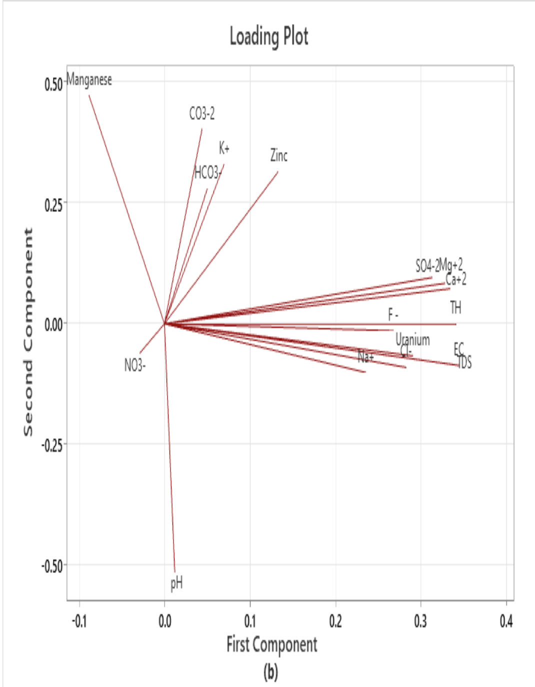

Figure 4. Score plot of groundwater of monsoon season of 2019.

Figure 5. Loading plot of groundwater of monsoon season of 2019.

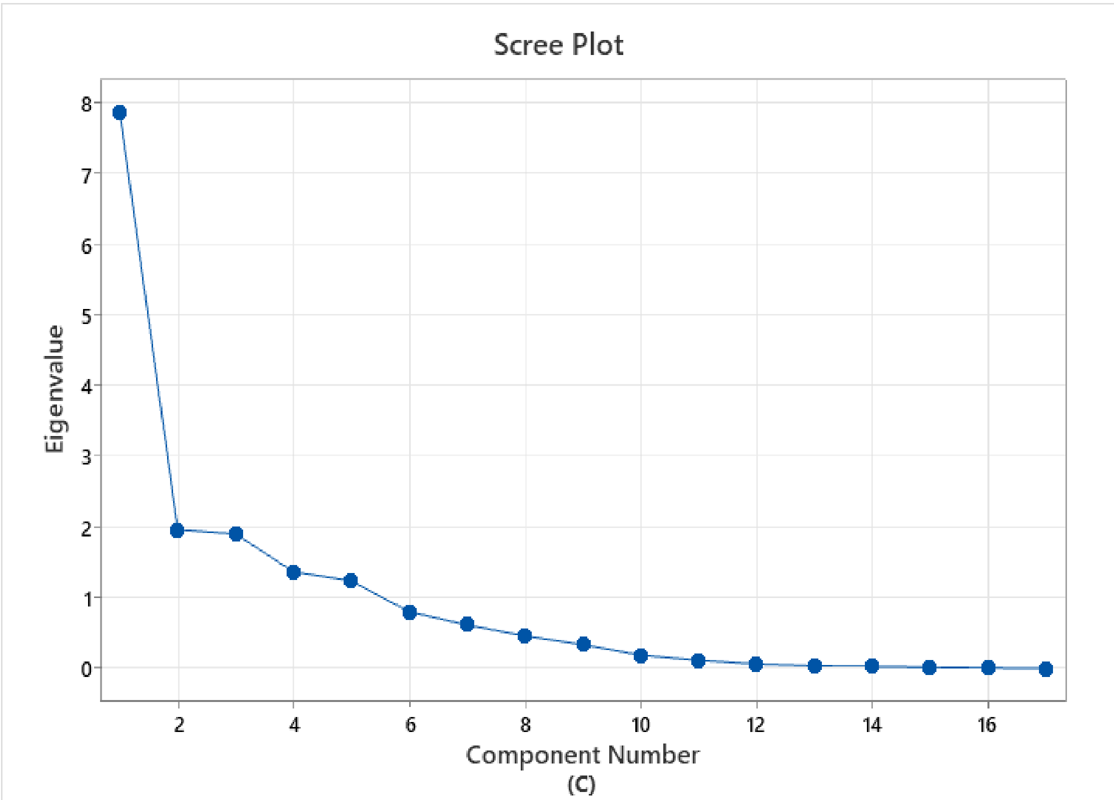

Figure 6. Scree plot of groundwater of monsoon season of 2019.

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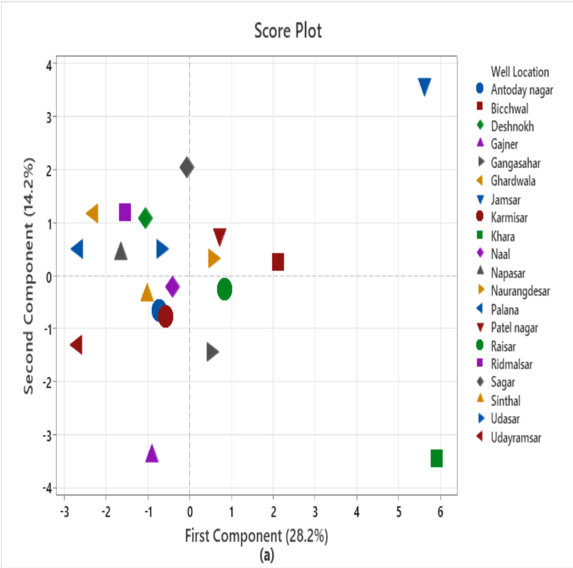

Figure 7. Score plot of groundwater of pre-monsoon season of 2020.

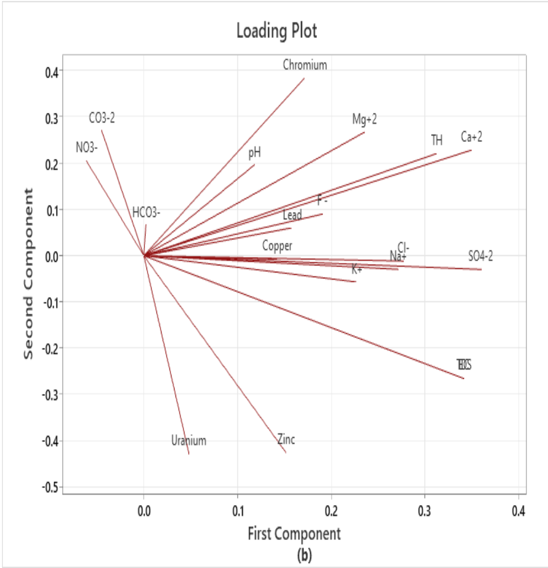

Figure 8. Loading plot of groundwater of pre-monsoon season of 2020.

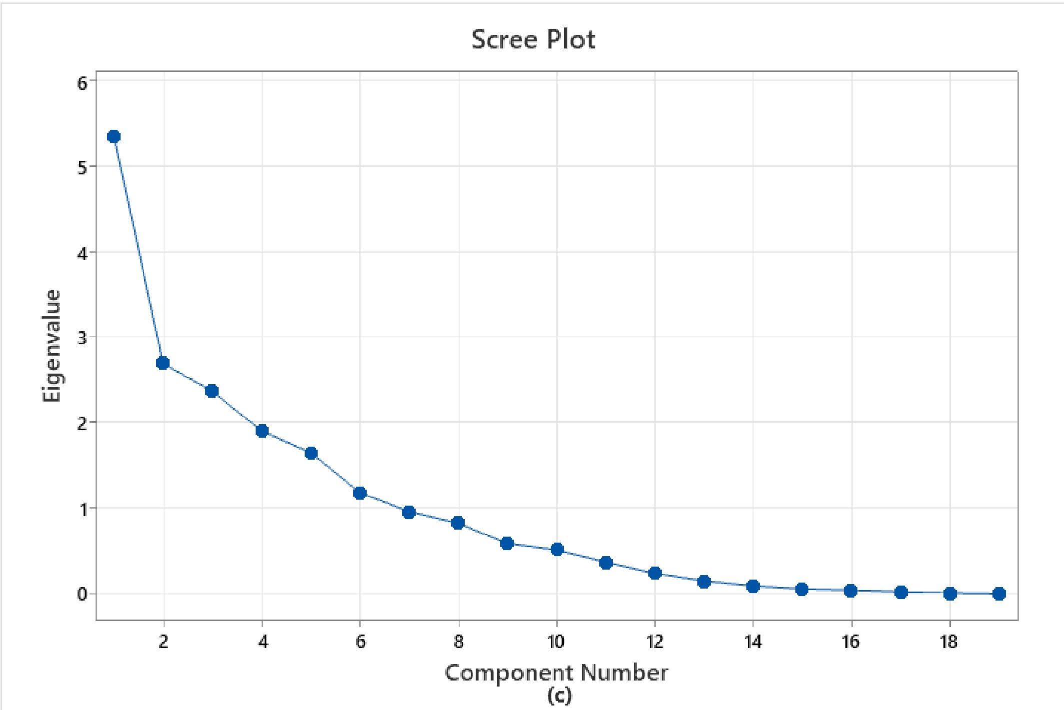

Figure 9. Scree plot of groundwater of pre-monsoon season of 2020.

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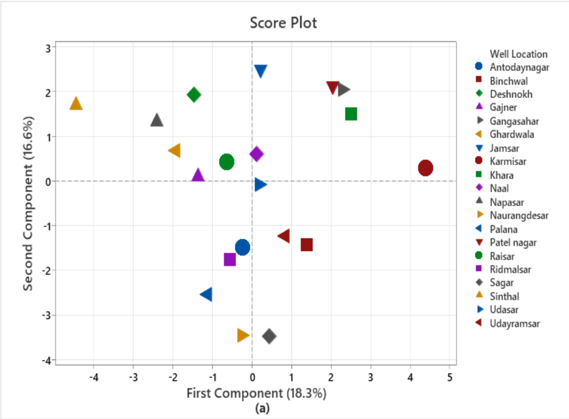

Figure 10. Score plot of groundwater of monsoon season of 2020.

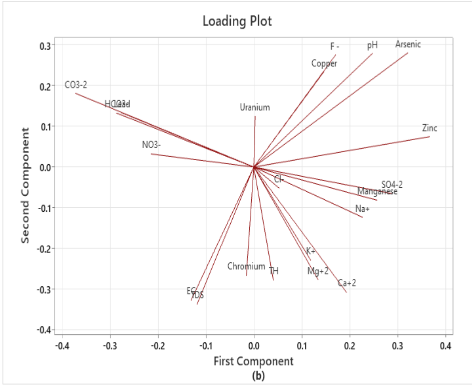

Figure 11. Loading plot of groundwater of monsoon season of 2020.

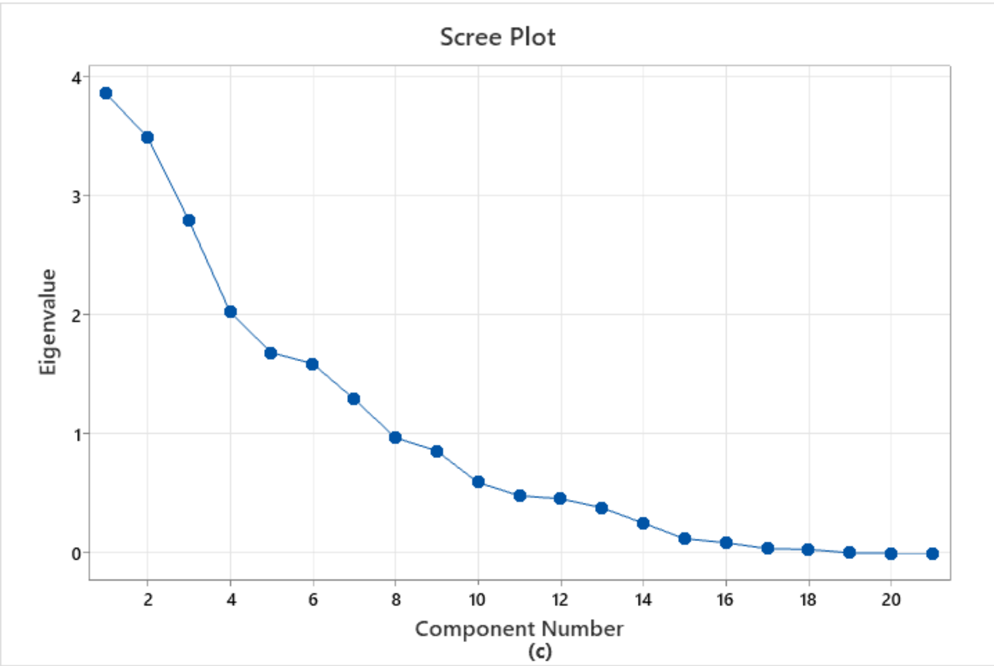

Figure 12. Scree plot of groundwater of monsoon season of 2020.

In the context of PCA, eigenvalues hold significant importance. Eigenvalues represent the amount of variance explained by each principal component. Larger eigenvalues indicate that the corresponding principal component captures more of the variance in the dataset. Typically, components with larger eigenvalues are kept, while those with smaller eigenvalues are discarded. This helps in reducing the dimensionality of the data without losing much information. Also, high eigenvalues suggest that the principal component is significant and contributes substantially to the structure of the data. Low eigenvalues suggest that the component is less important. Eigenvalues are used to rank the principal components. The components are sorted in descending order based on their eigenvalues, with the first principal component having the highest eigenvalue and explaining the most variance. We can calculate the total variance by summing the eigenvalues which is explained by the principal components. This cumulative variance helps in deciding how many components to keep to retain a desired level of total variance. Eigenvalues of principal components of pre-monsoon and monsoon seasons of 2019 and 2020 groundwater samples are depicted in Table 2 to Table 5 respectively.

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Table 2. Eigenvalues of principal components of pre-monsoon 2019 groundwater samples.

Variable	PC1	PC2	PC3	PC4
pH	-0.133	0.096	-0.521	-0.287
TDS	0.330	-0.114	-0.059	-0.135
EC	0.330	-0.116	-0.058	-0.137
TH	0.323	-0.136	0.015	0.033
Na^{+}	0.234	-0.260	-0.114	0.217
K^{+}	0.091	0.015	-0.313	0.126
Ca^{+2}	0.319	0.183	0.094	-0.125
Mg^{+2}	0.288	-0.075	-0.019	-0.102
Cl^{-}	0.306	-0.194	-0.072	0.064
F^{-}	0.277	0.237	-0.071	-0.212
NO_3^{-}	-0.093	-0.070	-0.494	-0.486
HCO_3^{-}	0.029	-0.412	0.273	-0.486
CO_3^{-2}	-0.164	-0.403	0.318	-0.273
SO_4^{-2}	0.303	0.272	0.047	-0.215
Manganese	-0.089	0.381	0.036	-0.132
Uranium	0.297	-0.055	-0.097	0.304
Zinc	0.131	0.430	0.399	-0.198

Table 3. Eigen values of principal components of monsoon 2019 groundwater samples.

Variable	PC1	PC2	PC3	PC4	PC5
pH	0.012	-0.514	0.355	-0.240	-0.064
TDS	0.345	-0.086	0.021	-0.018	0.138
EC	0.345	-0.086	0.023	-0.019	0.137
TH	0.341	-0.001	-0.043	-0.017	0.020
Na^{+}	0.236	-0.101	-0.166	-0.175	-0.172
K^{+}	0.070	0.330	-0.433	0.080	-0.022
Ca^{+2}	0.334	0.072	0.069	0.128	-0.173
Mg^{+2}	0.329	0.084	-0.134	0.034	-0.080
Cl^{-}	0.283	-0.090	-0.226	-0.063	0.282
F^{-}	0.268	-0.014	0.343	0.055	-0.016
NO_3^{-}	-0.029	-0.060	0.255	0.135	0.697
HCO_3^{-}	0.050	0.281	-0.124	-0.677	0.152
CO_3^{-2}	0.044	0.403	0.299	-0.462	0.145
SO_4^{-2}	0.313	0.096	0.297	0.098	-0.004
Manganese	-0.089	0.473	0.164	0.370	0.247
Uranium	0.291	-0.066	-0.234	0.193	0.135
Zinc	0.133	0.315	0.355	0.080	-0.449

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Table 4. Eigen values of principal components of pre-monsoon 2020 groundwater samples.

Variable	PC1	PC2	PC3	PC4	PC5	PC6
pH	0.118	0.196	0.055	0.401	0.043	-0.345
TDS	0.342	-0.266	0.055	0.080	-0.063	-0.241
EC	0.342	-0.266	0.055	0.080	-0.063	-0.241
TH	0.313	0.220	0.043	0.048	0.276	0.070
Na^{+}	0.272	-0.029	-0.101	-0.433	0.161	0.114
K^{+}	0.228	-0.057	-0.262	-0.148	0.317	0.118
Ca^{+2}	0.351	0.228	0.073	0.043	0.017	0.244
Mg^{+2}	0.236	0.267	0.160	-0.171	-0.231	0.268
Cl^{-}	0.277	-0.012	-0.134	-0.136	-0.452	-0.103
F^{-}	0.191	0.090	-0.433	0.091	0.017	-0.103
NO_3^{-}	-0.062	0.206	0.075	-0.306	0.509	-0.340
HCO_3^{-}	0.002	0.066	0.497	-0.246	0.066	-0.225
CO_3^{-2}	-0.045	0.270	0.447	-0.164	-0.310	-0.063
SO_4^{-2}	0.361	-0.030	-0.027	-0.247	-0.177	-0.120
Chromium	0.172	0.384	0.079	0.183	0.252	-0.054
Copper	0.142	-0.007	0.221	0.301	0.096	0.579
Lead	0.158	0.060	0.113	0.433	-0.031	-0.223
Uranium	0.048	-0.429	0.263	0.057	0.185	0.083
Zinc	0.152	-0.425	0.289	-0.011	0.176	0.028

Table 5. Eigen values of principal components of monsoon 2020 groundwater samples.

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
pH	0.248	0.280	0.263	-0.095	-0.063	0.014	0.093
TDS	-0.119	-0.337	0.292	-0.342	-0.116	-0.043	0.011
EC	-0.131	-0.328	0.290	-0.361	-0.071	-0.056	-0.038
TH	0.041	-0.277	-0.004	0.367	-0.023	-0.196	-0.366
Na^{+}	0.228	-0.124	0.123	0.160	-0.380	-0.225	0.393
K^{+}	0.119	-0.229	0.204	0.297	0.321	0.018	0.085
Ca^{+2}	0.194	-0.308	-0.315	0.119	-0.132	0.038	-0.193
Mg^{+2}	0.134	-0.277	-0.073	-0.066	-0.355	-0.179	-0.210
Cl^{-}	0.053	-0.052	-0.165	-0.432	0.127	-0.422	0.324
F^{-}	0.170	0.275	-0.239	-0.187	-0.308	-0.226	-0.093
NO_3^{-}	-0.215	0.032	-0.183	0.253	0.277	-0.409	0.219
HCO_3^{-}	-0.287	0.133	-0.231	0.067	-0.238	0.060	0.088
CO_3^{-2}	-0.372	0.181	-0.139	0.001	-0.090	0.003	0.200
SO_4^{-2}	0.289	-0.065	-0.317	-0.263	0.227	-0.133	-0.117
Arsenic	0.321	0.280	0.137	0.077	-0.274	0.079	0.048
Chromium	-0.016	-0.266	-0.142	-0.007	-0.134	0.462	0.400
Copper	0.146	0.234	0.194	0.067	0.084	-0.259	-0.166
Manganese	0.257	-0.082	-0.320	-0.151	0.319	0.164	0.088
Lead	-0.276	0.134	-0.153	-0.212	-0.070	0.183	-0.427
Uranium	0.003	0.125	0.319	-0.196	0.268	0.089	-0.096
Zinc	0.367	0.075	-0.070	-0.039	0.067	0.314	0.023

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Principal component analysis of groundwater samples of pre-monsoon 2019 shows that parameters like EC, TDS, TH, sodium, potassium, calcium, magnesium, chloride, fluoride, sulfate, bicarbonate, uranium, and zinc have major contribution in groundwater quality. All parameters come under first principal component (except carbonate and nitrate) in pre-monsoon 2020. While, the principal component analysis of monsoon season of 2019 and 2020 display that all the parameters fall under first principal component with exception of manganese and nitrate for monsoon 2019 and bicarbonate, carbonate, nitrate, EC, TDS and chromium in monsoon 2020.

4. Conclusion

Principal component analysis of 20 groundwater samples of pre-monsoon and monsoon seasons for two years were studied. The PCA of pre-monsoon season of 2019 and 2020 reveal that parameters such as electrical conductivity, total dissolved solids, total hardness, sodium, potassium, calcium, magnesium, chloride, fluoride, sulfate, bicarbonate, uranium, and zinc significantly influence groundwater quality. During the monsoon season of 2019 and 2020, PCA showed that most parameters fell under the first principal component, with the exception of manganese and nitrate in 2019 and bicarbonate, carbonate, nitrate, electrical conductivity, total dissolved solids, and chromium in 2020. Consequently, PCA proves highly useful in groundwater studies for simplifying complex datasets, identifying key parameters, recognizing patterns, and classifying samples. It offers a comprehensive and insightful analysis that aids in effective groundwater quality assessment and management.

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