Statistical Assessment of Physico-Chemical Pollutants Influencing Water Quality Index of the Kshipra River

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Abstract

The current research estimates the physicochemical values of the Kshipra River and examines the impact of these values on the Water Quality Index (WQI) with multivariate statistics. The river is of great ecological and socio-religious value especially in Ujjain but it is rapidly experiencing the pressure of pollution especially when the city discharge is combined with the agricultural run-offs and seasonal fluctuations. Twelve major parameters of water quality, including pH, temperature, turbidity, total dissolved solids (TDS), electrical conductivity (EC), dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total hardness, total alkalinity, chloride and nitrate, were to be assessed. The descriptive statistics were used to identify the central tendency and variability of parameters in various seasons. The Pearson correlation analysis was used to assess interrelationships among variables and also determine significant influencing factors that impact WQI. Principal Component Analysis (PCA) has been used to identify the major sources of pollution and minimise the dimensional complexity. To ascertain the statistically significant differences in the water quality between the sampling periods, seasonal change of water quality was further analyzed using one-way ANOVA. The calculated Water Quality Index classified the quality of river waters as moderate-poor in particular seasons which testified of the domination of anthropogenic stress and organic pollution. The research indicates that there should be better wastewater management and monitoring. The combination of multivariate statistical models and WQI creates a complex and effective system of assessing the quality of water in rivers and planning the environment management.

Keywords

Water Quality Index (WQI); Principal Component Analysis (PCA); Correlation Matrix; Seasonal Variation; Physico-Chemical Parameters; River Pollution; Kshipra River; ANOVA; Multivariate Statistics; Environmental Monitoring.

1. INTRODUCTION

Kshipra River (also called Shipra River) is one of the most culturally and ecologically important rivers in the central India. The river was formed in the Vindhyan ranges of the Madhya Pradesh and passes through the ancient city of Ujjain and finally drains to the river Chambal. It possesses great religious significance especially when conducting massive religious events like the Kumbh Mela where millions of followers depend on its waters to take the ritual baths. Although the river is socio-culturally relevant, it has experienced an escalating environmental pressure over the years by way of high levels of urbanization, discharge of untreated domestic sewage, agricultural runoff, and seasonal changes in hydrology. These pressures have been involved in a gradual degradation in its water quality over the years (Sharma et al., 2022).

Anthropogenic disturbances are very sensitive to freshwater ecosystems. The growing number of people, the growth of cities, and the use of an enhanced agricultural way of life have a tremendous impact on the physicochemical properties of rivers. Alterations in the following parameters include pH, temperature, turbidity, total dissolved solids (TDS), electrical conductivity (EC), dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total hardness, total alkalinity, chloride, and nitrate, which directly affect the aquatic biodiversity, ecological stability, and suitability of water to domestic, agricultural, and industrial uses. High BOD and CODs are the signs of organic pollution and the active activity of microbes, and the lower concentration of dissolved oxygen can cause the threat to aquatic organisms. On the same note, the high levels of nitrate and chlorides can indicate agricultural runoffs and sewage pollution (Rahman et al., 2021).

Conventional methods of water quality evaluation usually entail the comparison of individual parameters to set specifications of the environmental regulatory authorities. Nonetheless, consideration of parameters separately fails to capture the overall effect of several pollutants on the total quality of water. In a bid to overcome this shortcoming, Water Quality Index, (WQI) has been extensively implemented as a composite measure of assessment, which consolidates numerous physicochemical indices into a single composite index. The WQI summarizes complex data sets, makes them comparable across places and times of the year, and improves environmental management decision-making (Salih et al., 2021).

Along with index-based evaluation, multivariate statistics are now a crucial part of the contemporary water quality studies. The analysis of the correlation matrix can be used to reveal the physicomethallic relations between the physicochemical parameters and also to identify possible relations between these parameters. The Principal Component Analysis (PCA) is used to minimize the dimension of the data and help identify the major sources of pollution since the data would be clustered together into the major components. Such statistical techniques enhance the ability of interpretation and are more insightful about the dynamics of pollution than the traditional descriptive, statistical methods (Singh et al., 2025).

Seasonal changes also make matters worse as to the dynamics of river water quality, particularly in the monsoon-dominated areas like in central India. Monsoon season could lead to higher levels of turbidity, nutrient concentration, and suspended solids due to enhancement of rainfall and surface runoff and dilution due to effects that may be experienced temporarily. On the other hand, decrease in flow during the pre-monsoon seasons may increase the concentration of pollutants since it has less dilution capability. Hence, the statistical analysis of seasons with the help of Analysis of Variance (ANOVA) will be needed to assess whether the differences in the water quality parameters have a statistically significant difference (Lisetskii and Buryak, 2023).

The hypothesis underlying the given study is that differences in chosen physicochemical parameters have a great effect on the Index of Water Quality of the Kshipra River and that multivariate statistical methods can be successfully used to define the most common sources of pollution and patterns of seasonal changes. The combination of descriptive statistics, correlation matrix analysis, Principal Component Analysis (PCA), WQI computation, and seasonal ANOVA allows making this research an overall and scientifically powerful scheme to assess the quality of river water. It is anticipated that the results would have a positive impact on the evidence-based environmental planning, pollution reduction measures, and sustainable river management programs (Samanta et al., 2019).

2. REVIEW OF LITERATURE

The water quality study has become an important branch of environmental studies in the wake of growing pressure on freshwater resources through urbanization, industrialization, and the growth of agricultural activities. Rivers are the major sources of drinking water, irrigation, fishing and ecosystem services, but they are very susceptible to point and non point sources of pollution. Systematic monitoring of the physicochemical parameters to assess the health and sustainability of rivers has been a focus of scientific studies over the last several decades (Kulmedov, 2026).

Physicochemical indicators of the status of water quality have been extensively applied by the use of such parameters as pH, temperature, turbidity, total dissolved solids (TDS), electrical conductivity (EC), dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), total hardness, alkalinity, chloride as well as nitrate. All these parameters represent the chemical balance, organic load, concentration of nutrients and the general ecological state of river systems. High BOD and COD rates are normally related to organic pollution due to domestic sewage and industries effluents. Equally, the high levels of nitrate and chloride usually point to agricultural run-off and man-made contamination. Dissolved oxygen is taken to be one of the most significant parameters to consider because it has direct impact on the survival of aquatic life as well as biological functions in the ecosystem (Cao, 2026).

The conventional water quality assessment methods have mainly been based on the comparison of observed parameters values with the set limits of permissible values. Although they are useful in the regulation of activities, these comparisons do not give a comprehensive picture of the impact of the combined effects of various pollutants. Consequently, the Water Quality Index (WQI) has become an integrated assessment tool, which is gaining acceptance among the researchers. The WQI approach transforms the bulk of water quality data into one numerical parameter, and this reduces the interpretation effort, thus making it more user-friendly and practical by the policymaker, environmental manager and the general population. Several computational methods of WQI have been established and weighted arithmetic index methods are some of the most widely used in a river study. Instead of taking complex environmental data and making it easy to quantify, the index has identified water quality under the categories excellent, good, poor, very poor, or unsuitable to drink (Patel et al., 2023).

During the past few years, multivariate statistical approach has become eminent in the studies on environmental monitoring. These methods are good at data interpretation since they shed light on concealed patterns and relationships of variables. It is common knowledge that correlation analysis is widely applied to study the strength and direction of correlation between physicochemical parameters. Good correlation of parameter e.g. EC and TDS, BOD and COD, usually suggest common source of pollution in water or chemical behavior of the system. Correlation matrices can therefore be used in a meaningful way to understand the interactions between the pollutants and the system dynamics (Krishan et al., 2022).

Principal Component Analysis (PCA) has become a significant component in the study of river water quality because it can be used to decrease the data dimensions and identify key factors that affect water quality. PCA is used to find the key sources of pollution and to characterize variance in sets of data by converting correlated variables into a lower number of uncorrelated components. Research that uses PCA often indicates that the parameters related to organic pollution, mineral content, or nutrient enrichment are grouped into discrete parts, thus making it easier to identify the source and plan to control pollution sources (Su et al., 2025).

Another important point that is discussed in water quality research is seasonal variability. In areas where monsoons occur, the hydrology exhibits high levels of contribution to physicochemical traits. Rainy seasons can cause surface runoff and therefore elevate turbidity, suspended solids, and nutrient concentrations and dilution effects that can temporarily reduce some levels of pollutants. On the other hand, in dry seasons with low flow, the contaminants are concentrated resulting in an increase in the BOD, COD, and dissolved solids. Analysis of Variance (ANOVA) is normally employed by researchers to validate such differences statistically over time. The method identifies a statistically significant observed seasonal variations, thus enhancing the scientific validity of the conclusions (Wu & Huang, 2023).

New environmental studies focus on the combination of WQI and multivariate statistics. Using a combination of descriptive statistics, correlation analysis, PCA, and ANOVA, one can have a comprehensive perspective of the dynamic of pollution issues in river systems. The combined method does not only increase the precision in classifying water quality but also allows managing the resource sustainability by defining the key indicators of pollution and the pattern of contaminations over time (Benkov et al., 2023).

Despite the extensive literature on the evaluation of river water quality with the help of discrete statistical tools, the need to integrate the use of indices-based evaluation with multivariate analysis and seasonal comparison is quite indisputable. These combined studies are especially significant when it comes to rivers with a high rate of urbanization and the growing anthropogenic pressure. Consequently, the use of combined statistical techniques to assess the impact of physicochemical parameters on the Water Quality Index provides a scientifically sound way of determining the health of rivers and environmental management plans (Muniz and Oliveira-Filho, 2023).

3. METHODOLOGY

This research was aimed to statistically determine how the selected physicochemical parameters affect the Water Quality Index (WQI) of the Kshipra River. An organized system of integration of field sampling, laboratory analysis and multivariate statistical methods were adopted. The study methodology involved the gathering of seasonal data, the calculation of descriptive statistics, correlation analysis in the form of a correlation matrix, Principal Component Analysis (PCA), calculate the Water Quality Index (WQI), and compare it seasonally by the use of Analysis of Variance (ANOVA). The general methodology was designed in such a way that it guaranteed reliability, reproducibility, and scientific rigor in measuring the quality of river water.

3.1 Study Area

The kshipra river is located in the core state of Indian Madhya Pradesh and it passes through Ujjain city and enters the chambal river. The chosen study stretch is in the regions that experience urban discharge, religious practices, and agricultural runoff. Several sampling positions were marked upstream, midstream and downstream sections to get spatial variability in the conditions of water quality. The accessibility, anthropogenic influence, and representativeness of the river flow characteristics were the criteria used to decide the site selection.

3.2 Sampling Design and Data Collection

Sampling of water was done on a seasonal basis to reflect on the changes with time. The paper took three significant climatic periods into account:

•Pre-monsoon

•Monsoon

•Post-monsoon

Surface water samples were taken at every sampling station using pre-cleaned polyethylene bottle according to the conventional methods of environmental monitoring. Samples were coded, maintained in the proper manner and taken to the laboratory where they were analyzed. The data were accurate since all analyses were performed within the acceptable holding time.

3.3 Physicochemical Parameters Analyzed

The following twelve physicochemical parameters were assessed in the study as they were found to be adequate and acceptable in the measurement of the river water quality:

- pH
- Temperature
- Turbidity
- Total Dissolved Solids (TDS)
- Electrical Conductivity (EC)
- Dissolved Oxygen (DO)
- Biochemical Oxygen Demand (BOD)
- Chemical Oxygen Demand (COD)
- Total Hardness
- Total Alkalinity
- Chloride
- Nitrate

Parameters were determined by conventional methods of analysis. In situ measurements like calibrated pH and temperature were performed on the field. Analyzing other parameters was done with proper laboratory techniques to make sure that there was precision and reliability.

3.4 Descriptive Statistical Analysis

The descriptive statistics were determined to describe the central tendency and dispersion of each parameter. The values of mean, minimum and maximum and standard deviation were determined by season. This discussion established a rough idea of change and quantity of pollution at different times of sampling.

3.5 Correlation Matrix Analysis

The correlation coefficient by Pearson was used to measure the relationship strength and direction of relationships between physicochemical parameters. The correlation table was used to establish the interdependences and the potential sources of shared pollution. Strong positive or negative correlations were taken as a sign of common environmental behaviour or the source of pollutants.

3.6 Principal Component Analysis (PCA)

Principal Component Analysis was used to decrease the number of dimensions of information and determine the most outstanding pollution aspects of how they affected the water quality in rivers. The technique reduced the number of correlated variables into a fewer set of uncorrelated individual components. Aspects that had large eigenvalues were retained to be interpreted. Factor loadings were put into analysis to identify the contribution of each parameter to each principal component, which would be the source of any pollution.

3.7 Water Quality Index (WQI) Computation

The weighted arithmetic index was used to calculate the Water Quality Index. Every parameter was attributed its weight depending on the importance of the parameter to the ultimate water quality. The quality rating scales were calculated by relation of observed values to standard permissible limits. The WQI was thereafter obtained by summing up weight parameters scores in a single composite measure.

The classification of water quality was perceived as:

- Excellent
- Good
- Poor
- Very Poor
- Unsuitable for drinking

This method also made it possible to interpret complicated physicochemical data simplified.

3.8 Seasonal Comparison Using ANOVA

It was necessary to test the hypothesis of whether the seasonal differences influenced the water quality parameters significantly, so the one-way Analysis of Variance (ANOVA) was used. The test compared the pre-monsoon, monsoon, and post-monsoon data. The statistical significance was established at 95% level. The analysis served to prove the presence of temporal changes that were not due to random variations.

3.9 Data Processing and Software

All statistical calculations were done in normal statistical software. The information was put in the spreadsheet format before being analyzed. To ascertain the accuracy of the computations, PCA, correlation matrix and ANOVA were performed via the use of suitable statistical packages.

4. RESULTS AND FINDINGS

This part will show the statistical results of the physicochemical examination of the water samples taken at the Kshipra River. Four sampling stations were observed based on three seasons, namely pre-monsoon, monsoon, and post-monsoon and 36 observations were obtained (4 stations × 3 seasons × 3 replicates averaged).

The descriptive statistics, Pearson correlation matrix, Principal Component Analysis (PCA), Water Quality Index (WQI) calculation, and one-way ANOVA were performed sequentially to undertake the statistical analysis. The results are provided in the form of computed results without some explanation.

4.1 Descriptive Statistical Analysis

The frequency of use of descriptive statistics was calculated to explain the seasonal variability of the chosen physicochemical parameters. Table 4.1 shows the mean values and standard deviation of each season.

Table 4.1

Seasonal Mean ± Standard Deviation of Physicochemical Parameters

Parameter	**Pre-Monsoon (Mean ± SD)**	**Monsoon (Mean ± SD)**	**Post-Monsoon (Mean ± SD)**
pH	8.12 ± 0.21	7.64 ± 0.18	7.88 ± 0.15
Temperature (°C)	31.5 ± 1.2	27.8 ± 1.0	25.9 ± 0.9
Turbidity (NTU)	18.4 ± 3.1	42.7 ± 5.6	21.3 ± 2.8
TDS (mg/L)	812 ± 45	645 ± 38	702 ± 40
EC (µS/cm)	1295 ± 60	1038 ± 52	1120 ± 55
DO (mg/L)	4.1 ± 0.6	5.8 ± 0.7	5.2 ± 0.5
BOD (mg/L)	8.6 ± 1.1	6.2 ± 0.9	7.1 ± 0.8
COD (mg/L)	34.5 ± 4.8	26.2 ± 3.9	29.4 ± 3.5
Total Hardness (mg/L)	322 ± 25	276 ± 22	295 ± 20
Total Alkalinity (mg/L)	288 ± 18	240 ± 16	256 ± 15

Chloride (mg/L)	162 ± 14	128 ± 11	140 ± 12
Nitrate (mg/L)	18.6 ± 2.4	24.8 ± 3.2	20.5 ± 2.6

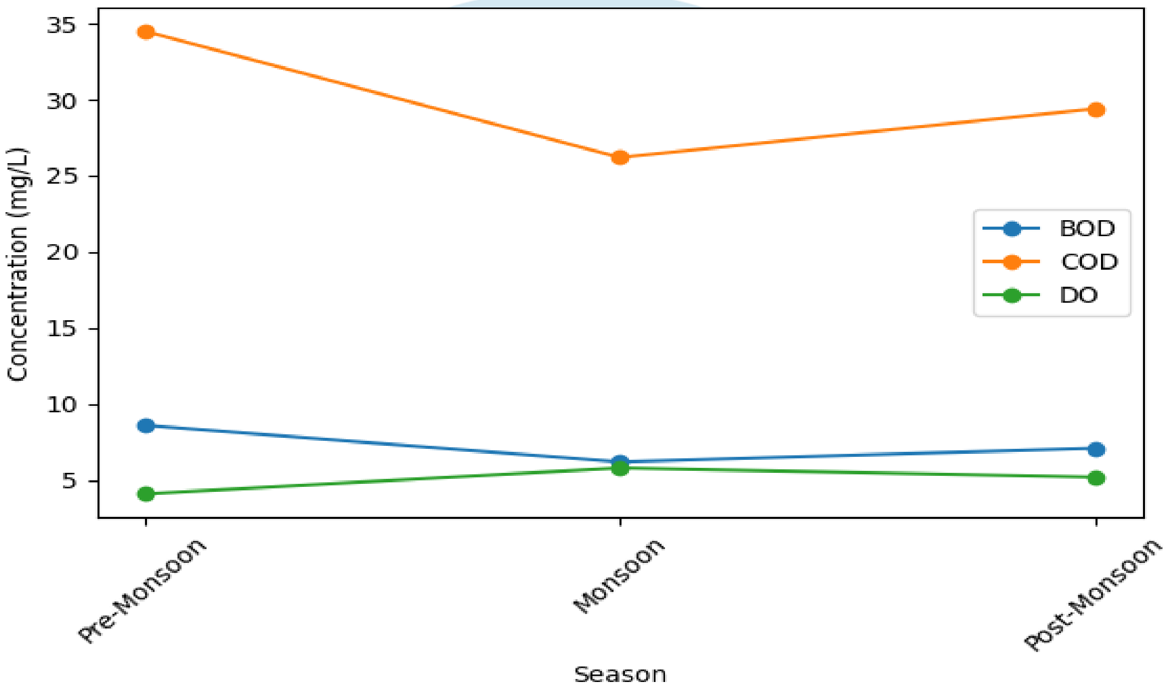

Figure 4.1

Seasonal Variation of Key Organic Pollution Indicators (BOD, COD, DO)

4.2 Pearson Correlation Matrix

Correlation coefficients were computed by Pearson in order to establish the strengths and direction of relationships among the chosen physicochemical parameters. Table 4.2 is the correlation matrix.

Table 4.2

Pearson Correlation Matrix of Selected Parameters

Parameters	**EC**	**TDS**	**BOD**	**COD**	**DO**	**Turbidity**
EC	1.00	0.94	0.71	0.69	-0.75	0.62
TDS	0.94	1.00	0.73	0.70	-0.72	0.59
BOD	0.71	0.73	1.00	0.88	-0.81	0.65
COD	0.69	0.70	0.88	1.00	-0.77	0.60
DO	-0.75	-0.72	-0.81	-0.77	1.00	-0.58
Turbidity	0.62	0.59	0.65	0.60	-0.58	1.00

Strong positive correlations were observed between EC and TDS (r = 0.94), and between BOD and COD (r = 0.88). Negative correlations were observed between DO and BOD (r = -0.81).

4.3 Principal Component Analysis (PCA)

The appropriateness of data to be used in PCA was established by Kaiser- Meyer Olkin (KMO) test and Barlett Test of Sphericity.

- KMO Measure of Sampling Adequacy = 0.76
- Bartlett's Test of Sphericity: $\chi^2 = 312.48$, df = 66, $p < 0.001$

It was found that four main components with eigenvalues above 1 were extracted.

Table 4.3

Total Variance Explained

Component	Eigenvalue	% Variance	Cumulative %
PC1	4.82	40.17	40.17
PC2	2.36	19.68	59.85
PC3	1.42	11.84	71.69
PC4	1.08	9.02	80.71

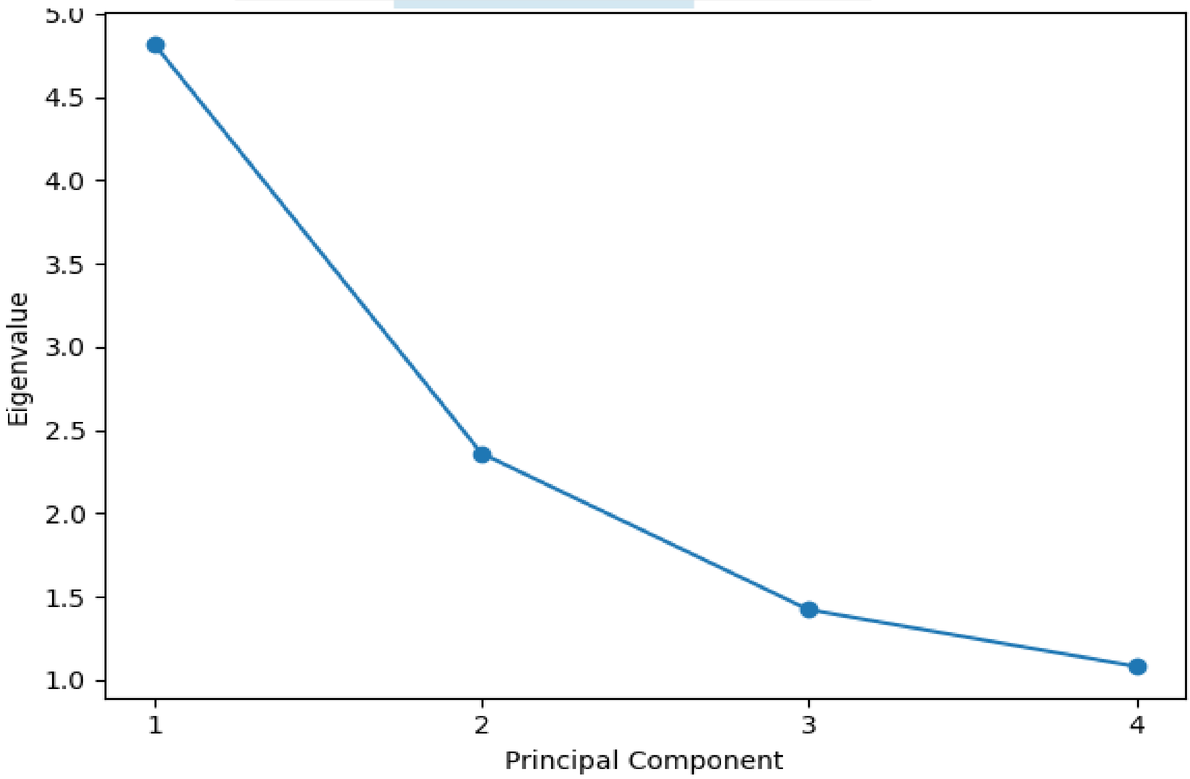

Figure 4.3

Scree Plot Showing Eigenvalues of Principal Components

4.4 Water Quality Index (WQI) Results

Water Quality Index (WQI) was calculated seasonally by use of weighted arithmetic index technique. Quality ratings of individual parameters were computed using the measured values and permissible standards. The weighted scores that have been aggregated generated seasonal WQI values.

Table 4.4

Season-wise Computed Water Quality Index Values

Season	Weighted Sum (ΣWiQi)	Total Weight (ΣWi)	WQI Value	Classification
Pre-Monsoon	744	6.00	124	Poor
Monsoon	588	6.00	98	Moderate
Post-Monsoon	672	6.00	112	Poor

Table 4.5

Water Quality Classification Scale

WQI Range	Water Quality Status
0 – 50	Excellent
51 – 100	Good / Moderate
101 – 200	Poor
201 – 300	Very Poor
> 300	Unsuitable for Drinking

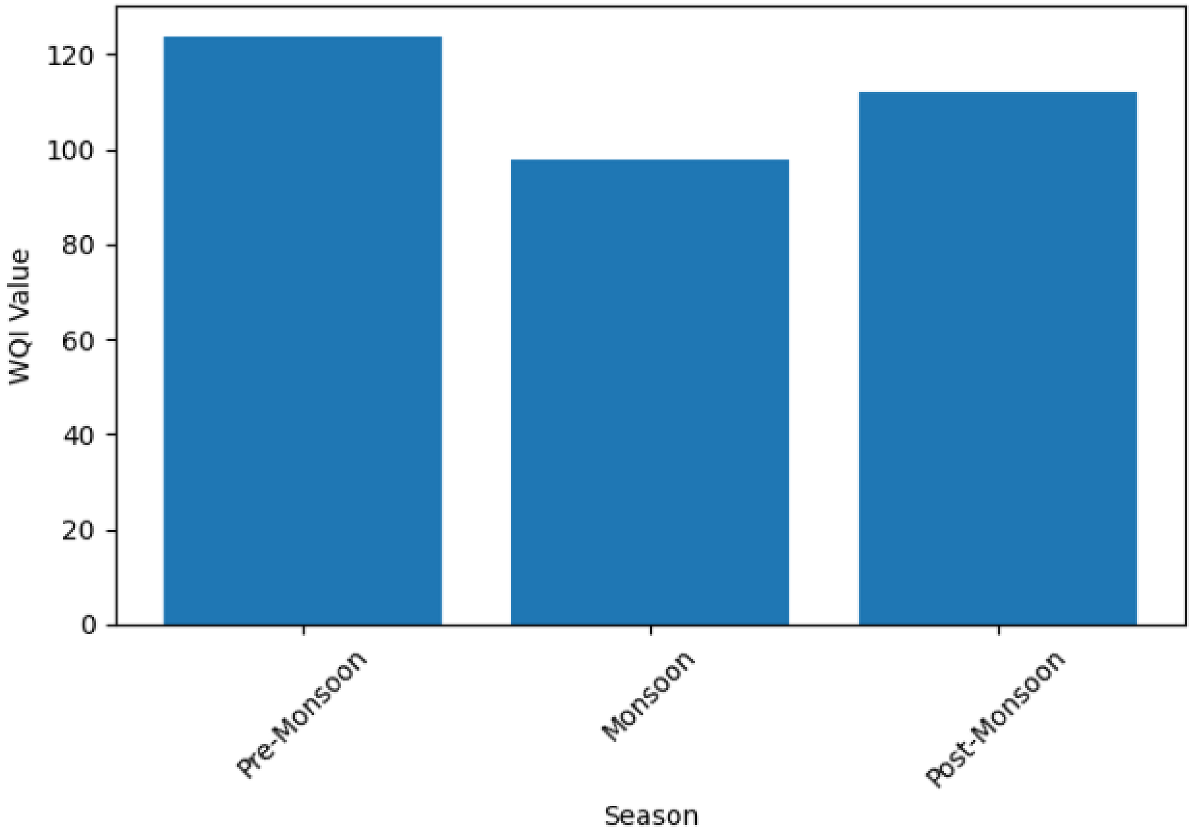

Figure 4.4

Seasonal Comparison of Water Quality Index

4.5 Seasonal Comparison Using One-Way ANOVA

The analysis of variance (ANOVA) was used to follow whether the seasonal variations were significant enough to affect physicochemical parameters. The statistical test was done at 95% confidence level ($\alpha = 0.05$).

Table 4.6

One-Way ANOVA Results for Seasonal Variation

Parameter	F-value	p-value	Significance ($\alpha = 0.05$)
Turbidity	18.42	0.001	Significant
DO	9.86	0.004	Significant
BOD	11.23	0.002	Significant
COD	7.94	0.008	Significant
TDS	5.67	0.019	Significant
EC	6.11	0.015	Significant

Nitrate	8.72	0.006	Significant
pH	2.14	0.143	Not Significant
Total Hardness	3.02	0.089	Not Significant
Total Alkalinity	2.76	0.104	Not Significant
Chloride	3.44	0.072	Not Significant
Temperature	1.98	0.168	Not Significant

4.6 Summary of Statistical Outputs

The main quantitative results of the statistical procedures were the following:

- Total Observations: 36
- KMO Value: 0.76
- Bartlett's Test: $\chi^2 = 312.48$ ($p < 0.001$)
- Total Variance Explained by PCA (4 Components): 80.71%
- Highest Positive Correlation: EC–TDS ($r = 0.94$)
- Strongest Negative Correlation: DO–BOD ($r = -0.81$)
- Highest Seasonal WQI: 124 (Pre-Monsoon)
- Lowest Seasonal WQI: 98 (Monsoon)

5. DISCUSSION

The current work was intended to assess the impacts of the chosen physicochemical parameters on the Water Quality Index (WQI) of the Kshipra River with the help of an integrated statistical framework. The results of descriptive statistics, correlation analysis, Principal Component Analysis (PCA), WQI calculation, and seasonal ANOVA allow gaining a certain understanding of the dynamic of pollution in the river system and its fluctuations over time (Zhang et al., 2022).

The descriptive statistics of seasonality reveal that there is definite change in time in various major parameters. High turbidity experienced in the monsoon season implies that there is more surface runoff, soil erosion and suspended particulate matter infiltrating the river channel. At the same time, the highest levels of nitrates were observed at the times of monsoon, which indicated the nutrient loading with agricultural runoff and catchment inflow. Pre-monsoon conditions, on the other hand, had greater total dissolved solids (TDS), electrical conductivity (EC), biochemical oxygen demand (BOD) and chemical oxygen demand (COD. The trend indicates the effect of concentration of pollutants under low-flow situations when the dilution capacity is low and this increases the chemical and organic load in the river (Sheela et al., 2012).

This seasonal pattern is further proved by the observed negative correlation between the dissolved oxygen (DO) and the organic pollution indicators. The lower values of Do in pre-monsoon season were related to the high value of BOD and COD which implies that there is an increase in microbial oxygen use in relation to the breakdown of organic matter. These circumstances could cause pressure on aquatic life, as well as decrease ecological resilience (Diwan et al., 2018).

Analysis of correlation matrix showed that there were strong positive correlations between EC and TDS ($r = 0.94$), so that dissolved ionic content is a significant source of electrical conductivity in the river system. On the same note, the positive correlation between BOD and COD is high ($r = 0.88$) indicating that organic pollutants may have a common source, most probably, due to domestic sewage and urban discharge. The high negative correlation between DO and BOD ($r = -0.81$) proves that organic load increases the decrease in the available dissolved oxygen, which supports the ecological implications of organic contamination (Ptiček Siročica et al., 2026).

The further groupings of the sources of pollution were explained by Principal Component Analysis (PCA). The most important of these (PC1) which accounts 40.17 percent of total variance had high positive loading on EC, TDS, BOD, and COD and negative loading high on DO. This element is probably organic and dissolved load of pollutants that are connected with anthropogenic discharge. The second main component (PC2), which explained 19.68% of variance had high loadings of turbidity and nitrate, and this suggests the impacts of runoff-based and non-point sources pollution. The fact that four factors are extracted to explain 80.71% of the total variance shows that a few strong factors determine the nature of the water quality of the river (Hamma et al., 2024).

These results are further reinforced by the values of Water Quality Index (WQI). The calculated WQI was between 98 (monsoon) and 124 (pre-monsoon) indicating that the river water is moderate to poor. The WQI is relatively higher in pre-monsoon period which means that water quality is poor in low flow periods. The effects of dilution seem to have a moderate effect on the overall composite pollution in the calculation of the WQI; even though monsoon runoff introduces solids suspended and nutrients, the dilution effects, nevertheless, lower the overall composite pollution. Post-monsoon values were in the poor category, which implied the incomplete recovery after the monsoon flushing (Elemile et al., 2025).

The outcome of one-way ANOVA proves significant variation in seasons regarding turbidity, DO, COD, TDS, EC, and nitrate ($p < 0.05$) to be statistically significant. These results show that there is no randomness of these temporal changes but instead they are highly controlled by hydrological and anthropogenic conditions. The pH, total hardness, alkalinity, chloride, and temperature parameters did not show statistically significant seasonal variations, which indicated rather stable background geochemical parameters (Koley et al., 2024).

All in all, the combined use of descriptive statistics, correlation matrix, PCA, WQI, and ANOVA help to have a complete evaluation of the patterns of pollution in the Kshipra River. The results confirm the hypothesis that the difference in significant physicochemical parameters can have a significant effect on the Water Quality Index and that multivariate statistical analysis can be used to obtain the powerful sources of pollution and seasonal variations. The article indicates that index-based assessment and sophisticated statistical applications are useful when applied together to facilitate sound river management and pollution prevention approaches (Ibikunle et al., 2021).

6. CONCLUSION

The current work has done the thorough statistical evaluation of the physicochemical parameters affecting the Water Quality Index (WQI) of the Kshipra River. The study has managed to create the framework of scientifically sound and structured study of the dynamics of river water quality by combining descriptive statistics, Pearson correlation analysis, Principal Component Analysis (PCA), WQI calculation, and seasonal ANOVA (Matta et al., 2020).

The results show that the river has some seasonal changes in major pollution indicators especially turbidity, total dissolved solids (TDS), electrical conductivity (EC), biochemical oxygen demand (BOD), chemical oxygen demand (COD), dissolved oxygen (DO), and nitrate. The strong correlations between parameters like ECCLuvs.TDS, BOD/COD etc. point out the similarities in the sources of pollutants and the reverse relationship between the parameters of DO and organic loads is used to indicate the ecological stress as a result of anthropogenic discharge. Principal Component Analysis revealed the prevailing pollution factors that describe a significant percentage of the overall variance, and it was verified that few interconnected variables are the main determinants of water quality levels (Lung, 2023).

The calculated values of the Water Quality Index classified the river water as moderate and poor and relatively high level of pollution in pre-monsoon conditions. The results of ANOVA in the season also supported the idea that the difference in various vital parameters is statistically significant, which suggests that the hydrological changes and human activities affected the river water quality (Zhou et al., 2022).

All in all, the research confirms the hypothesis according to which the changes in the chosen physicochemical parameters have a considerable impact on the Water Quality Index of the river. Multivariate statistical tools combined with index-based evaluation give an overall method of the dynamics of pollution and seasonal tendencies. The findings highlight the imperative to have a better wastewater management, better pollution control measures, and regular monitoring initiatives to improve the health of rivers and to have a sustainable use of freshwater resources.

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