



Spatiotemporal Assessment of River Water Quality and Pollution Status in Dhaka, Bangladesh

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Abstract

Rapid urbanization, industrial expansion, and seasonal hydroclimatic variability have placed increasing pressure on river systems in Dhaka, Bangladesh, making integrated assessment of water quality essential for effective environmental management. This study investigated the spatiotemporal variability of river water quality and pollution status using physicochemical, hydroclimatic, and multivariate statistical approaches. A total of 1,495 observations collected from multiple rivers and streams between 2017 and 2021 were evaluated for temperature, pH, dissolved oxygen, chemical oxygen demand, nitrate, turbidity, phosphate, rainfall, and Water Quality Index (WQI). Spearman correlation, principal component analysis, multivariate analysis of variance, hierarchical clustering, and robust multiple linear regression were applied. WQI was most strongly positively associated with pH ($\rho = 0.705$) and phosphate ($\rho = 0.468$), while dissolved oxygen showed a negative association ($\rho = -0.325$). The first three principal components explained 54.46% of total variance and represented hydroclimatic-oxygenation, organic-pollution, and nutrient-related gradients. Significant seasonal differences were observed, particularly between monsoon and winter conditions. Hierarchical clustering classified the monitored rivers into three distinct environmental groups. The regression model explained 16.6% of WQI variability, with dissolved oxygen emerging as the strongest independent correlate. These findings highlight the need for river-specific and season-sensitive monitoring and management strategies in Dhaka.

Keywords:

- River water quality
- Water Quality Index
- Spatiotemporal variation
- Multivariate analysis
- Dhaka

1. Introduction

River systems are vital parts of urban and regional environments, serving both water-supply and ecological functions for agriculture, industry, fisheries, transportation, domestic water supply and ecological purposes. The physicochemical properties of surface waters have been changing over the years, especially in rapidly developing areas, due to rapid urbanization, industrial growth, wastewater discharges, land-use changes, and poor pollution control. The degradation of river water is thus not just an environmental issue, but one that matters for the integrity of the ecosystem, water-resource security and sustainable urban development. Recent reviews point out that pollution of rivers is frequently attributed to the combined influence of industrial, agricultural, municipal, and diffuse pollution, and proper monitoring should involve comprehensive monitoring instead of relying on individual parameters of water quality (Sridhar, 2026).

Water quality is also highly variable in both space and time. The environmental conditions created by changes in rainfall, temperatures, runoff, hydrological flow, pollutant loadings, and human activity can vary considerably from season to season and location to location. The monitoring has been conducted over the long term and has shown that the temporal variation can show water-quality changes that may not be apparent if it is viewed as a pooled average (Marara & Palamuleni, 2020). The emphasis on repeated environmental observations to differentiate between persistent pollution and short-term fluctuations in surface-water characteristics has been illustrated by similar temporal changes in surface-water characteristics (Thanh Giao et al., 2021).

Spatial variability is also significant because pollutant pressures are not necessarily evenly distributed across a river system. There are potential significant differences between monitoring sites due to differences in land use, discharge points, industrial development, settlement density, and inputs from tributaries. Hence, spatial assessment of physicochemical and bacteriological conditions has emerged as an important tool for detecting areas of water-quality impairments and prioritization of environmental intervention (Kumar et al., 2022). Nutrient transport, sediment loads, hydrological connectivity, and pollutant concentration can be further altered by land use changes in watersheds, leading to complex spatial-temporal water-quality patterns (Zhang et al., 2025).

The surface-water degradation is especially critical in Bangladesh due to the high concentration of the growth of urban population and industrial activities around the major river systems. Previous study of the Shitalakhya River identified high spatiotemporal variations, indicating the importance of water-quality indices along with multivariate statistical analysis to assess the water-quality conditions of urban river water system (Kabir et al., 2020). A study conducted on the transboundary Shari-Goyain River also showed that water quality is different from one place to another and depending on the hydrological conditions of the season (Pandit et al., 2023). The results suggest that analytical tools that can resolve multiple interacting environmental gradients are needed to assess river quality in Bangladesh.

The Water Quality Index (WQI) offers a good way to combine multiple physicochemical data to form a single index for environmental interpretation. But WQI cannot reveal the relationships between the individual pollutants. As a result, the use of multivariate statistics in conjunction with an index-based evaluation of environmental structure and possible pollution sources has been increasingly used in studies (Azhari et al., 2022). Similarly, statistical and geostatistical methods have proven to be helpful for solving complex spatial and temporal patterns in river quality (Raman et al., 2023).

Principal component analysis, correlation analysis, and clustering are especially useful in cases where there is interdependency among environmental variables. They can be used together to detect dominant water-quality

gradients, classify environmentally similar river systems and to simplify complex data sets into interpretable patterns. Multivariate assessments have been successful for characterizing water-quality variability from mixed agricultural and urban watersheds (Nguyen et al., 2024). Environmental conditions and anthropogenic pressures have also been shown to interact to shape spatiotemporal patterns observed in analysis of trace pollutants (Wang, 2024). Spatial, temporal, chemical and health-related factors are increasingly being combined in comprehensive monitoring frameworks to better interpret river-water deterioration (Shibambu et al., 2025).

This study was aimed to investigate the spatiotemporal variation and pollution situation of river water in Dhaka city, Bangladesh. Specific objectives were to: (i) identify relationships between water-quality and hydroclimatic variables; (ii) identify dominant environmental gradients through principal component analysis; (iii) classify rivers in terms of similarities in their multivariate water-quality profiles; and (iv) quantify the independent association of environmental parameters with WQI through multivariable regression.

2. Methodology

2.1 Study Design, Data Structure, and Variables

The study adopted quantitative secondary data design which was used to review the physicochemical, hydroclimatic and spatial pattern of river and stream water quality. Data from 12 rivers, canals, and streams at various monitoring locations were analyzed for the period 2017-2021 and resulted in 1,495 observations. The observations were grouped into four seasons, namely, winter, pre-monsoon, monsoon and post-monsoon seasons. The spelling and capitalization of season and river names were standardized due to minor variations in these attributes between rivers (Sinha et al., 2026).

Environmental variables considered were water temp (C), pH, dissolved oxygen (DO, mg/L), chemical oxygen demand (COD, mg/L), nitrate (mg/L), turbidity (NTU), and phosphate (mg/L), as well as rainfall (mm). Water Quality Index (WQI) was the major integrated water-quality outcome. The dependent variable in the multivariable regression model was the total time spent in the hospital. The classification of the pollution status was not used in the model, but was retained for descriptive interpretation. The variables of river/stream identity, season and year were used as grouping variables for the spatial and temporal analysis.

2.2 Data Screening, Cleaning, and Missing-Data Treatment

Prior to statistical analysis, all variables were examined for discrepancies in labels, out of range values, and lack of observations. Common spellings for Pre-monsoon/Pre monsoon and Post-monsoon/Post monsoon were used, and variants for river names were standardized.

Physically implausible negative values in the COD records (not recoded or replaced) were present in 6 records. Only samples for COD analyses were excluded from the above observations. As a result, the number of observations used in the analyses involving COD was $n = 1,489$, and the number of observations used in the analyses that included CO and the multivariable procedures with all eight environmental predictors was $n = 1,495$. No statistical imputation was made. Available-case denominators were employed in the pairwise correlation analysis; thus, the number of observations for COD was 1,489 and for the other variables the number ranged up to 1,495. Wherever simultaneous availability of all required variables was required PCA, MANOVA, hierarchical clustering inputs and regression were completed using complete case analysis.

Z-scores were used for multivariate analysis due to significant differences in measurement scales among the environmental variables and some showing non-normal distribution. Two-sided 0.05 alpha level was used to determine statistical significance.

2.3 Correlation and Principal Component Analyses

Spearman's rank-order correlation coefficient (ρ) was used to determine bivariate association among temperature, pH, DO, COD, nitrate, turbidity, phosphate, rainfall and WQI. Several environmental parameters had extreme values and were skewed, and Spearman correlation was therefore chosen to evaluate these parameters instead of Pearson correlation. The absolute value of ρ was used to determine strength of correlation with the direction of the association and relative strength emphasized more than significance alone.

The eight standardized variables of the environment were used to perform principal component analysis (PCA) to recognize the latent dominant environmental gradients. WQI was not included in the PCA as it was an integrated outcome in the further analyses. The correlation matrix was broken down into components and those components with eigenvalues > 1.0 were retained on the Kaiser criteria. To interpret the environmental dimensions represented by each retained component, the loadings of the components were studied, as were the eigenvalues, percentage variance explained, and cumulative variance explained, in addition to communalities.

Seasonal differentiation on the PCA solution was evaluated by Kruskal-Wallis H test for PC1 and PC2 scores for different seasons: winter, pre-monsoon, monsoon and post-monsoon. Since the overall multivariate environmental profile had several dependent, correlated variables, the difference between the seasons for the environmental profile was also analyzed using multivariate analysis of variance (MANOVA). The eight environmental variables were entered as dependent variables and the grouping factor; season was entered as a fixed factor. Wilks' lambda with F statistic was used to check multivariate significance.

2.4 Hierarchical Cluster Analysis of River Systems

The water bodies were clustered hierarchically at the river/stream level to find water bodies which can be grouped together by similar environmental characteristics. Mean values of temperature, pH, DO, COD, nitrate, turbidity, phosphate and rainfall were obtained from the available observations for each of the 12 water bodies. Before clustering these river-level profiles were converted to standardized z-scores to avoid domination of the solution by

variables measured on larger numerical scales.

Ward's linkage method with Euclidean distance was used for agglomerative hierarchical clustering. The dendrogram was then analyzed to understand the multivariate similarity between rivers and streams. The three-cluster solution was retained due to an interpretable cluster of environmental profiles and meaningful separation between water bodies. The silhouette coefficient was then used to quantify the quality of the clusters, with larger positive numbers representing greater similarity within compared to between clusters.

The standardized environmental features of each cluster were considered in conjunction with the constituent rivers and their distribution of WQIs for interpretation. Each record was assigned to the cluster corresponding to the river to which it belonged, and observation-level cluster summaries were computed. There were 39 observations in Cluster 1, 540 in Cluster 2 and 910 in Cluster 3, for a total of 1,489 observations with valid COD information.

2.5 Multivariable Regression and Statistical Reporting

The environmental conditions were statistically associated with WQI independently using a multiple linear regression model. Temperature, pH, DO, COD, nitrate, turbidity, phosphate and rainfall were the independent variables and WQI was the continuous dependent variable. The 1,489 complete observations that were obtained after discarding the six invalid COD observations were used for regression analysis.

The continuous predictors and the WQI were standardized prior to model estimation to allow for direct comparison of the importance of the predictors even if they were measured in different units, and results were reported as standardized regression coefficients (beta). Inference was based on HC3 robust standard errors which are consistent with heteroscedasticity, instead of the ordinary least-squares (OLS) standard errors, as the variance of the residuals in the environmental observations is not necessarily equal. The standardized coefficient, robust standard error, 95% confidence interval and two-sided p value were presented for each predictor.

The R-squared, adjusted R-squared, and overall model significance test were used to summarize overall model performance. Multicollinearity among the predictors was evaluated by the variance inflation factor (VIF) and the values of the VIF's were checked to see if the coefficient estimates were significantly affected by the linear dependence among predictors. Results were considered statistically significant when the p-value was < 0.05 , and results near this value were reported as "borderline" but not statistically significant. No causal environmental effects were interpreted as being present for any inferential findings.

3. Results

3.1 Correlation Structure of Water-Quality and Hydroclimatic Variables

The associations of physicochemical and hydroclimatic data with water-quality data were found to be distinct using Spearman correlation analysis (Table 1; Figure 1). WQI had the highest positive correlation with pH ($\rho = 0.705$, $p < 0.001$) followed by concentration of phosphate ($\rho = 0.468$, $p < 0.001$). Dissolved oxygen had a moderate negative correlation with the WQI ($\rho = -0.325$, $p < 0.001$) on the other hand. The inverse relationship of WQI with temperature and rainfall was also found to be significant with coefficients of -0.208 and -0.190, respectively.

The best negative correlation was between dissolved oxygen and phosphate ($\rho = -0.657$), indicating a tendency towards higher phosphate levels in regions with lower oxygen levels. Rainfall was strongly correlated with temperature ($\rho = 0.594$), and was moderately positively correlated with dissolved oxygen ($\rho = 0.377$). COD was found to have positive correlation with pH ($\rho = 0.209$) and turbidity ($\rho = 0.197$). The entire inter-variable correlation structure is presented in Figure 1.

Table 1. Spearman Correlations Between Environmental Variables and Water Quality Index

Variable	rho with WQI	p-value	Interpretation
Temperature	-0.208	<0.001	Weak negative
pH	0.705	<0.001	Strong positive
Dissolved oxygen	-0.325	<0.001	Moderate negative
COD	0.193	<0.001	Weak positive
Nitrate	0.163	<0.001	Weak positive
Turbidity	0.131	<0.001	Weak positive
Phosphate	0.468	<0.001	Moderate positive
Rainfall	-0.190	<0.001	Weak negative

The correlation matrix (Figure 1) also shows that oxygen depletion, nutrient enrichment, rainfall and physicochemical conditions are not independent environmental processes but are interrelated.

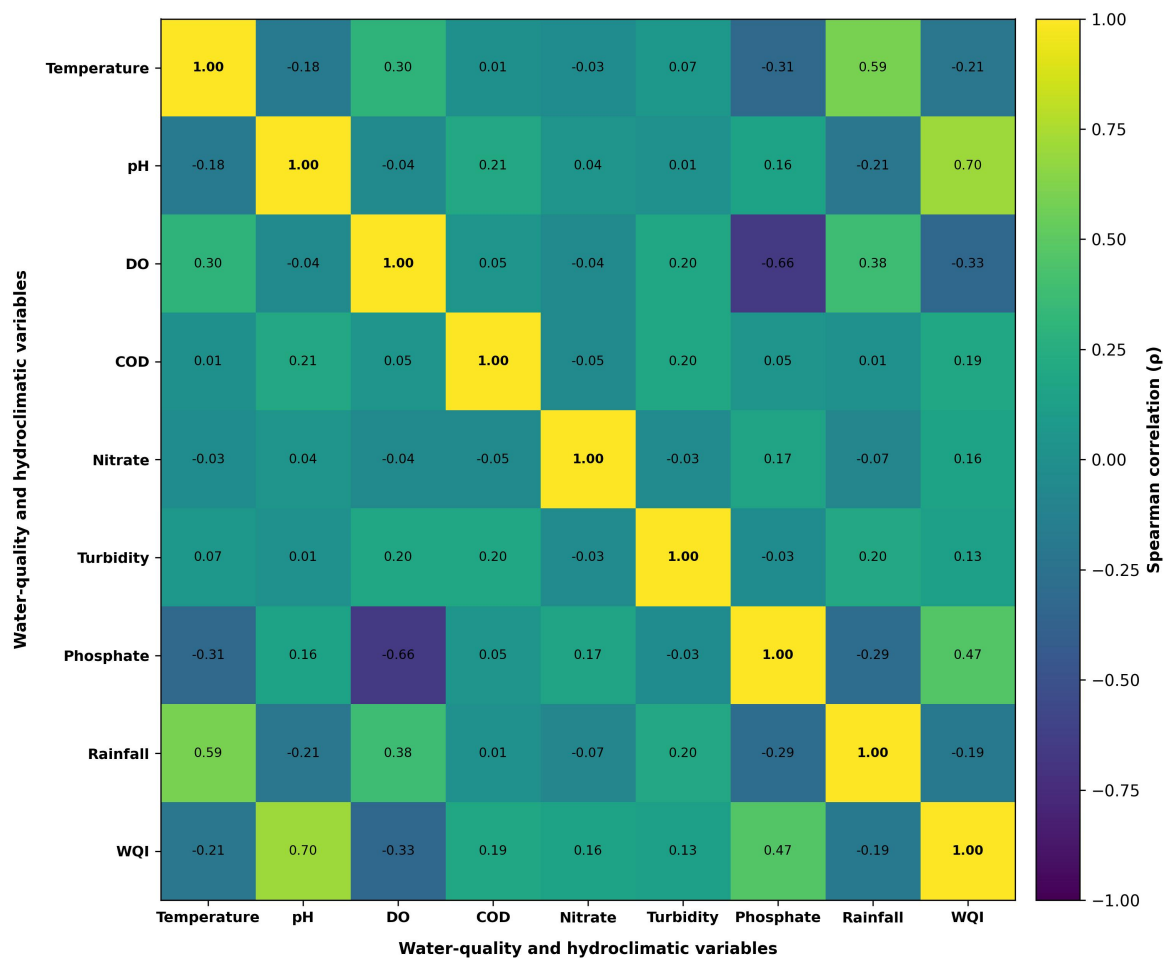


Figure 1. Spearman Correlation Structure Among Water-Quality and Hydroclimatic Variables

3.2 Principal Component Structure and Seasonal Multivariate Differentiation

Eight standardized water-quality and hydroclimatic variables were analyzed using PCA. Eigenvalues of the first three components were greater than 1 and they accounted for 54.46% of the total variance (Table 2). The first principal component (PC1) accounted for 23.83% of the total variance and showed strong positive loadings for dissolved oxygen (0.757), temperature (0.629), turbidity (0.591) and rainfall (0.492) while an opposing loading was seen for phosphate (-0.533). This component, therefore, was a hydroclimatic-oxygenation gradient that was in contrast between the wetter, oxygenated conditions and the phosphate-rich conditions.

An additional 17.61% of variance was explained by PC2, which was dominated by pH (0.756) and COD (0.741) and positively influenced by phosphate (0.398). PC3 accounted for 13.02% of the variance and was mainly associated with nitrate (0.862), which represented a fairly independent nutrient-loading axis.

Table 2. Principal Component Loadings for Major Environmental Variables

Variable	PC1	PC2	PC3	Communality
Temperature	0.629	-0.239	-0.102	0.463
pH	-0.064	0.756	0.162	0.601
Dissolved oxygen	0.757	0.063	0.278	0.655
COD	0.229	0.741	-0.073	0.607

Variable	PC1	PC2	PC3	Communality
Nitrate	-0.080	0.030	0.862	0.750
Turbidity	0.591	0.243	-0.012	0.408
Phosphate	-0.533	0.398	-0.242	0.501
Rainfall	0.492	0.104	-0.350	0.375
PC1 eigenvalue / variance (%)	1.908	23.83		
PC2 eigenvalue / variance (%)	1.409	17.61		
PC3 eigenvalue / variance (%)	1.043	13.02		
Cumulative variance (%)			54.46	

The PCA ordination presented in Figure 2 revealed a significant seasonal shift along PC1. The observations during the monsoon were mostly clustered in the positive part of the PC1 scores, while the observations during the winter were mostly clustered in the negative part of the PC1 scores. Mean PC1 scores were 1.310 for monsoon, 0.201 for post-monsoon, -0.398 for pre-monsoon, and -1.362 for winter. These differences were highly significant ($H = 985.81$, $p < 0.001$). PC2 also differed significantly among seasons ($H = 263.27$, $p < 0.001$).

A MANOVA indicated that the combined physicochemical profile was significantly different among the seasons (Wilks' lambda = 0.139, $F(24, 4287.25) = 173.73$, $p < 0.001$). So, seasonal changes in water quality were not due to one parameter but were results of a coordinated response over a number of environmental parameters.

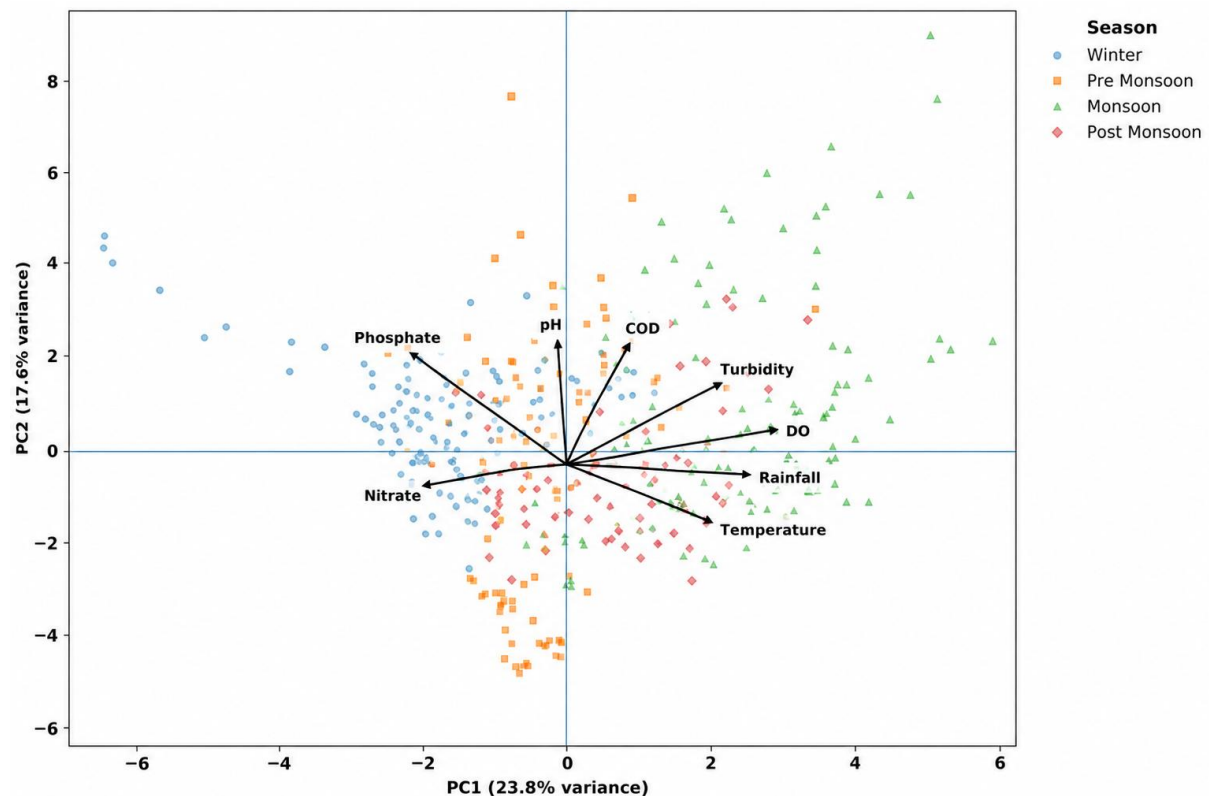


Figure 2. PCA Biplot Showing Seasonal Separation and Environmental-Variable Loadings

3.3 Hierarchical Classification of Rivers by Environmental Profile

The three groups of rivers from the hierarchical cluster analysis were interpretable and produced using Ward's linkage

and standardized river-level physicochemical profiles (Table 3; Figure 3). Cluster 1 comprised the two rivers Bangshi and Kaliganga with relatively high values of dissolved oxygen, nitrate, turbidity, temperature and pH. This cluster had a mean WQI of 86.69 ± 16.79 .

Tongi khal and Turag were part of cluster 2. The WQI for these water bodies was 93.16 ± 8.52 , and they were differentiated mainly based on the higher COD and rainfall levels. The other eight water bodies were grouped as Cluster 3 and represented a larger intermediate environmental group. The standardized profile was found to have significantly less dissolved oxygen, COD, turbidity and temperature, and a mean WQI of 90.53 ± 15.72 .

Table 3. Hierarchical Clustering of Rivers According to Multivariate Water-Quality Profile

Cluster	Rivers/streams	No. of observations	Dominant environmental characteristics	Mean WQI +/- SD
1	Bangshi; Kaliganga	39	High DO, nitrate, turbidity, temperature and pH	86.69 +/- 16.79
2	Tongi Khal; Turag	540	High COD and rainfall; moderate turbidity	93.16 +/- 8.52
3	Balu; Bangshi-Savar; Bashundhara Canal; Begunbari Canal; Buriganga; Dhaleshwari ; Pagar Canal; Shitalakhya	910	Lower DO, COD and turbidity with relatively heterogeneous nutrient profiles	90.53 +/- 15.72

The dendrogram in Figure 3 shows that Bangshi and Kaliganga were the most separated and distinct group under high nutrient/high turbidity while Tongi Khal and Turag were separated under hydroclimatic COD associated grouping. The other rivers were more multivariate similar and grouped at lower linkage distances. The three-cluster solution gave silhouette coefficient of 0.300, which means that the environmental river profiles were moderately separated.

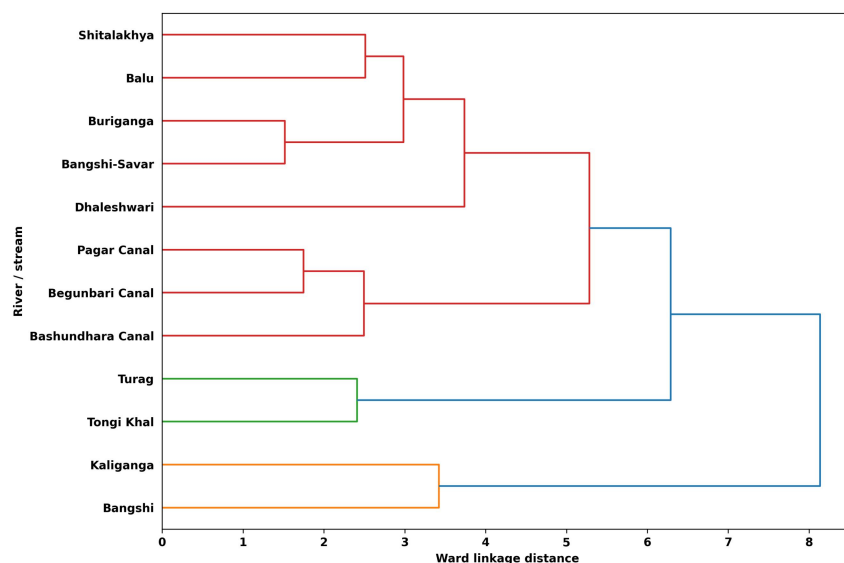


Figure 3. Hierarchical Clustering of Rivers and Streams Using Standardized Multivariate Water-Quality Profiles.

3.4 Independent Environmental Drivers of Water Quality Index

A HC3 heteroscedasticity-robust multiple linear regression model was fitted in order to determine which environmental factors remained independently associated with WQI when all other factors were simultaneously entered into the model (Table 4). The overall model is statistically significant with an R-squared of 0.166 and an

adjusted R-squared of 0.162, and the model showed that the overall p value is < 0.001 .

Dissolved oxygen, with a beta of -0.371, $p < 0.001$, was found to be the strongest independent predictor, implying that higher dissolved oxygen concentrations were negatively correlated with WQI values, relative to the others. Rainfall displayed the strongest positive independent association (beta = 0.111, $p < 0.001$), followed by COD (beta = 0.089, $p < 0.001$) and phosphate (beta = 0.070, $p = 0.003$). However, its unadjusted correlation with WQI was positive ($r = 0.710$, $p = 0.004$), but the adjusted coefficient (beta) was negative (beta = -0.087, $p = 0.004$); pH did not fit into the model even though it was significant.

However, after adjustment, temperature and turbidity were not significant, and there was borderline evidence of an independent association ($p = 0.057$) with nitrate. The variance inflation factors were between 1.01 and 1.39, suggesting that there was no significant multicollinearity. The standardized coefficients and 95% CIs are shown graphically in Figure 4.

Table 4. Standardized Multivariable Regression Predicting Water Quality Index

Predictor	Standardized beta	Robust SE	95% CI	p-value	VIF
Temperature	0.029	0.030	-0.031 to 0.088	0.343	1.19
pH	-0.087	0.030	-0.146 to -0.028	0.004	1.14
Dissolved oxygen	-0.371	0.055	-0.478 to -0.264	<0.001	1.39
COD	0.089	0.019	0.052 to 0.125	<0.001	1.15
Nitrate	0.043	0.023	-0.001 to 0.088	0.057	1.01
Turbidity	-0.024	0.047	-0.116 to 0.069	0.617	1.20
Phosphate	0.070	0.024	0.023 to 0.117	0.003	1.20
Rainfall	0.111	0.019	0.074 to 0.147	<0.001	1.09

Model statistics: $n = 1,489$; R-squared = 0.166; adjusted R-squared = 0.162. HC3 robust standard errors were used.

The water-quality system is structured by several interacting environmental gradients, as shown collectively by multivariate analyses. The overall physicochemical profile was significantly altered due to the seasonal hydroclimatic variation, multivariate environmental groups were identified for river systems, and DO was the most significant independent statistical correlate of WQI.

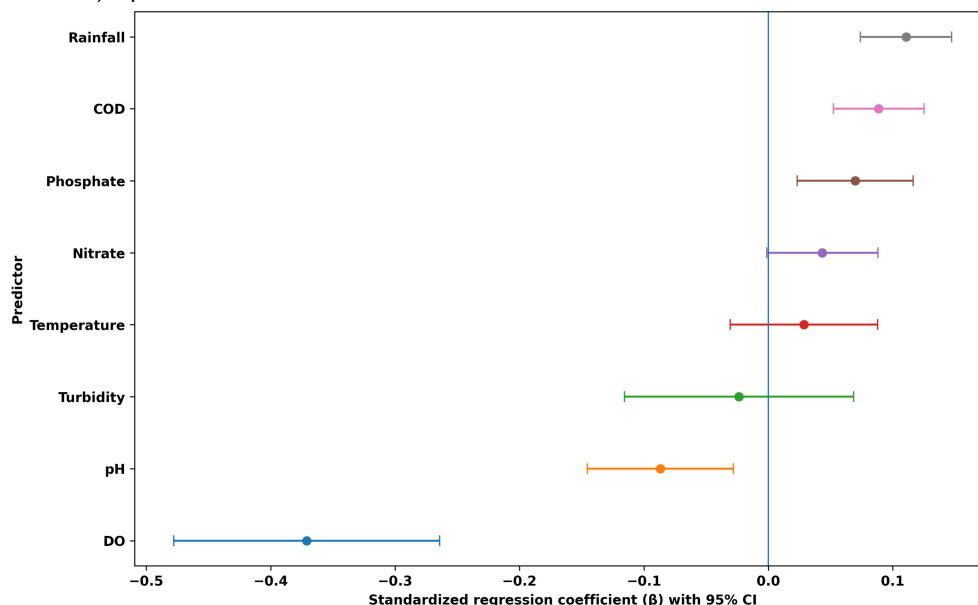


Figure 4. Standardized Independent Predictors of Water Quality Index With 95% Confidence Intervals

4. Discussion

The present study has shown that the physicochemical processes in the river-water of Dhaka are not influenced by the individual pollutants but by the interplay of different processes. The correlation analysis revealed that the pH, phosphate and dissolved oxygen had strong correlation with the WQI, whereas the temperature, rainfall, COD, nitrate and turbidity had weak but significant correlation with the WQI. The interdependence has been observed, for instance, in the lower Ganga, where the seasonal variability in hydrological parameters affects multiple environmental parameters, which in turn affect the integrated water-quality conditions (Kumar et al., 2021).

The inverse relationship between dissolved oxygen and phosphate was strong, suggesting that there was an important nutrient oxygen gradient within the water that was monitored. Elevated nutrient enrichment can encourage organic / biological processes that can result in oxygen depletion, and wastewater organic loading can serve to exacerbate oxygen stress. Multivariate analysis of the surface water in southwestern Bangladesh has also found interconnected hydrochemical characteristics and anthropogenic impacts (Shammi et al., 2023). The complex pollutant mixtures and anthropogenic pollution have also been linked to extremely hypoxic river environments, highlighting the value of oxygen conditions as an indicator of environmental disturbance (Tokatli & Islam, 2023).

PCA also confirmed that there are several environmental dimensions that structured river-water quality, as shown below. The dominant characteristics of PC1 were the levels of dissolved oxygen, temperature, turbidity, precipitation, and a negative phosphate contribution, suggesting a hydroclimatic-oxygenation gradient. The large shift of observations from both seasons along this axis shows that the changes in the season affect not just the concentration of the individual parameters but the overall environmental structure. Surface-water quality has been observed to vary significantly during the same season in the Himalayan river systems, where the runoff and hydrological changes significantly affect surface-water parameters (Kour et al., 2023). Similarly, temporal monitoring studies have demonstrated that water-quality trends are the result of both hydrological and environmental forcing (Pohrebennyk et al., 2021).

Positive PC1 scores were associated with increased rainfall, temperature, dissolved oxygen and turbidity and were found to occur during the monsoon period. Higher turbidity values in the wet season is likely to be attributed to inputs from the catchment, mobilization of sediments, and surface runoff. Research studies on sources of drinking water in rivers have shown that these seasonal variations could significantly impact the water-quality conditions and related exposure concerns (Sinha et al., 2022). Studies that have investigated the effects of land use have also revealed that land-use activities can alter the temporal water-quality variability in a catchment through their interaction with hydrological processes (Shibambu 2023).

The monitored rivers were classified into three environmental groups by hierarchical cluster analysis. However, Bangshi and Kaliganga created a separate group, which had relatively high levels of DO, nitrate, turbidity, temperature and pH, while Tongi khal and Turag were associated with higher levels of COD and rainfall influence. This shows that waterways that are associated with a geographical region are not necessarily environmentally homogeneous. Multivariate clustering has also been used to identify pollution-source clusters of river sites based on anthropogenic loading and environmental features (Allafta & Opp, 2020). Along with this, recent studies of river assessments have highlighted the significant advantage of using spatially distinct hydrochemical profiles for pollution-source apportionment (Gebisa et al., 2026).

The variance in the WQIs accounted for by the multivariable model was 16.6%, which suggested that measured physicochemical conditions did, but did not fully explain, WQI variability. The most significant single statistical correlations were for dissolved oxygen, followed by rainfall, COD, pH, and phosphate. The lack of explained variance

may be due to the influence of unmeasured factors like intensity of wastewater discharge, river flow, sediment interaction, land use, microbial contamination, and localized industrial discharges. Similarly, recent study of water quality in the rivers of Bangladesh highly stressed the role of source-specific industrial pressures in the spatiotemporal deterioration of water quality in the rivers (Hossain et al., 2026).

The WQI variability in the study period was also seasonally structured, which is similar to recent multi-variate analysis of the WQI of the Yamuna River, which found that water-quality conditions were also influenced by pollution loading, as well as by seasonality of the water (Nagar et al., 2026a). A related study also illustrated that multivariate approach can be useful for separating out the seasonal environmental dynamics that might not be discernible from single-parameter interpretation (Nagar et al., 2026b). Similar spatiotemporal variability has been reported for the Jeera River and monitoring should be conducted both within and between areas and seasons (Pati et al., 2025). Urban rivers, also heavily impacted by anthropogenic activities, also display high temporal and spatial variability, and pollution control must be managed at the watershed scale and not on a uniform basis (da Silva et al., 2026).

The results overall suggest that the sustainable management of Dhaka's rivers requires periodic monitoring (seasons) and pollution assessment specific to the river. Oxygen depletion, nutrient enrichment, organic pollution, turbidity from run-off, and specific anthropogenic inputs should be considered as priorities in this study, and are considered as possible future monitoring variables.

5. Conclusion

The results of this study showed that there is a high level of spatiotemporal heterogeneity in river water quality and pollution status in the city of Dhaka, in terms of pollution level and water quality. The results indicated that water quality patterns were not only influenced by the physicochemical factors, but also by the interaction between them and the hydroclimatic factors. The correlation analysis identified the variables pH, phosphate, dissolved oxygen (DO), rainfall, chemical oxygen demand (COD), nitrate, turbidity and temperature as significant correlated variables of WQI while the principal component analysis (PCA) showed the presence of the different gradients that were related to the hydroclimatic, oxygenation, organic-pollution and nutrient-related variables. The high seasonal differentiation was especially pronounced between the monsoon and winter seasons, supporting that hydrological variations are important in determining the characteristics of the river water. The monitored rivers were also shown to not be a uniform environmental system in the results of a hierarchical clustering, where the rivers were clustered in different groups that exhibited varying nutrient enrichment, turbidity, oxygen conditions, COD, and rainfall influence. The strongest independent statistical correlates of WQI were determined to be dissolved oxygen, rainfall, COD, pH, and phosphate through the use of multivariable regression. Overall, the findings show that there is a need for river-specific and season-specific water-quality management strategies in Dhaka. More comprehensive monitoring in the future should incorporate river discharge, land-use data, microbial data, wastewater data from industry and municipalities and sediment data to better identify sources of pollution and allow for more focused river restoration and sustainable urban water-resource management.

References

1. Allafta, H., & Opp, C. (2020). Spatio-temporal variability and pollution sources identification of the surface sediments of Shatt Al-Arab River, Southern Iraq. *Scientific Reports*, 10(1), 6979.
2. Azhari, H. E., Cherif, E. K., Sarti, O., Azzirgue, E. M., Dakak, H., Yachou, H., et al. (2022). Assessment of surface water quality using the water quality index (IWQI), multivariate statistical analysis (MSA) and geographic information system (GIS) in Oued Laou Mediterranean Watershed, Morocco. *Water*, 15(1), 130.
3. da Silva, A. L. S., Bezerra, H. N., Farias, P. K. P., da Silva, M. S. M., Costa, L. K. O., da Silva, L. V. M., et al. (2026). Water quality dynamics in urban river of the semiarid region under anthropogenic pressure: A spatiotemporal analysis in the stretch of the municipality of Mossoro (Brazil). *Environmental Monitoring and Assessment*, 198(6), 666.
4. Gebisa, L., Wachemo, A. C., Kasa, T., & Zawuga Babiso, W. (2026). Evaluations of spatio-temporal water quality variability and pollution source apportionment of Lelliso River at Upper Wabi Shebelle river Basin, Ethiopia. *Applied Water Science*, 16(1), 28.
5. Hossain, M. S., Ferdushy, T., Klanti, M. M., Bithi, U. H., Akbor, M. A., Akter, S., et al. (2026). Spatio-temporal variations of tanning industries induced river water quality in a developing country: Entropy-based water quality, pollution source tracing, and health risk appraisals. *Urban Water Journal*, 23(1), 51-76.
6. Kabir, M. H., Tusher, T. R., Hossain, M. S., Islam, M. S., Shammi, R. S., Kormoker, T., et al. (2020). Evaluation of spatio-temporal variations in water quality and suitability of an ecologically critical urban river employing water quality index and multivariate statistical approaches: A study on Shitalakhya river, Bangladesh. *Human and Ecological Risk Assessment: An International Journal*, 27(5), 1388-1415.
7. Kour, G., Tyagi, I., Dhar, S., Kumari, S., Pathania, D., & Kothari, R. (2023). Spatio-temporal evaluation of surface water quality of Tawi watershed in the Himalayan region of Jammu (J&K, UT) using algal pollution indices: A geospatial approach. *Environmental Monitoring and Assessment*, 195(12), 1402.
8. Kumar, A., Bojjagani, S., Maurya, A., & Kisku, G. C. (2022). Spatial distribution of physicochemical-bacteriological parametric quality and water quality index of Gomti River, India. *Environmental Monitoring and Assessment*, 194(3), 159.
9. Kumar, C., Ghosh, A., Yash, Debnath, M., & Bhadury, P. (2021). Seasonal dynamicity of environmental variables and water quality index in the lower stretch of the River Ganga. *Environmental Research Communications*, 3(7),

10. Marara, T., & Palamuleni, L. G. (2020). A spatiotemporal analysis of water quality characteristics in the Klip river catchment, South Africa. *Environmental Monitoring and Assessment*, 192(9), 578.
11. Nagar, V., Kumari, M., Verma, V. K., Kumari, M., & Garg, M. C. (2026a). Spatiotemporal assessment of water quality in the Yamuna River (Delhi-NCR Stretch) using water quality index and multivariate statistical analysis: A seasonal perspective.
12. Nagar, V., Kumari, M., Verma, V. K., Kumari, M., & Garg, M. C. (2026b). Spatiotemporal water quality dynamics of the Yamuna River (Delhi-NCR): A multivariate seasonal assessment. *Environmental Monitoring and Assessment*, 198(6), 608.
13. Nguyen, T. A., Nguyen, T. N., Dao, V. T., Schmalz, B., & Tran, L. L. (2024). Evaluating the spatiotemporal variation of Ba River water quality in the agricultural and urban watershed in the highland of Vietnam. *Water Environment Research*, 96(8), e11100.
14. Pandit, D., Haque, M. M., Harun-Al-Rashid, A., Sarker, B., Hossain, M. A., Schneider, P., & Kunda, M. (2023). Spatiotemporal variations in water quality of the transboundary Shari-Goyain River, Bangladesh. *Sustainability*, 15(6), 5218.
15. Pati, A., Mir, S. A., Padhiary, A., Baitharu, I., & Nayak, B. (2025). Evaluation of spatio-temporal water quality status of Jeera river, Odisha, India. *Discover Water*, 5(1), 6.
16. Pohrebennyk, V., Mitryasova, O., Salamon, I., Oleksiuk, A., & Mats, A. (2021). Temporal patterns of quality surface water changes. *Journal of Ecological Engineering*, 22(4), 283-295.
17. Raman, R. K., Bhor, M., Manna, R. K., Samanta, S., & Das, B. K. (2023). Statistical and geostatistical modelling approach for spatio-temporal assessment of river water quality: A case study from lower stretch of River Ganga. *Environment, Development and Sustainability*, 25(9), 9963-9989.
18. Shammi, R. S., Hossain, M. S., Kabir, M. H., Islam, M. S., Taj, M. T. I., Islam, M. S., et al. (2023). Hydrochemical appraisal of surface water from a subtropical urban river in southwestern Bangladesh using indices, GIS, and multivariate statistical analysis. *Environmental Science and Pollution Research*, 30(2), 3467-3489.
19. Shibambu, T. H. (2023). Assessment of potential temporal impacts of land use activities on water quality of the Luvuvhu River catchment, South Africa (Doctoral dissertation).
20. Shibambu, T. H., Kahler, D. M., Rose, K. C., Riddell, E., Oyebanjo, O. M., & Edokpayi, J. N. (2025). Comprehensive monitoring of the spatiotemporal variation of water quality and its associated human health risks in Luvuvhu river catchment, Vhembe biosphere reserve, South Africa. *Scientific Reports*, 15(1), 36319.
21. Sinha, K., Dwivedi, J., Singh, P., & Shankar Prasad Sinha, V. (2022). Spatio-temporal dynamics of water quality in river sources of drinking water in Uttarakhand with reference to human health. *Environmental Science and Pollution Research*, 29(43), 64756-64774.
22. Sinha, Parishmita; Debnath, Nirab ; Bhattacharjee, Prithwiraj (2026), "Water Quality and Hydroclimatic Dataset for Rivers and Streams of Dhaka, Bangladesh", Mendeley Data, V1, doi: 10.17632/xftpv7jvx3.1
23. Sridhar, D. (2026). Rivers under stress: A comprehensive review on pollutant sources, human and ecological impacts, analytical, statistical, and geospatial methods and restoration strategies, for evaluating river water quality in India. *Environmental Geochemistry and Health*, 48(4), 160.
24. Thanh Giao, N., Kim Anh, P., & Thi Hong Nhien, H. (2021). Spatiotemporal analysis of surface water quality in Dong Thap province, Vietnam using water quality index and statistical approaches. *Water*, 13(3), 336.
25. Tokatli, C., & Islam, A. R. M. T. (2023). Spatial-temporal distributions, probable health risks, and source identification of organic pollutants in surface waters of an extremely hypoxic river basin in Turkiye. *Environmental Monitoring and Assessment*, 195(3), 435.
26. Wang, Z. (2024). Characterizing spatiotemporal variation of trace pollutants in surface water and their driving forces.
27. Zhang, X., Yu, B., Xin, Z., Cong, M., & Zhang, C. (2025). Spatial-temporal variations of river water quality under human-induced land use changes in large river basins. *Scientific Reports*, 15(1), 36955.