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Research Article

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Posted Date: April 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-8914994/v1>

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Integrated Multivariate and Index-Based Assessment of Seasonal Water Quality and Heavy Metal Risks Surrounding a Coal Power Plant in Coastal Bangladesh

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Abstract

This study evaluates the water quality in areas surrounding a coal power plant in the Southwestern coastal region of Bangladesh, with a focus on potential risks to aquaculture suitability and drinking water security. To improve regional relevance, monsoonal hydrological variability was explicitly considered as a primary driver of water quality in this coastal deltaic environment. Multivariate analyses including the PERMANOVA, PCA and HCA was employed to identify patterns, group similarities and statistically quantify seasonal differences in water quality. Additionally, index-based analyses (CCME WQI, HPI, HEI and CF) were used to simplify the overall water status and pollution intensity for aquaculture and drinking purposes. The multivariate analysis indicated strong seasonal contrast, with the dry season showing high ionic concentrations whereas the wet monsoon was influenced by elevated turbidity, organic loads and

metal concentrations. The CCME WQI indicated that the water suitability for aquaculture declined notably during the wet season with 50% of the stations shifting from fair to marginal category mostly due to oxygen depletion and elevated heavy metal contents. Significant heavy metal contamination was found at multiple locations (e.g., S3, S6, and S8), particularly during the monsoon season, rendering them unfit for drinking water use. Furthermore, the spatial distribution patterns revealed high contamination zones near the discharge pathway. These localized effects highlight the sensitivity of coastal-marine transition zones to coal-based industrial operations and underscore the need for continuous monitoring and sustainable management in coastal areas.

Keywords: Coastal water quality assessment; Seasonal variability; Coal power plant discharge; Heavy metal contamination; Multivariate statistical analysis; CCME Water Quality Index

1. Introduction

Coastal and estuarine environments are fundamental for environmental sustainability, public health and maritime economy, especially in areas where aquaculture and small-scale fisheries dominate livelihoods. However, the exponential growth of the human population and anthropogenic activities impose growing strain on these environment, leading to increased pollution in rivers, lakes, oceans (Zaidi Farouk et al., 2023). Coal-fired power plants (CFPPs) are critical sources of environmental pollution (Mahlangeni et al., 2024), yet many developing and industrialized countries use CFPPs for base-load power generation due to their low operation and maintenance cost (Smith, 2018). CFPPs, acknowledged as global contributors to aquatic contamination, release heavy metals, fly ash and other combustion-related pollutants, resulting in serious ecological concerns worldwide (Chen et al., 2024; Ma et al., 2025; Park et al., 2023). In Bangladesh, coastal people and floodplain dwellers are particularly at risk due to their dependence

on open surface water like rivers, ponds, and other water bodies for domestic, drinking, and agricultural purposes (Khan & Paul, 2023; Tania et al., 2021).

The dispute between energy expansion and environmental safety in Bangladesh is particularly acute in the coastal regions. CFPPs remain a dominant source of power generation in the country considering their low upkeep cost (S. M. T. Rahman et al., 2024). The Rampal Coal Power Plant, located in the southwestern region of Bangladesh, lies in a coastal and ecologically fragile zone (Bedi, 2018). Following the establishment of the power plant in Rampal, satellite-based monitoring data confirm a sharp decline in the shrimp-farming area (Karim et al., 2019), indicating a possible link between industrial emission and the reduction in aquaculture productivity. The power plant's close proximity to the Sundarbans, a UNESCO World Heritage Site, highlights the need for urgent environmental management and water conservation initiatives to protect coastal ecosystems, reduce pollution and foster local economy (A. Ghosh et al., 2025; Mahmud et al., 2020). Thus, sustained monitoring, particularly approaches that consider monsoonal hydrology and seasonal fluctuations are essential to maintain balance between energy security and environmental safety.

Elevated levels of toxic metals, including manganese (Mn), iron (Fe), zinc (Zn) and lead (Pb), have been found in rivers, sediments and drinking water sources in Bangladesh, indicating both anthropogenic and geogenic influence (Islam et al., 2022). Multivariate statistical tools such as the principal component analysis (PCA) and cluster analysis have been effectively implemented in these cases to determine pollution sources in the Pasur River system (Islam et al., 2022). A case study from the Kutubdia Channel near the Matarbari coal power plant revealed seasonal shifts in metal concentrations in water and sediment, suggesting the strong influence of hydrological cycles on pollution dynamics (Md. S. Hossain et al., 2021). The study used pollution indices and

multivariate clustering to evaluate ecological risk and pollution sources. However, despite the recognized susceptibility of coastal regions, there is a lack of research that integrates seasonal monitoring, multivariate source allocation and comprehensive risk assessment (aquaculture, human health) in the tropical deltaic environments influenced by CFPPs.

This study aims to address these gaps by evaluating the seasonal variation of physicochemical and toxic metal parameters in the adjacent Pasur River and other water bodies surrounding the Rampal coal power plant using multivariate analyses. The Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) was applied to assess the aquaculture suitability in nearby areas, while the Heavy Metal Pollution Index (HPI), Heavy Metal Evaluation Index (HEI), and Contamination Factor (CF) were used to quantify drinking water safety under their respective guidelines from the World Health Organization (WHO). The insights presented in this study can inform coastal water quality governance, encourage adaptive aquaculture practices and aid policymakers to develop context-sensitive, evidence-based measures in Bangladesh as well as other low-lying industrial regions.

2. Materials and Methods

2.1 Study Area

Rampal Coal Power Plant (22° 35' 44" N, 89° 33' 14.5" E), also known as the Maitree Super Thermal Power Project, is located in Rampal Upazila of Bagerhat District, in the southwestern region of Bangladesh (Fig. 1). It is situated along approximately 2.45 kilometers of the Pasur River bank and is the largest coal power plant in Bangladesh in terms of geographic expanse, at 1834 acres. Rampal Upazila in Bagerhat is a vital shrimp farming area that plays an essential role in Bangladesh's economy. The site is located in the lower Ganges-Brahmaputra-Meghna (GBM) deltaic which is a tidally-influenced estuarian landscape with high sediment

dynamics and pronounced seasonal hydrology. These coastal features with dynamic tide-water migration make the Rampal area particularly sensitive to industrial effluents and changes in freshwater discharge (M. K. Ghosh et al., 2018; Manna et al., 2010; Raff et al., 2023).

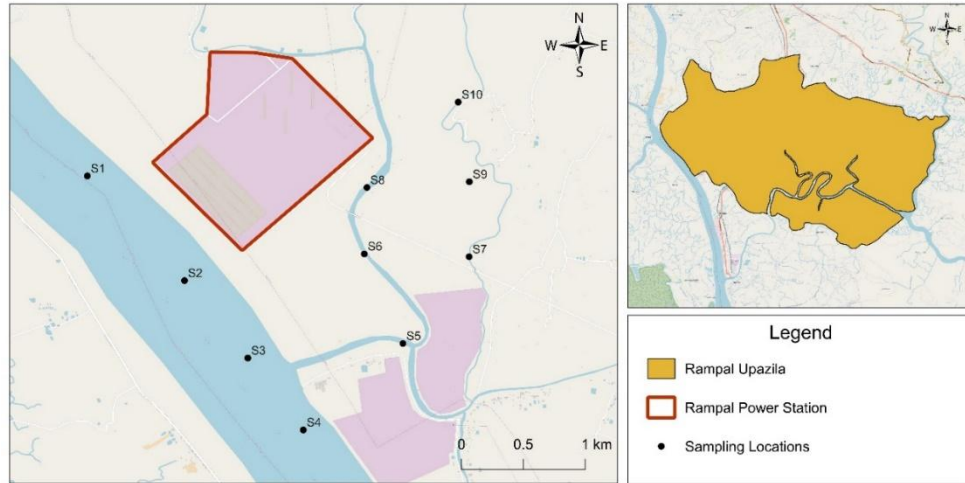


Fig. 1 Location map of the study area, showing the administrative boundaries of Rampal Upazila and the Rampal Coal Power Plant, along with the sampling stations

2.2 Sampling Procedure and Analytical Methods

Corresponding average rainfall data (1981–2020) in Bangladesh show that July recorded the highest rainfall (520.59 mm) during the year, accounting for 21.7% of the annual total. On the other hand, January accounted for 0.3% (7.8 mm) of the total annual rainfall, which was the lowest (Monir et al., 2023). Therefore, July is considered the wettest month of the year, and January is the driest in the country's precipitation pattern. Water samples were collected during January (dry winter) and July (wet monsoon), from fixed sampling stations determined using GPS coordinates. Ten samples were collected in both seasons, resulting in a total of twenty water samples from the study location. The grab sampling method was used following the standard protocols described in the Standard Methods for the Examination of Water and Wastewater (Bridgewater et al., 2017). Samples were collected in 500 ml high-density polyethylene (HDPE) bottles pre-cleaned with 10%

(v/v) HNO₃ and rinsed with deionized water. The bottles were triple rinsed with site water during collection and submerged approximately 20 cm below the surface to avoid surface film interference. pH, dissolved oxygen (DO), and electric conductivity (EC) were measured in situ using calibrated handheld meters. Calibration of the probe was done before the field test according to the manufacturer's specifications. To minimize contamination during handling and transport, field blanks and trip blanks were included as part of the quality control protocol. The sampling bottles were kept in an ice-box to maintain a temperature of around 4°C and transported to the laboratory as soon as possible to perform the remaining tests. Table 1 shows the selected parameters and the methods used for analysis.

Table 1 Summary of selected physicochemical parameters and heavy metals, and their analytical methods

Parameters	Abbreviation	Units	Methods
pH	–	–	Electrometric method
Turbidity	–	NTU	Nephelometric method
Total dissolved solids	TDS	mg/L	Gravimetric method
Suspended solids	SS	mg/L	Gravimetric method
Electric conductivity	EC	μS/cm	Membrane conductivity method
Dissolved oxygen	DO	mg/L	Electrochemical method
Biochemical oxygen demand	BOD	mg/L	5-day BOD test
Chemical oxygen demand	COD	mg/L	Closed reflux colorimetric method
Lead	Pb	μg/L	Atomic Absorption Spectrophotometer
Cadmium	Cd	μg/L	Atomic Absorption Spectrophotometer
Total Chromium	Total Cr	μg/L	Atomic Absorption Spectrophotometer
Arsenic	As	μg/L	Atomic Absorption Spectrophotometer

2.3 Statistical Analysis

2.3.1 Bootstrapping

To evaluate the reliability of the statistical estimates of the water quality data, a non-parametric bootstrapping technique was employed using R (v.4.4.3) with the boot package. Given the small sample size ($n = 10$ per season), bootstrapping was chosen to develop dependable estimates of variability and confidence intervals (Kostanek et al., 2024). For every parameter, the median and the interquartile range (IQR) were determined. For a stable confidence interval (CI), 5000 bootstrap resamples were performed for each parameter in both seasons, which allowed for formally testing the reliability of median and IQR values despite a small sample size, providing a statistically valid basis for subsequent analysis. Bias-corrected and accelerated (BCa) with 95% CI level were calculated, correcting both bias and skewness in the bootstrap distribution.

2.4 Multivariate Analyses

2.4.1 Permutational Multivariate Analysis of Variance (PERMANOVA)

PERMANOVA was performed to evaluate the seasonal variation in water quality profiles. The data set contained 10 samples and 12 physicochemical and heavy metal parameters from each season. To eliminate the impact of different measurement units, all variables were standardized using the z-score transformation, prior to analyses. Euclidean distance matrix was computed to represent dissimilarities among samples. The analysis divides the total sum of squares of the distance matrix by the groups factor (season) and tests for differences among groups by permutation-based tests. The pseudo-F statistic in PERMANOVA is calculated as follows.

$$F = \frac{SS_A / (n_A - 1)}{SS_W / (n_T - n_A)} \quad (1)$$

Where SS_A is the among-group sum of squares, SS_W is the within-group sum of squares, n_A is the number of groups (seasons), and n_T is the total number of samples. Statistical significance

was tested using 999 data permutations under the null hypothesis of no group difference. The analysis was conducted using the `adonis2` function of the `vegan` package for R (v.4.4.3). PERMANOVA replaced the traditional MANOVA because it does not involve multivariate normality, thus may be utilized for small-sample data.

2.4.2 Principal Component Analysis (PCA)

In order to explore patterns in the multivariate water quality data set and to identify the major parameters influencing seasonal variability, principal component analysis (PCA) was applied. The data comprised 12 quantitative variables analyzed in 20 samples covering dry and wet seasons. PCA transforms a set of correlated variables into a smaller number of uncorrelated principal components, defined as linear combinations.

$$Z_j = a_{1j}x_1 + a_{2j}x_2 + \cdots + a_{pj}x_p \quad (2)$$

Where, a_{ij} are the eigenvector coefficients from the correlation matrix of standardized variables. The corresponding eigenvalue (λ_j) indicates the amount of total variance explained by each principal component (PC). The total variance explained by the j -th component is calculated as:

$$\text{Variance } (Z_j) = \frac{\lambda_j}{\sum_{k=1}^p \lambda_k} \times 100\% \quad (3)$$

The first few components with eigenvalues greater than 1 (Kaiser's criterion) were retained for interpretation. Loadings of variables on these components were examined to determine which parameters had the most influence on seasonal differentiation.

2.4.3 Hierarchical Cluster Analysis (HCA)

In this study, Hierarchical Cluster Analysis (HCA) was used to determine water groupings and similarities of physicochemical characteristics of water samples. The dissimilarity measure used in the paper was the Euclidean distance, computed as follows.

$$d_{ij} = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2} \quad (4)$$

where d_{ij} is the distance between sample i and j , and x_{ik} and x_{jk} are the standardized values of the k -th parameter. We subsequently employed the agglomerative hierarchical clustering algorithm using Ward's minimum variance method (Ward.D2), which at every step minimizes the total within-cluster variance. Statistical analyses and visualizations were performed in R (v.4.3.0) using the stats, pheatmap, and readxl packages.

2.5 Water Quality and Pollution Indices

To provide a general water quality assessment for aquaculture, the CCME WQI was adopted. Additionally, to evaluate heavy metal contamination in drinking water, three indices were computed: HPI, HEI, and CF.

2.5.1 Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI)

The CCME WQI was used to assess the appropriateness of surface water for aquaculture and shellfish culture, following the guidelines from Bangladesh Environmental Conservation Rules (ECR) 2023. Three components are integrated to define the approach: scope (F_1): number of parameters exceeding the water quality guidelines; frequency (F_2): number of times guideline values are not met; and amplitude (F_3): the degree by which guideline values are not met. Combining these three factors, the CCME WQI is calculated as:

$$CCME - WQI = 100 - \left[\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732} \right] \quad (5)$$

The approach combines specific indicators into a single score on a scale of 0 – 100 for easy interpretation of the result, as shown in Table 2.

Table 2 Categorization of CCME-WQI values

CCME-WQI Value	Categories
95 – 100	Excellent
80 – 94	Good
65 – 79	Fair
45 – 64	Marginal
0 – 44	Poor

2.5.2 Heavy Metal Pollution Index (HPI)

The HPI provides a comprehensive overview of the collective influence of multiple heavy metals on overall water quality (Mohan et al., 1996; Prasad & Bose, 2001). It summarizes the concentration of selected metals into a single dimensionless value representing the pollution burden relative to specified water quality criteria. HPI in the current study was computed taking the World Health Organization (WHO, 2022) guidelines for drinking water as reference permissible limits to evaluate the suitability of surface water for human consumption, and is calculated following the weighted arithmetic mean approach as:

$$HPI = \frac{\sum_{i=1}^n W_i Q_i}{\sum_{i=1}^n W_i} \quad (6)$$

Q_i is calculated as:

$$Q_i = \frac{M_i - I_i}{S_i - I_i} \times 100 \quad (7)$$

Where M_i is the measured concentration of the i -th metal, I_i is the ideal value (set to zero for toxic metals), and S_i is the corresponding permissible value according to WHO guidelines. The unit weight W_i represents the relative importance of each metal in water quality assessment and is inversely proportional to the permissible standard.

$$W_i = \frac{K}{S_i} \quad (8)$$

Where K is a proportionality constant validating that the sum of all weights equals unity. HPI effectively integrates both concentration magnitude and toxicological importance, and thereby is a superior indicator than the straightforward arithmetic mean in expressing health-based risk potential. The calculated HPI values were compared to generally accepted classification criteria, where $HPI < 100$ represents low pollution, and $HPI \geq 100$ represents high pollution or health concern (Prasad & Bose, 2001).

2.5.3 Heavy Metal Evaluation Index (HEI)

Heavy Metal Evaluation Index (HEI) provides an overall estimate of the water quality, as such on the basis of heavy metal contamination (Edet & Offiong, 2002). It estimates the cumulative concentration of various metals in terms of their respective guideline values so that the level of contamination can be interpreted with ease. The HEI was calculated using the following expression.

$$HEI = \sum_{i=1}^n \frac{C_i}{H_i} \quad (9)$$

Here, C_i indicates the measured concentration and H_i denotes the World Health Organization (WHO, 2022) permissible concentration of the i -th metal. $HEI < 10$ indicates low

contamination, $10 \leq \text{HEI} \leq 20$ is moderate contamination, and $\text{HEI} > 20$ is high contamination (Edet & Offiong, 2002). HEI is particularly ideal for surface water analysis as it provides a rapid, dimensionless estimation of the overall heavy metal presence in a single index (Proshad et al., 2025) without the need for weighting factors.

2.5.4 Contamination Factor (CF)

To determine the degree of contamination of individual heavy metals in water samples, the contamination factor (CF) was computed. CF is a simple yet useful index that compares observed concentration with a reference background level (Hakanson, 1980). The following expression was used to estimate the CF of each heavy metal.

$$\text{CF}_i = \frac{C_i}{B_i} \quad (10)$$

Here, C_i is the measured concentration of the i -th metal, and B_i is the corresponding permissible limit (WHO, 2022) used as the reference baseline. $\text{CF} < 1$ signifies low contamination, $1 \leq \text{CF} < 3$ signifies moderate contamination, $3 \leq \text{CF} < 6$ signifies important contamination, and $\text{CF} \geq 6$ signifies very high contamination (Hakanson, 1980). The measure is most useful when used to identify metals that are influencing collective deterioration in water quality and complements other indexes such as HPI and HEI.

3. Results and Discussions

3.1 Bootstrapped Analysis of Seasonal Dynamics

Due to the small sample size and potential non-normality, the median and IQR of parameters from both seasons were obtained from bootstrapping with 5000 resamples (Table 3). Seasonal fluctuations were evident across multiple parameters. Median suspended solids and turbidity were considerably higher during the wet season at 54.5 NTU (95% CI: 50.5–58) and 69

mg/L (95% CI: 63–73), compared to the dry season at 41.5 NTU (95% CI: 37–43) and 53.5 mg/L (95% CI: 46–54.5). The broader IQRs in the wet season also indicate greater hydrological variability due to surface runoff and soil erosion during monsoon rains (Ciupa & Suligowski, 2020; Imad et al., 2023). Alternatively, EC and TDS decreased from 1970 $\mu\text{S}/\text{cm}$ (95% CI: 1767.5–2245) and 872.5 mg/L (95% CI: 842.5–910) during the dry season to 1467.5 $\mu\text{S}/\text{cm}$ (95% CI: 1312.5–1695) and 725 mg/L (95% CI: 685–755) in the wet season, indicating dilution effects due to increased flow and decreased solute concentration (Haq et al., 2024). pH turned slightly acidic during the rainy season from 7.1 (95% CI: 6.8–7.1) to 6.9 (95% CI: 6.7–6.9), while maintaining favorable conditions for aquatic health.

Dissolved oxygen (DO) declined in the wet season from 6.95 mg/L (95% CI: 6.6–7.5) to 5.75 mg/L (95% CI: 4.75–6.35), mostly due to reduced reaeration under higher turbidity and more organic breakdown during monsoon inflows. BOD and COD increased significantly during the rainy season (BOD: 19.3 mg/L, COD: 26.3 mg/L) compared to the winter season (BOD: 5.45 mg/L, COD: 7.7 mg/L), showing more organic loading and microbial growth due to surface runoff. The trace metal concentrations in surface water also showed seasonal differences. Pb, Cr, and As displayed greater wet-season medians (26 $\mu\text{g}/\text{L}$, 41.5 $\mu\text{g}/\text{L}$, and 27 $\mu\text{g}/\text{L}$) compared to the dry season (25 $\mu\text{g}/\text{L}$, 27 $\mu\text{g}/\text{L}$, and 20.5 $\mu\text{g}/\text{L}$), suggesting mobilization by runoff of industrial particulates, leaching of heavy metals from nearby sources, and soil-attached contaminants (M. N. Hossain et al., 2021; Rahi et al., 2024). Conversely, Cd was observed to be slightly lower in the rainy season (dry: 4 $\mu\text{g}/\text{L}$ to wet: 3 $\mu\text{g}/\text{L}$), probably due to adsorption onto suspended sediments under high-flow conditions.

The bootstrapped analysis reveals that hydrological seasonality has a major impact on water quality patterns around the coal power plant. The monsoonal fluxes accelerate organic and

particle transport, leading to pollution dispersion and ecological strains. On the other hand, the dry season promotes ionic enrichment through evaporation and lower dilution. This profound seasonal duality highlights the importance and season-specific monitoring and adaptive management strategies, particularly introducing run-off control and effluent control measures during peak monsoon periods.

Table 3 Bootstrapped median (95% CI: IQR) values of water quality parameters during dry and wet seasons

Parameter	Unit	Dry Season Median (95% CI)	Wet Season Median (95% CI)	Dry Season IQR (95% CI)	Wet Season IQR (95% CI)
pH	–	7.1 (6.8–7.1)	6.9 (6.7–6.9)	0.325 (0.075–0.8)	0.225 (0–0.45)
Turbidity	NTU	41.5 (37–43)	54.5 (50.5–58)	3.5(1–9.5)	6 (2.25–11.75)
TDS	mg/L	872.5 (842.5–910)	725 (685–755)	61.25(26.25–98.75)	62.5 (32.5–83.75)
SS	mg/L	53.5 (46–54.5)	69 (63–73)	5.5 (0.75–9.5)	7.25 (2.25–14)
EC	μS/cm	1970 (1767.5–2245)	1467.5 (1312.5–1695)	423.75 (235–600)	326.25 (168.75–441.23)
DO	mg/L	6.95 (6.6–7.5)	5.75 (4.75–6.35)	0.675 (0.2–1.225)	1.425 (0.8–1.875)
BOD	mg/L	5.45 (4.85–6.05)	19.3 (17.9–20.5)	1.175 (0.6–1.575)	2.725 (1–5.8)
COD	mg/L	7.7 (6.9–9)	26.3 (24.35–27.3)	1.6 (0.5–2.725)	2.7 (0.925–6.525)
Pb	μg/L	25 (8–31)	26 (12–45)	21.5 (11–34.75)	28.5 (14–41.75)
Cd	μg/L	4 (2–4)	3 (2–3)	2.5 (0–4.74)	1.75 (0–6.25)
Cr	μg/L	27 (15–35)	41.5 (24.5–59)	15.5 (4.5–39.5)	0.225 (0–0.45)
As	μg/L	20.5 (12.5–26)	27 (13–35)	11.25 (4–26.5)	6 (2.25–11.75)

3.2 Multivariate Differentiations of Water Quality Profiles

3.2.1 Seasonal Variability Assessment Using PERMANOVA

A permutational multivariate analysis of variance (PERMANOVA) based on the Euclidean distance revealed that 47.8% of the total water quality variance could be explained by seasonal variation (Table 4). The high explanatory power indicates the significance of hydrological seasonality in the multivariate pattern of the observed physicochemical and heavy metal parameters. The remaining 52.2% variation may be caused by localized anthropogenic emissions, spatial source heterogeneity, and natural site-specific processes.

Table 4 PERMANOVA summary of seasonal variation in multivariate water quality profiles

	Df	Sum of Squares	R²	F	Pr (>F)
Model	1	109.023693	0.47817409	16.4942629	0.001
Residual	18	118.976307	0.52182591	-	-
Total	19	228	1	-	-

The noted seasonal demarcation implies that hydrological alteration induced by monsoons has a major impact on altering aquatic conditions around the coal-fired power plant. Wet season high flow will thereby evidently increase surface run-off, resuspension, and transport of particle-bound contaminants, while dilution can also occur to reduce ionic as well as oxygen-related concentrations (Cui et al., 2022; Lee et al., 2020). Multivariate distinction by PERMANOVA therefore provides firm statistical justification for subsequent ordination (PCA) and clustering (HCA) analysis to elucidate additional parameters distinguishing seasonal water quality divergence.

3.2.2 Identification of Seasonal Drivers Using PCA

Principal Component Analysis (PCA) was applied to the standardized data of the dry and wet seasons to identify the key gradients governing water quality variation. PC1, PC2, and PC3 accounted for 50.1%, 31.7%, and 8.3% of the total variance, respectively, cumulatively representing 90.1% of the overall variability of the data set. The scree plot (Fig. 2) showed a clear inflection after the third component. However, the first two principal components (PC1 and PC2) accounted for the main variability structure (81.8%).

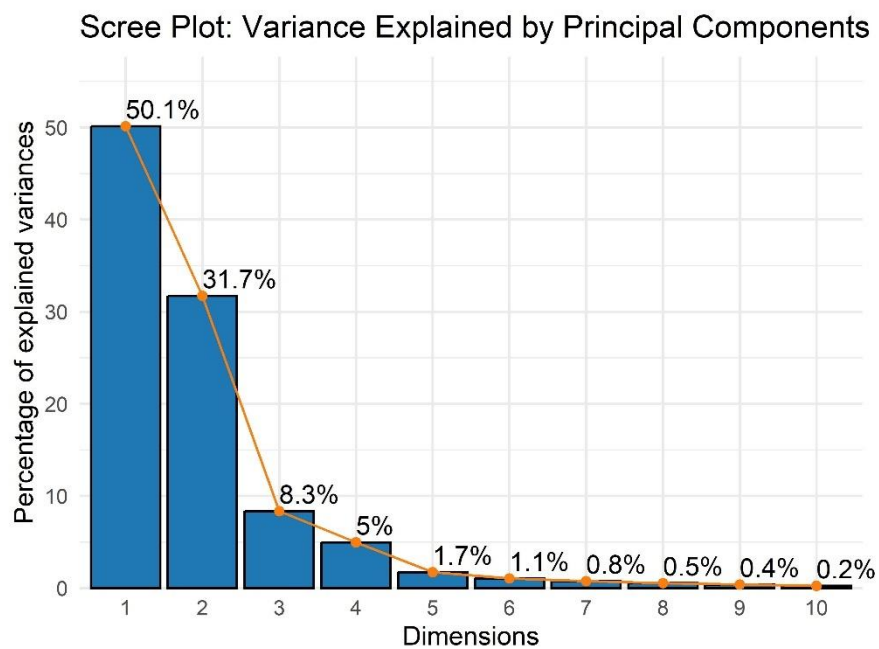


Fig. 2 Scree plot showing variance explained by PCs for dry and wet season datasets.

The PCA biplot (Fig. 3) displayed a distinct split of dry and wet season samples along PC1, showing sharp seasonal differences. Wet season samples positively clustered along PC1 and were mostly associated with higher loadings of BOD, COD, turbidity, SS, and heavy metals (Pb, Cr, As), indicating the influence of monsoonal runoff, greater particulate resuspension, and higher organic matter decomposition. On the other hand, dry season samples clustered negatively on PC1

and were correlated strongly with EC, TDS, DO, and pH, reflecting concentrated ionic composition, reduced dilution, and better oxygenation under low-flow conditions.

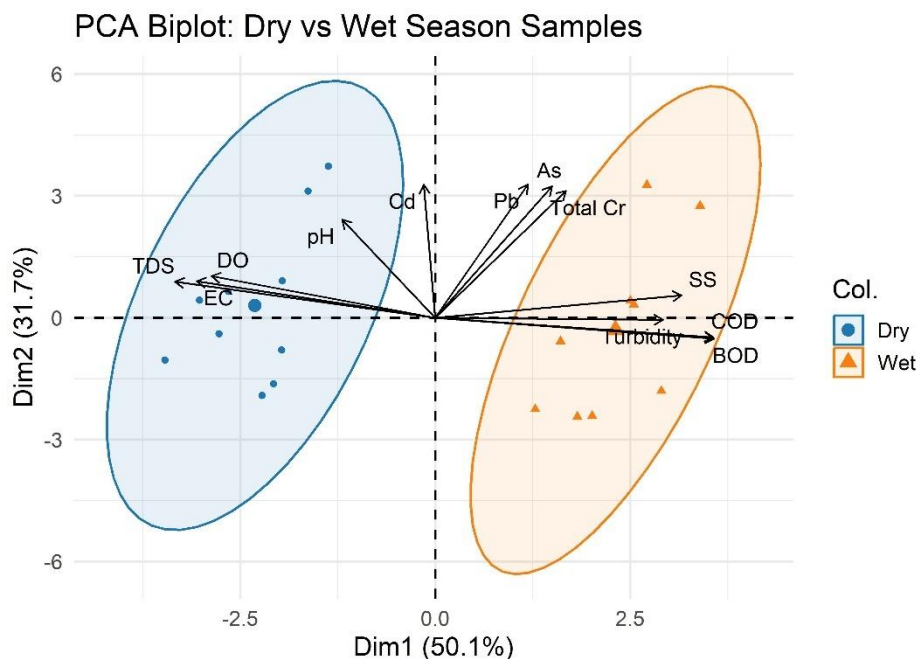


Fig. 3 PCA biplot showing parameter loadings and sample groupings for dry and wet seasons

PC2, which accounted for 31.7% of variance, was strongly governed by Cd and pH and represents site-specific enrichment most likely linked to localized sediment resuspension or industrial effluent. Overall, the results from PCA confirm the PERMANOVA outcomes, with a pronounced seasonal difference in water quality dynamics associated with hydrological fluctuation and pollutant inputs which underscore the necessity of season-adaptive management techniques.

3.2.3 HCA-Based Grouping of Sampling Stations

Hierarchical cluster analysis (HCA) under Ward's method and Euclidean distance using standardized data identified two primary clusters as depicted in Fig. 4. The first major cluster, approximately at linkage distance 4.8, consisted mostly of dry season samples (S1–S5, S7, S9, S10), reflecting relatively uniform hydrochemical conditions under the low flow period. The

second dominant cluster, at linkage distance 11, was composed mostly of wet season samples reflecting a marked deviation in water quality parameters under monsoonal hydrology.

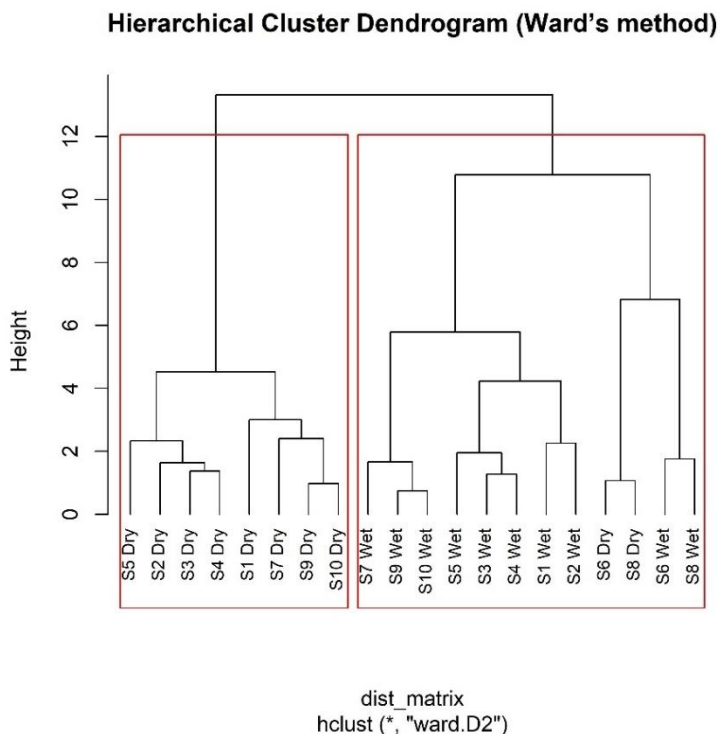


Fig. 4 Hierarchical dendrogram showing clustering of sampling sites based on multivariate water profiles.

Within the second major cluster, a sub-clustering of stations S6 and S8 was formed at a linkage distance of about 7, possibly reflecting site-specific anthropogenic or hydrodynamic impacts. The consistent grouping of stations throughout seasons indicates spatial coherence of hydrochemical signatures, likely indicative of catchment-scale processes and land use regimes (Shrestha & Kazama, 2007; Varol et al., 2012). In general, the HCA results reinforce the seasonal hydrochemical differentiation evident in PCA and PERMANOVA and validate the categorization of the sampling sites into clear seasonal water quality domains. From a management viewpoint, this indicates that season-blind remedial measures (e.g., year-round treatment or buffer areas) may be required for certain areas with close proximity to a pollution source.

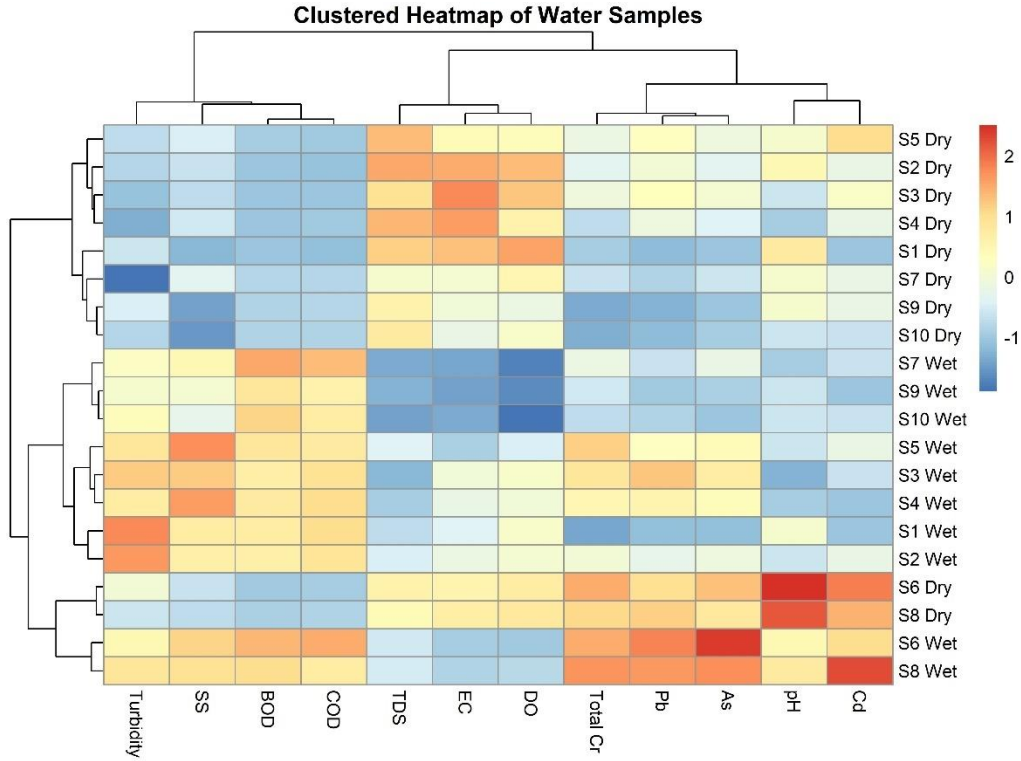


Fig. 5 Clustered heatmap showing spatial and seasonal variation

The clustered heatmap (Fig. 5) also captures the similar grouping patterns in the dendrogram. Parameters such as BOD, COD, SS, and turbidity grouped consistently with high levels in the majority of wet-season samples, indicating the effect of elevated runoff and organic loading during monsoon flow. On the other hand, during the dry season, EC, TDS, and DO more strongly grouped, indicating increased ionic concentrations and oxygen retention under decreased flow and dilution. Notably, S6 and S7 (dry) showed parameter signatures similar to those of wet-season samples, especially higher As, Cd, and Pb. This dual parameter and sample clustering within the heatmap indicates that both seasonal hydrological variation and site-specific pollution stressors organize the whole water quality framework—an observation consistent with other river system multivariate examinations (Wijayaweera et al., 2024).

3.3 Aquaculture Suitability Assessment using CCME WQI

Rampal Upazila is well known for shrimp farming and, thus, for the calculation of CCME Water Quality Index, the guidelines for aquaculture and shellfish culture were used as the standard reference. Eleven parameters were chosen for the assessment of water quality, suitable for shrimp farming, and are shown in Table 5.

Table 5 Parameters for aquaculture water suitability assessment using CCME WQI, along with standards

Parameter	Unit	Coastal Surface Water Standard for Aquaculture and Shellfish Culture (ECR 2023)
pH	-	6.5-8.5
Turbidity	NTU	≤ 10
TDS	mg/L	1000
SS	mg/L	50
DO	mg/L	≥ 5
BOD	mg/L	≤ 6
COD	mg/L	≤ 50
Pb	$\mu\text{g/L}$	≤ 50
Cd	$\mu\text{g/L}$	≤ 5
Total Cr	$\mu\text{g/L}$	≤ 50
As	$\mu\text{g/L}$	≤ 3

Aquaculture water suitability clearly varies with the seasons, according to the CCME WQI scores of the sampling stations. During the dry season, the WQI values ranged from 48.42 to 76.26, with a mean of roughly 63, indicating conditions from Marginal to Fair quality (Fig. 6a). On the other hand, index value range decreased to 34.08–59.19 during the wet season, with an average of roughly 50, indicating a drop to Poor category (Fig. 6b). This reduction in the wet season is a reflection of increased organic pollution, leaching of heavy metals and dilution of critical

parameters such as dissolved oxygen, which reduce aquaculture suitability. Previous studies across diverse aquatic systems have consistently reported lower CCME WQI values during wet or high-flow periods compared to dry seasons, reflecting seasonal water quality deterioration associated with increased turbidity, runoff-driven contaminant transport, and reduced dissolved oxygen levels (Maansi et al., 2022; Rajabova et al., 2025).

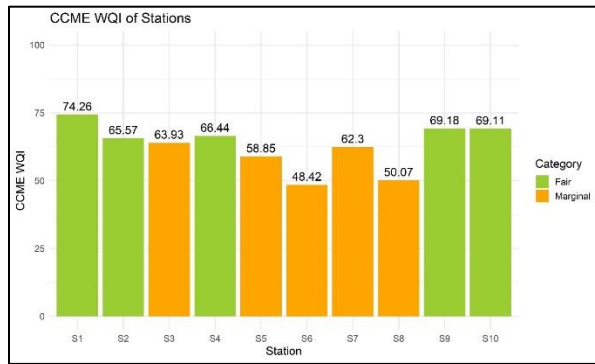


Fig. 6a Station-based CCME WQI in dry season

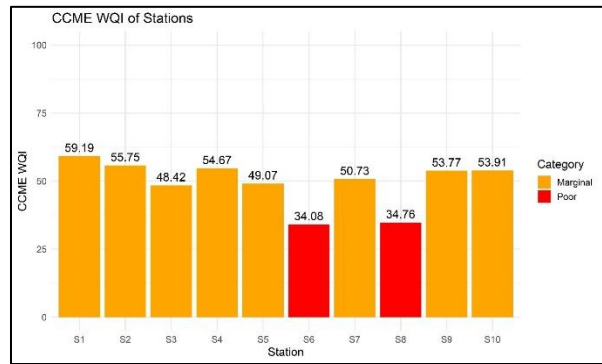


Fig. 6b Station-based CCME WQI in wet season

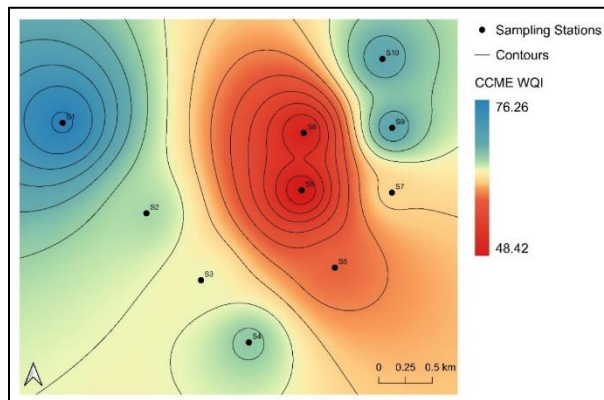


Fig. 7a Aquaculture suitability map with pollution-risk areas (dry season)

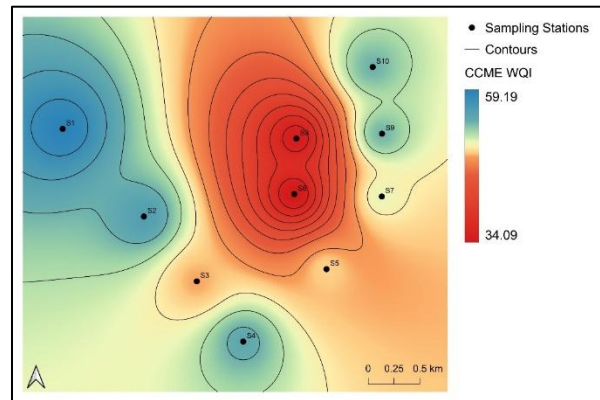


Fig. 7b Aquaculture suitability map with pollution-risk areas (wet season)

The spatial interpolation of the CCME WQI using the Inverse Distance Weighted (IDW) approach revealed notable variation across the study area in both seasons (Fig. 7). Poor water

quality and limited aquaculture suitability was evident by the lower WQI values, found close to the central zones, especially around stations S5, S6 and S8. The nearby power plants effluent and coal-ash discharge may cause such localized degradation. In contrast, Stations S9 and S10, located at the northeastern part of the study area, and S1 and S2, at the western portion, exhibited the highest WQI scores, reflecting better conditions and higher aquaculture potential. The observed spatial gradient demonstrates the significance of proximity and hydrodynamic flow for regulating the distribution of contaminants throughout the aquatic system by highlighting a dilution and dispersal effect with increasing distance from the source.

3.4 Assessment of Heavy Metal Risks and Contamination Hotspots

The spatial and seasonal trends of heavy metal risk were analyzed using the Heavy Metal Pollution Index (HPI), Heavy Metal Evaluation Index (HEI), and Contamination Factor (CF) using threshold values from the WHO drinking water guideline (World Health Organization, 2022) as shown in Table 6. All three indices collectively provide an overall assessment of the total heavy metal burden at each sampling location.

Table 6 WHO recommended standard limits of heavy metals in drinking water

Parameters	Unit	WHO standards for drinking water
Pb	µg/L	10
Cd	µg/L	3
Cr	µg/L	50
As	µg/L	10

3.4.1 Heavy Metal Pollution Index (HPI)

All sites, except station S1, had HPI values greater than the critical pollution threshold (100), which ranged from 77.61 to 335.42 during the dry season (Fig. 8a), and from 77.03 to 384.71 during the wet season (Fig. 8b). Stations S6 and S8 produced the highest HPI values followed by Stations S3 and S5, indicating that these are clearly defined areas of high contaminant concentration. The persistence of these hotspots, even during the wet season, strongly implies that metal mobilization and runoff processes in the vicinity of the power plant are actively exacerbating contamination levels. The higher index values during the monsoon can be attributed to surface runoff remobilizing particle-bound metals from the nearby catchments. Consistent with recent studies highlighting heavy metal enrichment close to coal-based industrial zones (M. M. Rahman et al., 2020; Temesgen et al., 2024), the interpretation of the HPI confirms that several stations near the power plant pose serious risks to drinking water quality. Spatial mapping clearly indicates that regions with high HPIs are concentrated close to the power plant, gradually diminishing with increased distance (Fig. 9). This spatial gradient reflects the expected pattern of leachate dispersion and subsequent dilution, suggesting that the observed station-wise HPI variation represent the pollution plume centered around the power plants discharge area.

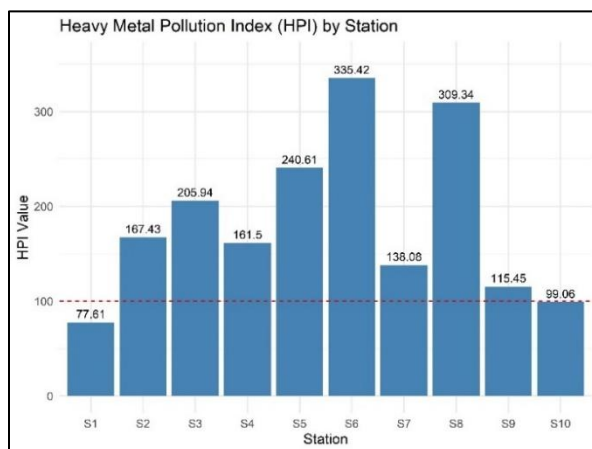


Fig. 8a HPI by station in dry season

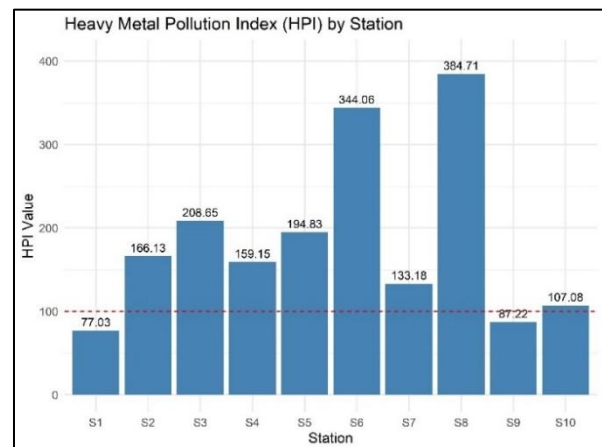


Fig. 8b HPI by station in wet season

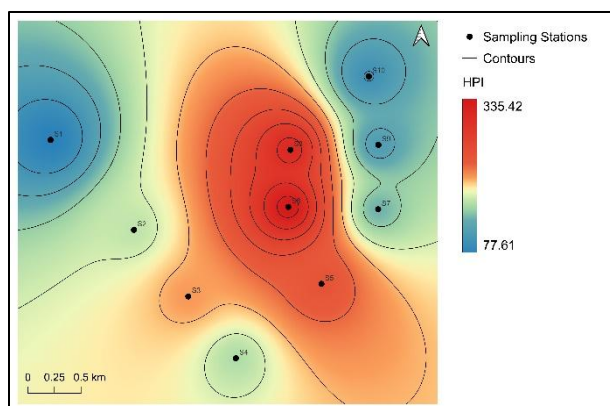


Fig. 9a HPI-based distribution of heavy metal contamination hotspots (dry season)

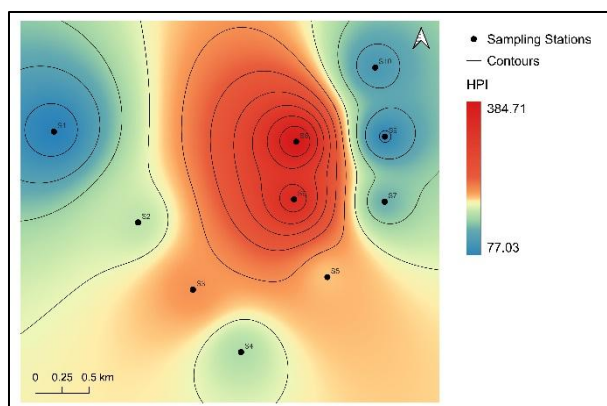


Fig. 9b HPI-based distribution of heavy metal contamination hotspots (wet season)

3.4.2 Heavy Metal Evaluation Index (HEI)

According to HEI classification, most sampling stations fell into the low pollution category in both seasons. A low to moderate degree of heavy metal contamination was also indicated by the HEI values, which varied from 2.87 to 14.63 in the wet season with Station S3, S6, and S8 exceeding low pollution category (Fig. 10a). During the dry period, HEI value ranged from 3.03 to 12.6 and 80% of the sampling stations were in the low pollution category except Station 6 and 8 (Fig. 10b). Due to possible industrial effluent and atmospheric deposition, these two stations near the power plant area had the highest contamination level, indicating localized accumulation of heavy metals. Upstream locations like S1 and S2, and stations located far from the facility, on the other hand, showed relatively lower index values, indicating a smaller pollution impact.

The spatial interpolation results as illustrated in Fig. 11 essentially reflect the HEI distribution with the highest HEI values clustered around stations like S6 and S8, tapering off toward the periphery. Stations located farther from the facility (e.g., S7, S9, and S10) exhibited minimum to negligible metal contamination in both seasons. This spatial pattern visually affirms

the gradient decay moving outward and highlights how local heavy metal accumulation significantly influences water quality, particularly in effluent discharge or leachate zones.

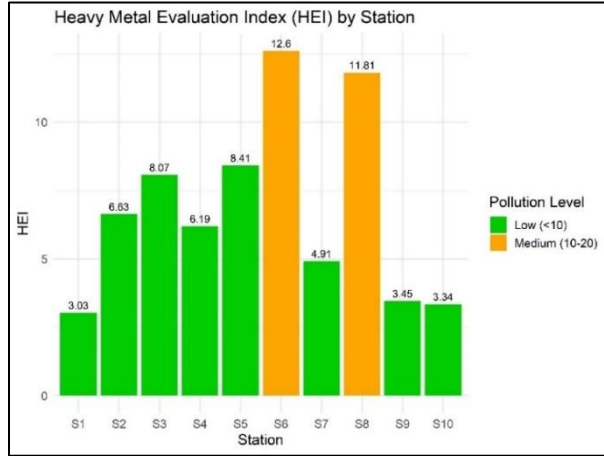


Fig. 10a HEI by station in dry season

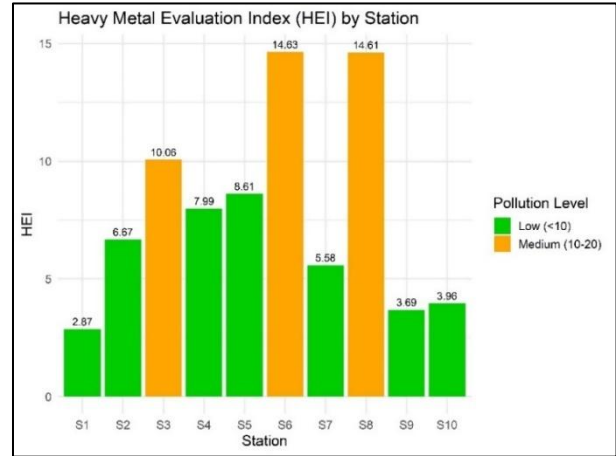


Fig. 10b HEI by station in wet season

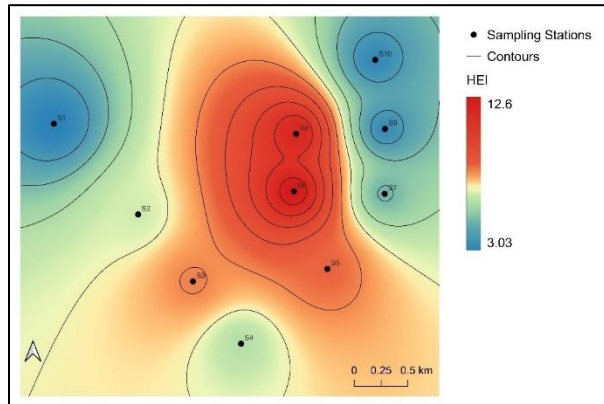


Fig. 11a HEI-based distribution of heavy metal contamination hotspots (dry season)

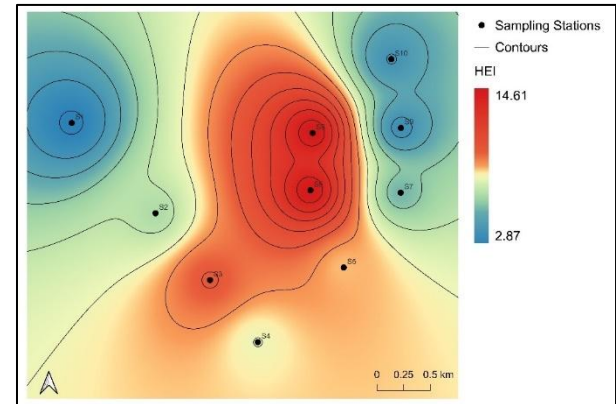


Fig. 11b HEI-based distribution of heavy metal contamination hotspots (wet season)

3.4.3 Contamination Factor (CF)

With a range of 0.72–3.15 in the dry season, 60% of the sampling stations had moderate contamination levels (Fig. 12a). On the other hand, ranging from 0.72–3.66 in the wet season (Fig. 12b), the mean CF values by station showed a steady trend (50% moderate). Station S6 consistently displays elevated CF values, reflecting ongoing heavy metal accumulation. Notably, during the

wet season, CF values at station S8 also rise sharply, nearly reaching the considerable contamination threshold. Spatial interpolation maps, presented in Fig. 13, also reveal that CF contours peak around S6 and may extend toward neighboring sites like S5 and S8, during both seasons, reflecting hydrological connectivity. This spatial pattern of CF aligns with the distribution observed in HPI and HEI maps, collectively identifying zones experiencing the highest pressure from heavy metals.

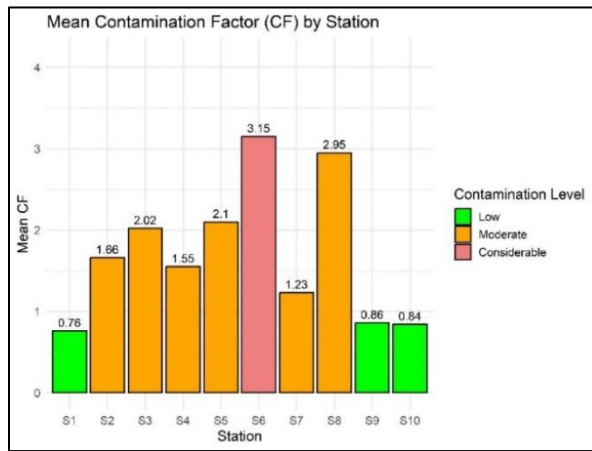


Fig. 12a Mean CF by sampling stations in dry season

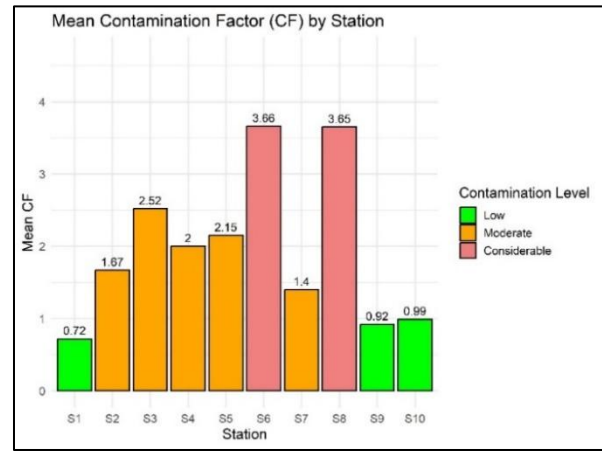


Fig. 12b Mean CF by sampling stations in wet season

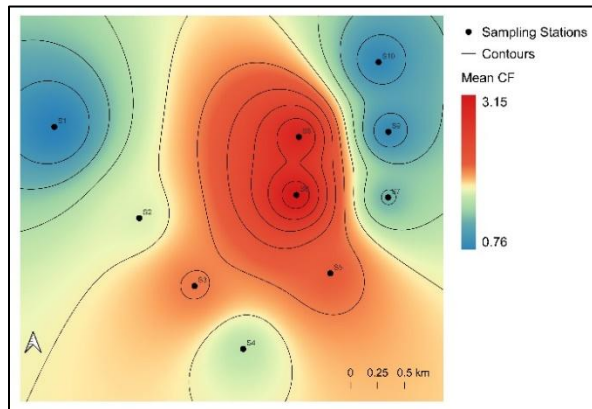


Fig. 13a CF-based distribution of heavy metal contamination hotspots (dry season)

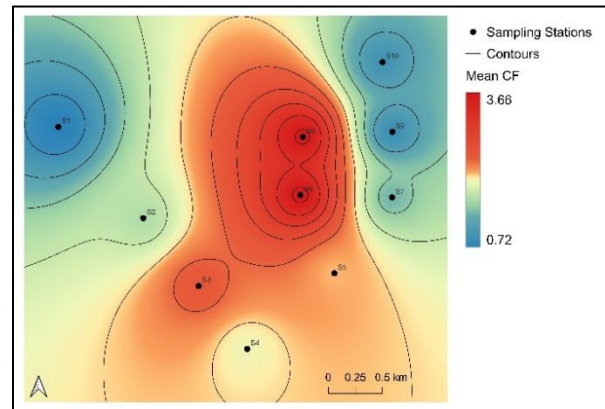


Fig. 13b CF-based distribution of heavy metal contamination hotspots (wet season)

4. Conclusion

The integrated implementation of multivariate (PERMANOVA, PCA, and HCA) and index-based (CCME WQI, HPI, HEI, and CF) analyses provided a multi-perspective view of seasonal shifts in water quality and potential risks related to human and ecological health. Bootstrapping ($R = 5000$ and $CI = 95\%$) ensured statistically dependable results despite the small sample size. Results from the multivariate analyses indicated strong seasonal differences in water quality (PERMANOVA; $p = 0.001$, $R^2 = 0.478$), where the water profile in dry winter was mostly related to high ionic concentrations, and the wet monsoon showed elevated organic loads and metal contamination in specific stations. Furthermore, PCA effectively decreased the dimensionality of the dataset, highlighting key parameters responsible for spatial and seasonal variability. The hierarchical clustering grouped samples primarily based on season, although a sub-cluster was seen to group samples ignoring seasonal separation (e.g., S6 and S8), indication localized hydrogeochemical influences and site-specific discharge effects. According to the CCME WQI, water suitability for aquaculture is relatively better during the winter but falls within the marginal to poor category during the monsoon. This depletion is mostly due to increased organic loads, reduced oxygen levels, and elevated levels of trace metals. Spatial distribution analysis revealed distinct zones for aquaculture suitability, distinguishing low risk areas from those with high contamination risk near power plant. The heavy metal indices (HPI, HEI and CF) further indicated notable contamination, posing significant health risks when used as drinking water sources. The spatial distribution maps based on the heavy metal indices clearly distinguished between highly polluted and less affected areas.

In addition to quantifying pollution patterns, the findings also highlight vulnerability of coastal deltaic systems where industrial growth meets climate-driven hydrological variability. The

study presents a transferable monitoring and assessment framework that integrates globally recognized analytical methods with specific coastal dynamics, supporting adaptive management of industrial water pollution. Given the region's financial dependency on aquaculture and shrimp farming, the framework contributes to sustaining local livelihoods while also supporting broader international commitments to Sustainable Development Goals (SDGs 6 and 14), ensuring a functional ecological service and community resilience despite growing industrial pressure.

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Statements and Declarations

Acknowledgements

The authors gratefully acknowledge the Department of Civil Engineering, Rajshahi University of Engineering and Technology (RUET), for providing laboratory facilities and technical support essential to this research.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Ethical Approval

This is not applicable

Consent to Participate

This is not applicable

Consent to Publish

This is not applicable

Competing Interests

The authors have no relevant financial or non-financial interests to disclose

Data Availability Statement

The datasets used and analyzed during this study are available from the corresponding author upon reasonable request

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