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Comprehensive Spatiotemporal Water Quality Assessment in Industrially Polluted Digaru River of Assam, India: Multivariate Statistics, Water Quality Indexing, and Human Health Risks

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Abstract:

Environmental contamination from poor industrial and sewage management causes river pollution, a major global issue. The current study, on the Digaru River in India, a tributary of the Brahmaputra River passing through the polluted Byrnihat Industrial Clusters (BIC), analyses physicochemical water quality, including heavy metals, through monthly monitoring; identifies pollution sources and correlations using multivariate statistics; employs a novel Modified Entropy-Weighted Water Quality Index (MEWQI); and assesses human health risks. Based on 144 samples collected over a year, the study highlighted strong spatiotemporal variability and limited self-replenishment; monsoon months showed significantly elevated pollutants, including turbidity (> 500 NTU, mean: 56 ± 104), BOD_5 (47 mg/L), COD (290 mg/L, mean: 111 ± 85), and NO_3^- (56 mg/L, mean: 07 ± 10). Among metals, Al (81%), Mn (69%), Fe

(97%) and Pb (20%) exceeded safe limits, while Cr, Ni, Co, Zn, and Pb were regularly detected. The MEWQI reveals 45% of water quality classes are 'Extremely Poor', with 93.75% unsuitable for consumption. PCA bi-plots and HCA show complex seasonal groupings of physicochemical parameters and stations, indicating water quality decline due to sewage and industrial effluents from BIC and nearby zones. Non-carcinogenic risk assessments highlight higher CDI, HQ, and HI in children, driven by metals like Fe, Mn, and Cr. Furthermore, Incremental Carcinogenic Lifetime Risk (ICLR) values estimated for Cr (51×10^{-6}) and Pb (95×10^{-8}) indicate potential carcinogenic hazards to the exposed population. Collectively, the study offers vital insights into spatiotemporal pollution dynamics, providing a scientific basis for targeted water quality control and remediation strategies.

Keywords: Heavy Metals, Industrial Pollution, Multivariate Statistics, Spatiotemporal Monitoring, Risk Assessment, Water Quality Indices.

Introduction:

Freshwater, one of the most crucial resources for all lifeforms on earth, for the sustenance of ecological diversity and sustainable development, is highly at stake and has become a global issue (Ustaoglu et al., 2021). Natural rivers flowing within anthropogenic establishments, such as industrial clusters, agricultural lands, municipal areas, etc., often suffer from an influx of organic and inorganic contaminants, subsequently surpassing the natural self-replenishing capabilities, causing severe human and ecological risks (Alam et al., 2022; Tian et al., 2011). River's self-purification involves physicochemical and biological processes maintaining water quality, incorporating biotic and abiotic factors. (Kotnala et al., 2016). Streeter and Phelps noted that when pollution enters a water body saturated with dissolved oxygen (DO), the DO level first decreases and then slowly increases downstream, creating a

spoon-shaped pattern curve (González et al., 2014; Omole et al., 2012). Apart from the natural factors such as velocity, depth, discharge, temperature, seasons, biodegradation, nature of sediment and suspended particles, etc., which influence the river's self-purification, the introduction of pollutants at various stages often creates complexities in the river chemistry (Wilkinson et al., 2017).

Various researchers have assessed the spatial distribution, source apportionment, and ecological risks associated with river water contamination.(Celen et al., 2022; Goswami & Kalamdhad, 2022; Han et al., 2021; Zheng et al., 2016; Zheng et al., 2020). However, owing to the high spatio-temporal dynamics of water quality, studies conducted for low-frequency monitoring may not fully capture the full range of scenarios. In tropical climates, such as those in North-East India, where precipitation patterns are highly unpredictable and exacerbated by climate change, rivers are highly dynamic. For this, a sufficiently frequent monitoring of the river ecosystem is essential for accurate pollutant source apportionment, understanding the effects of upstream contaminants, and evaluating the river's self-cleansing capacity, given its complex role in human consumption and ecological functions (Kotnala et al., 2016). This data is vital for effective mitigation strategies, although the process can be time-consuming and labour-intensive.

Water Quality Index (WQI) modelling is a method that condenses complex parameter variations into combined values. It includes four main components: selecting indicators, assigning weights, constructing sub-indices, and performing aggregate interpretation. Each component can introduce uncertainty into the overall water quality assessment due to variations in weight assignment(Alam et al., 2022; Chidiac et al., 2023; Dash & Kalamdhad, 2021; K. R. Singh et al., 2019). Notable WQIs widely used were the Canadian Council of Ministers of the Environment WQI (CCME WQI); the NSF Water Quality Index developed by the USA (NSF WQI); the Oregon Water Quality Index (OWQI), Entropy-weighted WQI

(EWQI); Modified Entropy-weighted Water Quality Index (MEWQI) and Fuzzy Water Quality Index (Chidiac et al., 2023; Dash & Kalamdhad, 2021; Marselina et al., 2022; Patel & Chitnis, 2022; Singh et al., 2019). Among others, EWQI is an improved version of WQI, where the weightage on parameters is considered based on assignments of normalised weights, which are then computed using Claude Shannon's formula (Singh et al., 2019) using each parameter's information entropy. Dash and Kalamdhad (2021) modified the EWQI and proposed the MEWQI, which addresses certain vital issues of the existing EWQI by incorporating a multi-dimensional water-quality dataset comprising the water quality parameter datasets along with sampling locations and the temporal monthly repeat sampling data. It also employs sensitivity analysis, cluster analysis and probability estimation to prove the model's reliability and is found to be dynamic and reliable (Dash & Kalamdhad, 2021).

The Brahmaputra River supports the ecology and livelihood of millions of people, especially in Northeastern India and Bangladesh. Unfortunately, Byrnihat Industrial Clusters (BIC) has emerged as the "World's Most Polluted City" according to the Swiss IQAIR (2024) report's PM_{2.5} measurements, also the highest average PM₁₀ in India as per the National Ambient Air Quality Standard (Dahiya & Sivalingam, 2024) report of 2024 (**Fig. S1**). Effluents from BIC ultimately drain into the Brahmaputra River via the Digaru River, a tributary. While air quality in the BIC has been systematically monitored, the ecological and human impacts of water pollution in the Digaru and Brahmaputra Rivers remain largely unexplored. Thus, the current study aims to provide insights into pollution loads through extensive spatiotemporal monitoring and the application of advanced statistical tools and indices, with the goal of understanding water quality and identifying potential risks to inhabitants and the downstream ecosystem. Therefore, the following objectives were addressed in the current study: (i) to understand the spatiotemporal water quality variations of the Digaru River and its pollution due to the Byrnihat Industrial Clusters; (ii) to identify key influencing pollution sources using

multivariate statistics and indices; (iii) to integrate a comprehensive WQI to address the feasibility of the water for domestic use and (iv) to estimate the human health risks for the potentially toxic metals.

2. Materials and Methods

2.1 Study area

(Insert Figure 1)

The Digaru River, also known as Umtrew, is a significant tributary of the Brahmaputra River, located between the states of Assam and Meghalaya in India (**Fig.1**). The catchment areas are undulating to the south, whose geographical coordinates range from 25°35'150" to 26°14'180"N latitude and 91°35'170" to 92°00'150"E longitude with an elevation between 1856m and 65m above msl, with a humid subtropical to tropical-humid monsoon climate and abundant rainfall ranging from 1500 to 2000 mm/year (PCBA, 2020). The perennial river is about 47 km long, rising on the western slopes of the Sohpetbneng range in the East Khasi Hills, Meghalaya. It flows through BIC to Sonapur, where it joins the Kopili River and eventually merges with the Brahmaputra. The river sustains the ecosystem, supports local livelihoods and agriculture, and supplies water to residents and industries in the BIC areas. However, the river is contaminated by point and nonpoint sources, such as industrial effluents and municipal sewage from urban BIC areas (PCBA, 2020). The environmental quality of the study area has been significantly impacted by the presence of coke industries, cement and brick industries, which utilise fly ash, raising potential threats to the residents living near these industrial zones, posing a major threat to human activities (Deka & Kumar, 2023).

2.2 Sampling strategy

A total of 144 samples were collected from 12 sampling stations (**Fig.1**), conducted monthly year-round, which were selected based on year-round feasibility and approximate

equidistance along the river, as determined from initial reconnaissance surveys and GIS mapping (Goswami, 2022). The first station, L1, serves as a control point upstream of the BIC. Subsequent stations are influenced by effluent, runoff, and sewage from BIC areas, agricultural fields, and the Sonapur market areas. The details and geocoordinates of the sampling stations are given in **(Table-S1)**. Fourteen critical physicochemical water parameters and 15 metals were analysed in water samples collected in clean, pre-washed 1 L HDPE bottles, sealed tightly, and transported to the laboratory. Additionally, for metal assessment, a separate 50 mL centrifuge tubes (PP tubes, Tarsons) were used and added with 0.01N Nitric acid on-site.

2.3 Analytical methods

Analysis was conducted within 6 hours for pH, DO, BOD₅, COD, Turbidity, Electrical Conductivity, and TDS using portable kits and laboratory titration methods, following the APHA standard protocol (APHA, 2012; Dash et al., 2018). The water samples are then stored at 4°C for analysis of other parameters, such as F⁻, Cl⁻, NO₃⁻, SO₄²⁻, PO₄³⁻, total alkalinity, and hardness, within 48 hours. For metals, the acidified samples were then filtered using a 0.45µm syringe filter and analysed by ICP-MS (Make: Agilent, Model: 7850). The full list of analytical methods and instruments used is presented in **Table-1**.

(Insert Table 1)

2.4 Quality Control and Assurance

Strict protocol was followed during conducting sampling, laboratory analysis and data interpretation (Dash & Kalamdhad, 2022). All bottles used in the sampling were pre-cleaned by dipping in 20% nitric acid (6 M), and air-drying prior to filling. Blanks of milliQ water are used before each kit-based test, and triplicate samples are considered. All reagents and chemicals used for titrimetric analysis are of analytical grade. For the analysis of anions using IC (Metrohm 792 Basic IC, Switzerland), a standard 5-point calibration curve with an r² value

>0.9 for each anion. For heavy metals analysis, procedural blanks were used at regular intervals between analyses, and a standard calibration check of r^2 value > 0.97 with an 8-point calibration for every 15 metals (**Fig. S2**) was conducted prior to each instrumental analysis.

2.5 Multivariate Statistical tools and techniques

Multivariate statistics were conducted using OriginPro 2025, Microsoft Excel, and IBM SPSS Statistics 21. Each of the fourteen physico-chemicals and fifteen metals is depicted as a spatiotemporal heatmap (**Fig. 2 and Fig. 3**) for trend visualisation. Pearson's Correlation matrix is used to visually identify the strength and direction of linear relationships and to interpret associations or patterns among various parameters, grouped by season. To reduce the dimensionality of the complex dataset, PCA is performed in OriginPro 2025. PCA is a statistical technique that analyses extensive and intricate datasets by eliminating insignificant features while minimising information loss by generating new variables, known as principal components (PCs) (Bramhankar et al., 2026; Ustaoglu et al., 2021; Zhang et al., 2022) In this study, varimax rotations are applied to principal components (PCs) with eigenvalues exceeding 1 to generate additional variables known as varimax factors (VFs), and displayed in PC biplots as well as eigenvalue graphs (Goswami & Kalamdhad, 2022). Hierarchical Cluster Analysis (HCA) is a multivariate statistical method used to identify patterns in complex water-quality data (Singh et al., 2020). It groups water samples seasonally by similar contamination profiles, revealing the distribution of water quality. Using IBM SPSS Statistics 21, up to 4 clusters in a dendrogram with Ward linkage and the rescaled distance cluster analysis.

2.6 Computation of MEWQI

MEWQI is a three-dimensional water quality index suitable for datasets with multiple physicochemical parameters, varying sampling frequencies, and diverse spatial distributions. It uses an entropy probabilistic weighting method that objectively balances the influence of measured water quality parameters and their uncertainties relative to standard limits, which

dynamically reduces human subjectivity (Dash & Kalamdhad, 2022). Mathematically, it may be computed as follows:

Step 1: Water Quality Matrix Preparation

Initially, a dataset matrix $Y_{\{k \in (1, M)\}}$ is created for each individual water quality parameter, where $k \in (1, p)$, as represented in Equation.1(Koley et al., 2024):

$$Y_{\{k \in (1, M)\}} = \begin{bmatrix} y_{11} & y_{12} & y_{13} & \dots y_{1N} \\ y_{21} & y_{22} & y_{23} & \dots y_{2N} \\ y_{31} & y_{32} & y_{33} & \dots y_{3N} \\ \vdots & \vdots & \ddots & \vdots \\ y_{L1} & y_{L2} & y_{L3} & \dots y_{LN} \end{bmatrix} \quad (\text{Eqn.1})$$

Where Y_k represents the dataset matrix for the k^{th} water quality parameter, y_{ij} denotes the observed value at the i^{th} sampling location ($i \in (1, L)$) during $\{j \in (1, N)\}$ sampling frequency, L denotes the total number of sampling locations, N is the total number of water quality parameters.

Step 2: Calculate of the probabilities.

The probability figures are derived from the ratio of instances where water quality values are less than the acceptable limits laid down by different established agencies to total samples (**Eqn. 2**).

$$P_{\delta} = \frac{1}{4} * \left\{ \frac{\text{Number of occurrences the observed values adhere to standard limits}}{\text{Total number of sampling frequency}} \right\} \quad (\text{Eqn.2})$$

A scaling factor of 0.25 is used to enhance the probability estimate using the formula $\{-P_{\delta} \ln(P_{\delta})\}$. The maximum value of this function occurs at $1/e^{-1/2.718} \approx 0.368$ and decreases after that point. The probability value P_{δ} is about 0.37. The 0.25 factor simplifies calculations and keeps $\{-P_{\delta} \ln(P_{\delta})\}$ an increasing function, ensuring the probability value stays between 0 and 0.25 (Dash & Kalamdhad, 2021; Koley et al., 2024).

Step 3: Preparation of the dataset matrix for estimation of the ultimate water quality for the study area

The matrix $Y_{\{k \in (1, M)\}}$ of step-1 is thus reorganised for the sampling stations, whereby each sampling station is represented as $n \in (1, \alpha)$, and each contains an independent dataset matrix $Z_{\{n \in (1, L)\}}$ as displayed in Eqn.(Dash & Kalamdhad, 2021)

$$Z_{\{n \in (1, L)\}} = \begin{bmatrix} Z_{11} & Z_{12} & Z_{13} & \dots Z_{1M} \\ Z_{21} & Z_{22} & Z_{23} & \dots Z_{2M} \\ Z_{31} & Z_{32} & Z_{33} & \dots Z_{3M} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{N1} & Z_{N2} & Z_{N3} & \dots Z_{MN} \end{bmatrix} \quad (\text{Eqn.3})$$

Whereby, Z_n represents the n^{th} sampling station's dataset matrix and z_{pq} represents the observed value of the q^{th} $\{k \in (1, M)\}$ water quality parameter for the p^{th} $\{p \in (1, N)\}$ sample collection duration.

Step 4: Information entropy assessment and its sub-indices allocation.

For each water quality parameter, we estimate the entropy values $\mathcal{E}_{q\{q \in (1, b)\}}$ using the equation given in (Eqn. 4)

$$\mathcal{E}_{q\{q \in (1, b)\}} = \{ -P_{\delta} \ln(P_{\delta}) \} \quad (\text{Eqn.4})$$

In case of parameter readings with null or zero probability value, the value of $\{ -P_{\delta} \ln(P_{\delta}) \}$ is considered as 0,

$$\lim_{p \rightarrow 0^+} P \ln(p) = 0 \quad (\text{Eqn.5})$$

Then, the entropy weights were thus estimated using (Eqn. 6).

$$W_{\mathcal{E}_{q\{q \in (1, M)\}}} = \frac{1 - \mathcal{E}_q}{\sum_{q=1}^b 1 - \mathcal{E}_q} \quad (\text{Eqn.6})$$

Step 5: Computation of the MEWQI table

Employing the above equation (Eqn. 6), the MEWQI values of each of the 12 monthly samples from 12 sampling sites (Fig.5a) were estimated from fourteen selected

physicochemical water quality parameters and 14 metals. The final MEWQI formula is given as

$$MEWQI_N = \sum_{q=1}^b Wq \times \left\{ \frac{Cq}{Sq} \times 100 \right\} \quad (\text{Eqn. 7})$$

In this context, Sq refers to the standard limits, while Cq denotes the observed concentrations.

Step 6: Assigning a category for each MEWQI value.

The final MEWQI values are then categorised into six classes to simplify the interpretation, a novel modification from Dash & Kalamdhad (2021) as given in **(Fig. 5b)**.

2.7 Assessment of Human Health Risk

In the current study, human health risks from exposure to potentially toxic elements amongst metals, through river water, are estimated separately for ingestion pathways and dermal routes, for adults and children, respectively.

Human health risks associated with exposure to contaminated environments are broadly classified into two categories: non-carcinogenic and carcinogenic. Non-carcinogenic risks are evaluated using threshold-based indices that account for adverse effects such as irritation and organ damage, while carcinogenic risks estimate the probability of cancer development over an individual's lifetime (Nur et al., 2025). For non-carcinogenic assessment, Chronic Daily Intake (CDI) is calculated for both oral ingestion and dermal contact pathways, separately for adults and children, following standard protocols for human health risk assessment. The resulting Hazard Quotient (HQ) for each exposure route and the cumulative Hazard Index (HI) serve as primary indicators, with values exceeding 1 indicative of potential adverse health effects (Eris & Ça, 2020; Nur et al., 2025). Carcinogenic risk is quantified as the Incremental Lifetime Cancer Risk (ILCR), derived by multiplying the CDI by the corresponding Cancer Slope Factor (CSF); an ILCR within the range of 10^{-6} to 10^{-4} is considered acceptable (Zakir et al., 2020). The mathematical parameters and reference values applied in this assessment are detailed in **Table S4**.

The CDI via ingestion, CDI_{oral} (mg/kg/day), is evaluated using the formula (Eqn. 8):

$$CDI_{oral} = \frac{C \times DI \times ABS_g \times ED \times EF}{BW \times AT}, \quad (\text{Eqn. 8})$$

where C is the contaminant concentration in water,

DI is the daily water ingestion rate,

ABS_g is the oral absorption factor (gastrointestinal),

ED is the exposure duration,

EF is the exposure frequency,

BW is the average body weight,

AT is the averaging time for non-carcinogenic effects.

Similarly, dermal exposure is estimated by CDI_{dermal} (mg/kg/day), calculated as (Eqn. 9):

$$CDI_{dermal} = \frac{C \times SA \times K_p \times ABS_d \times ET \times EF \times ED \times CF}{BW \times AT}, \quad (\text{Eqn. 9})$$

where SA is the exposed skin surface area,

ABS_d is the dermal absorption factor (in %)

K_p is the dermal permeability coefficient (in cm/h),

ET is the exposure time/day

CF represents the unit conversion factor.

The oral and dermal Hazard Quotients are then calculated using (Eqn. 10 and Eqn. 11)

$$HQ_{oral} = \frac{CDI_{oral}}{RfD_{oral}} \text{ and} \quad (\text{Eqn. 10})$$

$$HQ_{dermal} = \frac{CDI_{dermal}}{RfD_{dermal}}, \quad (\text{Eqn. 11})$$

where RfD_{oral} and RfD_{dermal} are the reference doses for each exposure route (Nur et al., 2025;

Zakir et al., 2020).

For the evaluation of the combined non-carcinogenic risk from multiple metals, the Hazard Index for oral exposure (HI_{oral}) are computed as the sum of individual HQ values for each metal, i.e. (Eqn. 12),

$$HI_{oral} = \sum_{i=1}^n HQ_{oral,i} = HQ_{Cr} + HQ_{Mn} + HQ_{Pb} + HQ_{Cu} + HQ_{Fe} + HQ_{Zn} + HQ_{Co} \dots \text{(Eqn. 12)}$$

Similarly, HI_{dermal} is calculated by adding together all the dermal HQs of the same type of metals. Additionally, the Total of Total Hazard Quotient (TTHQ) will be determined by summing the hazard quotients of all studied metals. (e.g., $TTHQ = THQ_x + THQ_y + \dots + THQ_n$), which provides an integrated measure of non-carcinogenic risk from combined multi-metal exposure (Moradnia et al., 2024; Nur et al., 2025; Gurudatta Singh et al., 2025; Zakir et al., 2020). Risk interpretation follows standard criteria: HI or TTHQ values below 1 indicate no significant non-carcinogenic health risk, whereas values above 1 imply potential health concerns for the exposed population (Nur et al., 2025), highlighting the need for careful water quality management and mitigation strategies.

3. Results and Discussion

The comprehensive water quality analysis results from the 144 samples collected across four seasons, with fourteen physico-chemicals and fifteen metals, were discussed below, and their descriptive statistics were presented in **Table S2** and **Table S3**.

3.1 Spatiotemporal Water Quality

(Insert Figure 2)

Dissolved oxygen (DO) is critical for the health of aquatic ecosystems, influencing processes such as organic matter decomposition and nutrient cycling (Goswami & Kalamdhad, 2022). The DO of the Digaru River ranges from 5.4 mg/L to 8.95 mg/L (mean 7.44 ± 0.78 SD) (Fig. 2a). Comparatively, a sharp dip in the DO values is visible during the monsoon season, gradually recovering to the end of the post-Monsoon season, also towards the drier months. Overall pH within the Digaru River is slightly acidic, ranging from 4.82 to 7.42 (mean 6.55 ± 0.38 SD). About 43.75% of the samples (**Fig. 2b**) fall beyond the acceptable limit (BIS, 2012).

The BIC zones (L4 to L7) exhibit low pH values and the greatest variation (0.52), indicating potential discharge of acidic effluents. Downstream, pH approaches neutrality, with moderate fluctuations and less significant spatiotemporal shifts. The slightly acidic condition during the monsoon may result from runoff carrying acidic pollutants from industrial regions. However, natural buffering from limestone and carbonate rocks,(Herojeet et al., 2017; Singh et al., 2025) due to dilution and mixing, helps neutralise pH levels downstream.

Mean TDS and EC were 75.69 ± 19.51 mg/L and 40.09 ± 19.86 mg/L, respectively, with maximums of 156.5 mg/L and 95.4 mg/L (**Fig. 2c and 2d**) during the monsoon near the Brahmaputra River. Both values followed a Pre-monsoon > Winter > Monsoon > post-monsoon pattern. TDS increased downstream, indicating poor contaminant removal. Elevated EC and TDS in April-May likely stem from agricultural runoff, brick kiln ash, and industrial pollutants, with salts from surface runoff. Spatially, EC and TDS increased gradually downstream, influenced by runoff and by municipal sewage intrusion. Although the values were within BIS limits (BIS, 2012), an upward trend suggests a low self-replenishment capacity.

The river's turbidity exhibits high variability, ranging from 502 to 2.70 NTU (mean 76.56 ± 104.8) (**Fig. 2e**). Spatiotemporally, the turbidity is highly correlated with rainfall-induced surface runoff (Singh et al., 2020), with the highest concentrations during the monsoon. About 97.22% of the turbidity analysis exceeds the permissible limit of 5 NTU as per the BIS 10500 standard (BIS, 2012), which is a concern. This indicates that river water is unfit for human consumption without proper water treatment.

The BOD₅ of the Digaru River ranges from 5.1 mg/L to 47 mg/L (mean 19.9 ± 8.83 SD) (**Fig.2f**). In July, BOD₅ increased significantly due to the highest rainfall months, causing substantial runoff from catchment areas within the BIC carrying large organic loads (MoEFCC, 2000). However, COD has seen comparatively higher concentrations in the later part of the

monsoon to the post-monsoon. The COD ranges from 11.99 to 290 mg/L (mean 111.85 ± 85 SD) (**Fig. 2g**). All locations exceeded the BOD₅ levels of 5 mg/L, and 87.5% of COD measurements also surpassed 25mg/L, indicating that both BOD₅ and COD values were high above safe thresholds for human consumption (BIS, 2012). Another crucial parameter is the BOD/COD ratio, which indicates biodegradability: >0.5-0.6 is high, 0.3-0.5 moderate, and <0.3 poor (Singh et al., 2020). In the Digaru River, ratios range from 0.1 to 0.9, averaging 0.3 ± 0.23 . From January to March, ratios are >0.5, but during other months, increased effluent discharge with high COD during precipitation months drops the ratio below 0.3, indicating poor biodegradability. Total alkalinity and hardness range from 20.5-56.90 mg/L (mean 35.57 ± 8.88) and 11-77.60 mg/L (mean 44.74 ± 16.7 SD) of CaCO₃, respectively. Both parameters spiked during the monsoon, especially in July, and were aligned with the upstream limestone-rich geological composition (Singh et al., 2021), as evidenced by L1 and the BIC areas. However, the water quality of the Digaru River falls under the 'Soft' water to 'Moderately Hard' category. All the anions analysed also exhibit spatiotemporal variations. Fluoride (**Fig.2k**) and chloride (**Fig. 2l**) range from 0.03-1.0 mg/L (mean 0.37 ± 0.3 SD) and 0.6-11.42 mg/L (mean 4.08 ± 1.8 SD), respectively. Seasonally, fluoride levels vary in the following order: Monsoon > Pre-Monsoon > Winter > Post-monsoon. In general, Fluoride, at both ends of the spectrum, either deficient or excessive, have been associated with dental problems, including fluorosis (Goswami & Kalamdhad, 2022). Chloride levels remained within limits, with no significant variation along the river, and levels were slightly higher in winter but overall stable across seasons. Nitrate levels ranged from 0.3 to 56.0 mg/L (average 11.07 ± 10.7 SD), with 2.08% of samples exceeding the limit. Nitrate concentrations >10 mg/L indicate enhanced microbiological contamination, suggesting runoff-sourced surface drainage (Koley et al., 2024), sewage, or animal wastes within the BIC regions. Consumption of water contaminated with nitrate above the acceptable limit of 45mg/L (BIS, 2012) is expected to cause "blue baby"

syndrome or methemoglobinemia in newborns (Goswami & Kalamdhad, 2022). Sulphate ranged from 0.3 to 27.3 mg/L (mean 5.69 ± 4.9 SD). Another study of the Brahmaputra downstream of Digaru found similar sulphate levels of about 28mg/L. While sulphate isn't highly toxic, ingestion can cause diarrhoea, dehydration, and catharsis, and may alter methemoglobin and sulfohemoglobin levels due to increased dietary absorption (Koley et al., 2024). A sharp spike in concentrations of nitrate and sulphate observed during the monsoon was due to agricultural runoff from the eastern side of the Kopili River (L11) and within the BIC regions (L4-L6) as well. Phosphate is present at lower concentrations, ranging from 0.01 to 0.41 mg/L (mean 0.16 ± 0.09 SD) within the safe limits. Hence, amongst the anions from the pollution point of view, the concern is mainly for the nitrate and phosphate concentrations.

3.2 Metals

(Insert Figure 3)

Altogether, 15 metals were identified whose concentrations exceeded the detection limit using ICP-MS for metal analysis, as listed in **(Fig.3)**. The full list of descriptive statistics of metals is given in **Table S3**. Among the major alkaline metals, such as Na, Mg, K, Ca, Sr, and Ba, all were detected in the river water. However, their levels remained within the permissible limits (BIS, 2012) for Na (0.63 - 65.20 mg/L, mean: 4.55 ± 0.55 SD), Mg (0.53 - 2.86 mg/L, mean: 1.38 ± 0.45), K (1.90 - 5.92 mg/L, mean: 3.08 ± 0.8 SD), Ca (0.75 - 3.82 mg/L, mean: 1.73 ± 0.56 SD), Sr (12.37 - 40.31 μ g/L, mean: 23.06 ± 5.03), and Ba (0.01 - 58.59 μ g/L, mean: 24.06 ± 12.93). Significant spatial variation was observed in the concentrations of these alkaline metals. Elevated concentrations of Na, K, Ca, and Ba were notably recorded at sites L5, L6, L9, and L10. Seasonal variations showed higher cation concentrations during the pre-monsoon and winter, while seasonal spikes during the monsoon were observed for Ca, Sr, and Ba, mainly due to sediment resuspension and runoff contributions, consistent with other reports elsewhere such as from Sirsa River, Himachal

375 Pradesh (Herojeet et al., 2017), Nile River, Upper Egypt (Khalil et al., 2023), Deepor Beel,
376 Assam (Dash et al., 2021). Additionally, during the monsoon, these major cations dominated
377 PC2 in the PCA biplot (**Fig. 7a**). Among the trace metals detected, Al (81.9%), Mn (0.69%),
378 and Fe (97%) exceeded the standard permissible limits of 200, 300, and 300 µg/L respectively
379 (BIS, 2012) (**Fig. 3c, 3g, and 3h**). Al concentrations ranged from 18.12 to 2497.92 µg/L, with
380 a mean of 517.51 ± 431.64 SD. Mn varied from 5.44 to 321.82 µg/L (mean: 86.23 ± 52.63 SD),
381 and Fe ranged from 80.36 to 3938.69 µg/L, with a mean of 1253.16 ± 568.33 SD. These metals
382 showed sharp concentration spikes, particularly at sites L2, L4, L8, and L10, with higher levels
383 recorded during pre-monsoon, followed sequentially by winter, monsoon, and post-monsoon
384 seasons. The occurrence of Cr, Co, Cu, Ni, Zn, and Pb in the river water is consistent with
385 multi-metal contamination profiles documented in rivers subjected to industrial effluent
386 discharge, urban runoff, and agricultural inputs (Bramhankar et al., 2026; Goswami &
387 Kalamdhad, 2023; Herojeet et al., 2017; Khalil et al., 2023). Notably, 88.20% of Pb samples
388 exceeded the permissible limit of 10 µg/L (BIS, 2012). Concentration ranges were as follows:
389 Cr from 0.03 to 8.92 µg/L (mean: 2.49 ± 1.54 SD), Co from 0.003 to 7.84 µg/L, Ni from 0.12
390 to 9.24 µg/L (mean: 2.973 ± 2.14 SD), Cu from 0.03 to 116.72 µg/L (mean: 27.58 ± 25.53 SD),
391 Zn from 12.62 to 369.98 µg/L (mean: 103.86 ± 53.45 SD), and Pb from 0.90 to 68.52 µg/L
392 (mean: 23.99 ± 13.76 SD). Heavy metal seasonal partitioning is observed across sampling
393 periods. Cr and Co, in particular, exhibited elevated levels during the monsoon, largely due to
394 enhanced surface runoff, remobilisation of metal-laden bed sediments under high-flow
395 conditions, and soil leaching (Goswami & Kalamdhad, 2022; Herojeet et al., 2017). By contrast,
396 Ni, Cu, Zn, and Pb show higher concentrations during the pre-monsoon period, reflecting the
397 cumulative effects of reduced water volume, lower discharge, and the continued input of
398 industrial effluents and municipal sewage (Bramhankar et al., 2026; Goswami & Kalamdhad,
399 2022; Herojeet et al., 2017; K. R. Singh et al., 2021). Significant spikes in metal concentrations

were observed at sites L2 and L4 (BIC areas), L8 (Sonapur market area), and L11, where the Digaru River conjoins the Kopili River from the southwest. These peaks primarily occurred during the monsoon, probably due to rainfall flushing pollution sources (Gurudatta Singh et al., 2025).

3.3 Statistical Correlations between physicochemical and metals across four seasons

(Insert Figure 4)

Pearson's correlation matrix was computed for fourteen (14) physicochemical parameters versus fifteen (15) detected metals (Fig. 4). During the pre-monsoon season, highly significant ($p < 0.05$, $p \leq 0.01$) correlations were observed with major pollutants such as DO, turbidity, BOD₅, TDS, NO₃⁻, PO₄³⁻, COD, along with alkali metals such as Na, Al, K, Ca, and heavy metals including Cr, Mn, Ni, Sr, Ba, Pb, signifying shared industrial effluent sources, such as cement, electroplating, chemicals, metal smelting, and coal-to-coke industries, mainly within specific inlet points during low-flow events (Das, 2025; Herojeet et al., 2017). However, during the monsoon season, strong significant ($p < 0.05$, $p \leq 0.01$) correlations were observed mainly for EC, TH, BOD₅, TDS, NO₃⁻, PO₄³⁻, COD with Mg, Al, Cr, Cu, Ba, Pb, and for F⁻ with almost all metals, signifying intense monsoon precipitation and associated runoff acting as drivers of both particulate and dissolved-phase pollutants, with nutrient flushes from agricultural lands too, collectively reflecting diffuse pollution sources. The observed pattern aligns well with earlier studies, which have identified temporally varying river discharge as a key determinant of seasonal shifts in water quality, ionic chemistry, and the statistical inter-relationships among physicochemical parameters (Das, 2025; Goswami & Kalamdhad, 2022; Herojeet et al., 2017). During the post-monsoon and winter, fewer correlations were observed, yet highly specific and significant correlations between parameters were noted. Post-monsoon, anions and TDS, COD showed a strong affinity for major cations such as Na, Mg, Ca, Cr, and Cu, possibly reflecting residual effects

of monsoon flushing (Bramhankar et al., 2026; Das, 2025). During winter, turbidity, BOD₅, and COD correlated inversely with most heavy metals, likely because metal concentrations were detectable even in less polluted, less turbid conditions along the river, indicating that metals persist during lean seasons (Das, 2025; Goswami & Kalamdhad, 2022).

3.4 MEWQI

(Insert Figure 5)

In the current study, a novel modification of MEWQI is used to comprehensively compute the water quality of the Digaru River, incorporating all basic physicochemical parameters and metals, and assigning a new set of classes. MEWQI surpasses traditional WQI by employing objective entropy-based weights that account for data variability (Dash et al., 2019; Dash & Kalamdhad, 2021). It also allows for easy integration of new parameters without losing focus on the primary pollutants, even as additional factors are included. The MEWQI categories are classified into six classes with a maximum of >250 values as given in (Fig. 5b) (Dash & Kalamdhad, 2021). The values range from 73.93 (L1 during April) to whopping 1345.20 (L12 during July) (Fig. 5a). Among the parameters, Turbidity, BOD₅, and COD received the highest weightage at each sampling point, according to the $W_{eq} \{q \in (1, b)\}$. Spatially, the MEWQI tend to increase downstream. A Maximum of 45.1% of the cells fall under the “Extremely Poor Category”, followed by “Fair-Category” (20.8%) and “Poor-Category” (15.3%). None of the cells falls into the excellent category, and only 6.25% are in the 'Very Good' category (Fig. 5c). Spatially, the WQI of the initial control point, upstream to the BIC, is in the “Very Good ” category, highlighting clear effluent intrusion from Industrial establishments as the major contributor. Across the seasons, the post-monsoon to Winter seasons ranked comparatively higher WQI ratings. Hence, overall, the WQI of Digaru is unfit for human consumption. The Digaru river's water is heavily relied upon, apart from groundwater extraction for industrial and domestic purposes within the BIC, and it adjoins the

Brahmaputra downstream, where several WTP inlets are established (Datta et al., 2017). Thus, the influx of water from the Digaru River into the downstream Brahmaputra River is worrisome and requires urgent remedial measures.

3.5 Hierarchical Cluster Analysis (HCA) across four seasons

(Insert Figure 6)

This study employed agglomerative hierarchical clustering analysis (HCA) to assess the similarity among sampling locations across four seasons (**Fig.6**). HCA was performed on z-transformed datasets using Ward's linkage (Koley et al., 2024) and rescaled distance clustering (Dash et al., 2020; Singh et al., 2021), with up to 4 clusters. During the monsoon season, the most prominent clusters emerged: Cluster-1 includes L1, representing a point just before BIC industrial interference; Cluster-2 comprises L2 and L3, where noticeable pollutant buildup occurs; Cluster-3 covers stations from Byrnihat Bridge to 6.8 km downstream of the lowermost BIC, where runoff from industrial areas significantly affects water quality's physicochemical properties; and Cluster-4 involves L8 to the convergence with the Brahmaputra, indicating similar contamination profiles. In the pre-monsoon period, Cluster-1 (L1 to L3) shows limited discharge from L2 and L3 due to less precipitation, while Cluster-4 mainly consists of pollution from regular sewage discharges downstream. During post-monsoon, Cluster 2, accounting for 50%, includes BIC regions up to L9, reflecting extended residual runoff from the monsoon and contributions from agricultural lands(Goswami & Kalamdhad, 2022; Herojeet et al., 2017). Winter HCA reveals irregular spatial patterns along the river. Overall, clear seasonal distinctions can be observed, with BIC regions forming distinct clusters separate from the downstream river sections near agricultural fields and settlements(Khalil et al., 2023). A similar pattern of sampling location clusters is also observed in the season-wise Bi-plot PCA (**Fig. 7a**).

3.6 Principal Component Analysis (PCA) across four seasons

(Insert Figure 7)

The PCA results in **(Fig.7)** show four seasonal PCAs analysing physicochemical parameters and seasonal variations. During pre-monsoon, the first two PCs account for 50.89% of total variance, with 7 PCs having eigenvalues above 1. All PCs' loadings decrease as metal data are added with 14 parameters, which should be balanced. PC1 (33.29%) shows strong positive loadings on Sr, TDS, Ba, Mn, Ni, Zn, Cu, Pb, BOD₅, Cr, COD, NO₃⁻, PO₄²⁻ and turbidity, indicating organic pollution and nutrient enrichment from sewage, industrial effluents, and agricultural runoff, with a negative DO, which is consistent with other studies (Bramhankar et al., 2026; Sojka & Jaskula, 2022). This worsens under low-flow. PC2 (17.60%) highlights salinity/alkalinity and geogenic ions from natural processes, with high positive loadings on F⁻, Turbidity, COD, Na, PO₄³⁻, and negative loadings on Cl⁻, pH, NO₃⁻, Zn, Al and Ba. Overall, PCs show pollution buildup before the monsoon dilutes it.

Monsoon PCA identified 8 principal components with eigenvalues >1. PC1 and PC2 explain 47.56% of the variance, indicating increased pollutant interactions during the monsoon, a runoff effect that mobilises pollutants amid upstream dilution and pre-monsoon buildup. PC1 (31.09%) indicates erosion or runoff-driven sediment and pollutant mobilisation mostly due to high rainfall, with high loadings for COD, Mn, Ba, TDS, Cr, F⁻, Pb, Co, Cu, Ni, and negative loadings for DO and pH. PC2 (16.47%) reflects baseline alkalinity and heavy-metal dilution from increased rainfall, with loadings including Na, Ca, Mg, K, SO₄²⁻, TDS, Turb, EC, pH, and negative loadings for Cr, Sr, Ba, and Mn, consistent with other reports (Bramhankar et al., 2026; Herojeet et al., 2017; Singh et al., 2025).

During the post-monsoon **(Fig. 7a)** on period, PC1 (24.91%) shows high loadings for NO₃⁻, SO₄²⁻, TDS, COD, Turbidity, and metals such as Mg, Cr, Cu, Ca, and Ni **(Fig. 7c)**. This likely indicates runoff recession and decreased flows, leading to higher concentrations of soluble ions from sewage or fertilisers, as well as to metals settling out from monsoon turbidity.

Similar findings were observed in studies elsewhere, too (Bramhankar et al., 2026; Fatima et al., 2022; Herojeet et al., 2017; Singh et al., 2020; Zhang et al., 2022). PC2 (19.41%) was highly dominated by anions such as Cl^- , F^- , and Pb, as well as by B, S, Co, K, Mn, and Ni (**Fig. 7c**), which may be due to declining flows that promote anoxic bottom layers, which mobilise metals from sediments and promote mineral dissolution (Zhang et al., 2022).

Winter PCAs reveal the least variance: PC1 (24.91%) shows positive loadings for TA, EC, TDS, pH, NO_3^- , Fe, Ca, and Zn (**Fig. 7a**), indicating alkalinity or salt stress rather than organic stress, possibly due to lower temperatures and milder flow, which slow resuspension (Soetan et al., 2024). PC2 (18.14%) (**Fig 7b**) shows high loadings for Mg, Cl, Ba, Cr, Al, Pb, with negative loadings for Turbidity, Fe, Na, Mn. Comparing the seasonal PCAs, the variance loadings decrease in the order Pre-Monsoon > Monsoon > Post-Monsoon > Winter, quite a similar trend to other studies (Goswami & Kalamdhad, 2022), thus indicating a slowdown in hydrological activity. Overall, the scree plots of PC1 for pre-monsoon and monsoon show a sharp peak, accounting for the majority of the dataset's total variance. PC1 shifts from being dominated by organics and metals to reflecting runoff and flushing caused by precipitation, with a move towards alkaline stability in winter. Organic pollution peaks during the monsoon (Koley et al., 2024), likely due to surface runoff (Devi et al., 2026) from BIC industrial areas and downstream market zones. An elbow-shaped graph in the scree plot after PC1 indicates the number of components to retain. These loadings, overall, highlight organic pollution and nutrient enrichment from sewage and industrial effluents discharged via inlet drains within the BIC, and at peak monsoon precipitation, when specific pollutants are swept along with sediment resuspension, intensifying contaminant transport (Soetan et al., 2024) and shaping the main river pollution pattern.

3.7 Human Health Risk Assessment (HHRA)

(Insert Figure 8)

Human Health Risk assessment estimates the potential adverse effects of heavy metal pollution on humans, focusing on carcinogenic and non-carcinogenic risks through two primary pathways: ingestion and dermal absorption of various heavy metals during the utilisation of polluted water (Goswami & Kalamdhad, 2023; Nur et al., 2025; Zakir et al., 2020). As per the USEPA (2004) protocol, the chronic daily intake (CDI), Hazard Quotient (HQ), Hazard Index (HI), and Incremental Lifetime Cancer Risk (ILCR) were measured for both oral and dermal routes, separately for adults and children (**Fig. 8**). Among the non-carcinogenic health risks of metals, estimated CDI_{oral} and CDI_{dermal} risks were highest for Fe for children, followed by Fe for adults (**Fig.8a and 8b**). The CDI_{oral} and CDI_{dermal} values for adults range from 1.35×10^{-4} (Fe) to 1.02×10^{-10} (Co) $mg\ kg^{-1}\ day^{-1}$ and 6.85×10^{-7} (Fe) to 2.09×10^{-12} (Co) $mg\ kg^{-1}\ day^{-1}$ for adults. The CDI_{oral} and CDI_{dermal} values for children are both higher than those for adults, with iron (Fe) dominating in both cases, reaching up to 5.4×10^{-4} (Fe) and 2.36×10^{-6} (Fe) respectively (**Fig.8a and 8b**). The overall CDI risk ranking for heavy metal values is $Fe > Zn > Mn > Cu > Pb > Cr > Co > Ni$. The highest non-carcinogenic hazard quotient (HQ) via oral routes for both adults and children is 0.79×10^{-3} (Mn) and 3.14×10^{-3} (Mn), respectively (**Fig.8c**). The respective HQ_{oral} risk values for metals in adults and children follow the order $Mn > Pb > Fe > Cr > Cu > Zn > Ni > Co$ and $Mn > Pb > Fe > Cr > Cu > Zn > Ni > Co$. Conversely, for dermal exposure (HQ_{dermal}), Cr accounts for the highest risk among the detected heavy metals in river water for both adults and children, with values of 0.1×10^{-3} and 0.35×10^{-5} , respectively (**Fig.8d**). The risk ranking for HQ_{dermal} in adults and children is as follows: $Cr > Mn > Pb > Fe > Cu > Zn > Ni > Co$ and $Cr > Mn > Zn > Pb > Fe > Cu > Ni > Co$, respectively. Overall, these findings indicate that children are at higher risk, a trend supported by other studies too (Nur et al., 2025; Zakir et al., 2020). Among non-carcinogenic health risks, HI from heavy metals is estimated as the sum of HQs via the dermal and oral routes (USEPA, 2004). The HI values for adults (**Fig.8e**) range from 0.86×10^{-3} (Mn) to 1.59

x 10⁻⁶ (Co), and metals risks ranking as Mn>Pb>Cr>Fe>Cu>Zn>Ni>Co. HI values for children (Fig. 8e) are higher than those for adults, ranging from 3.2 x 10⁻³ (Mn) to 4.85 x 10⁻⁷ (Co), maintaining the same risk ranking as adults. Since all HQ and HI values are below 1.0, the detected metal concentrations are within acceptable non-carcinogenic health risk levels at all locations(Samaila et al., 2021; Zakir et al., 2020). Another study on BIC areas by Sangma et al. (2024) on metals in fly-ash and autoclaved aerated cement (AAC) also reported that HQ and HI values are below the safe limit, indicating low risk from exposure. Among the carcinogenic cancer risks, the ICLR values for Cr and Pb are separately estimated for both adults and children. In both cases, the ICLR values for children are higher than those for adults, similar to various other studies (Samaila et al., 2021; Zakir et al., 2020). The maximum ICLR risks of Cr are estimated as 0.51 × 10⁻⁶ and 0.13 × 10⁻⁶ for children and adults, respectively. Also, the maximum ICLR risks for Pb are estimated as 7.95 x 10⁻⁸ and 1.99 x 10⁻⁸, respectively, for children and adults (Fig. 8f).

Environmental Implications

High-frequency monthly sampling reveals a significant environmental threat to the river from contaminant influxes from multiple sources, mainly industrial clusters, with additional contributions from municipal discharges and agricultural runoff. The river has limited self-replenishing capacity and high seasonal variation, as shown by spatiotemporal monitoring. Improperly managed industrial effluents and municipal sewage are discharged into the river, directly or indirectly, severely affecting its natural ecosystem, polluting the water, and making it unsafe for human use. These pollutants also pose health hazards through ingestion and skin contact. Seasonal accumulation worsens ecological stress, especially during low-flow periods, increasing toxicity risks to aquatic life. Over time, this accumulation deteriorates water quality and poses adverse long-term health risks for humans. The study emphasises the urgent need for water management in pollution hotspots like Byrnihat

Industrial Clusters (BIC), as the river feeds into downstream water treatment plants, amplifying risks for local populations and ecosystems.

4. Conclusion

This study investigates pollution in India's Digaru River, using high-resolution data to assess water quality via MEWQI, PCA, and HCA, and to evaluate health risks. MEWQI indicates the water is unfit for consumption despite heavy use. PCA shows the highest variance in the pre-monsoon and monsoon seasons, correlating with pollutant runoff. HCA identifies pollution clusters mainly from BIC, with minor contributions from downstream agriculture and settlements. Correlations link poor water-quality parameters to heavy metals, particularly in the pre-monsoon and monsoon seasons. Non-carcinogenic metal risks are acceptable, except for the carcinogenic ICLR for Cr and Pb, which are concerning. Findings emphasise that high spatiotemporal resolution is crucial for understanding pollutant interactions and transfer, especially during monsoon runoff in BIC. The study also emphasises the need to explore other contaminants (PAHs, PFAS, microplastics), examine physicochemical correlations, and establish effluent treatment plants to reduce risks and promote sustainable management, thereby supporting SDG 6, particularly 6.3 on reducing pollution and hazardous discharges and improving sanitation. This research enhances understanding of pollution dynamics, aiding control and remediation.

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Statements & Declarations

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships, which may be considered as potential competing interests:

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Competing Interests

The authors declare no known financial or personal conflicts of interest that could have influenced the work reported in this paper.

Author Contributions

K Zamminson (conceptualization, investigation, methodology, writing-original draft, writing – review & editing); **Jasraj Kumawat** (investigation, methodology, writing-original draft); **Siddhant Dash** (supervision, writing – review & editing); **Ajay S. Kalamdhad** (conceptualization, funding acquisition, supervision, writing – review & editing). All authors read and approved the final manuscript.

Ethical approval

The authors declare that the submitted manuscript is original. They also acknowledge that the current research has been conducted ethically and that all the authors have agreed upon the final shape of the research.

Consent to publish

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840 **Table 1:** Lists of analytical Instruments/ techniques used in the current study

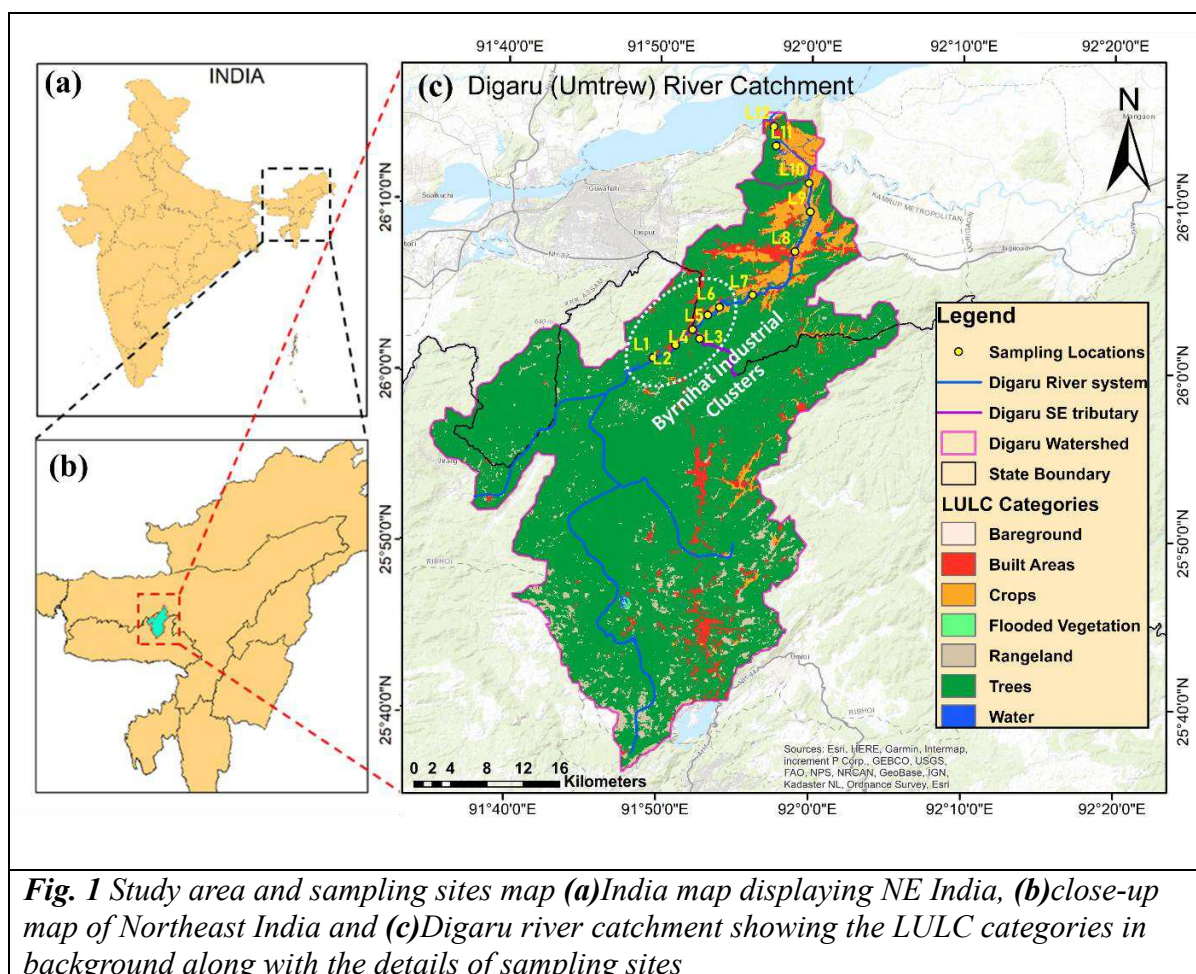
Parameters	Unit	Analytical methods
DO	mg/L	Multiparameter (LDO 101 probe, HQ40d multi, Hach)
pH	-	pH-meter (Mettler Toledo FiveEasyPlus)
EC	µs/cm	Multiparameter (CDC 401 probe, HQ40d multi, Hach)
Turbidity	NTU	Nephelometric Turbidimeter (Systronics)
Total alkalinity	mg/L as CaCO ₃	APHA titrimetric method
Total hardness	mg/L as CaCO ₃	APHA titrimetric method
BOD ₅	mg/L	5-day Biochemical Oxygen Demand
COD	mg/L	Closed reflux titrimetric method
TDS (Total dissolved solids)	mg/L	Multiparameter (CDC 401 probe, HQ40d multi, Hach)
All anions	mg/L	Ion Chromatography (Metrohm 792 Basic IC, Switzerland)
All Metals	µg/L	ICP-MS (Make: Agilent, Model: 7850)

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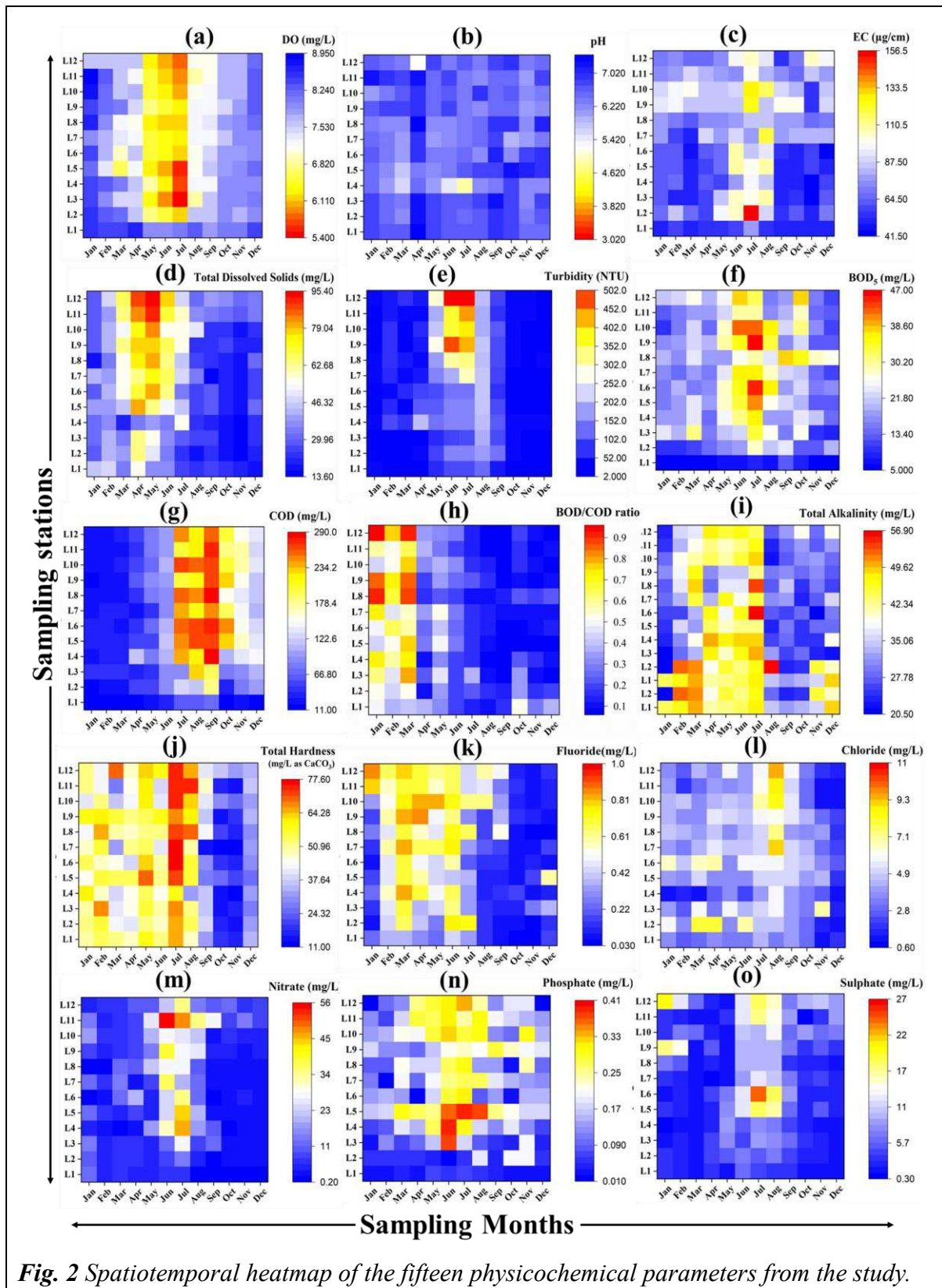


Fig. 2 Spatiotemporal heatmap of the fifteen physicochemical parameters from the study.

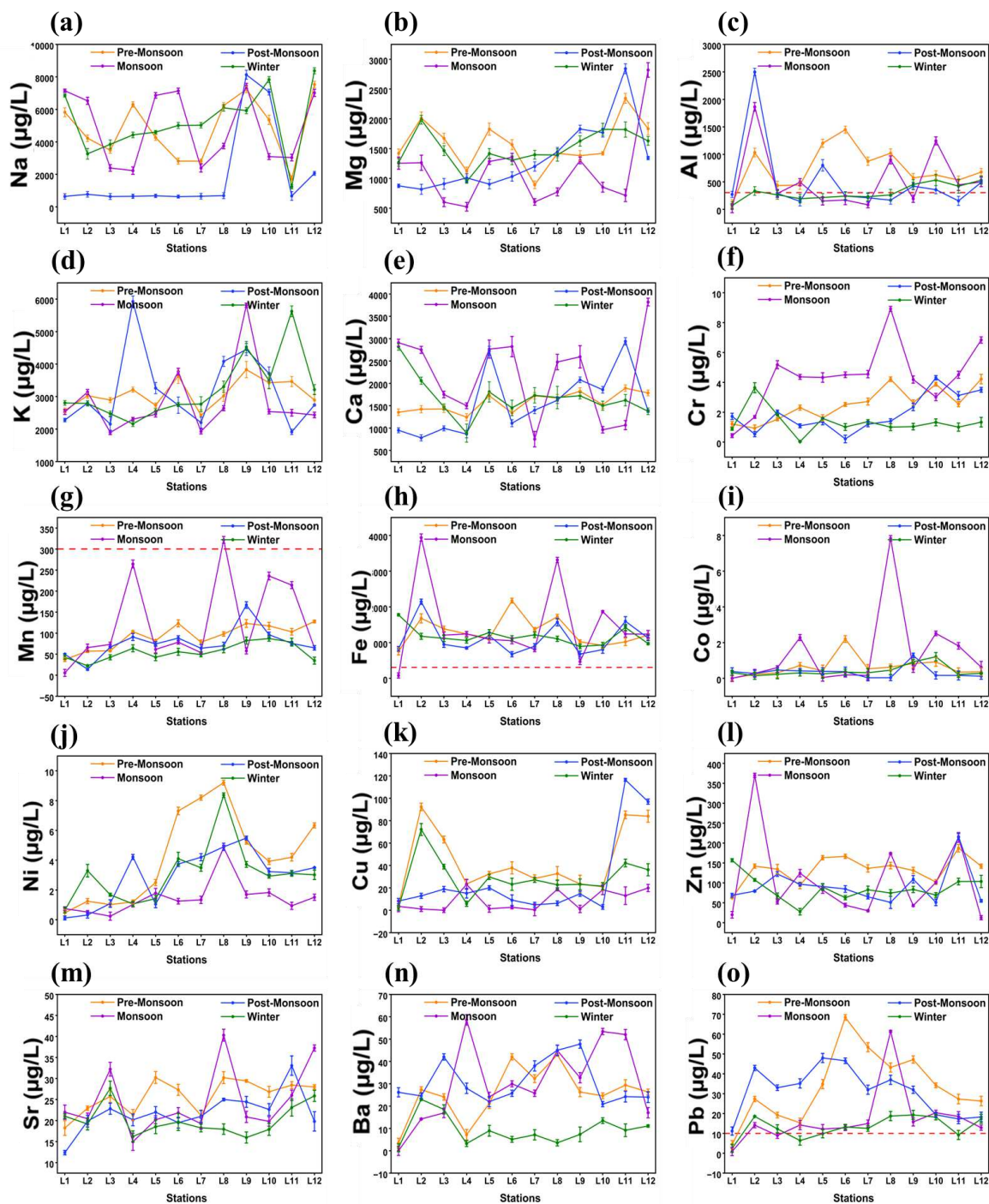
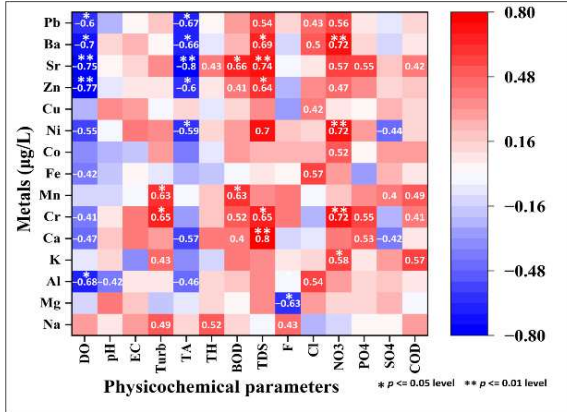


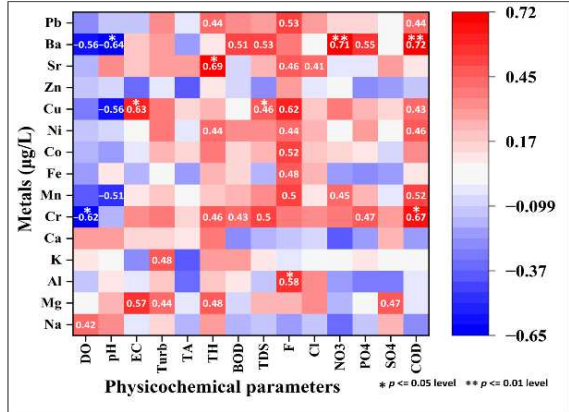
Fig. 3 Season-wise spatiotemporal heatmap of the fifteen (15) metals detected from the study

Pearson's Correlation between physicochemical and metals across four seasons:

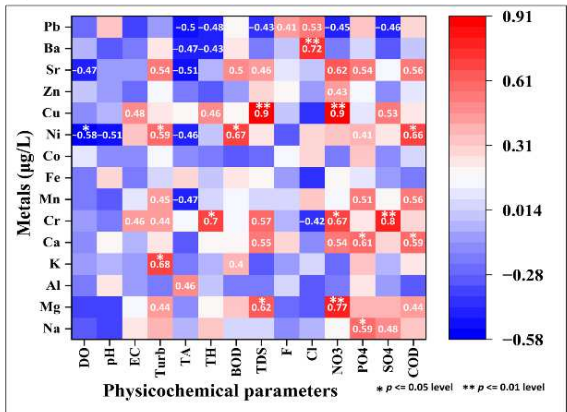
(a) Pre-Monsoon



(b) Monsoon



(c) Post-Monsoon



(d) Winter

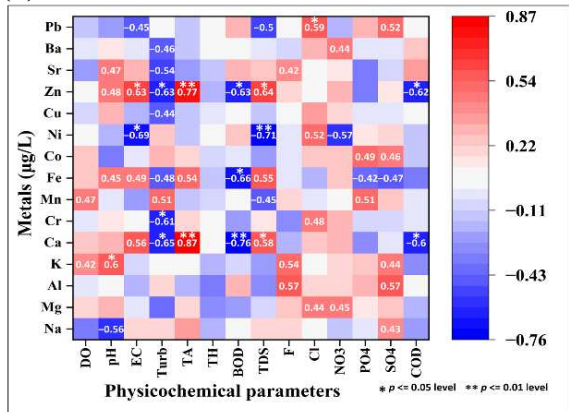
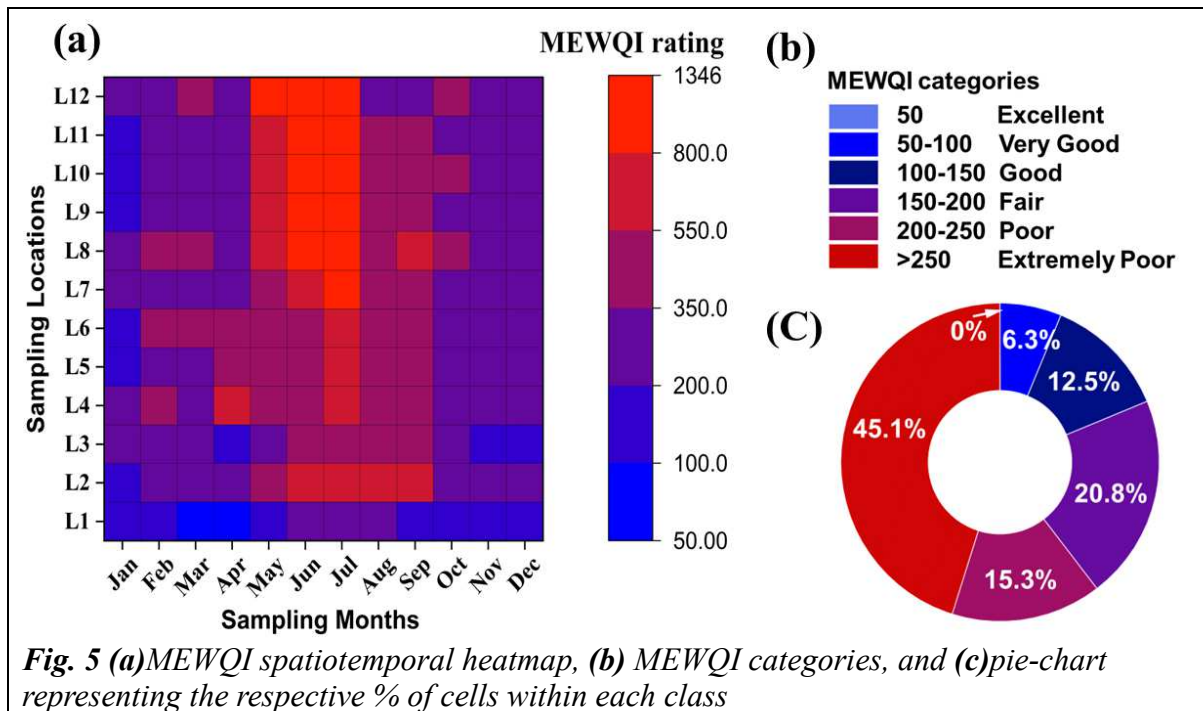
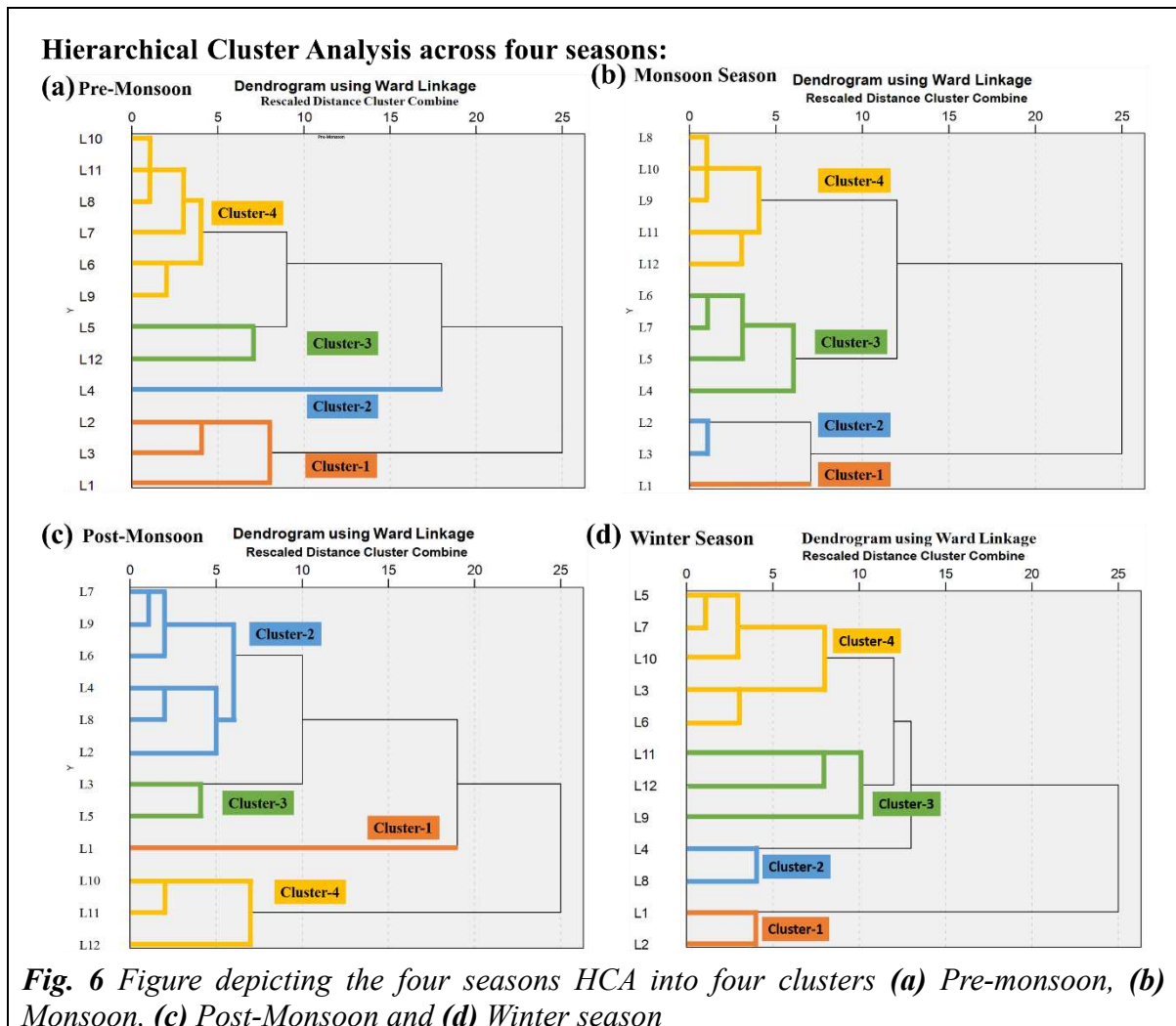


Fig. 4 Pearson's Correlation heatmap season-wise between the physicochemical parameters and the metals, along with their significance values.



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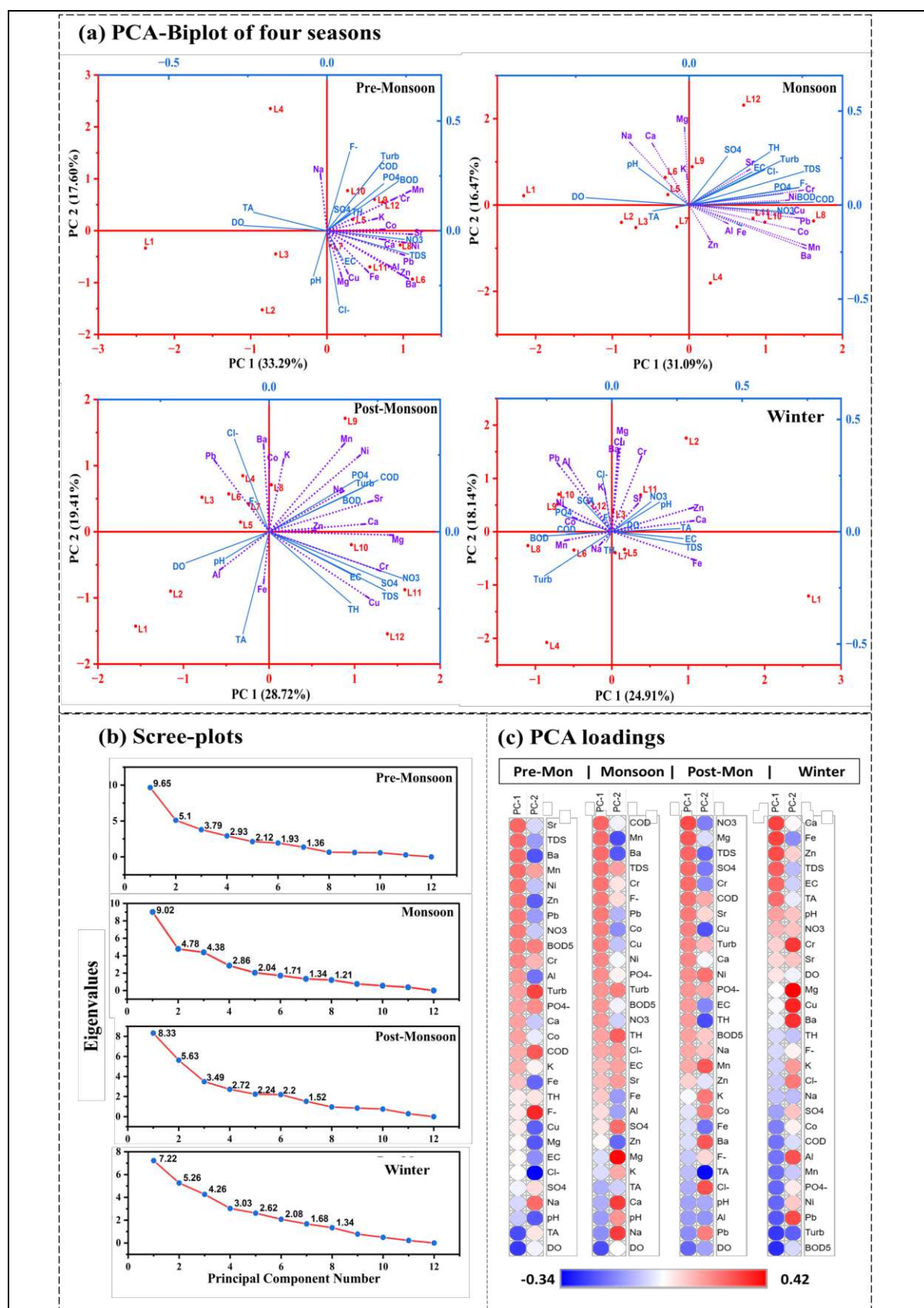


Fig. 7 PCA analysis season-wise. **(a)**PCA Biplot of the four seasons, highlighting the physico-chemicals in blue, metals in purple and sampling locations as red, **(b)** Scree-plots of the four season's PCA, **(c)** Colour gradient representing PC1 and PC2 loadings

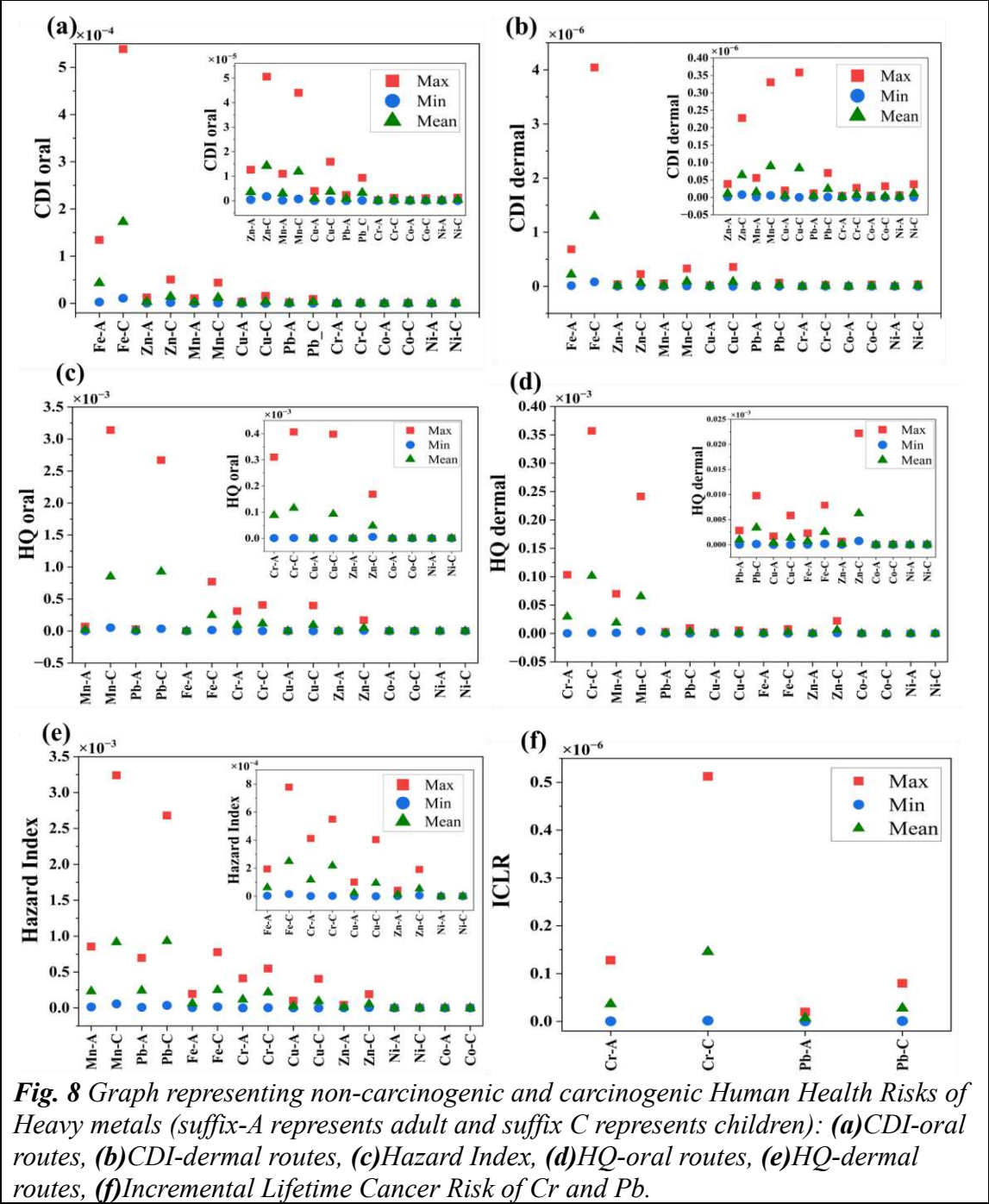


Fig. 8 Graph representing non-carcinogenic and carcinogenic Human Health Risks of Heavy metals (suffix-A represents adult and suffix C represents children): (a)CDI-oral routes, (b)CDI-dermal routes, (c)Hazard Index, (d)HQ-oral routes, (e)HQ-dermal routes, (f)Incremental Lifetime Cancer Risk of Cr and Pb.

Supplementary Files

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