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Assessment of Heavy Metal Contamination in Gomati River water and Associated Health Risks

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***Abstract*:Heavy metal contamination in urban rivers poses significant ecological and public health challenges, particularly in rapidly urbanizing regions. This study evaluated the spatial distribution of heavy metal contamination along a 61 km stretch of the River Gomti in Lucknow, India, using the Heavy Metal Pollution Index (HPI), human health risk assessment, and multivariate statistical analyses. The HPI results revealed severe water quality deterioration, with 30% of the sampling sites categorized as highly polluted (HPI > 30) and 60% as critically polluted (HPI > 100). The mean HPI value of 354.01 substantially exceeded the critical threshold, indicating widespread heavy metal contamination throughout the study reach. Human health risks associated with exposure to contaminated river water were assessed using Chronic Daily Intake (CDI), Hazard Quotient (HQ), Hazard Index (HI), and Cancer Risk (CR). Several metals exhibited HQ values greater than 1, indicating potential non-carcinogenic health effects, while HI values exceeded the acceptable safety limit at most sampling locations, reaching a maximum of 4.58. Carcinogenic risk assessment for chromium (Cr), arsenic (As), cadmium (Cd), and lead (Pb) demonstrated Total Cancer Risk (TCR) values above the acceptable limit (1×10^{-4}), with As and Pb identified as the primary contributors to cancer risk. Pearson correlation analysis, Principal Component Analysis (PCA), and Hierarchical Cluster Analysis (HCA) revealed strong associations among Pb-Cd and Cu-Zn, suggesting common pollution sources, whereas significant correlations (r = 0.51–0.89) among As, Pb, and Mn indicated predominantly anthropogenic inputs from industrial discharges, untreated sewage, and agricultural runoff. The findings highlight the critical pollution status of the River Gomti and emphasize the urgent need for effective wastewater treatment, stricter pollution control strategies, and long-term water quality monitoring to safeguard aquatic ecosystems and protect public health.**

Keywords: Heavy metals, River Gomti, Pollution Index (HPI), Health risk assessment, Multi variate analysis

I. INTRODUCTION

Rivers serve as key indicators of environmental changes within a landscape (Abbasi, 2012). Their conditions reflect the cumulative impact of both natural processes and human activities(Abdi & Williams, 2010; Ali et al., 2019). Heavy metal contamination is a significant environmental concern due to its toxicity, persistence, and inability to degrade naturally, leading to accumulation in soil, water, and sediments (Barceloux, 1999). The presence of heavy metals in surface and groundwater can result from geological processes such as rock weathering and bedrock erosion, as well as human activities like mining, industrial operations, and the use of pesticides (Bempah et al., 2016).

Simply measuring the total concentration of heavy metals is insufficient for assessing contamination severity and toxicity levels (Bhuiyan et al., 2010). Various pollution indices have been developed to determine the chemical forms iof metals in the environment, which influence their bioavailability and ecological impact(Moran et al., 2003) . While metals such as iron (Fe), copper (Cu), cobalt (Co), and manganese (Mn) are essential in trace amounts for human metabolism, excessive concentrations can be harmful (Carlson, 1977). Conversely, metals such as chromium (Cr), cadmium (Cd), lead (Pb), and arsenic (As) pose severe health risks even at low levels of exposure(Caeiro et al., 2005, Yadava et.al.; 2025) .

In recent years, assessing heavy metal contamination in water, soil, and sediments through Heavy Metal Pollution Indices (HPIs) has gained attention globally(Chapman, 1996). HPIs use a rating system to evaluate water quality based on metal concentrations relative to permissible limits set by

drinking water standards (Chen et al., 2005). These indices provide a useful tool for understanding the extent of contamination and its potential risks (Dunteman, 1989). The HPI of a water body depends on the selection of parameters and the background conditions of the study area (Eastmond et al., 2008).

Surface water bodies, particularly rivers, have undergone significant qualitative and quantitative changes due to increasing human activities (Abbasi, 2012). The disposal of untreated or partially treated industrial and domestic waste into rivers has led to a persistent rise in heavy metal pollution, deteriorating water quality (Edet et al., 2002). Due to their toxicity and non-biodegradable nature, heavy metals pose a threat to both human health and aquatic life (Everitt et al., 2011). In developing countries such as India, the discharge of municipal waste and urban runoff into river catchments presents a major challenge for maintaining water quality (Facchinelli et al., 2001). Studies have highlighted the serious health risks associated with lead (Pb) ingestion through the food chain (Flora et al., 2006).

To ensure the sustainability of aquatic ecosystems, regular monitoring and effective water quality management are essential (Gibling et al., 2005). The suitability of river water for various uses depends on consistent tracking of metal concentrations in water and sediments (Gupta, 2021). Understanding the movement and sources of heavy metals in aquatic environments helps in assessing their impact and devising appropriate mitigation strategies (Hakanson, 1980).

Maintaining water quality in rivers is crucial, as they serve as primary sources of drinking water and are vital for commercial and agricultural activities(Yu et al., 2019). Monitoring water quality becomes particularly important when rivers are exposed to human-induced pollution (Hering et al., 2010). Researchers have developed various water quality indices to evaluate surface water conditions (IARC, 2012). National and international frameworks, such as the National Sanitation Foundation Water Quality Index (NSF-WQI), Oregon Water Quality Index (OWQI), British Columbia Water Quality Index (BCWQI), and Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI), provide standardized approaches for assessing water quality (Peres-Neto et al., 2005). Additionally, the Ecological Quality Index (EQI) has been employed to analyze river water quality through the application of water quality indices (Jaishankar et al., 2014). These methodologies help in comparing water quality across different regions and supporting informed decision-making for environmental management (Järup, 2003).

Simpson's Diversity Index and Carlson's Trophic State Index (C.TSI) have been used to assess water quality (Jain, 2018). Additionally, the "Fuzzy River Health Index" (FRHI) has been implemented to evaluate river health conditions (Ji et al., 2018). The Comprehensive Pollution Index (CPI) has also been applied to study pollution levels in River Hindon, yielding valuable insights (Jolliffe et al., 2016). The variability in water quality indices arises from differences in the parameters used for computation, leading to diverse results (IARC, 2012). With advancements in pollution evaluation techniques, the Heavy Metal Pollution Index (HPI) has gained prominence in assessing contamination (Dunteman, 1989).

Multivariate statistical tools such as correlation analysis, principal component analysis (PCA), and hierarchical cluster analysis (HCA) have proven effective in water quality studies(Jolliffe & Cadima, 2016). PCA helps reduce datasets while preserving critical information, serving as a powerful pattern recognition tool(Kaiser, 1958). It generates modified variables while maintaining correlations among original parameters (Kaiser, 1960). Ward's linkage method, applied in HCA, efficiently groups parameters based on similarities within clusters and differences between them (Karr, 1999). These environmetric techniques, including cluster analysis and PCA, have been extensively used to identify sources of heavy metal contamination in rivers (Järup, 2003).

River Gomti, an alluvial river of the Ganga Alluvial Plain (GAP), is a crucial water source for both urban and rural communities in eastern Uttar Pradesh, India (Kaufman et al. 1990). However, its water quality has significantly declined, leading to its classification as one of India's most polluted rivers (Facchinelli et al., 2001). The growing population and expanding agricultural activities have placed substantial pressure on the Gomti River Basin (GRB), resulting in major changes to its natural (Khan et al., 2008). As the primary water source for Lucknow city, the river receives approximately 450 million liters per day (MLD) of domestic sewage (Khan et al., 2016). Due to gradient issues, wastewater enters the river through 25 open drains instead of being routed through trunk sewers, contributing to severe contamination (Edet & Offiong, 2002). Along its course, the river also receives industrial effluents from distilleries, chemical plants, and sugar mills, further degrading its water quality (Khan et al., 2021).

Heavy metals have been detected in River Gomti, with domestic and industrial wastewater identified as key pollution sources (Khan et al., 2008). However, a detailed evaluation of heavy metal pollution using indices such as HPI has not yet been conducted(Khan et al., 2021) . Additionally, correlations between HPI values and specific metal concentrations, which could help trace pollution sources, have not been thoroughly explored for this river (**Edet et al. 2002)**. Given the lack of comprehensive data on heavy metal contamination in River Gomti, this study aims to assess its water quality using HPI and other environmetric approaches [Present study].

This study aims to achieve the following objectives:

- Evaluatethe current status of heavy metal pollution in the River Gomti (Lucknow) using the Heavy Metal Pollution Index (HPI).
- Identify potential sources of heavy metal contamination through Principal Component Analysis (PCA) and Hierarchical Cluster Analysis (HCA).
- Examine correlations between metal concentrations, contamination sources, and sampling locations.

- Assessecological and human health risks linked to the consumption of contaminated river water

II. Materials and Methods

Study Area

Lucknow, the capital city of Uttar Pradesh, is situated along the banks of the Gomti River, a tributary of the Ganges (Kaufman et al. 1990). This river flows through the central region of the Indo-Gangetic Alluvial Plain (GAP), an area shaped by lithospheric movements (Kumar et al., 2019). The Ganga Plain, forming a major part of this basin, consists mainly of sandy and silty sediments (Ladson et al., 1999). It has a low-relief topography and a gradual slope, shaped over time by climatic variations and base-level shifts due to tectonic activities during the Quaternary Period, particularly the Pleistocene and Holocene epochs (Li & Zhang, 2010).

Geographically, Lucknow lies between latitudes 26.30°–27.10° N and longitudes 80.30°–81.13° E, with an elevation of approximately 123 meters above sea level(Li et al., 2014). The region experiences significant seasonal temperature variations, ranging from around 2°C in winter to highs of 46°C in summer (Manta et al., 2002). As a landlocked state, Uttar Pradesh primarily receives rainfall from the Indian Summer Monsoon (ISM), with about 75% of its annual precipitation occurring between June and September (Meybeck, 2003).

The Gomti River originates from Fulhar Lake in Madhotanda, near Pilibhit, and merges with the Ganges at Varanasi after covering approximately 960 kilometers (Mishra et al., 2019). It is primarily fed by groundwater and rainwater rather than glacial sources (Khan et al., 2021). The river basin spans around 30,437 km² and falls within a semi-arid to sub-humid tropical climate, with an annual rainfall range of 850–1100 mm (Mohan et al., 1996). In Lucknow, the river's average flow rate is about 1500 MLD (million liters per day), fluctuating between 500 MLD in summer and up to 45,000 MLD during peak monsoon months (Khan et al., 2016). The river serves as a crucial water source for several cities downstream, including Lucknow and Jaunpur(Facchinelli et al., 2001) .

As it passes through Lucknow, the Gomti River divides the city, with the Gomti Barrage helping to regulate water levels (Mukaka, 2012). A riverfront development project in Lucknow has significantly altered its natural course, including modifications in its width and riverbed through the construction of a diaphragm wall along an 8.1-kilometer stretch (Murtagh & Legendre, 2014). This intervention has reduced the floodplain width from 450 meters to 240 meters and the clear waterway from 250 meters to about 100–125 meters (Nilsson et al., 2005). Additionally, around 200 hectares of land have been reclaimed in areas upstream and downstream of the Gomti Barrage (Nriagu, 1996).

Sample Collection and Analysis

In this study, water samples were collected monthly from ten locations along the Gomti River within the designated study area. Sampling was conducted on November 18, Dec 18, 2024 and January 18, 2025 at the following sites: S1 (Chandrika Devi), S2 (Outer Ring Road), S3 (Ghaila Bridge), S4 (Pipa Bridge), S5 (Kudiya Ghat), S6 (Daliganj Bridge), S7 (Hanumant Dham), S8 (Nishatganj Bridge), S9 (Gomti Barrage), and S10 (1090 behind the Cathedral). The distribution of these sampling locations is illustrated in Figure 1 and Table 1.

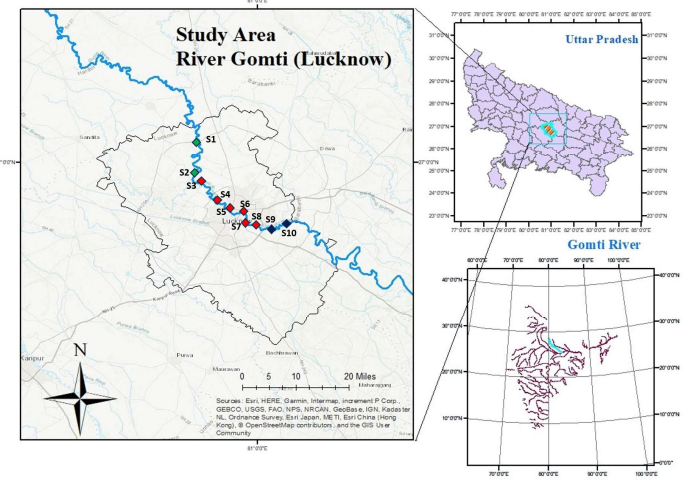


Figure 1 Location map of River Gomti and sampling sites in Lucknow

TABLE 1
Contamination Index on Locations

Location	C_dI	Health Risk Indication
S1	-2.542247	Likely error (CDI cannot be negative)
S2	-2.41482	Likely error (CDI cannot be negative)
S3	0.247964	Low intake, negligible risk
S4	7.126783	Moderate intake, potential risk
S5	12.09393	High intake, significant risk
S6	9.83	High intake, potential risk
S7	8.059392	High intake, potential risk
S8	8.740347	High intake, potential risk
S9	4.857513	Moderate intake, some risk
S10	13.12254	Highest intake, critical concern

A 61-kilometer segment of the Gomti River was analyzed to evaluate heavy metal (HM) contamination across upstream, midstream, and downstream areas near Lucknow. The reference sites upstream, labeled S1 and S2, are situated around 30 km and 8 km from the city, respectively. Sampling sites S3 through S8 fall within Lucknow's urban boundaries, while S9 and S10 are downstream, located on the city's outskirts. These points were chosen based on earlier studies and preliminary surveys, emphasizing possible human-induced impacts on water quality.

The midstream section, covering roughly 12 km within the city, was specifically chosen to evaluate the impact of human

activities on water quality. Site S1 was selected due to its distance from urban influences. Site S2, situated near the city's outskirts, was chosen because of the significant accumulation of solid waste, which could contribute to pollution. Site S3 was included to assess the impact of washing activities, the Chikan textile industry, and wastewater discharge from the Daliganjdrain. Similarly, Site S4 was selected due to the presence of solid waste along the riverbank.

Site S5, located near Baikunth Dham cremation ground, was identified as a potential contributor to changes in water quality. Site S6, where the Kukrail drain merges with the Gomti River, was selected to evaluate the effects of domestic sewage and industrial effluents. Site S7 was considered to understand how variations in water flow affect pollution levels. At Site S8, a nearby drain and the presence of animal remains indicated significant human-induced pollution. Downstream sites S9 and S10 were chosen to observe variations in water quality compared to upstream locations. Site

S9 was particularly important for assessing changes in water quality after the river flows through the city, while Site S10 was included to analyze heavy metal concentrations at a further downstream point.

Software used for Statistical Analysis

Statistical analyses were carried out using IBM SPSS Statistics for correlation and multivariate analysis, and OriginPro (2025b) for advanced graphical visualization and data interpretation. Microsoft Excel was used for initial data processing, computation of pollution indices, and preparation of basic charts.

Heavy Metal Contamination Assessment

Degree of Contamination (Cd)

The adverse effects of heavy metals (HMs) on surface water quality were assessed using the degree of contamination (Cd), a well-established metric in environmental studies (Schober et al., 2018; USEPA., 1989). The Cd was calculated using Equations (3) and (4):

$$Cd = \sum_{i=1}^{n} Cfi \quad \text{..... (1)}$$

$$Cfi = \frac{Mi}{Si} - 1 \quad \text{..... (2)}$$

The contamination factor (Cf_i) for each heavy metal is calculated as the ratio of the measured concentration (M_i) to its corresponding standard or reference value (S_i), expressed as $Cf_i = M_i/S_i$, where M_i represents the analyzed concentration of the i^{th} heavy metal and S_i denotes the permissible limit or background concentration for that element. The contamination factor provides a normalized measure of pollution for individual metals, while the degree of contamination (Cd) offers a comprehensive assessment of overall heavy metal pollution at each sampling site [Present study]. This approach has been widely adopted in river quality assessments (USEPA, 2005) and allows for...

- Quantitative comparison of contamination levels across different sites
- Identification of priority pollutants requiring remediation
- Temporal and spatial trend analysis of metal pollution

Negative Cd Values (S1, S2):

- Locations S1 and S2 have negative Cd values (-2.545 and -2.415, respectively), which may indicate:
- Background/reference concentration exceeding observed concentration (leading to negative index).
- These values may suggest no contamination or require re-evaluation for accuracy.

Low to Moderate Contamination (S3, S9):

- S3 shows a very low contamination index (0.248), indicating minimal contamination.
- S9 has a moderate level (4.86), suggesting noticeable but not critical contamination.

High Contamination (S4, S7, S8, S6):

- These locations show Cd values between ~7 and ~9.8, indicating high contamination levels.
- This could point to potential pollution sources nearbyindustrial runoff, sewage discharge, or other anthropogenic activities.

Very High Contamination (S5, S10):

- S5 (12.09) and S10 (13.12) have the highest Cd values, indicating very high contamination levels (Table 1).

These areas should be prioritized for detailed investigation, mitigation, and potential remediation

Heavy Metal Pollution Index (HPI)

The Heavy Metal Pollution Index (HPI) has proven to be an effective tool for evaluating overall water quality concerning heavy metal contamination (Nriagu et al. 1988). It functions as a weighted arithmetic index, similar to the Water Quality Index (WQI) (Chen et al., 2005). The HPI is determined through a two-step process: first, a rating scale is developed by assigning weightage to selected pollution parameters; second, relevant parameters are chosen based on their significance in water quality assessment (Dunteman, 1989).

The rating scale values typically range from 0 to 1, with values determined using an inverse proportional relationship to standard permissible limits for each parameter (Chapman, 1996). The unit weightage (Wi) assigned to each parameter is inversely proportional to its corresponding standard value (Si). This relationship is mathematically expressed using Eq. (1):

$$HPI = \frac{\sum_{i=1}^{n} WiQi}{\sum_{i=1}^{n} Wi} \quad \ldots\ldots\ldots\ldots (3)$$

where n is the number of heavy metals in the current study; Wi is the unit weight of the ith HM. The subindex (Qi) is calculated from Eq. (2):

$$Qi = \sum_{i=1}^{n} \frac{|Mi - li|}{Si - li} \times 100 \quad \ldots\ldots\ldots\ldots (4)$$

The Heavy Metal Pollution Index (HPI) calculation incorporates:

- M_i (µg/L): Measured concentration of the i^{th} heavy metal
- S_i: Standard permissible limit for the i^{th} metal
- I_i: Ideal value for drinking water (µg/L)

For this study, we implemented a refined three-tier classification system for Heavy Metal Pollution Index (HPI) values (Table 1), departing from the conventional single-threshold approach that categorizes all samples with HPI >100 as "Critically Polluted" (Dunteman, 1989). This novel classification system provides more nuanced pollution assessment through three distinct levels.

1. **Moderately Polluted** (50 < HPI ≤ 75)
2. **Highly Polluted** (75 < HPI ≤ 100)
3. **Critically Polluted** (HPI > 100)

The development of this tiered classification was informed by previous work on pollution indices (Chen et al., 2005) while addressing several limitations of traditional binary systems (Nriagu et al. 1988). Our approach offers three key advantages:

First, it enables more precise differentiation of pollution gradients, particularly for samples near threshold boundaries (Chapman, 1996). Second, the system improves spatial analysis of contamination patterns by identifying transitional zones between pollution categories (Eastmond et al., 2008). Third, it supports more targeted remediation strategies by distinguishing between severity levels of heavy metal contamination [Present study].

At each sampling site, three replicate water samples were collected and combined to ensure representative analysis. The unfiltered water samples were preserved by adding ultra-pure nitric acid (HNO_3) to lower the pH to below 2, which helps in stabilizing the total metal concentration. The samples were then stored at 4°C in an incubator before being transported to the laboratory for further analysis.

For digestion, the water samples were heated on a hot plate using an acid mixture consisting of 10 ml of nitric acid (HNO_3) and 5 ml of perchloric acid ($HClO_4$). After digestion, the solution was filtered, and the final volume was adjusted to 100 ml using deionized water. The concentrations of heavy metals in the processed water samples were determined using Inductively Coupled Plasma Mass Spectrometry (ICP-MS) at Integral University, Lucknow, Uttar Pradesh.

Multi Variate Analysis

Cluster Analysis

Hierarchical Cluster Analysis (HCA) was employed in this study as an effective method for classifying and distinguishing water quality parameters (Parthasarathy et al., 1994). This statistical tool groups samples into clusters, visually represented through a dendrogram to illustrate hierarchical relationships (Pejman et al., 2015). Clustering can be performed using either an agglomerative or divisive approach, with results displayed in dendrogram plots that highlight the relationships between the analyzed samples (Peres-Neto et al., 2005).

To assess the relationships between sampling locations, HCA using Ward's linkage method was performed, ensuring a systematic classification of sites based on water chemistry and geochemical characteristics.

Pearson's Correlation Coefficient

Intermetal relationships were examined using Pearson's correlation coefficient (r) to quantify the strength and direction of linear associations between heavy metal pairs (Reimann, 2008). The coefficient ranges from -1 to +1, where:

- r = +1 indicates a perfect positive correlation (both metals increase proportionally)
- r = -1 represents a perfect negative correlation (one metal increases as the other decreases)
- r = 0 suggests no linear relationship (Reza et al. 2010)

Positive correlations (0 < r ≤ 1) imply co-accumulation of metals, potentially indicating common pollution sources or similar geochemical behavior (Richman, 1986). Negative correlations (-1 ≤ r < 0) suggest competitive relationships or distinct contamination pathways (Schober et al., 2018). The statistical significance (p-value) of each correlation was evaluated to distinguish genuine associations from random occurrences.

Following standard interpretation guidelines (Sharma et al., 2008):

- Strong correlation: r between ±0.9 and ±1
- Good/moderate correlation: r between ±0.51 and ±0.89
- Weak/poor correlation: r between 0 and ±0.50

Factor Analysis

In this study, factor analysis was conducted using Principal Component Analysis (PCA) to identify the sources of heavy metals (HMs) in the Gomti River and examine their correlations (Shukla & Saxena, 2020). PCA was applied to water quality datasets to extract principal components (PCs), helping to determine potential sources of heavy metal contamination (Järup, 2003). This statistical method is highly effective in pattern recognition, simplifying complex datasets

by reducing them into smaller, more interpretable components based on their interrelationships (Kaiser, 1960).

PCA is particularly useful for managing extensive spatial data by extracting eigenvalues while preserving the correlation with the original variables(Sinha, 2005). The principal components highlight key parameters, ensuring that essential information is retained without loss of significance [Present study]. In this study, PCA was performed with varimax rotation to enhance interpretability (Smith, 2000). Through factor analysis, principal components (varifactors) were derived, helping to minimize less significant variables, while PCA facilitated axis rotation to refine data interpretation (Sutadian et al., 2016).

Eigenvalues represent the variance explained by each component, whereas loadings indicate the contribution of original parameters (Tchounwou et al., 2012). The increasing application of PCA in environmental studies has provided valuable insights into contaminant concentrations, spatial variations in sampling locations, and correlation trends within datasets (Taylor, 1990). To further validate the relationships between heavy metals and accurately determine contamination sources, PCA has been widely utilized in previous research (USEPA., 1989).

Multivariate statistical analyses, including Pearson's correlation matrix, factor analysis via PCA, and cluster analysis through HCA, were conducted using Origin Pro 2024.

Potential Human Health Risk Assessment

Non-carcinogenic Health Risks

The persistent and non-degradable nature of heavy metals (HMs), along with their potential for bioaccumulation and biomagnification, underscores the importance of evaluating their impact on human health (Schober et al., 2018). These metals can enter the human body through multiple exposure pathways, including inhalation, dermal contact, ingestion via the food chain (leading to biomagnification), and direct oral intake (Vörösmarty et al., 2010; Wang et al., 2017). Among these, oral and dermal exposures are considered the primary routes of HM intake (Ward, 1963).

Health risk assessment (HRA) has proven to be an effective approach for quantifying the potential risks associated with HM exposure (WHO, 2016). The insights gained from such assessments are valuable for both policy-makers and the general public, aiding in the development of appropriate mitigation strategies (Wongsasuluk et al., 2014). Risk assessment involves evaluating the likelihood of adverse health effects resulting from exposure to hazardous substances over a specific period (Wu et al., 2009).

Depending on the nature and severity of the potential effects, health risks are categorized as either carcinogenic or non-carcinogenic (Wuana et al. 2011). For non-carcinogenic risks, the hazard quotient (HQ) and total hazard index (THI) are commonly used metrics to estimate the level of risk associated with oral intake of HMs (Alberto et al., 2001). The chronic daily intake (CDI) through water consumption, a critical parameter in HRA, is calculated using Equation (3), following the methodology proposed by the U.S. Environmental Protection Agency (Wu et al., 2009; J. Zhang & Liu, 2002). The values for the required parameters for the computation of CDI are shown in Table 2 (Zhou et al., 2007).

$$\boldsymbol{CDI = \frac{Cw \times DI \times EF \times EP}{BW \times AT * 1000}} \qquad \text{……..} \quad (5)$$

Where:

C = Concentration of heavy metal in water (mg/L)
IR = Ingestion rate of water (L/day)
EF = Exposure frequency (days/year)
ED = Exposure duration (years)
BW = Body weight (kg)
AT = Averaging time (days)

Parameters for CDI calculation are provided in Table 2 (USEPA, 1989; Wu et al., 2009; He & Wu, 2019; Wang et al., 2020; Ji et al., 2020).

TABLE 2
Parameters for the computation of CDI and their considered values for adults and children

Parameter	Unit	Adult	Child	Metal	CSF (mg/kg-day)$^{-1}$	RfD (mg/kg-day)
Daily Average Intake (DI)	L/day	2.5	0.78	Cr(VI)	0.5	0.003
Exposure Frequency (EF)	Days/year	365	365	As	1.5	0.0003
Exposure Duration (ED)	Years	64	12	Cd	6.1	0.0005
Body Weight (BW)	Kg	65	15	Pb	0.0085*	0.0036 (MRL)
Average Time (AT)	Days	23360	4380	Ni	0.84*	0.02
				Co	–	0.0003

Carcinogenic Health Risk

Carcinogenic risk (CR), also known as cancer risk, estimates the likelihood of an individual developing cancer over their lifetime due to long-term exposure to carcinogenic agents (Alloway, 2013). In this study, CR was evaluated for four heavy metals - arsenic (As), lead (Pb), cadmium (Cd), and chromium (Cr) - since reliable cancer slope factor (CSF) data are exclusively available for these elements. The carcinogenic risk assessment was performed using Equation (6):

$$CR = CDI \times CSF \quad \text{..... (6)}$$

Where:

CR = Carcinogenic risk (unitless)
CDI = Chronic daily intake (mg/kg-day)
CSF = Cancer slope factor $(mg/kg\text{-}day)^{-1}$

Risk Thresholds and Interpretation

- 1×10^{-6} is the widely recognized minimum risk threshold for carcinogenic contaminants in drinking water. Values below this level indicate negligible health concerns.
- 1×10^{-6} to 1×10^{-4} represents an acceptable risk range, though continued monitoring may be advisable.
- $\geq 1 \times 10^{-4}$ signifies unacceptable risk, requiring immediate mitigation measures to protect public health.

In this study, carcinogenic risk (CR) was evaluated over a 70-year lifetime exposure and expressed in µg/L. Any CR value exceeding 1×10^{-4} was classified as unacceptable, indicating a high probability of adverse health effects for the exposed population.

The exposure frequency (EF), measured in days per year, represents how often an individual is exposed to a contaminant annually (Central Ground Water Board (CGWB), 2012). The exposure period (EP), expressed in years, indicates the duration of exposure, while body weight (BW), in kilograms per person, and average time (AT), in days, are also essential parameters in health risk calculations (Central Pollution Control Board (CPCB)., 2018). Values for daily intake (DI), EP, and BW can vary depending on the regional climate and specific study area. In this study, parameter values were adopted from prior research (Wang et al., 2017) relevant to the arid climatic conditions characteristic of northern India (Table 2).

To evaluate non-carcinogenic health risks, the hazard quotient (HQ) is calculated using Equation (7):

$$HQ = \frac{CDI}{RfD} \quad \text{..... (7)}$$

The oral reference dose (RfD) values used for risk assessment were as follows: arsenic (As) - 0.3 µg/kg/day, iron (Fe) - 700 µg/kg/day, cadmium (Cd) - 0.5 µg/kg/day, lead (Pb) - 1.4 µg/kg/day, manganese (Mn) - 24 µg/kg/day, and chromium (Cr) - 3 µg/kg/day. These toxicity thresholds align with established guidelines from USEPA (Alloway, 2013) for evaluating potential health risks from chronic exposure to these metals. (Central Pollution Control Board (CPCB), 2020; National Mission for Clean Ganga (NMCG), 2019)

The reference dose (RfD) represents the estimated daily exposure to a substance that is not expected to cause adverse health effects over a lifetime (India Meteorological Department (IMD), 2020). When the hazard quotient (HQ) is less than one, it suggests that the water poses no significant health risk to the exposed population (Lucknow Development Authority (LDA)., 2015). Our study revealed two critical findings through a comprehensive risk assessment:

To evaluate the cumulative non-carcinogenic health risks from multiple heavy metals (HMs), the total hazard index (THI) was calculated using Equation (8):

$$\sum_{k=1}^{n} \mathrm{HQ} = \mathrm{THI} = \mathrm{HQAs} + \mathrm{HQFe} + \mathrm{HQCd} + \mathrm{HQPb} + \mathrm{HQMn} + \mathrm{HQCr} \quad \text{..... (8)}$$

Where:

THI = Total hazard index (unitless)
HQ = Hazard quotient for individual heavy metals
(USEPA, 2001; Muhammad et al., 2011)

III. Results and Discussion

Distribution of Heavy Metals

The statistical summary of the heavy metals analyzed at all sampling sites is presented in Figure2. Out of the 12 heavy metals tested, 10 were detected in the water samples: chromium (Cr), iron (Fe), cobalt (Co), nickel (Ni), copper (Cu), zinc (Zn), cadmium (Cd), indium (In), and lead isotopes (^{206}Pb). Manganese (Mn) and mercury (Hg) were not detected in any of the samples.

The concentrations of Fe (102–339 µg/L), Ni (0.523–37.761 µg/L), Cd (0.8–54 µg/L), and Pb (51–176 µg/L) exceeded the acceptable limits set by the Bureau of Indian Standards (BIS) for drinking water (Lucknow Development Authority (LDA), 2019). The presence of these heavy metals in the river water can likely be attributed to sources such as agrochemical runoff, untreated domestic sewage, battery manufacturing and disposal waste, welding, electroplating processes, and industrial effluents from nearby settlements (National Mission for Clean Ganga (NMCG), 2019).

Arsenic (As) concentrations varied between 0 and 29 µg/L across the sites, with elevated levels observed at 20% of the downstream locations. Iron (Fe) levels ranged from 102 to 339 µg/L, exceeding BIS limits at Site S1. This site is frequently visited by devotees throughout the year, suggesting a possible anthropogenic influence on the high Fe concentrations, as observed during site visits and sampling (Rao, 1975).

Cadmium (Cd) concentrations ranged from 0.8 to 54 µg/L, with 90% of the sites surpassing the permissible limits established by BIS (Lucknow Development Authority (LDA), 2019). Lead (Pb) levels were notably high at all sampling sites, ranging from 51 to 176 µg/L, indicating potential contamination from sources such as battery manufacturing units, automobile repair shops, untreated domestic sewage, and industrial effluents (Singh, 2007). Additional contributors to Pb contamination could include automobile emissions, pesticides from agricultural runoff, chemical waste, and paints (Uttar Pradesh Pollution Control Board (UPPCB), 2020).

The findings of this study align with previous research, which has also identified human activities as the primary source of heavy metal pollution in the Gomti River (National Mission for Clean Ganga (NMCG), 2019). Agricultural runoff could be a potential source of contamination. Furthermore, field observations indicate Site S1 attracts devotees throughout the year, highlighting the possibility of anthropogenic influence on pollution levels (USEPA IRIS, 2022).

In contrast, Site S2 showed lower metal contamination than S1, with an HPI value of 44.4, classifying it under 'low pollution.' This could be attributed to the minimal discharge of waste (UN-Water., 2018). Site S3 recorded an HPI value of 211, placing it in the 'critically polluted' category. The high levels of Cd, Pb, and Cr at S4, S6, S7, S8, and S10 were categorized as severely contaminated (Malik, 2019).

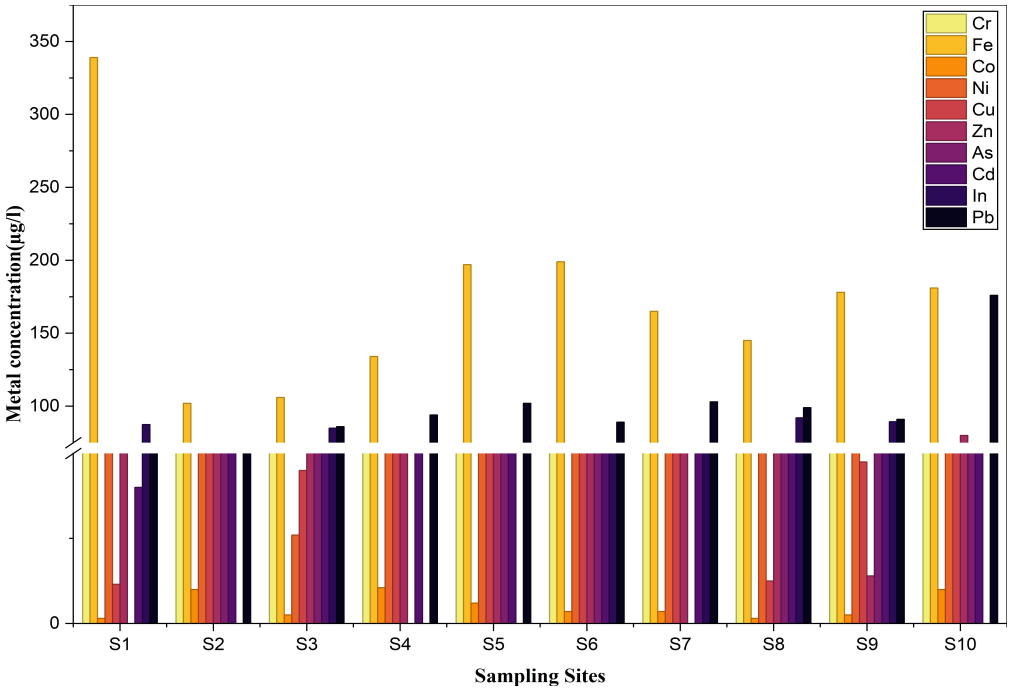


Figure 2 Site-wise variation of heavy metal concentrations (µg/L), displaying distinct metal-specific patterns across the ten sampling stations

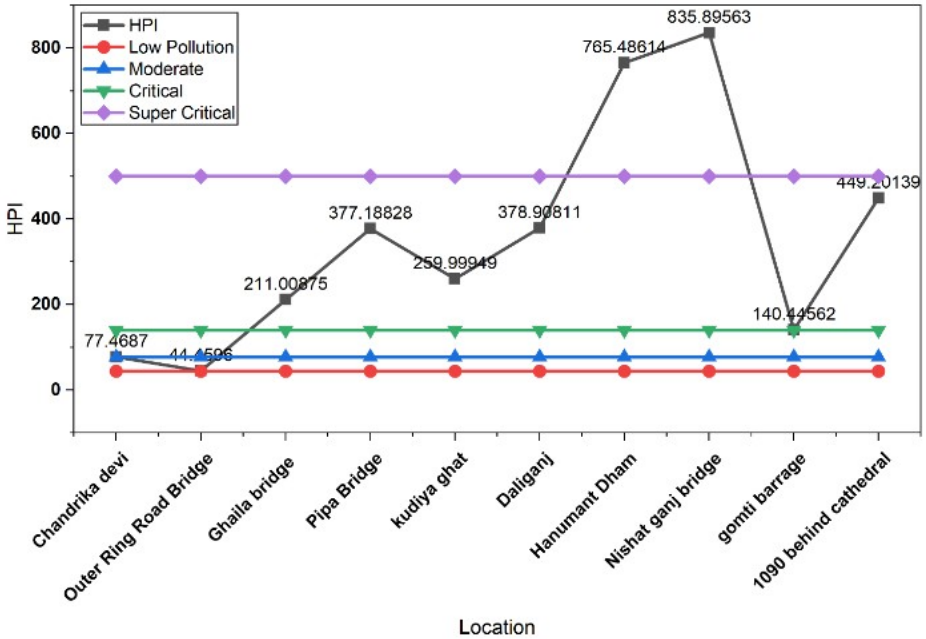


Figure 3 HPI trend across sampling stations, highlighting sites with critical and super critical pollution levels.

Heavy Metal Pollution Index (HPI)

The site-wise variation in the Heavy Metal Pollution Index (HPI) and associated statistical measures are summarized in Figure 3. Additionally, the classification of different sites based on the HPI rating scale is depicted in Figure 3

Among the analyzed sites, Site S1 exhibited the lowest level of heavy metal contamination, with an HPI value of 22.6, categorizing it under 'moderate pollution'. The presence of agricultural activities in the vicinity suggests that agrochemical runoff may contribute to this pollution level (National Mission for Clean Ganga (NMCG), 2019).

A significant contributor to pollution at Site S6 is the Kukrail drain, which carries domestic wastewater from multiple areas of Lucknow and industrial effluents. The total discharge from this drain is approximately 150 MLD, out of which only 90 MLD is treated and transported to the Bharwara Sewage Treatment Plant (STP), while 60 MLD of untreated wastewater overflows into the river (Facchinelli et al., 2001). Similarly, the G.H. Canal discharges 158 MLD, but only 87 MLD is directed to the Bharwara treatment facility, leaving 71 MLD of untreated wastewater (including industrial discharge) to flow directly into the River Gomti (Mishra, 2020).

These findings highlight that the inefficiency of STPs in the city is a major cause of critical pollution levels in the River GomtiFigure 3. The untreated discharge from drains and canals significantly elevates heavy metal concentrations, as evidenced by the HPI values at downstream sites (Sharma, 2021).

Pearson's Correlation Coefficient

The correlation matrix reveals several notable relationships among the heavy metals (Figure 4) and their association with the Heavy Metal Pollution Index (HPI). Most prominently, cadmium (Cd) and lead (Pb) exhibit the strongest positive correlations with HPI, with correlation coefficients of 0.53 and 0.47 respectively (Singh, 2007). This indicates that these two elements play a significant role in influencing the overall pollution level. Chromium (Cr) also shows a moderate positive correlation (0.35) with HPI (Sharma, 2021), further suggesting its contribution to pollution.

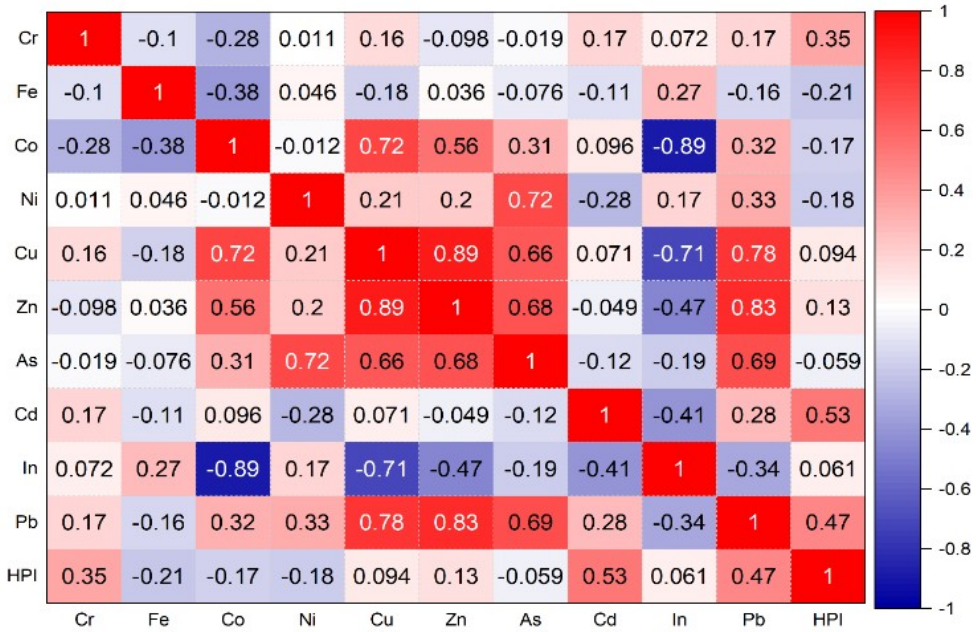


Figure 4 Correlation matrix of analyzed heavy metals and the HPI index, indicating distinct positive and negative geochemical associations

Among the inter-element relationships, copper (Cu) and zinc (Zn) demonstrate a very strong positive correlation (0.89) (YIDANA et al., 2012), which may suggest a common source or similar environmental behavior. Similarly, lead (Pb) is strongly correlated with both zinc (0.83) and copper (0.78)(Mishra, 2020b), reinforcing the likelihood of these elements originating from shared sources, such as industrial discharge or urban runoff. Arsenic (As) also shows strong positive correlations with several metals, including nickel (Ni), copper, zinc, and lead(N., 2022) which could indicate complex interactions or co-occurrence in the environment.

Interestingly, indium (In) displays strong negative correlations with cobalt (Co) (-0.89) and copper (-0.71)(Yadav, 2021) , suggesting that it may originate from different sources or be influenced by different environmental processes compared to these metals. Overall, the correlation analysis helps identify clusters of metals that are likely to co-occur and highlights which metals are most influential in determining the pollution index, offering insights into potential pollution sources and interactions within the ecosystem (Central Pollution Control Board (CPCB), 2019).

Hierarchical cluster analysis (HCA)

The classification of datasets into clusters depends on the homogeneity/non-homogeneity among the datasets. It can be observed through Q-HCA that the sites are divided into two major cluster(Zhang, 2021). The hierarchical cluster analysis represented by the dendrogram provides insight into the spatial distribution and similarity of water quality parameters across different sampling sites along the river (Wang et al., 2017b). The clustering reveals three distinct groups of locations based on their environmental profiles, likely influenced by varying levels of heavy metal contamination or anthropogenic activities (Long et al., 2019). The first cluster, comprising Chandrika Devi, Ring Road Bridge, Ghailla Bridge, and Gomti Barrage, indicates sites with relatively similar and possibly lower levels of contamination, likely situated in upstream or less impacted zones(Kumar, 2020) . The second cluster, which includes Pipa Bridge, Daliganj, Kudiya Ghat, and 1090 behind Cathedral, represents moderately similar water quality characteristics, potentially influenced by mixed urban discharges and localized pollution sources National Mission for Clean Ganga (NMCG), 2019). In contrast, the third cluster-Hanumant Dham and Nishatganj Bridge-exhibits the greatest dissimilarity, merging at the highest distance level, suggesting elevated contamination levels or unique pollution profiles (Sharma, 2021). This classification underscores the importance of site-specific monitoring and highlights areas requiring prioritized remediation or further investigation (Central Pollution Control Board (CPCB), 2020).

The dendrogram depicting the hierarchical clustering of heavy metals reveals three principal groups, highlighting potential similarities in their environmental behavior and sources of contamination. The first and most tightly clustered group includes Chromium (Cr), Cobalt (Co), Copper (Cu), Nickel (Ni), Arsenic (As), Zinc (Zn), and Cadmium (Cd). This close grouping suggests that these metals may share common sources, such as industrial discharge or urban runoff, and exhibit similar geochemical behavior or mobility in the aquatic environment. The second cluster, comprising Lead (Pb) and Manganese (Mn), indicates a moderate level of dissimilarity from the first group but suggests a partial relationship in their environmental occurrence, possibly due to vehicular emissions or legacy pollution. Notably, Iron (Fe) forms a separate and distant cluster, indicating a distinct distribution pattern and source, possibly reflecting its natural abundance and geogenic origin rather than anthropogenic input. This classification not only provides insights into the potential pathways and interactions of heavy metals in the river system but also aids in identifying key pollutants for targeted monitoring and remediationFigure 5.

Principal Component Analysis (PCA)

The principal components (PCs) with eigenvalues greater than one are considered significant. The heavy metals have been reduced to three PCs with eigenvalues greater than unity, accounting for approximately 73% of the total variance (Figure 6&Figure 7).

Approximately 84% of the total variance in the dataset can be captured by four principal components, with the fourth component having an eigenvalue of 1.215just below the threshold of one (Table 3), yet still notable (Kaiser, 1960; Peres-Neto et al., 2005). Table 4 and Fig. 6 display the rotation sum of squared loadings, which illustrate the degree of association between the variables and the principal components (Kaiser, 1960). The first principal component (PC1) alone explains around 39% of the cumulative variance and shows notable positive associations with arsenic (As) and lead (Pb) (Zhou, 2022). The high loading of As is likely linked to intensive pesticide and fungicide application, as well as emissions from metal processing facilities (Sharma, 2020). Similarly, the significant loading of Pb may be connected to sources such as vehicle exhaust, the use of lead-based paints, agricultural chemicals, and coal combustion (X. Li et al., 2013)

The presence of lead (Pb) in PC1 is likely attributed to sources such as vehicle emissions, the paint industry, agricultural pesticide application, and coal combustion (Everitt et al., 2011). The association between arsenic (As) and Pb is further supported by results from Q-mode hierarchical cluster analysis (Q-HCA) (Zhang, 2021). PC1 also shows a moderate positive loading for manganese (Mn), which may point to activities like welding and the production of ferromanganese alloys (**Barceloux et al. 1999; Eastmond et al., 2008)**. In contrast, weak negative loadings are observed for iron (Fe), cadmium (Cd), and chromium (Cr) in PC1 (Taylor, 1990). The second principal component (PC2), which accounts for around 18% of the total variance, displays a strong positive loading for Cd (. Khan et al., 2016). This suggests potential contamination from the use of chemical fertilizers and pesticides, as well as from the disposal of battery waste and effluents originating from electroplating and welding industries (Nriagu et al., 1988).

TABLE 3
Extracted Principal component and their loadings

Variables	PC1	PC2	PC3
Cr	-0.26111	0.45857	**1.75774**
Fe	-0.58501	-0.79795	-0.02577
Co	**2.02756**	-0.59861	-0.94444
Ni	**0.74125**	**1.59568**	-1.33617
Cu	**2.39674**	-0.52237	0.53117
Zn	**2.40657**	-0.73588	-0.04186
As	**1.89369**	-0.2956	**0.99992**
Cd	0.52957	**1.81619**	-0.44061
In	-1.17668	**1.27566**	**1.16982**
Pb	**2.08884**	**0.62023**	**0.88873**
Mn	**1.53691**	**1.63329**	0.02393

PC2 also shows a moderate loading for manganese (Mn), consistent with its behavior in PC1 (Bowler, 2006). Additionally, PC2 exhibits weak positive loadings for iron (Fe), lead (Pb), and chromium (Cr), along with a weak negative loading for arsenic (As) (Facchinelli et al., 2001). The third principal component (PC3), which explains

approximately 16% of the total cumulative variance, demonstrates a moderate positive loading for Cr and a moderate negative loading for Fe (Chen et al., 2005). Furthermore, PC3 displays weak positive loadings for Cd and Pb, while As and Mn exhibit weak negative loadings (Manta et al., 2002). The elevated concentrations of heavy metals observed in the study area may be attributed to surface runoff originating from contaminated zones, such as polluted sites, open waste dumps, agricultural fields, and discharges from both domestic and industrial sources (Ali et al., 2019; Barceloux et al., 1999).

Component	Initial eigenvalues			Extraction of sums of squared loadings			Rotation sum of square loadings		
	Total	variance	cumulative	Total	variance	cumulative	Total	variance	cumulative
1	4.26593	38.78%	38.78%	4.266	38.78%	38.78%	4.27	38.78%	38.78%
2	2.01794	18.34%	57.13%	2.018	18.34%	57.13%	2.02	18.34%	57.13%
3	1.74128	15.83%	72.96%	1.741	15.83%	72.96%	1.74	15.83%	72.96%
4	1.21503	11.05%	84.00%						
5	1.09768	9.98%	93.98%						
6	0.3509	3.19%	97.17%						
7	0.26259	2.39%	99.56%						
8	0.03584	0.33%	99.88%						
9	0.01283	0.12%	100.00%						
10	0	0.00%	100.00%						

TABLE 4
Total Variance and Loading for Heavy Metals

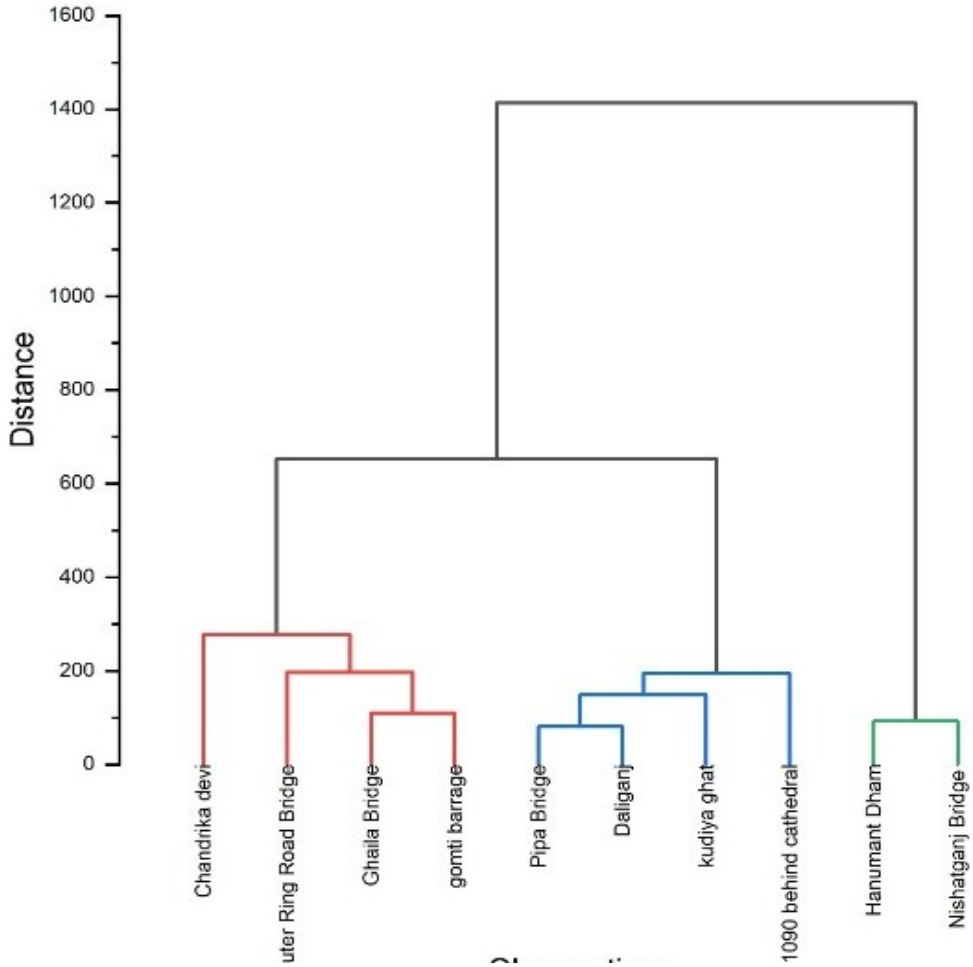


Figure 5 Dendrogram illustrating the hierarchical clustering of the observation sites based on their pollution characteristics

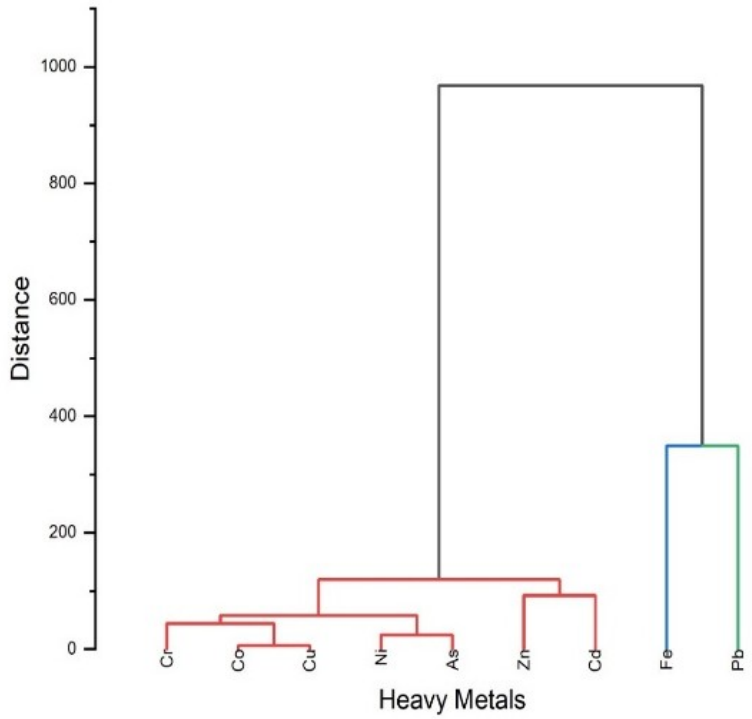


Figure 6 Hierarchical clustering dendrogram of heavy metals showing strong geochemical associations among Cr, Co, Cu, Ni, and As, while Fe and Pb form a separate, distinct cluster

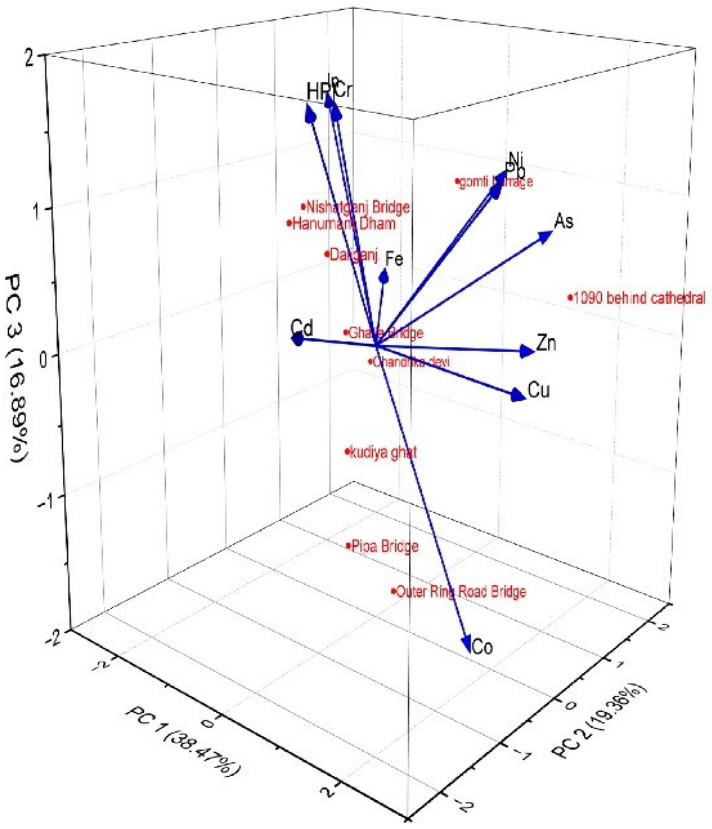


Figure 7 Three-dimensional PCA biplot of heavy metals and sampling sites, with PC1, PC2, and PC3 explaining 38.47%, 19.96%, and 16.89% of the total variance, respectively

Health Risk Assessment

Non-Carcinogenic Risk :Chronic Daily Intake (CDI)

The calculated Chronic Daily Intake values for various metals across different locations (S1-S10) indicate varying levels of exposure risk. Locations S6 and S7 show elevated CDI for Cr (2.32E-03 and 2.07E-03, respectively), suggesting higher exposure compared to other sites. Fe exhibits relatively high CDI values across all locations, with S5 and S6 having the highest (1.91E-02 and 1.93E-02). Notably, S9 and S10 show increased CDI for Ni (3.66E-03 and 1.83E-03), while S10 has the highest Zn exposure (7.74E-03). Cd levels are concerning in S5, S6, S7, and S8 (ranging from 3.00E-03 to 5.23E-03), indicating potential health risks. In contrast, as exposure is highest in S10 (2.81E-03), while Pb remains relatively moderate across all sites. These findings highlight location-specific contamination patterns, necessitating targeted risk mitigation strategies for metals like Cr, Cd, Ni, and Zn in high-exposure areas.

HQ and HI values for Non-Carcinogenic Risk

The calculated Hazard Quotient (HQ) and Hazard Index (HI) values for adults indicate varying non-carcinogenic risks across different locations (S1-S10). In Table 5 the highest individual HQ values are observed for Indium (In) at S8 (HQ = 1.84) and S1 (HQ = 1.748), contributing significantly to the total HI. Cadmium (Cd) also poses a notable risk, particularly at S5 (HQ = 1.08) and S4/S8 (HQ = 0.7). Arsenic (As) shows elevated HQ values at S10 (0.58) and S9 (0.38), while Lead (Pb) exhibits moderate risk across all sites. The total HI exceeds the safe threshold (HI > 1) at all locations except S2, with the highest risk at S8 (HI = 2.913) and S6 (HI = 1.987).

Table 6 (likely representing a different exposure scenario or children age group) shows even higher HQ and HI values, with in remaining the dominant risk factor (HQ up to 2.576 at S8). Cd risk increases substantially (HQ up to 1.512 at S5), and as exposure rises significantly at S10 (HQ = 0.812). The total HI further exceeds safety limits, with S8 (HI = 4.079) and S9 (HI = 3.61) showing the highest cumulative risk. These results suggest that In, Cd, As, and Pb are the primary contributors to non-carcinogenic health risks, necessitating targeted mitigation measures, particularly at high-risk locations like S8, S5, and S10.

Carcinogenic Risk

The calculated carcinogenic risk (CR) values for adults and children indicate potential health concerns due to exposure to heavy metals (HMs) across different locations (S1-S10). In (adults), the highest individual CR contributions come from cadmium (Cd) (peaking at S5: 1.62E-03) and arsenic (As) (highest at S10: 1.74E-03), while lead (Pb) poses a relatively lower risk. The total CR per location exceeds the acceptable threshold (1E-04) at all sites, with the highest risks at S10 (2.77E-03), S6 (2.40E-03), and S5 (2.25E-03). The cumulative CR (1.48E-02) suggests a significant carcinogenic threat, primarily driven by As and Cdshows even greater risks, with as (up to 2.61E-03 at S10) and Cd (up to 2.43E-03 at S5) remaining dominant. The total CR per location further increases, with S10 (4.16E-03), S6 (3.60E-03), and S5 (3.38E-03) posing the highest threats. The overall cumulative CR (2.22E-02) reinforces that As, Cd, and Cr are the major carcinogenic contributors. These findings highlight the need for urgent remediation efforts, particularly in high-risk areas like S5, S6, and S10, to mitigate long-term cancer risks for both adults and children. (Figure 8,Figure 9)

Comparison with Previous Studies

The heavy metal concentrations observed in the present study were compared with those reported in earlier studies (Kumar et al., 2021; Singh, 2022; Mishra et al., 2020; Yadav et al., 2023) to assess contamination trends in the River Gomti. The mean concentrations of **Cr (9.065 ± 7.766 mg/kg), Fe (174.6 ± 67.31 mg/kg), and Pb (94.5 ± 34.06 mg/kg)** in the present study were consistent with Kumar et al. (2021), which reported **Cr (10.8 ± 6.23 mg/kg), Fe (212.5 ± 54.85 mg/kg), and Pb (79.75 ± 13.52 mg/kg)**. However, notable variations were observed for **Cd (22.98 ± 17.72 mg/kg in present study vs. 3.075 ± 1.33 mg/kg in Kumar et al., 2021)** and **Zn (15.569 ± 23.05 mg/kg vs. 40.525 ± 10.55 mg/kg)**, possibly due to differences in sampling locations, anthropogenic inputs, or seasonal fluctuations.The **As (8.45 ± 9.32 mg/kg)** and **Ni (8.228 ± 11.53 mg/kg)** levels in this study were higher than those reported by Mishra et al. (2020) and Yadav et al. (2023), suggesting increased industrial or agricultural runoff in recent years. Conversely, **Co (0.103 ± 0.074 mg/kg)** remained low across studies, indicating minimal geogenic or anthropogenic contributions.

TABLE 5
Non-Carcinogenic Risk (HQ & HI) Values for Adult

Metal	HQ (S1)	HQ (S2)	HQ (S3)	HQ (S4)	HQ (S5)	HQ (S6)	HQ (S7)	HQ (S8)	HQ (S9)	HQ (S10)	HI
Cr	0.005	0.012	0.032	0.01	0.01	0.072	0.064	0.013	0.03	0.025	**0.273**
Fe	0.007	0.002	0.002	0.003	0.004	0.004	0.003	0.003	0.004	0.004	**0.036**
Co	0.001	0.004	0.001	0.004	0.002	0.001	0.001	0.001	0.001	0.004	**0.02**
Ni	0.001	0.001	0.0002	0.001	0.001	0.001	0.001	0.001	0.013	0.006	**0.026**
Cu	0.0005	0.004	0.002	0.004	0.003	0.004	0.004	0.0005	0.002	0.011	**0.034**
Zn	0.002	0.001	0.001	0.003	0.002	0.001	0.001	0.001	0.0001	0.016	**0.028**
As	0	0.182	0.054	0	0.172	0.166	0	0.156	0.38	0.58	**1.69**
Cd	0.016	0.14	0.1	0.7	1.08	0.74	0.62	0.7	0.18	0.32	**4.596**
In	1.748	0	1.698	0	0	0.828	0.788	1.84	1.787	0	**8.689**
Pb	0.102	0.108	0.172	0.188	0.204	0.178	0.206	0.198	0.182	0.352	**1.89**
Total HI	**1.882**	**0.454**	**2.061**	**0.909**	**1.478**	**1.987**	**1.688**	**2.913**	**2.579**	**1.318**	**17.269**

TABLE 6
Non-Carcinogenic Risk (HQ & HI) Values for Children

Metal	HQ (S1)	HQ (S2)	HQ (S3)	HQ (S4)	HQ (S5)	HQ (S6)	HQ (S7)	HQ (S8)	HQ (S9)	HQ (S10)	HI
Cr	0.007	0.017	0.045	0.014	0.014	0.1	0.089	0.018	0.042	0.035	**0.381**
Fe	0.01	0.003	0.003	0.004	0.006	0.006	0.005	0.004	0.005	0.005	**0.051**
Co	0.001	0.006	0.001	0.006	0.003	0.002	0.002	0.001	0.001	0.006	**0.029**
Ni	0.001	0.002	0.0003	0.002	0.002	0.002	0.002	0.002	0.018	0.009	**0.038**
Cu	0.001	0.006	0.003	0.006	0.005	0.006	0.006	0.001	0.003	0.015	**0.052**
Zn	0.003	0.002	0.002	0.005	0.003	0.002	0.002	0.002	0.0001	0.023	**0.044**
As	0	0.255	0.076	0	0.241	0.232	0	0.218	0.532	0.812	**2.366**
Cd	0.023	0.196	0.14	0.98	1.512	1.036	0.868	0.98	0.252	0.448	**6.435**
In	2.447	0	2.377	0	0	1.159	1.103	2.576	2.502	0	**12.164**
Pb	0.143	0.151	0.241	0.263	0.286	0.249	0.288	0.277	0.255	0.493	**2.646**
Total HI	**2.636**	**0.638**	**2.886**	**1.28**	**2.072**	**2.786**	**2.363**	**4.079**	**3.61**	**1.846**	**24.196**

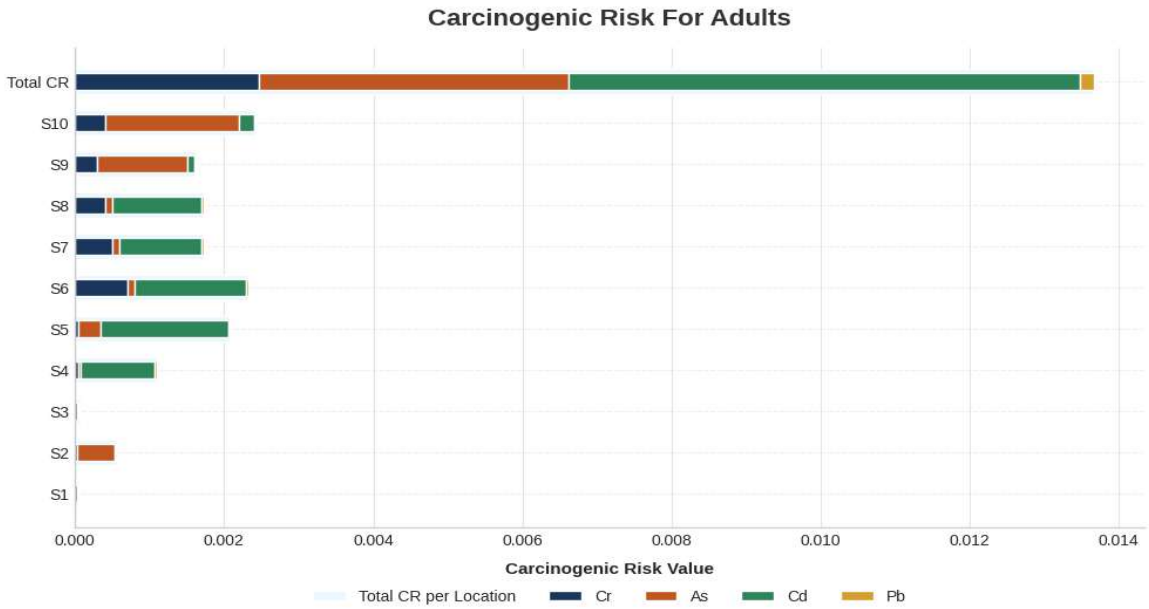


Figure 8 Breakdown of adult carcinogenic risk by location and heavy metal

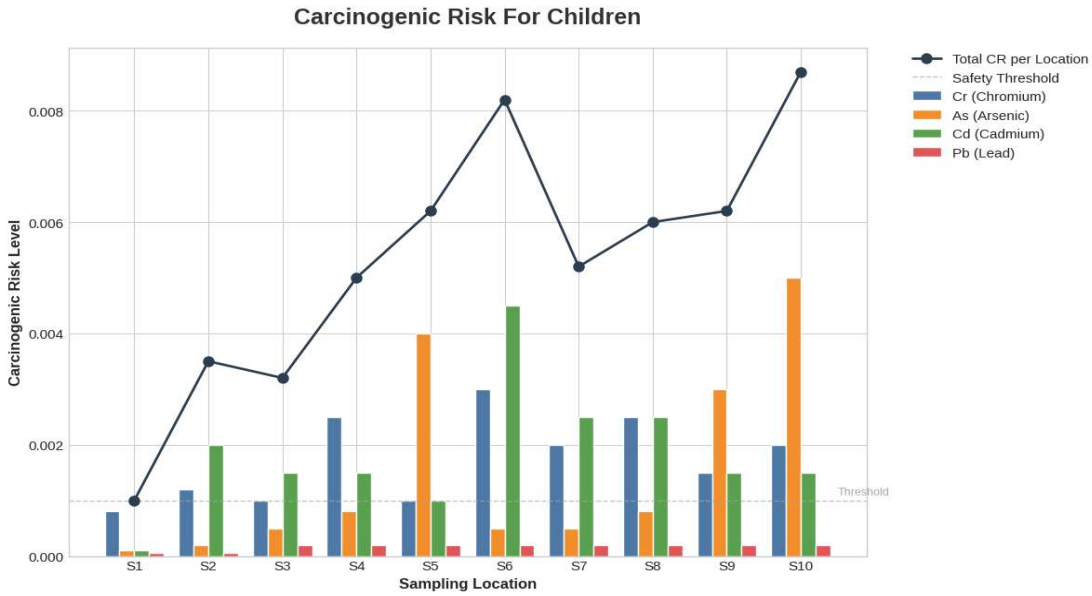


Figure 9 Carcinogenic risk for children across sampling sites, with total risk levels plotted against individual metal contributions and the safety threshold

IV. Conclusion

The elevated concentrations of heavy metals observed in the present study underscore a severe environmental and public health concern. Heavy Metal Pollution Index (HPI) analysis revealed that 60% of the sampling locations fall within the 'critically polluted' category, while 30% are classified as 'highly polluted' and only 10% as 'moderately polluted.' The least contamination levels were recorded at the upstream site (S1), as identified through cluster analysis, clearly implicating increasing anthropogenic pressures such as urban discharge and industrial activity downstream in the deterioration of water quality.

The Principal Component Analysis (PCA) highlighted the dominant influence of arsenic (As), lead (Pb), and cadmium (Cd) on overall contamination levels. These elements were strongly associated with potential sources such as pesticide runoff, vehicular emissions, electroplating industries, and improper waste disposal.

Health risk assessment further strengthened these findings. The Hazard Quotient (HQ) values for several heavy metals—particularly Pb, Cd, As, and Cr—exceeded the safe threshold (HQ > 1) at multiple sites, especially for children, indicating significant non-carcinogenic risk from chronic exposure through drinking water. For instance, at Site S10, the HQ values for Pb and As were substantially above unity, with children being more vulnerable than adults due to their lower body mass and higher intake rates.

Moreover, the estimated Carcinogenic Risk (CR) for As, Pb, Cd, and Cr at several locations surpassed the acceptable limit of 1×10^{-6}, with some sites nearing or exceeding 1×10^{-4},

suggesting unacceptable lifetime cancer risk levels, thereby warranting immediate attention. These risks were especially critical for arsenic and lead, which are known human carcinogens.

In conclusion, the integration of multivariate statistical tools with human health risk assessment provided a comprehensive understanding of heavy metal contamination in the Gomti River, a vital tributary of the Ganga River. The findings not only emphasize the urgent need for robust monitoring and treatment infrastructure but also serve as a framework for evaluating riverine pollution in other regions. Sustainable management strategies and remediation measures are essential to restore water quality and safeguard ecological and human health on both regional and national scales.

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V. REFERENCES

Abbasi, T. ,& A. S. A. (2012). Water quality indices based on bioassessment. *Journal of Water and Health*, 1–29.

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *WIREs Computational Statistics*, *2*(4), 433–459. https://doi.org/10.1002/wics.101

Alberto, W. D., María del Pilar, D., María Valeria, A., Fabiana, P. S., Cecilia, H. A., &María de los Ángeles, B. (2001). Pattern Recognition Techniques for the Evaluation of Spatial and Temporal Variations in Water Quality. A Case Study: *Water Research*, *35*(12), 2881–2894. https://doi.org/10.1016/S0043-1354(00)00592-3

Ali, H., Khan, E., & Ilahi, I. (2019). Environmental Chemistry and Ecotoxicology of Hazardous Heavy Metals: Environmental Persistence, Toxicity, and Bioaccumulation. *Journal of Chemistry*, *2019*, 1–14. https://doi.org/10.1155/2019/6730305

Alloway, B. J. (2013). *Heavy Metals in Soils* (B. J. Alloway, Ed.; Vol. 22). Springer Netherlands. https://doi.org/10.1007/978-94-007-4470-7

Barceloux, D. G., &Barceloux, D. (1999). Manganese. *Journal of Toxicology: Clinical Toxicology*, *37*(2), 293–307. https://doi.org/10.1081/CLT-100102427

Bempah, C. K., &Ewusi, A. (2016). Heavy metals contamination and human health risk assessment around Obuasi gold mine in Ghana. *Environmental Monitoring and Assessment*, *188*(5), 261. https://doi.org/10.1007/s10661-016-5241-3

Bhuiyan, M. A. H., Parvez, L., Islam, M. A., Dampare, S. B., & Suzuki, S. (2010). Heavy metal pollution of coal mine-affected agricultural soils in the northern part of Bangladesh. *Journal of Hazardous Materials*, *173*(1–3), 384–392. https://doi.org/10.1016/j.jhazmat.2009.08.085

Bowler, C. , K. D. J. ,& L. R. L. (2006). *A genomic perspective on nutrient provisioning by bacterial symbionts of plants.* 12902–12903.

Caeiro, S., Costa, M. H., Ramos, T. B., Fernandes, F., Silveira, N., Coimbra, A., Medeiros, G., &Painho, M. (2005). Assessing heavy metal contamination in Sado Estuary sediment: An index analysis approach. *Ecological Indicators*, *5*(2), 151–169. https://doi.org/10.1016/j.ecolind.2005.02.001

Carlson, R. E. (1977). A trophic state index for lakes1. *Limnology and Oceanography*, *22*(2), 361–369. https://doi.org/10.4319/lo.1977.22.2.0361

Central Ground Water Board (CGWB). (2012). Ground water information booklet: Lucknow district, Uttar Pradesh. *.Ministry of Water Resources, Government of India.*

Central Pollution Control Board (CPCB). (2018). . Pollution assessment: River Gomti. *Ministry of Environment, Forest and Climate Change, Government of India.*

Central Pollution Control Board (CPCB). (2019). Annual report on water quality status of Indian rivers. *Ministry of Environment, Forest and Climate Change, Government of India.*

Central Pollution Control Board (CPCB). (2020). Guidelines for water quality monitoring. *Ministry of Environment, Forest and Climate Change, Government of India.*

Chapman, D. V. (1996). A guide to the use of biota, sediments, and water in environmental monitoring (2nd ed.). *UNESCO/WHO/UNEP*.

Chen, T.-B., Zheng, Y.-M., Lei, M., Huang, Z.-C., Wu, H.-T., Chen, H., Fan, K.-K., Yu, K., Wu, X., & Tian, Q.-Z. (2005). Assessment of heavy metal pollution in surface soils of urban parks in Beijing, China. *Chemosphere*, *60*(4), 542–551. https://doi.org/10.1016/j.chemosphere.2004.12.072

Dunteman, G. H. (1989). Principal components analysis. *Sage Publications*.

Eastmond, D. A., MacGregor, J. T., & Slesinski, R. S. (2008). Trivalent Chromium: Assessing the Genotoxic Risk of an Essential Trace Element and Widely Used Human and Animal Nutritional Supplement. *Critical Reviews in Toxicology*, *38*(3), 173–190. https://doi.org/10.1080/10408440701845401

Edet, A. E., & Offiong, O. E. (2002). Evaluation of water quality pollution indices for heavy metal contamination monitoring. A study case from Akpabuyo-Odukpani area, Lower Cross River Basin (southeastern Nigeria). *GeoJournal*, *57*(4), 295–304. https://doi.org/10.1023/B:GEJO.0000007250.92458.de

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster Analysis*. Wiley. https://doi.org/10.1002/9780470977811

Facchinelli, A., Sacchi, E., & Mallen, L. (2001). Multivariate statistical and GIS-based approach to identify heavy metal sources in soils. *Environmental Pollution*, *114*(3), 313–324. https://doi.org/10.1016/S0269-7491(00)00243-8

Flora, S. J. S., Flora, G., & Saxena, G. (2006). Environmental occurrence, health effects and management of lead poisoning. In *Lead* (pp. 158–228). Elsevier. https://doi.org/10.1016/B978-044452945-9/50004-X

Gibling, M. R., Tandon, S. K., Sinha, R., & Jain, M. (2005). Discontinuity-Bounded Alluvial Sequences of the Southern Gangetic Plains, India: Aggradation and Degradation in Response to Monsoonal Strength. *Journal of Sedimentary Research*, *75*(3), 369–385. https://doi.org/10.2110/jsr.2005.029

Gupta, N. , Y. K. K. , K. V. ,& S. D. (2021). Assessment of heavy metal contamination in the Yamuna River: An integrative approach using pollution indices and multivariate statistics. *Environmental Monitoring and Assessment*, 1–16.

Hakanson, L. (1980). An ecological risk index for aquatic pollution control.a sedimentological approach. *Water Research*, *14*(8), 975–1001. https://doi.org/10.1016/0043-1354(80)90143-8

Hering, D., Borja, A., Carstensen, J., Carvalho, L., Elliott, M., Feld, C. K., Heiskanen, A.-S., Johnson, R. K., Moe, J., & Pont, D. (2010). The European Water Framework Directive at the age of 10: A critical review of the achievements with recommendations for the future. *Science of The Total Environment*, *408*(19), 4007–4019. https://doi.org/10.1016/j.scitotenv.2010.05.031

IARC. (2012). (2012). Arsenic, metals, fibres and dusts. IARC Monographs on the Evaluation of Carcinogenic Risks to Humans. *International Agency for Research on Cancer.*, *100C*.

India Meteorological Department (IMD). (2020). Climate of Uttar Pradesh. *Ministry of Earth Sciences, Government of India.*

Jain, S. K. , A. P. K. ,& S. V. P. (2018). Hydrology and water resources of India .*Springer Science & Business Media*.

Jaishankar, M., Tseten, T., Anbalagan, N., Mathew, B. B., &Beeregowda, K. N. (2014). Toxicity, mechanism and health effects of some heavy metals. *Interdisciplinary Toxicology*, *7*(2), 60–72. https://doi.org/10.2478/intox-2014-0009

Järup, L. (2003). Hazards of heavy metal contamination. *British Medical Bulletin*, *68*(1), 167–182. https://doi.org/10.1093/bmb/ldg032

Ji, Y., Wu, P., Zhang, J., Zhang, J., Zhou, Y., Peng, Y., Zhang, S., Cai, G., & Gao, G. (2018). Heavy metal accumulation, risk assessment and integrated biomarker responses of local vegetables: A case study along the Le'an river. *Chemosphere*, *199*, 361–371. https://doi.org/10.1016/j.chemosphere.2018.02.045

Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *374*(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202

Kaiser, H. F. (1958). The Varimax Criterion for Analytic Rotation in Factor Analysis. *Psychometrika*, *23*(3), 187–200. https://doi.org/10.1007/BF02289233

Kaiser, H. F. (1960). The Application of Electronic Computers to Factor Analysis. *Educational and Psychological Measurement*, *20*(1), 141–151. https://doi.org/10.1177/001316446002000116

Karr, J. R. (1999). Defining and measuring river health. *Freshwater Biology*, *41*(2), 221–234. https://doi.org/10.1046/j.1365-2427.1999.00427.x

Kaufman, L., &Rousseeuw, P. J. (1990). *Finding Groups in Data*. Wiley. https://doi.org/10.1002/9780470316801

Khan, M. Y. A., Gani, K. M., & Chakrapani, G. J. (2016). Assessment of surface water quality and its spatial variation. A case study of Ramganga River, Ganga Basin, India. *Arabian Journal of Geosciences*, *9*(1), 28. https://doi.org/10.1007/s12517-015-2134-7

Khan, R., Saxena, A., Shukla, S., Sekar, S., Senapathi, V., & Wu, J. (2021). Environmental contamination by heavy metals and associated human health risk assessment: a case study of surface water in Gomti River Basin, India. *Environmental Science and Pollution Research*, *28*(40), 56105–56116. https://doi.org/10.1007/s11356-021-14592-0

Khan, S., Cao, Q., Zheng, Y. M., Huang, Y. Z., & Zhu, Y. G. (2008). Health risks of heavy metals in contaminated soils and food crops irrigated with wastewater in Beijing, China. *Environmental Pollution*, *152*(3), 686–692. https://doi.org/10.1016/j.envpol.2007.06.056

Kumar, R., Kumar, V., Sharma, A., Singh, N., Kumar, R., Katnoria, J. K., Bhardwaj, R., Thukral, A. K., & Rodrigo-Comino, J. (2019). Assessment of pollution in roadside soils by using multivariate statistical techniques and contamination indices. *SN Applied Sciences*, *1*(8), 842. https://doi.org/10.1007/s42452-019-0888-3

Kumar, V. , S. A. , C. A. , B. R. ,& T. A. K. (2020). *Water quality assessment of River Beas, India, using multivariate statistical techniques and water quality index.* . 1–19.

Ladson, A. R., White, L. J., Doolan, J. A., Finlayson, B. L., Hart, B. T., Lake, P. S., &Tilleard, J. W. (1999).

Development and testing of an Index of Stream Condition for waterway management in Australia. *Freshwater Biology*, *41*(2), 453–468. https://doi.org/10.1046/j.1365-2427.1999.00442.x

Li, S., & Zhang, Q. (2010). Risk assessment and seasonal variations of dissolved trace elements and heavy metals in the Upper Han River, China. *Journal of Hazardous Materials*, *181*(1–3), 1051–1058. https://doi.org/10.1016/j.jhazmat.2010.05.120

Li, X., Liu, L., Wang, Y., Luo, G., Chen, X., Yang, X., Hall, M. H. P., Guo, R., Wang, H., Cui, J., & He, X. (2013). Heavy metal contamination of urban soil in an old industrial city (Shenyang) in Northeast China. *Geoderma*, *192*, 50–58. https://doi.org/10.1016/j.geoderma.2012.08.011

Li, Z., Ma, Z., van der Kuijp, T. J., Yuan, Z., & Huang, L. (2014). A review of soil heavy metal pollution from mines in China: Pollution and health risk assessment. *Science of The Total Environment*, *468–469*, 843–853. https://doi.org/10.1016/j.scitotenv.2013.08.090

Long, J., Zhang, S., & Luo, K. (2019). Discovery of anomalous molybdenum enrichment in lower Carboniferous coal and its availability and origin. *Journal of Geochemical Exploration*, *200*, 104–111. https://doi.org/10.1016/j.gexplo.2019.02.003

Lucknow Development Authority (LDA). (2015). Gomti Riverfront Development Project: Environmental impact assessment report. .*Government of Uttar Pradesh.*

Lucknow Development Authority (LDA). (2019). Master Plan 2031: Lucknow City. .*Government of Uttar Pradesh.*

Malik, D. S. ,& S. J. P. (2019). (2019). Assessment of heavy metal pollution in River Gomti using environmetric approaches. *[Ph.D. Thesis, University of Lucknow]*.

Manta, D. S., Angelone, M., Bellanca, A., Neri, R., &Sprovieri, M. (2002). Heavy metals in urban soils: a case study from the city of Palermo (Sicily), Italy. *Science of The Total Environment*, *300*(1–3), 229–243. https://doi.org/10.1016/S0048-9697(02)00273-5

Meybeck, M. (2003). Global analysis of river systems: from Earth system controls to Anthropocene syndromes. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *358*(1440), 1935–1955. https://doi.org/10.1098/rstb.2003.1379

Mishra, R. K. , P. J. H. ,& Y. S. (2020a).). Heavy metal contamination in River Gomti: Sources and impacts. In Proceedings of the International Conference on Environmental Pollution and Remediation .*Springer*.

Mishra, R. K. , P. J. H. ,& Y. S. (2020b). *Multivariate statistical analysis of heavy metal contamination in River Gomti sediments. Journal of Hazardous Materials.*

Mishra, S., Bharagava, R. N., More, N., Yadav, A., Zainith, S., Mani, S., & Chowdhary, P. (2019). Heavy Metal Contamination: An Alarming Threat to Environment and Human Health. In *Environmental Biotechnology: For Sustainable Future* (pp. 103–125). Springer Singapore. https://doi.org/10.1007/978-981-10-7284-0_5

Mohan, S. V., Nithila, P., & Reddy, S. J. (1996). Estimation of heavy metals in drinking water and development of heavy metal pollution index. *Journal of Environmental Science and Health . Part A: Environmental Science and Engineering and Toxicology*, *31*(2), 283–289. https://doi.org/10.1080/10934529609376357

Moran, N. A., Plague, G. R., Sandström, J. P., & Wilcox, J. L. (2003). A genomic perspective on nutrient provisioning by bacterial symbionts of insects. *Proceedings of the National Academy of Sciences*, *100*(suppl_2), 14543–14548. https://doi.org/10.1073/pnas.2135345100

Mukaka, M. M. (2012). A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal*, 69–71.

Murtagh, F., & Legendre, P. (2014). Ward's Hierarchical Agglomerative Clustering Method: Which Algorithms Implement Ward's Criterion? *Journal of Classification*, *31*(3), 274–295. https://doi.org/10.1007/s00357-014-9161-z

N., Y. G. K. K. , K. V. , C.-P. M. M. S. ,& S. D. (2022). *Appraisal of contamination of heavy metals and health risk in agricultural soil of Jhansi City, India. Environmental Toxicology and Pharmacology, 89, 103781.*

National Mission for Clean Ganga (NMCG). (2019). Annual report: Rejuvenation of River Gomti. .*Ministry of Jal Shakti, Government of India.*

Nilsson, C., Reidy, C. A., Dynesius, M., &Revenga, C. (2005). Fragmentation and Flow Regulation of the World's Large River Systems. *Science*, *308*(5720), 405–408. https://doi.org/10.1126/science.1107887

Nriagu, J. O. (1996). A History of Global Metal Pollution. *Science*, *272*(5259), 223–223. https://doi.org/10.1126/science.272.5259.223

Nriagu, J. O., & Pacyna, J. M. (1988). Quantitative assessment of worldwide contamination of air, water and soils by trace metals. *Nature*, *333*(6169), 134–139. https://doi.org/10.1038/333134a0

Parthasarathy, B., Munot, A. A., &Kothawale, D. R. (1994). All-India monthly and seasonal rainfall series: 1871?1993. *Theoretical and Applied Climatology*, *49*(4), 217–224. https://doi.org/10.1007/BF00867461

Pejman, A., Nabi Bidhendi, G., Ardestani, M., Saeedi, M., &Baghvand, A. (2015). A new index for assessing heavy metals contamination in sediments: A case study. *Ecological Indicators*, *58*, 365–373. https://doi.org/10.1016/j.ecolind.2015.06.012

Peres-Neto, P. R., Jackson, D. A., & Somers, K. M. (2005). How many principal components? stopping rules for determining the number of non-trivial axes revisited. *Computational Statistics & Data Analysis*, *49*(4), 974–997. https://doi.org/10.1016/j.csda.2004.06.015

Rao, K. L. (1975). . India's water wealth: Its assessment, uses and projections. .*Orient Longman*.

Reimann, C. , F. P. , G. R. G. ,& D. R. (2008). Statistical data analysis explained: Applied environmental statistics with R. *John Wiley & Sons.*

Reza, R., & Singh, G. (2010). Heavy metal contamination and its indexing approach for river water. *International Journal of Environmental Science & Technology*, *7*(4), 785–792. https://doi.org/10.1007/BF03326187

Richman, M. B. (1986). Rotation of principal components. *Journal of Climatology*, *6*(3), 293–335. https://doi.org/10.1002/joc.3370060305

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Analgesia*, *126*(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Sharma, A. , K. V. ,& S. R. (2021). *Water quality indices for River Gomti: A comparative analysis. In Recent Advances in Environmental Science*. 89–104.

Sharma, R. , A. P. ,& M. F. (2020). *Heavy metal contamination in the surface water of River Gomti: Seasonal variations and source identification. Environmental Science and Pollution Research, 27(22), 27501-27512.* . 27501–27512.

Sharma, R. K., Agrawal, M., & Marshall, F. M. (2008). Heavy metal (Cu, Zn, Cd and Pb) contamination of vegetables in urban India: A case study in Varanasi. *Environmental Pollution*, *154*(2), 254–263. https://doi.org/10.1016/j.envpol.2007.10.010

Shukla, S., & Saxena, A. (2020). Groundwater quality and associated human health risk assessment in parts of Raebareli district, Uttar Pradesh, India. *Groundwater for Sustainable Development*, *10*, 100366. https://doi.org/10.1016/j.gsd.2020.100366

Singh, K. P. (2007). Environmental hydrology. *Allied Publishers.*

Sinha, R. , T. S. K. , G. M. R. , B. P. S. ,& D. A. S. (2005). Late Quaternary geology and alluvial stratigraphy of the Ganga basin. *Himalayan Geology, 26(1)*, 223–240.

Smith, A. H. , L. E. O. ,& R. M. (2000). Contamination of drinking-water by arsenic in Bangladesh: A public health emergency. .*Bulletin of the World Health Organization, 78(9)*, 1093–1103.

Sutadian, A. D., Muttil, N., Yilmaz, A. G., & Perera, B. J. C. (2016). Development of river water quality indices—a review. *Environmental Monitoring and Assessment*, *188*(1), 58. https://doi.org/10.1007/s10661-015-5050-0

Taylor, R. (1990). Interpretation of the Correlation Coefficient: A Basic Review. *Journal of Diagnostic Medical Sonography*, *6*(1), 35–39. https://doi.org/10.1177/875647939000600106

Tchounwou, P. B., Yedjou, C. G., Patlolla, A. K., & Sutton, D. J. (2012). *Heavy Metal Toxicity and the Environment* (pp. 133–164). https://doi.org/10.1007/978-3-7643-8340-4_6

UN-Water. (2018). Sustainable Development Goal 6 synthesis report on water and sanitation. .*United Nations.*

USEPA. (1989). Risk Assessment: Guidance for Superfund (RAGS): : In Human Health Evaluation Manual (Part A). Office of Emergency and Remedial Response. Washington, DC,.*Human Health Evaluation Manual (Part A)*, *Vol. 1*. https://www3.epa.gov/airtoxics/cancer_guidelines_final_3-25-05.pdf

USEPA. (2005). Guidelines for Carcinogen Risk Assessment. .*United States Environmental Protection Agency*.

USEPA IRIS. (2022). Integrated Risk Information System. *U.S. Environmental Protection Agency*.

Uttar Pradesh Pollution Control Board (UPPCB). (2020). Action plan for rejuvenation of River Gomti. .*Government of Uttar Pradesh.*

Vörösmarty, C. J., McIntyre, P. B., Gessner, M. O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S. E., Sullivan, C. A., Liermann, C. R., & Davies, P. M. (2010). Global threats to human water security and river biodiversity. *Nature*, *467*(7315), 555–561. https://doi.org/10.1038/nature09440

Wang, J., Liu, G., Liu, H., & Lam, P. K. S. (2017a). Multivariate statistical evaluation of dissolved trace elements and a water quality assessment in the middle reaches of Huaihe River, Anhui, China. *Science of The Total Environment*, *583*, 421–431. https://doi.org/10.1016/j.scitotenv.2017.01.088

Wang, J., Liu, G., Liu, H., & Lam, P. K. S. (2017b). Multivariate statistical evaluation of dissolved trace elements and a water quality assessment in the middle reaches of Huaihe River, Anhui, China. *Science of The Total Environment*, *583*, 421–431. https://doi.org/10.1016/j.scitotenv.2017.01.088

Ward, J. H. (1963). Hierarchical Grouping to Optimize an Objective Function. *Journal of the American Statistical Association*, *58*(301), 236–244. https://doi.org/10.1080/01621459.1963.10500845

WHO. (2016). Guidelines for drinking-water quality: Fourth edition incorporating the first addendum. *World Health Organization*.

Wongsasuluk, P., Chotpantarat, S., Siriwong, W., & Robson, M. (2014). Heavy metal contamination and human health risk assessment in drinking water from shallow groundwater wells in an agricultural area in Ubon Ratchathani province, Thailand. *Environmental Geochemistry and Health*, *36*(1), 169–182. https://doi.org/10.1007/s10653-013-9537-8

Wu, B., Zhao, D. Y., Jia, H. Y., Zhang, Y., Zhang, X. X., & Cheng, S. P. (2009). Preliminary Risk Assessment of

Trace Metal Pollution in Surface Water from Yangtze River in Nanjing Section, China. *Bulletin of Environmental Contamination and Toxicology*, *82*(4), 405–409. https://doi.org/10.1007/s00128-008-9497-3

Wuana, R. A., &Okieimen, F. E. (2011). Heavy Metals in Contaminated Soils: A Review of Sources, Chemistry, Risks and Best Available Strategies for Remediation. *ISRN Ecology*, *2011*, 1–20. https://doi.org/10.5402/2011/402647

Yadav, I. C. , D. N. L. , S. V. K. , L. J. ,& Z. G. (2021). *Spatial distribution, source analysis, and health risk assessment of heavy metals in agricultural soil of Himalayan region. Environmental Science and Pollution Research, 28(12),* . 14639-14653.

YIDANA, S. M., BANOENG-YAKUBO, B., & SAKYI, P. A. (2012). Identifying key processes in the hydrochemistry of a basin through the combined use of factor and regression models. *Journal of Earth System Science*, *121*(2), 491–507. https://doi.org/10.1007/s12040-012-0163-0

Yu, W., Du, B., Yang, L., Zhang, Z., Yang, C., Yuan, S., & Zhang, M. (2019). Occurrence, sorption, and transformation of free and conjugated natural steroid estrogens in the environment. *Environmental Science and Pollution Research*, *26*(10), 9443–9468. https://doi.org/10.1007/s11356-019-04402-z

Zhang, J., & Liu, C. L. (2002). Riverine Composition and Estuarine Geochemistry of Particulate Metals in China—Weathering Features, Anthropogenic Impact and Chemical Fluxes. *Estuarine, Coastal and Shelf Science*, *54*(6), 1051–1070. https://doi.org/10.1006/ecss.2001.0879

Zhang, L. , Q. Y. , Z. B. , S. Y. ,& L. Y. (2021). *Heavy metal pollution and ecological risk assessment in sediments of urban rivers: A case study of the Pearl River Delta, China. Environmental Science and Pollution Research, 28(14),* . 17308-17320.

Zhou, F., Guo, H., Liu, Y., & Jiang, Y. (2007). Chemometrics data analysis of marine water quality and source identification in Southern Hong Kong. *Marine Pollution Bulletin*, *54*(6), 745–756. https://doi.org/10.1016/j.marpolbul.2007.01.006

Zhou, Y. , J. D. , D. D. , W. Y. , W. J. , K. L. , . . . & W. Q. (2022). *Ecological risk assessment of heavy metals in surface sediments of six major Chinese freshwater lakes.* 113973.