Assessment of heavy metal content in rivers and sediments: exploring relationships with land use and soil characteristics

Evaluación del contenido de metales pesados en ríos y sedimentos: exploración de las relaciones con el uso del suelo y las características del suelo

Guillermo Clavo-Brenes[1], Noemi Quirós-Bustos[2]

Fecha de recepción: 5 de diciembre, 2025
Fecha de aprobación: 18 de abril, 2026

Clavo-Brenes, G; Quirós-Bustos, N. Assessment of heavy metal content in rivers and sediments: exploring relationships with land use and soil characteristics. *Tecnología en Marcha*. Vol. 39 Nº 4. Octubre-Diciembre, 2026. Pág. 41-64.

https://doi.org/10.18845/tm.v39i4.8333

1 Environmental Protection Research Center, School of Chemistry, Instituto Tecnológico de Costa Rica, Cartago, Costa Rica.
calvogmo@yahoo.com
https://orcid.org/0000-0002-7021-3509
2 Center for Research and Chemical and Microbiological Services, School of Chemistry, Instituto Tecnológico de Costa Rica, Cartago, Costa Rica.
nquiros@itcr.ac.cr
https://orcid.org/0000-0002-2064-4300

Keywords

Heavy metal; land use, river, sediment.

Abstract

Heavy metal(s) (HM, HMs) are essential to biological and environmental processes, but excessive concentration threaten ecosystems and human health. This study assessed HM concentrations in river water and sediments, examining their relationships with land use and soil characteristics. A total of 26 sampling points were selected across Costa Rica, primarily based on land use: Arenal, Caño Negro, Tempisque, Pital, Toro, Tigre, Rincón, Sierpe, Torres, Poás, Segundo, Pacuare, Penshurt, and Birrís. The sampling period extended from September 2017 to July 2020. Most sampling sites showed detectable HM levels, with arsenic, nickel, and mercury sometimes exceeding thresholds for probable toxicity, most metals in sediments fell within an "undefined toxicity" range, though cadmium levels were notably high. Predictive models in sediments were more accurate: lead (70%), chromium (73%), arsenic (71%), and nickel (74%). The main predictors are: Urban land use (89%) for Lead; industrial activity (41.5%) and bare soil (17.7%) for Chromium; Cane (52%), Coffee (14%) and Cassava (13%) for Arsenic; and Bare Soil (78%) for Nickel. Models showed variable and complex patterns, but bivariate correlations were strong (80%, 90%, and 95%). Effective management strategies and continuous monitoring are critical to reducing contamination risks and protecting river ecosystems and water quality.

Palabras clave

Metales pesados; uso del suelo; río; sedimento.

Resumen

Los metales pesados (MP) son esenciales para los procesos biológicos y ambientales; sin embargo, su concentración excesiva amenaza los ecosistemas y la salud humana. Este estudio evaluó las concentraciones de MP en el agua y los sedimentos de los ríos, examinando su relación con el uso de la tierra y las características del suelo. Se seleccionaron un total de 26 puntos de muestreo a lo largo de Costa Rica, basados principalmente en el uso de la tierra: Arenal, Caño Negro, Tempisque, Pital, Toro, Tigre, Rincón, Sierpe, Torres, Poás, Segundo, Pacuare, Penshurt y Birrís. El periodo de muestreo se extendió desde septiembre de 2017 hasta julio de 2020. La mayoría de los sitios de muestreo mostraron niveles detectables de MP. El arsénico, el níquel y el mercurio superaron en ocasiones los umbrales de toxicidad probable. Aunque la mayoría de los metales en los sedimentos se ubicaron dentro de un rango de "toxicidad no definida", los niveles de cadmio fueron notablemente altos. Los modelos predictivos en sedimentos resultaron más precisos para el plomo (70%), cromo (73%), arsénico (71%) y níquel (74%). Los principales predictores identificados son: uso de suelo urbano (89%) para el Plomo; actividad industrial (41.5%) y suelo descubierto (17.7%) para el Cromo; Caña (52%), Café (14%) y Yuca (13%) para el Arsénico; suelo descubierto (78%) para el Níquel. Los modelos mostraron patrones variables y complejos, pero las correlaciones bivariadas fueron fuertes (80%, 90% y 95%). Las estrategias de gestión eficaces y el monitoreo continuo son fundamentales para reducir los riesgos de contaminación, así como para proteger los ecosistemas fluviales y la calidad del agua.

Introduction

Water is vital for numerous aspects of life, including drinking, sanitation, agriculture, industry, livestock, and ecosystems. Pollution arises both from direct wastewater discharges into rivers and from diffuse sources like agriculture runoff and air pollution [1], [2], [3], [4]. Pollutants bound to particulate matter in the air [5] eventually settle on the soil. Combined with existing soil contaminants, these pollutants are transported to rivers and coastal areas via erosion and surface runoff during rainfall events [6], [7].

HMs are significant pollutants with adverse effects on humans, animals, and plants health when their concentrations in water, air, soil, or sediments exceed permissible limits [8], [9]. Human exposure to HMs has been associated with various health issues, including developmental delays, cancer, kidney damage, and even fatalities [8]. While certain HMs occur naturally and some play essential roles in metabolic processes in flora and fauna [10] elevated concentrations render them hazardous pollutants [7]. HMs are introduced into the environment through both natural sources, such as rock weathering and mineral deposits, and anthropogenic activities, including agriculture, industrial processes, mining, power generation, and transportation [11], [12], [13].

Within living organisms, heavy metals can bioaccumulate, leading to long-term toxic effects when their concentrations exceed environmental or food safety thresholds [8]. As apex predators in the food chain, humans are particularly vulnerable to higher heavy metal concentrations due to biomagnification [12]. Elevated metal levels in plants can induce phytotoxic effects, such as reduced growth and disruptions in physiological processes [9].

Heavy metal pollution in the environment can occur through five main pathways: retention in soil, uptake by plants, deposition in airborne particulate matter, accumulation in urban dust, and changes in river physicochemical conditions that release metals from sediments. [9], [11].

Environmental factors such as rainfall, forest cover, soil characteristics, and land use significantly affect river water quality [14], [15], with pesticides and other agrochemicals being major contributors (Zhang et al., 2022). Therefore, monitoring water quality, assessing potential risks, and identifying HM sources in rivers and sediments are essential (Luo et al., 2021). Nonetheless, many existing studies face limitations in model accuracy, feature selection, and interpretability—challenges that become especially pronounced in high-dimensional, heterogeneous settings where traditional methods struggle to generalize [16].

The aim of the study was to investigate the relationships between various heavy metals and land cover/ use, including specific agricultural practices, as well as soil texture.

Materials and methods

Study area

Costa Rica, located in Central America, features a diverse landscape that includes mountain ranges, coastal plains, and tropical rainforests. The country's climate and weather patterns vary significantly by region, altitude, and season. In high-altitude areas, temperatures can drop to near 0°C, while coastal and northern regions may reach up to 40°C. Annual precipitation also varies widely, from over 3,000 mm in some regions to as little as 100 mm in others.

Land cover/use in Costa Rica consists of a mix of agricultural lands, forests, and urban areas. The country's varied microclimates support the cultivation of different crops, with agriculture playing a crucial role in the economy. Major exports include coffee, bananas, and pineapples.

Coastal regions experience a tropical climate with high temperatures and humidity, while inland areas tend to have a more temperate climate with cooler temperatures. Costa Rica also experiences distinct wet (May to November) and dry (December to April) seasons.

Sampling sites

A total of 26 sampling points were carefully selected across Costa Rica, primarily based on land cover/use (detailed further below), as this variable significantly influences the quality of surface water and sediments (Calvo-Brenes, 2015). The study sites encompassed basins, sub-basins, and micro-basins in diverse regions, including San Carlos, Guanacaste, the Atlantic, the Greater Metropolitan Area, and the Osa Peninsula, each characterized by distinct land cover/uses Table 1). These regions span Costa Rica's total area of 51,000 square kilometers, as illustrated in Figure 1. Sampling points were located along major rivers such as Arenal, Caño Negro, Tempisque, Pital, Toro, Tigre, Rincón, Sierpe, Torres, Poás, Segundo, Pacuare, Penshurt, and Birrís, strategically positioned within their respective basins to capture regional variations in water quality.

Over nearly three-year period, surface water and sediment samples were collected mostly every two-three months from these sites. The samples were subsequently analyzed for a range of HMs, including lead (Pb), copper (Cu), cadmium (Cd), arsenic (As), chromium (Cr), nickel (Ni), and mercury (Hg).



Figure 1. Locations of sampling sites across Costa Rica's basins, sub-basins, and micro-basins, covering regions such as San Carlos, Guanacaste, the Atlantic, the Greater Metropolitan Area, and the Osa Peninsula, with varied land uses.

Table 1. Land cover/use in relation to sampling sites.

Land cover/ use	Sampling sites in basin scales												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Forest	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chaparral											Yes		
Grass	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Housing	Yes	Yes		Yes	Yes	Yes		Yes	Yes				
Industry					Yes								
Temporary crops							Yes						
Rice	Yes									Yes	Yes		
Sugar cane	Yes			Yes									
Banana								Yes	Yes	Yes			
Coffee				Yes									
Ferns				Yes									
Palm									Yes		Yes		
Yucca			Yes										
Pineapple			Yes										Yes

Note: 1 = Tempisque, 2=Arenal, 3=Toro, 4 = Poas, 5 = Segundo, 6 = Torres, 7 = Birris, 8 = Pacuare, 9 = Penshure, 10 = Sierpe, 11 = Rincon, 12 = Tigre, 13 = Pital.

Land cover/use

Land cover/use was classified into the following categories: forest, chaparral, pasture, urban, industrial, agricultural, and bare soil. The agricultural category was further divided into specific crop types, including rice, sugar cane, banana, coffee, fern, palm, cassava, and pineapple, as well as temporary crops like onion, potato, and carrot. Table 1 relates the land cover/ use for each sampling site. Land use assessment utilized satellite imagery from Sentinel 2 and Landsat 8 through USGA databases. Scenes were selected based on criteria including acquisition date, cloud cover threshold (e.g. <10 %), and spatial resolution (10-30 m depending on sensor). Supervised classification was performed using Quantum GIS software, applying training samples to assign land use categories. All imagery was retrieved through the USGS EarthExplorer platform (https://earthexplorer.usgs.gov/)

Other environmental variables

Other factors were considered in the study: dry or rainy season, soil texture and infiltration rate for every sampling site (Table 2).

Table 2. Some variables measured at each sampling site.

Sampling site	Soil Texture (%)			Infiltration Rate (mm/hr)
	Sand	Limus	Clay	
Arenal	69.7	22.3	8	25.9
Birris	50	48	2	25.9
Guanacaste	20	20	60	0.5
Penshurt	62	23	15	25.9
Pacuare	70	25	5	25.9
Poas	70	25	5	25.9
Rincon	75	10	15	25.9
Segundo	50	35	15	13.2
Sierpe	67	13	20	25.9
Tigre	37	38	25	13.2
Toro	32	51	17	6.9
Torres	65	23	12	25.9
Pital	57	21	22	4.3

Soil texture was determined with the Bouyoucos hydrometer method and classified using the USDA textural triangle. Based on these classes, field infiltration rates were measured with a double-ring infiltrometer to assess the relationship between texture and infiltration capacity.

Water and sediment sampling

Water and sediment samples were collected from all sampling points mostly every two-three months over nearly three years, allowing for the evaluation of heavy metal content during both the rainy and dry seasons, from September 2017 to July 2020, according to the "Standard Methods for the Examination of Water and Wastewater" (APHA, AWWA and AEF, 2022). Samples were collected as follows, in 2017: September and November; in 2018: January, March, May, July, September and November; and then in October 2019; in 2020: February, May and August. A total of 26 water and 26 sediment samples were collected from 26 sampling sites every two to three months, without considering replicates.

Water samples were collected in duplicate and sediment samples in triplicate at each sampling location. All replicate samples were collected simultaneously and handled following standard protocols to preserve their physical and chemical properties until laboratory analysis. Sample preservation was carried out using HNO_3 to adjust the pH to below 2.

Heavy metal analysis in water:

The water samples were analyzed for the following metal contents: Pb, Cr, Cd, Hg, Cu, As, and Ni. Prior to analysis, samples were preserved and subjected to acid digestion following the guidelines of the "Standard Methods for the Examination of Water and Wastewater". Method 3111A [17]. Mercury was measured with the AAnalyst 800 using hydride generation and flame atomic absorption, ensuring accurate concentration readings and the rest of HMs, using graphite furnace atomic absorption spectrometry (GF-AAS) with a Perkin Elmer model AAnalyst 800.

Heavy metal analysis in sediments:

Sediment samples were dried at 45°C for 48 hours and coarse particles were removed by sieving to <2 mm, ensuring consistency in the analyzed material [18], [19]. Digestion followed the EPA method SW-846 3051A [18].

Hg content was performed using the hydride generation technique and the remaining metals were analyzed using graphite furnace atomic absorption spectrometry, according to Method 3111A in the "Standard Methods for the Examination of Water and Wastewater" [17].

Verification of Methodologies:

Method validation was carried out using certified reference materials. Performance parameters, including accuracy, precision, detection and quantification limits, working range, and linearity, were evaluated. Additionally, the acceptance criteria established in the reference standard were applied.

Statistical Analysis

Regression analysis was performed in SPSS (version 28) [20]. The basic form of the regression equation is:

$$Y = \beta_1 X_1 + \ldots + \beta_n X_n + \beta_o + \varepsilon \quad (1)$$

where:

Y = HM concentration (mg/L).

$X_{1\text{-}n}$ = type of environment parameter.

$\beta_{1\text{-}n}$ = coefficients of each of the environmental variables

β_o = intercept value

ε = error

For the analysis, data was organized in an Excel spreadsheet. Each column represents a different variable, including sampling site, season, heavy metal concentrations, land cover/use, soil texture, and infiltration rate. Each row corresponds to an individual observation.

Several statistical assumptions were assessed through various tests. Normality was evaluated via residual analysis using histograms and normal probability plots. Homogeneity of variances was tested with Levene's test ($p = 0.05$).

Pearson correlation analysis evaluated bivariate relationships between each metal and their respective independent variables. The correlation coefficient (r) measures the strength and direction of linear relationships between continuous variables [15]. Correlation significance levels were categorized into three ranges: $p < 0.05$ (confidence level ≥ 95%, red-coded), 0.05–0.10 (confidence level 90–<95%, green-coded), and 0.10–0.20 (confidence level 80–<90%, yellow-coded). Only correlations with confidence levels above 80% were deemed significant.

In the variable selection stage, we adopted a significance level of $p \leq 0.2$ as the screening criterion. Although this threshold is more liberal than the conventional $\alpha = 0.05$, Mickey and Greenland (1989) demonstrated that stricter cutoffs can lead to the exclusion of potentially important variables, particularly confounders, in multivariable models. By using a higher threshold, like 0.25, in the exploratory phase, we reduce the risk of prematurely discarding predictors that may become significant once other variables are accounted for. This approach

is consistent with recommendations in epidemiological and environmental modeling, where the primary goal of initial screening is to ensure that relevant factors are considered for subsequent model refinement [21].

Modelling was combined with variable reduction, which differs from Pearson's bivariate correlation by considering multiple variables simultaneously and providing partial correlations. The "Stepwise" method streamlined the model, with an input alpha of 0.10 and an output alpha of 0.15.

Additionally, the adjusted R-squared (R^2) coefficient was calculated to assess the model's goodness of fit, indicating the proportion of variance in the dependent variable explained by the independent variables. Its variability depends on factors such as sample size, linearity assumptions, and outliers (Montgomery et al., 2021). The Variance Inflation Factor (VIF) was used to detect collinearity, with values exceeding 10 suggesting potential issues (Montgomery et al., 2021).

Water quality guidelines

The water quality (WQ) of the rivers (Table 3) was assessed based on the maximum limits specified for Class I water, which is the classification used for drinking water supply in Costa Rica [22]. Color coding refers to sites with "Not probable toxicity" (green-coded), while those with "Probable toxicity" (red-coded).

Sediment quality guidelines (SQG)

Numerous international guidelines exist for evaluating heavy metals in sediments. In this study, we used the consensus-based sediment quality guidelines developed in the United States [23], which define Threshold Effect Concentrations (TEC) and Probable Effect Concentrations (PEC) for individual metals in freshwater sediments. According to this schema, sediments with metal concentrations below the TEC are unlikely to pose adverse effects; concentrations above the PEC suggest probable toxicity, and values in between require further assessment. We coded values below TEC as "Not Probable Toxicity" (green), values above PEC as "Probable Toxicity" (red), and the intermediate range as "Toxicity Undefined" (yellow) (see Table 3 and Figure 4).

Table 3. HMs limits for water and sediment quality classification.

HM	Water (Class I, mg/L)	Sediments	
		TEC (mg/Kg DW)	PEC (mg/Kg DW)
Pb	<0.03	35.8	128
Cr	<0.05	43.4	111
Cd	<0.005	0.99	4.98
Hg	<0.001	0.15	1.00
Cu	<0.5	31.6	149
As	<0.01	9.79	33.6
Ni	<0.05	22.7	48.6

Note: Hg limits were taken from the Australian regulations [24]
Values below the TEC are green-coded (Not probable toxicity), between TEC and PEC are yellow-coded (Undefine toxicity), and over PEC are red-coded (Probable toxicity).

Results and discussion

Seasonal Variability

Based on the data gathered in an Excel spreadsheet, most metal concentrations showed minimal variability across seasons, with Pb, Cr, Cu, As, and Cd generally remaining at or near zero during both the dry and wet periods. Pearson's bivariate correlation analysis in river samples indicated an 80–90% confidence level for the relationship between season and Ni content. In sediments, Cr and Cu were associated with season at a confidence level between 90% and <95%. However, when modeling heavy metal content against multiple variables, only Pb in sediments retained season as a significant predictor in the final equation (Figure 2).

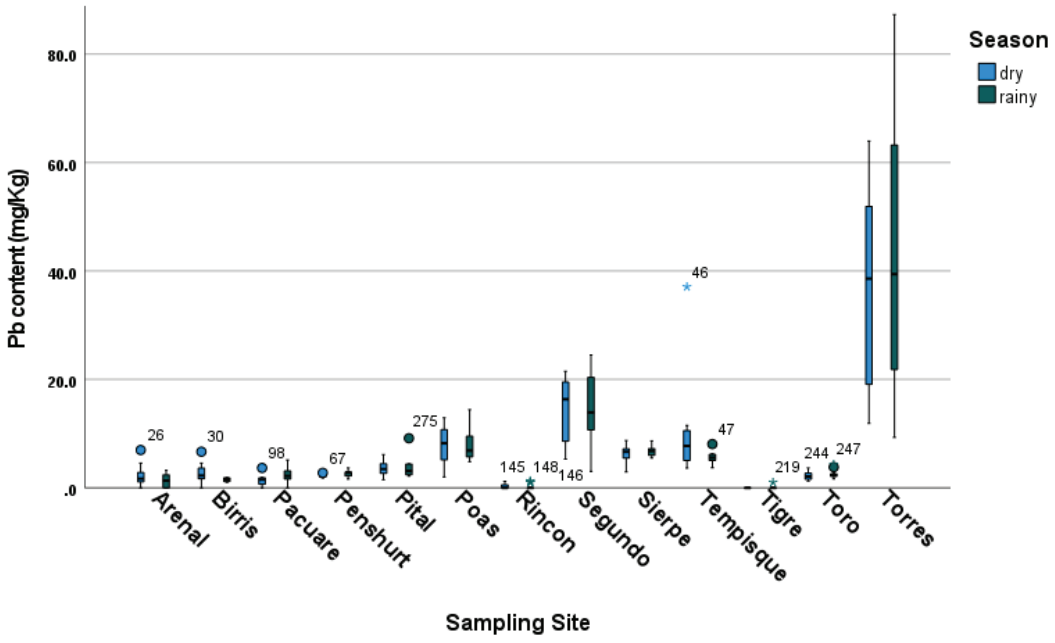
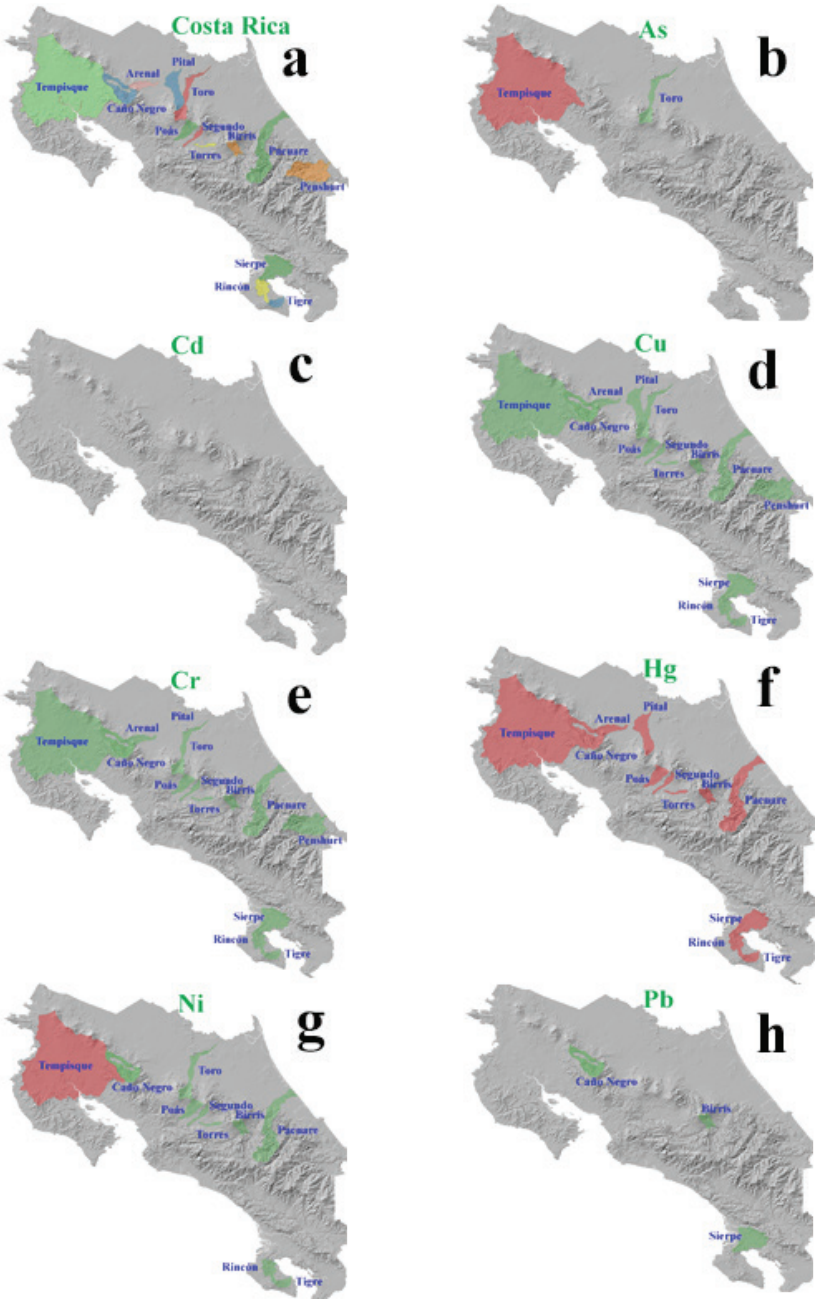


Figure 2. Variation of Pb content in relation to Season and sampling sites.

Although the statistical model indicated a significant correlation between Pb concentrations and season, the boxplots (Figure 2) reveal that this relationship is not consistent across sites showing minimal seasonal variation.

Heavy metals in rivers

Figure 3a shows the different sampling sites, with colors used solely to distinguish sites and not to indicate contamination levels. Figures 3b–3h illustrate toxicity levels of various heavy metals: As (3b), Cd (3c), Cu (3d), Cu and Ni (3e), Hg (3f), Ni (3g), and Pb (3h). These figures highlight the varying toxicity levels across sites, offering insight into the potential ecological impact of these contaminants in the rivers. A key finding from Figure 3 is that As and Ni at the Tempisque site were classified as 'Probable toxicity.' Hg showed 'Probable toxicity' at twelve sites, highlighting its widespread environmental concern. Other heavy metals remained at 'Not probable toxicity' levels across various sites.



Note:

Color	Classification
	Not Probable toxicity
	Probable toxicity

Figure 3. HMs toxicity levels in water for each sampling site.

While most rivers show low metal contamination, Tempisque and Birris have higher copper, mercury, and arsenic levels, suggesting localized pollution sources. Seasonal trends indicate higher lead and arsenic concentrations in the dry season, likely due to reduced dilution. Cadmium and chromium are not significant contaminants. Mercury levels exceeding permissible limits

pose serious health risks, including neurological and cardiovascular effects, and environmental threats through bioaccumulation. This can disrupt ecosystems, harm biodiversity, and impact local economies, underscoring the need for effective management and awareness efforts.

Pearson's Bivariate Correlation Analysis

The assessment of HMs included correlation analyses to identify relationships with environmental factors (Table 4).

Table 4. Pearson Bivariate Correlations were identified between HMs in river waters and land use activities.

Variable	Heavy metal content (mg/L)						
	Pb	Cr	Cu	As	Cd	Ni	Hg
Season	X	X	X	X	X	+	X
Forest	X	+	X	X	X	+	-
Chaparral	+	+	X	X	X	X	X
Grass	X	X	X	X	X	X	X
Housing	X	X	X	X	X	X	X
Industry	X	+	X	X	X	X	X
Temporary crops (onion, potato, carrot)	X	-	X	X	X	X	+
Rice	+	+	X	X	X	X	X
Sugar cane	X	+	+	+	X	+	X
Banana	X	X	X	X	X	-	X
Coffee	X	X	X	X	X	-	X
Ferns	X	X	X	X	X	-	X
Palm	+	-	X	X	X	X	X
Yucca	X	-	-	X	X	X	X
Pineapple	X	-	X	X	X	X	X
Bare soil	+	+	X	X	X	X	X
Sand	X	-	-	-	X	+	X
Lime	+	-	X	X	X	X	+
Clay	X	+	+	+	X	+	X
Infiltration Speed	X	-	X	X	X	-	X

Notes:

	Correlated (confidence level≥95%)
	Correlated (confidence level 90-<95%)
	Correlated (confidence level 80-<90%)

X = Not correlated
- = Negative correlation
+ = Positive correlation

Pearson's analysis showed significant correlations ($p < 0.05$) between Pb and land uses like Chaparral, Bare Soil, and Rice crops, while Cr correlated strongly with Forest, Chaparral, Industry, Sugarcane, Pineapple and Bare soil. Cu and As were linked to Sugarcane crops, and Cd showed no correlations. Ni ($p < 0.1$) correlated with Banana, Cane, and Forest, while Hg was associated with Temporary Crops. Correlations with other variables are shown in Table 4.

These correlations, whether positive or negative, suggest that certain plants may influence HM levels through hyper-bioaccumulation. Some species act as biofilters, reducing metal concentrations in soil or water [25], [26]. However, further research is needed to understand its long-term ecological effects [27]. These findings provide insights into the impact of land use on HM contamination and potential remediation strategies.

Although agricultural practices are likely contributors to the observed HM concentrations, the specific sources remain uncertain. Farmers were often reluctant to share detailed information about agrochemical use, limiting direct evidence. Thus, while the possibility of excessive or even prohibited agrochemical application cannot be ruled out, this study does not provide proof of such practices.

Predictive models in rivers, according to land use

Lead

The predictive model for Pb, incorporating land use and environmental variables, showed a significant correlation ($p < 0.05$) with a probability ≥95%. However, the adjusted R^2 was low (0.037), indicating limited explanatory power. Key variables influencing Pb levels included season, temporary crops, bare ground, ferns, and palm, suggesting that land use and seasonal changes impact Pb contamination (formula 1). Despite the low R^2, the strong p-value highlights the relevance of these factors. This model provides a foundation for refining predictions and exploring additional variables to better understand Pb dynamics in rivers.

$$[Pb] = 0.001185*Season+0.000173*Temporary\ Crops+ 0.007143*Bare\ soil+0.002576*Berns+0.000229*Palm\ +0.00005 \quad (1)$$

Despite its limited explanatory power, the model captures significant relationships between Pb levels and specific variables. The low R^2 suggests that additional factors influence Pb concentrations, highlighting the complexity of environmental interactions and the need for further research to improve model accuracy.

Chrome

Cr model showed a strong correlation ($p \leq 0.001$), indicating a robust relationship between chromium content and environmental variables. The adjusted R^2 values (0.356–0.376) suggest that 35.6% to 37.6% of Cr variability is explained by industry, sugarcane, banana, bare soil, and ferns (formula 2). While the model highlights key influencing factors, a significant portion of variability remains unexplained, suggesting other contributors.

$$[Cr] = 0.0305*Industry+ 0.00152*Cane+ 0.000345*Banana+ 0.006626*Bare\ soil- 0.006877*Ferns-5.130 \quad (2)$$

In conclusion, while the Cr model offers valuable insights into chromium concentrations and land use variables, its limitations must be acknowledged.

Copper

Cu model showed a strong correlation ($p \leq 0.001$), indicating a significant relationship between copper content and environmental variables. The adjusted R^2 values (0.156–0.191) suggest that 15.6% to 19.1% of copper variability is explained by sugarcane, ferns, cassava, and infiltration rate. Despite the strong correlation, the low R^2 values indicate that much of the variability remains unexplained.

$$[Cu] = 0.003089*Cane- 0.029293*Ferns- 0.001319*Cassava+ 0.000075*infiltration\ rate+0.012544 \quad (3)$$

Arsenic

As has a strong correlation ($p \leq 0.001$), indicating a significant relationship between arsenic content and environmental variables. The adjusted R^2 values (0.178–0.232) suggest that 17.8% to 23.2% of arsenic variability is explained by cane, ferns, and other factors. The highest R^2 value was observed in the model including cane and ferns (formula 4), highlighting the importance of these variables in influencing arsenic levels and underscoring the impact of agricultural practices on arsenic contamination.

$$[As] = 0.001368*Cane- 0.011485*Ferns+ 0.000045 \quad (4)$$

Cadmium

The absence of Cd at most sampling points prevents the creation of a predictive model for its relationship with land use and environmental variables.

Níckel

Ni showed a strong correlation ($p \leq 0.001$), indicating a significant relationship between the selected variables and nickel concentrations in rivers. The adjusted R^2 values (0.410–0.419) suggest that 41% to 42% of the variability in nickel levels can be explained by the model's variables. These include land use factors such as pasture, urbanization, industry, and crops, as well as environmental factors like infiltration rate (formula 5). Despite the model's strong correlation, the R^2 value suggests that additional factors may influence nickel levels, warranting cautious interpretation of the results.

$$[Ni] = -0.000190*Pasture-0.000233*Urbanism+ 0.013704*Industry- 0.000199*Temporary\ crops+ 0.001128*cane- 0.00056*Banana- 0.003953*Bare\ soil- 0.017404*Ferns- 0.00033*Palm- 0.000786*Cassava- 0.000051*Infiltration\ rate+0.015182 \quad (5)$$

Mercury

The predictive model for mercury (Hg) showed strong partial correlations ($p \leq 0.001$), indicating a significant relationship with selected variables. However, the low R^2 value of 0.090 suggests that only 9% of the variability in mercury levels can be explained by the model's variables. Key contributors were temporary crops and sugarcane (formula 6), likely influencing mercury distribution in river systems. Despite the strong bivariate correlations, the low R^2 indicates that other factors may also affect mercury levels.

$$[Hg] = 0.000427*Temporary\ crops+ 0.000186*cane+0.001403 \quad (6)$$

A summary table is as follows:

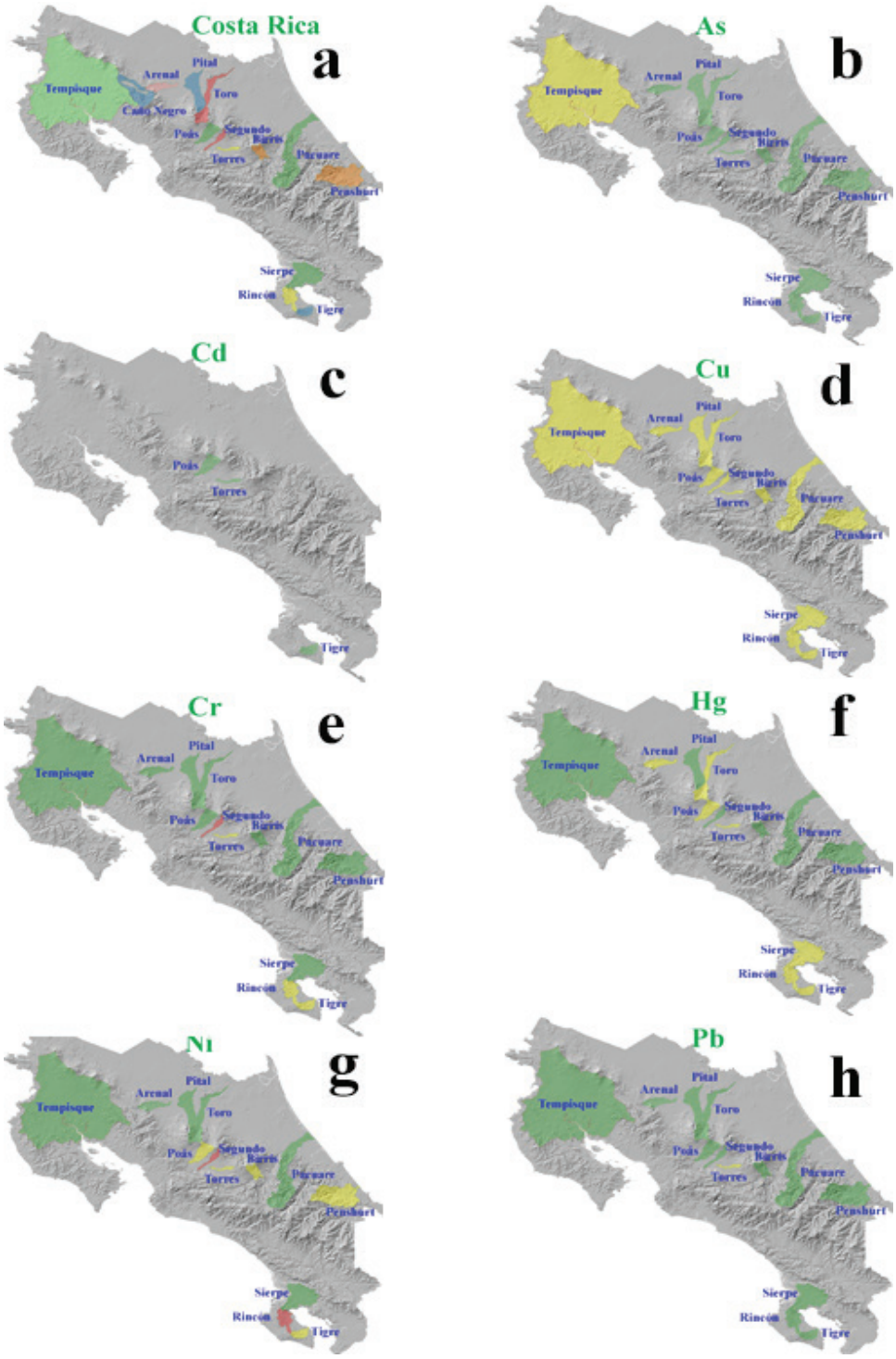
Table 5. Summary of predictive model performance for heavy metals (HMs) in river waters.

Metal	Key predictors	Adj. R^2	p-value	Notes / limitations
Pb	Season, temporary crops, bare soil, ferns, palm	0.037	<0.05	Statistically significant but weak explanatory power
Cr	Industry, sugarcane, banana, bare soil, ferns	0.356–0.376	≤0.001	Stronger model, ~36% variance explained
Cu	Sugarcane, ferns, cassava, infiltration rate	0.156–0.191	≤0.001	Moderate significance, low explanatory power
As	Sugarcane, ferns	0.178–0.232	≤0.001	Key role of agricultural practices
Cd	–	–	–	Too few data to model
Ni	Pasture, urbanism, industry, crops, infiltration rate	0.410–0.419	≤0.001	Strongest model, ~42% variance explained
Hg	Temporary crops, sugarcane	0.090	≤0.001	Low explanatory power despite significance

Predictive models for HMs varied considerably in their explanatory power (Table 5). Ni and Cr showed the strongest models, with adjusted R^2 values up to ~42% and ~37%, respectively, indicating that land use and environmental variables account for a substantial portion of their variability. In contrast, Pb and Hg models had very low adjusted R^2 values (<10%), suggesting that additional unmeasured factors play a key role in their distribution. Cu and As models were intermediate (Adj. R^2 ~16–23%), while Cd could not be modeled due to sparse occurrence. Across metals, agricultural variables (e.g., sugarcane, banana, cassava, palm, temporary crops) and land cover (bare soil, ferns, pasture) consistently appeared as significant predictors, underscoring the influence of both crop type and land disturbance on HM concentrations. Industrial and urban land uses were also recurrent drivers, particularly for Ni and Cr. Despite statistical significance ($p \leq 0.05$), the generally modest R^2 values highlight the complexity of HM dynamics and the need to incorporate additional explanatory variables such as geology, hydrology, and agrochemical inputs in future models.

HMs in sediments

Figure 4 presents the average toxicity levels of various metals across sampling zones, including basins and watersheds. Figure 4a shows the different sampling sites, with colors used solely to distinguish sites and not to indicate contamination levels, the remaining subfigures depict metal-specific toxicity distributions. Notably, Ni shows probable toxicity in Rincón and Segundo, and undefined levels at three other sites (Figure 4g). As appears with undefined toxicity only in Tempisque (Figure 4b). Cu shows the same level across 13 sites (Figure 4d), and Hg across six (Figure 4f), highlighting spatial patterns and potential contamination risks.



Note:

Color	Classification
	Not probable toxicity
	Undefined toxicity
	Probable toxicity

Figure 4. HMs toxicity levels in sediments for each sampling site.

The analysis of HM contamination across sites (Figure 4) reveals both positive and concerning trends, highlighting the need for continuous monitoring and management. While Cd and Hg were detected in low concentrations or isolated sites, Cu, Ni, Cr, Pb and As showed broader distribution.

Though many metals fall within the "not probable toxicity" range, the frequent detection of Cu, Ni, and Hg in "undefined" or "probable toxicity" categories is concerning due to their risks to aquatic life and human health via bioaccumulation.

Sites like Torres, Segundo, and Rincón showed elevated levels and should be prioritized for intervention. The findings support adaptive monitoring and watershed-based management to address pollution effectively. A multifaceted strategy involving science, community engagement, and regulation is essential for sustainable water resource protection.

Pearson's Bivariate Analysis in Sediments

Pearson's bivariate analysis (Table 6) showed significant positive correlations ($p < 0.05$) between Pb concentrations and land use types such as Forest, Chaparral, Urbanism, and Industry, as well as crops like Banana, Yucca, and Pineapple. Pb also correlated with bare soil, silt and clay textures, and infiltration rate.

These results suggest that urban, industrial, and certain agricultural activities contribute to elevated Pb levels, likely through runoff and soil erosion. Weaker correlations ($0.1 < p < 0.2$) were observed with Rice and Temporary crops, indicating a less pronounced influence.

Understanding these associations is key for developing targeted strategies to mitigate Pb contamination and safeguard environmental and public health.

Table 6. Pearson's Bivariate Correlations identified between HMs in river sediments and land use activities.

Variable	Heavy metal content (mg/L)						
	Pb	Cr	Cu	As	Cd	Ni	Hg
Season	X	+	+	X	X	X	X
Forest	+	+	X	-	X	+	-
Chaparral	-	+	X	-	X	+	-
Grass	X	X	-	-	X	-	X
Housing	+	+	+	+	+	X	+
Industry	+	+	+	-	X	+	X
Temporary crops (onion, potato, carrot)	-	X	-	-	X	X	X
Rice	+	-	+	+	-	+	+
Sugar cane	X	-	X	+	-	-	X
Banana	-	-	X	-	-	-	-
Coffee	X	-	X	+	X	X	+
Ferns	X	-	X	+	X	X	+
Palm	X	-	+	X	X	-	+
Yucca	-	-	-	+	X	-	-
Pineapple	-	-	-	+	-	-	-
Empty soil	-	+	X	-	X	+	-
Sand	X	-	-	-	-	-	-
Lime	-	+	-	-	+	+	+
Clay	+	+	+	+	X	X	X
Infiltration Speed	+	-			-	-	-

Notes:

	Correlated (confidence level≥95%)
	Correlated (confidence level 90-<95%)
	Correlated (confidence level 80-<90%)

X = Not correlated
- = Negative correlation
+ = Positive correlation

Pearson's analysis revealed significant positive correlations ($p<0.05$) between HM concentrations and various land cover/uses, crop types, and soil properties. Cu and As showed strong associations with land covers like Forest and Chaparral. Urbanism, and Industry, and with crops such as Sugarcane, Banana, and Palm. As also showed correlations with some temporary crops, Coffee and Ferns (Table 6). Cu correlates with Grass, Housing, Industry, Temporary Crops and Rice and Palm. Cd correlates with Housing, some relationship with Sugar Cane and Banana. Ni has strong correlations with Forest, Charral-Tacotal, Industry, Rice, Palm and Sugar Cane. Hg is related to Charral-Tacotal, Urbanism, Banana, Coffee, Ferns and Palm.

These results indicate that urban, industrial, and agricultural activities significantly influence HM concentrations in sediments. Crops like Sugarcane, Rice, and Pineapple are frequently associated with higher metal levels, likely due to intensive agrochemical use. Phosphate fertilizers and some pesticides are known to contain trace metals such as Cd, As, and Pb; although farmers in the study area did not disclose specific inputs, these agrochemicals may contribute to the observed patterns. Additionally, hyper-bioaccumulation processes may explain negative correlations, where certain vegetation absorbs metals from sediments.

The findings highlight the environmental risks posed by land use change, particularly through deforestation, soil disturbance, and runoff, all of which can mobilize stored metals. These dynamics threaten aquatic and terrestrial ecosystems through bioaccumulation, especially of metals like Hg, which pose toxic risks across the food web.

Given the variability of HM distribution across regions, local geological, climatic, and land use histories should be considered. Future monitoring programs should assess both water and sediment quality, incorporating community participation to enhance awareness and conservation efforts.

Sediment predictive models by land use

Higher adjusted R^2 values in sediment models indicate that land use and environmental factors better explain HM content in sediments than in rivers. Sediments act as long-term sinks, integrating historical inputs and cumulative land use effects, while river concentrations fluctuate with flow, dilution, and seasonal changes. Fine particles such as clay and silt enhance sediment capacity to retain metals through adsorption and related processes, making them more stable and reliable indicators of contamination. Thus, sediments provide clearer insights into long-term HM dynamics and are valuable for guiding pollution mitigation strategies.

Lead

The adjusted R^2 of 0.696 after variable reduction indicates a strong model fit. Including all correlated variables yielded a nearly identical R^2 (0.695), suggesting that just five key predictors—Urbanism, Industry, Palm, Pineapple, and Sugarcane—are sufficient to explain most of the variance in HM content in sediments.

This simplified model enhances practical applicability, aiding environmental managers by identifying priority land uses for intervention. Targeted strategies, such as promoting sustainable agriculture or regulating industrial discharges, can help reduce contamination risks.

$$[Pb] = 0.911*Urbanism - 35.922*Industry + 0.178*Palm + 0.097*Pineapple - 0.303*Cane - 0.084 \quad (7)$$

The calculated incremental contribution of each land-use variable using forward selection. Urban land use alone explained Adjusted $R^2 = 0.620$, while the full model reached Adjusted $R^2 = 0.691$. Thus, urbanism represents ~89.7% of the total explained variance, and the other variables collectively contributed ~10% (Adjusted R^2 for Industry = 0.038, for Palm = 0.018, for Pineapple = 0.012, for Sugarcane = 0.007). This indicates that while other land uses provide additional explanatory power, urban land use is the dominant predictor of heavy-metal concentrations in the study area.

Chrome

The predictive model for Cr in sediments, with an adjusted R^2 of 72.7%, demonstrates strong explanatory power. Key variables include Urbanism, Industry, Chaparral, Pasture, Bare Soil, Silt Texture, and crops like Rice, Cassava, Banana, and Temporary Crops.

These findings underscore the influence of urban, industrial, and agricultural activities on Cr accumulation. Targeted interventions, such as pollution control and erosion-reducing agricultural practices, could help mitigate contamination. The inclusion of soil-related variables highlights the importance of land management and soil conservation in maintaining sediment quality.

$$[Cr] = +0.466*Urbanism + 168.615*Industry - 59.364*Chaparral - 0.259*Pasture + 242.434*Bare\ soil + 0.938*Silt - 30.994*Rice - 2.275*Cassava - 1.173*Banana - 0.954*Temporary\ crops + 10.237 \quad (8)$$

For chromium (Cr), the regression model explained 72.7% of the variance in concentrations (Adjusted $R^2 = 0.727$). The largest contribution was from industrial land use (0.302, 41.5% of explained variance), followed by bare soil (0.129, 17.7%), urban land use (0.092, 12.7%), and limus (0.069, 9.5%). Other land uses such as Rice (0.046, 6.3%), Chaparral (0.030, 4.1%), Temporary Crops (0.031, 4.3%), Cassava (0.016, 2.2%), Pasture (0.012, 1.7%), and Banana (0.010, 1.4%) contributed smaller increments. This indicates that industrial activities and bare soil exposure are the dominant predictors of Cr distribution, while agricultural and secondary land covers make comparatively minor contributions.

Copper

Copper (Cu) exhibits significant bivariate correlations with various variables, but the predictive model's low adjusted R^2 (0.227 for the full model and 0.226 for the reduced one) suggests that these variables do not fully explain Cu concentrations in sediments. This indicates that other, unexamined factors may play a significant role in Cu accumulation.

The similarity in R^2 values between the models calls for further investigation to identify additional variables, such as land use practices or localized pollution sources, that may influence Cu levels.

Arsenic

The predictive model for As in sediments, with an adjusted R^2 of 0.713, indicates that the selected variables—Forest, Pasture, Industry, Sugar Cane, Coffee, Rice, Cassava, and Temporary Crops—effectively explain a significant portion of As concentration variability (formula 9). Human activities, especially in urban and industrial areas, play a crucial role in As accumulation, highlighting the need for targeted land use management.

The correlation between As and agricultural practices, particularly with crops like Rice and Cassava, suggests that sustainable farming practices could help reduce As levels in sediments. Soil composition and land management practices, such as soil conservation, are also vital in mitigating As accumulation.

$$[As] = -0.084*Forest – 0.054*Pasture - 3.354*Industry + 0.637*Cane - 0.189*Coffee + 0.298*Cassava + 0.674*Rice - 0.068*Temporary\ crops + 8.321 \quad (9)$$

For arsenic, the stepwise contributions of land cover types to the total adjusted R^2 of 0.705 show that Cane alone explains the largest portion, accounting for approximately 52% of the model's explanatory power. Coffee and Cassava follow, contributing around 14% and 13% respectively, while Forest and Pasture add roughly 8% and 9%. The remaining land uses—Temporary Crops, Industry, and Rice—have minimal influence, each explaining less than 2% of the total variance. Overall, this indicates that the majority of arsenic variability in the study area is strongly associated with Cane, Coffee, Cassava, Pasture, and Forest cover, with other land uses playing only a minor role.

Cadmium

Cd concentrations in sediments exhibit significant bivariate correlations with variables such as Urbanism, Rice, Sugarcane, Banana, and Pineapple crops, as well as soil textures like Sand and Silt and Infiltration Rate (Table 3). However, the predictive model, after variable reduction, reveals a low adjusted R^2 of 0.178, indicating that the selected variables do not explain a significant portion of the variability in Cd levels.

Nickel

The predictive model for sediment Ni content, with an adjusted R^2 of 0.741, indicates a strong ability to explain the variability in Ni concentrations. The model includes key predictor variables such as Urbanism, Industry, Chaparral, Rice, Pasture, Bare Soil, and Silt Texture, (formula 10) which collectively capture significant relationships influencing Ni levels in sediments.

The model highlights the impact of human activities, particularly urbanization and industrialization, on Ni accumulation. These findings emphasize the importance of effective land use planning and pollution management to reduce Ni contamination in aquatic ecosystems. Additionally, the inclusion of agricultural practices, particularly Rice and Sugarcane cultivation, suggests that farming can contribute to Ni accumulation, making sustainable agricultural practices vital for mitigating pollution.

The role of sediment composition, especially Silt Texture in Ni dynamics is also significant. Understanding how soil properties interact with metal accumulation can inform land management strategies aimed at reducing contamination.

$$[Ni] = +84.791*Industry + 0.170*Urbanism – 0.274*Pasture – 22.609*Chaparral + 137.479*Bare\ soil – 26.420*Rice – 2.184*Cassava – 0.540*Banana + 493*Silt + 17.081 \quad (10)$$

For nickel, the total adjusted R^2 of 0.741 is largely explained by Bare Soil, which alone accounts for approximately 78% of the model's explanatory power. Adding Industry increases the explanatory power to 0.637, followed by Limus (0.660), Rice (0.695), Cassava (0.713), and Pasture (0.731), each providing moderate incremental contributions. Urbanism, Banana, and Chaparral add only minor increments, bringing the final adjusted R^2 to 0.741. Overall, the results indicate that Bare Soil is the dominant factor driving nickel variability, while other land uses—particularly Agriculture and Pasture—contribute smaller but meaningful amounts, and urban and natural covers have minimal impact.

Mercury

The predictive models for sediment Hg content, both with and without variable reduction, show relatively low adjusted R^2 values of 0.351 and 0.352, respectively, indicating limited ability to explain variability in Hg concentrations. These low values suggest that the selected predictor variables do not adequately capture the complex factors influencing Hg accumulation in sediments.

The findings highlight the need for caution in using these models for Hg contamination predictions and emphasize the importance of exploring additional variables that may influence Hg levels.

The complexity of Hg accumulation in sediments suggests that interactions among a wider range of factors could be influencing its concentrations. To enhance understanding of Hg contamination, further research is needed, focusing on local pollution sources, sediment geochemistry, hydrological factors, and climate influences.

A summary of the models is as follows:

Table 7. Predictive model performance for heavy metals in sediments.

Metal	Adj. R^2	Key predictors	Main insights	Notes/limitations
Pb	0.696	Urbanism, Industry, Palm, Pineapple, Sugarcane	Urban land use dominates (≈90% of explained variance); other variables add ~10%	Strong model; requires validation elsewhere
Cr	0.727	Industry, Bare soil, Urbanism, Chaparral, Pasture, Rice, Cassava, Banana, Temporary crops, Silt	Industrial land use (42%) and bare soil (18%) are main drivers; urbanism secondary	High explanatory power; still needs mechanistic exploration
Cu	0.227	Sugarcane, Ferns, Cassava, Infiltration rate (weak effect)	Weak model; suggests other unmeasured factors control Cu	Needs more variables/ localized pollution sources
As	0.713	Cane, Coffee, Cassava, Pasture, Forest, Rice, Temporary crops, Industry	Cane explains ~52%, coffee 14%, cassava 13%; agricultural practices key	Strong model; underscores farming impacts
Cd	0.178	Urbanism, Rice, Sugarcane, Banana, Pineapple, Sand/Silt textures, Infiltration rate	Weak model; large portion of variability unexplained	Likely influenced by historical/point sources
Ni	0.741	Bare soil, Industry, Silt, Rice, Cassava, Pasture, Urbanism, Chaparral, Banana	Bare soil dominates (~78%); other uses add incrementally	Strongest model overall; sediment texture important
Hg	0.351	Temporary crops, Sugarcane (weak influence)	Limited explanatory power; suggests missing factors (e.g., atmospheric deposition)	Model underperforms; needs broader environmental scope

Predictive models for heavy metals in sediments showed variable performance (Table 7). Strong explanatory power was achieved for Ni (Adj. R^2 = 0.741), Cr (0.727), Pb (0.696), and As (0.713), indicating that land use and soil properties account for a substantial share of their variability. In particular, Bare Soil (Ni), Industrial land use (Cr), Urbanization (Pb), and Sugarcane (As) emerged as dominant predictors, often explaining more than half of the modeled variance. By contrast, models for Cu, Cd, and Hg had low explanatory power (Adj. R^2 < 0.35), suggesting that other unmeasured factors—such as local pollution sources, atmospheric deposition, or historical land use—likely govern their distribution. Across metals, three patterns are consistent: (i) urban and industrial activities are recurrent drivers of contamination; (ii) agricultural practices, especially Sugarcane, Rice, and Pineapple cultivation, are frequently linked to HM variability; and (iii) soil properties (e.g., Silt, Infiltration) play a significant but secondary role. These findings underscore that HM accumulation in sediments is shaped by an interplay of anthropogenic activities and environmental conditions. Collectively, the models highlight priority land uses for management (urban, industrial, and intensive agriculture), but also point to the need for additional explanatory variables to improve predictive accuracy. Integrating hydrogeological, climatic, and agrochemical data in future models will be essential for capturing the full complexity of HM dynamics in sediments.

In this study, several factors were identified that could further improve predictive models of heavy metal (HM) dynamics, including seasonal hydrological variations, soil and sediment physicochemical properties (e.g., organic matter content, particle size), and specific anthropogenic activities such as agricultural runoff and urban wastewater inputs. Understanding the underlying mechanisms of HM accumulation and transport—particularly the role of sediments as long-term sinks versus water as a snapshot of current contamination—provides a more comprehensive assessment of environmental risks. The correlation analyses and predictive models developed here reveal patterns not previously reported in the region, such as the stronger retention of metals in fine sediment particles and the significant influence of land use on sediment HM levels, highlighting the added value of integrating sediment and water data. These findings have immediate practical applications for local stakeholders: they can guide targeted land management practices, inform monitoring programs by identifying potential contamination hotspots, and support evidence-based policy development to mitigate HM pollution in both water and sediment environments.

Conclusions

This study provides a comprehensive assessment of HMs contamination in river water and sediments, revealing that metal concentrations are spatially heterogeneous and strongly influenced by land use. Sediments acted as long-term sinks for contaminants, while water reflected more immediate conditions, with certain metals—such as Pb, Cr, Cu, As, Ni, and Hg—exceeding permissible limits in specific locations.

Significant correlations between HM concentrations and urban, agricultural, and industrial activities underscore the role of land use in shaping contamination patterns. Certain plant species demonstrated hyper-bioaccumulation potential, suggesting a possible mitigation pathway, though further research is needed to clarify mechanisms and long-term effects.

While some predictive models effectively captured metal dynamics, others, particularly for Hg, revealed limitations, highlighting the need to incorporate additional factors for improved accuracy. This emphasizes the importance of understanding both water and sediment dynamics to accurately predict contamination risks.

Overall, the study contributes new insights into the combined analysis of water and sediment, informs targeted monitoring and management strategies, and provides evidence to support policy development for protecting aquatic ecosystems and public health.

Recommendations

Integrated Land Management: To mitigate heavy metal pollution, it is crucial to implement sustainable land management practices. This includes promoting agricultural practices that reduce runoff and soil erosion, as well as controlling industrial discharges.

Monitoring Programs: Establishing comprehensive monitoring programs that assess both water and sediment quality can provide valuable insights into the extent of contamination and its impacts on ecosystem health.

Policy Development: Policymakers should consider the correlations identified in this study when formulating regulations and guidelines for land use and agricultural practices. Stricter regulations on industrial activities and urban development can help protect water quality and ecosystem integrity.

In conclusion, this research highlights the need for a multidisciplinary approach to understanding and managing heavy metal contamination in aquatic systems. Continued research is essential to explore the underlying mechanisms driving the observed correlations and to develop effective strategies for mitigating heavy metal pollution, ultimately contributing to the preservation of environmental health and community well-being.

Acknowledgments

The authors express their gratitude to the Instituto Tecnológico de Costa Rica for providing financial and administrative support throughout the duration of the project. They also extend their appreciation to the Centro de Investigación en Protección Ambiental (CIPA) and the Centro de Investigación y Servicios Químicos y Microbiológicos (CEQIATEC) for their valuable assistance and support in conducting the research. Their contributions were instrumental in the successful execution of the project.

Compliance with ethical standards No samples collected were required to compliance with the ethical standards of the Technological Institute of Costa Rica.

Consent to participate: Not applicable

Consent for publication: All author's consented for publication

Conflict of interest: The authors declare that they have no conflict of interest.

Availability of data and material: Upon request contacting Dr. Guillermo Calvo-Brenes, email calvogmo@yahoo.com

Code availability Not applicable

References

[1] G. Calvo-Brenes, *Indices e indicadores sobre la calidad del agua*, First. Cartago, Costa Rica: Editorial Tecnológica, 2018.

[2] N. Gil-Rodas, G. Calvo-Brenes, A. Guerra, and A. Perdomo, "Water quality assessment of six rivers of the Pacific side of Guatemala," *Environ Earth Sci*, vol. 80, no. 5, p. 196, Mar. 2021, doi: 10.1007/s12665-021-09505-w.

[3] N. Gil-Rodas *et al.*, "A comparative study of several types of indices for river quality assessment," *Water Quality Research Journal*, vol. 58, no. 3, pp. 169–183, Aug. 2023, doi: 10.2166/wqrj.2023.029.

[4] R. Khan, A. Saxena, S. Shukla, S. Sekar, V. Senapathi, and J. Wu, "Environmental contamination by heavy metals and associated human health risk assessment: a case study of surface water in Gomti River Basin, India," *Environ Sci Pollut Res*, vol. 28, no. 40, pp. 56105–56116, Oct. 2021, doi: 10.1007/s11356-021-14592-0.

[5] T. Salazar-Rojas, F. R. Cejudo-Ruiz, and G. Calvo-Brenes, "Assessing magnetic properties of biomonitors and road dust as a screening method for air pollution monitoring," *Chemosphere*, vol. 310, p. 136795, Jan. 2023, doi: 10.1016/j.chemosphere.2022.136795.

[6] G. Calvo-Brenes, *Ríos: Fundamentos sobre su calidad y su relación con el entorno socioambiental*, First. Cartago, Costa Rica: Editorial Tecnológica, 2015.

[7] J. Lebepe, M. C. Selala, Y. Takai, N. M. Maleka, and S. B. S. Hlatshwayo, "Accumulation of Heavy Metals in Tissues of Oreochromis Mossambicus from the uMgeni River and Human Health Risk Assessment," *Water Air Soil Pollut*, vol. 235, no. 11, p. 726, Nov. 2024, doi: 10.1007/s11270-024-07553-z.

[8] Y. Hong *et al.*, "Progress in the Research of the Toxicity Effect Mechanisms of Heavy Metals on Freshwater Organisms and Their Water Quality Criteria in China," *Journal of Chemistry*, vol. 2020, pp. 1–12, May 2020, doi: 10.1155/2020/9010348.

[9] X. Zeng, J. Du, S. Zhang, and T. Ni, "Spatial-Temporal Characteristics of Ecological Risks from Heavy Metals for Aquatic Fauna in Drinking Water Sources of China," *Water Air Soil Pollut*, vol. 234, no. 12, p. 733, Dec. 2023, doi: 10.1007/s11270-023-06734-6.

[10] T. Salazar-Rojas, F. R. Cejudo-Ruiz, and G. Calvo-Brenes, "Comparison between machine linear regression (MLR) and support vector machine (SVM) as model generators for heavy metal assessment captured in biomonitors and road dust," *Environmental Pollution*, vol. 314, p. 120227, Dec. 2022, doi: 10.1016/j.envpol.2022.120227.

[11] H. Ali, E. Khan, and I. Ilahi, "Environmental Chemistry and Ecotoxicology of Hazardous Heavy Metals: Environmental Persistence, Toxicity, and Bioaccumulation," *Journal of Chemistry*, vol. 2019, pp. 1–14, Mar. 2019, doi: 10.1155/2019/6730305.

[12] J. Briffa, E. Sinagra, and R. Blundell, "Heavy metal pollution in the environment and their toxicological effects on humans," *Heliyon*, vol. 6, no. 9, p. e04691, Sept. 2020, doi: 10.1016/j.heliyon.2020.e04691.

[13] U. C. Nkwunonwo, P. O. Odika, and N. I. Onyia, "A Review of the Health Implications of Heavy Metals in Food Chain in Nigeria," *The Scientific World Journal*, vol. 2020, pp. 1–11, Apr. 2020, doi: 10.1155/2020/6594109.

[14] P. Luo *et al.*, "Heavy metals in water and surface sediments of the Fenghe River Basin, China: Assessment and Source Analysis," *Water Science and Technology*, vol. 84, no. 10–11, pp. 3072–3090, 2021, doi: 10.2166/wst.2021.335.

[15] L. Zhang, X. Tan, H. Chen, Y. Liu, and Z. Cui, "Effects of Agriculture and Animal Husbandry on Heavy Metal Contamination in the Aquatic Environment and Human Health in Huangshui River Basin," *Water*, vol. 14, no. 4, p. 549, Feb. 2022, doi: 10.3390/w14040549.

[16] Y. Xu *et al.*, "Integrating machine learning for enhanced spatial prediction and risk assessment of soil heavy metal(loid)s," *Environmental Pollution*, vol. 383, 2025, [Online]. Available: https://doi.org/10.1016/j.envpol.2025.126919

[17] APHA, AWWA and AEF, *Standard Methods for the Examination of Water and Wastewater*, 23rd ed. WA, DC, USA, 2017.

[18] N. P. Castro-González, F. Calderón-Sánchez, R. Moreno-Rojas, J. V. Tamariz-Flores, and E. Reyes-Cervantes, "Heavy metals pollution level in wastewater and soils in the alto balsas sub-basin in tlaxcala and puebla, Mexico," *Revista Internacional de Contaminacion Ambiental*, vol. 35, no. 2, pp. 335–348, 2019, doi: 10.20937/RICA.2019.35.02.06.

[19] C. Montalvo *et al.*, "Metal Contents in Sediments (Cd, Cu, Mg, Fe, Mn) as Indicators of Pollution of Palizada River, Mexico," *EP*, vol. 3, no. 4, p. p89, Sept. 2014, doi: 10.5539/ep.v3n4p89.

[20] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to linear regression analysis*, Sixth edition. in Wiley series in probability and statistics. Hoboken, New Jersey: Wiley, 2021.

[21] R. M. Mickey and S. Greenland, "A study of the impact of confounder-selection criteria on effect estimation," *American Journal of epidemiology*, vol. 129, no. 1, pp. 125–137, 1989, doi: https://doi.org/10.1093/oxfordjournals.aje.a115101.

[22] MINAE, "Reglamento para la evaluación y clasificación de la calidad de cuerpos de agua superficiales," vol. Decreto # 33903-MINAE-S, 2007.

[23] D. D. MacDonald, C. G. Ingersoll, and T. A. Berger, "Development and Evaluation of Consensus-Based Sediment Quality Guidelines for Freshwater Ecosystems," *Archives of Environmental Contamination and Toxicology*, vol. 39, no. 1, pp. 20–31, June 2000, doi: 10.1007/s002440010075.

[24] DEC, "Assessment levels for soil, sediment and water." 2010. [Online]. Available: https://www.der.wa.gov.au/images/documents/your-environment/contaminated-sites/guidelines/2009641_-_assessment_levels_for_soil_sediment_and_water_-_web.pdf

[25] H. Juarez, "Contaminación del río Rimac por metales pesados y efecto en la agricultura en el Cono Este de Lima Metropolitana." 2012. [Online]. Available: file:///C:/Users/XPC/Downloads/Contaminacion_del_Rio_Rimac_por_metales.pdf

[26] M. M. Uddin, M. C. M. Zakeel, J. S. Zavahir, F. M. M. T. Marikar, and I. Jahan, "Heavy Metal Accumulation in Rice and Aquatic Plants Used as Human Food: A General Review," *Toxics*, vol. 9, no. 12, p. 360, Dec. 2021, doi: 10.3390/toxics9120360.

[27] E. M. Eid *et al.*, "Prediction Models Founded on Soil Characteristics for the Estimated Uptake of Nine Metals by Okra Plant, Abelmoschus esculentus (L.) Moench., Cultivated in Agricultural Soils Modified with Varying Sewage Sludge Concentrations," *Sustainability*, vol. 13, no. 22, p. 12356, Nov. 2021, doi: 10.3390/su132212356.

Declaración sobre uso de Inteligencia Artificial (IA)

Los autores declaraamos haber utilizado *ChatGPT* para múltiples tareas: la revisión gramatical y de estilo y el apoyo en la estructura y redacción. Todos los resultados e información asistidos por IA fueron revisados, verificados y validados minuciosamente por los autores, quienes asumen plena responsabilidad por la precisión, coherencia e integridad del contenido publicado.