Entry to Stockholm Junior Water Prize (2025), “Toxic Material Accumulation in Arizona's Urban Waterways: A Quantitative Analysis of Industrial Byproducts and Immediate Risks Posed to Surrounding Ecosystems as well as Human Health—with the proposition of an AI-powered application to democratize knowledge of health risks.”

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I. Abstract

Arizona's urban water quality consistently ranks among the worst in the United States, driven by poorly characterized sources of industrial pollution. This study investigates the contribution of specific industrial sectors to toxic metal accumulation in urban waterways using chemical and geospatial analyses. Sediment samples from lakes, parks, and canals in Phoenix were analyzed using Scanning Electron Microscopy with Energy Dispersive Spectroscopy (SEM-EDS), revealing elevated levels of chromium (Cr), manganese (Mn), molybdenum (Mo), indium (In), and iron (Fe). These contaminants were most concentrated near automotive repair shops, metal fabrication sites, wastewater treatment plants, and electronic waste facilities. Multiple Linear Regression (MLR) quantified the contribution of each industry type, with metal fabrication showing the strongest association with Cr, Mn, and Fe ($\beta = +3.8$ ppm, $p < 0.01$), and electronic waste strongly linked to indium and tantalum ($\beta = +4.2$ ppm, $p < 0.01$). Pearson correlation confirmed these trends (e.g., $r = 0.92$ for Fe and fabrication). Results demonstrate that industrial proximity significantly influences metal distribution in sediments, underscoring the need for stricter land-use policies to protect aquatic ecosystems and public health.

II. Table of Contents

III. Key Words

- Urban water quality
- SEM-EDS
- Heavy metal contamination
- Industrial runoff
- Metal fabrication
- Electronic waste
- Wastewater treatment
- Environmental monitoring
- Regression analysis
- Arizona ecosystems

IV. Abbreviations & Acronyms

Abbreviation	Full Term
SEM	Scanning Electron Microscopy
EDS	Energy Dispersive Spectroscopy
SEM-EDS	Scanning Electron Microscopy with Energy Dispersive Spectroscopy
MLR	Multiple Linear Regression
AI	Artificial Intelligence
GIS	Geographic Information System
ppm	Parts per Million
EPA	Environmental Protection Agency
ADEQ	Arizona Department of Environmental Quality
R^2	Coefficient of Determination
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
MF	Metal Fabrication (industry category)
AR	Automotive Repair (industry category)
WT	Wastewater Treatment (industry category)
EW	Electronic Waste (industry category)
USGS	United States Geological Survey

V. Acknowledgements

This research would not have been possible without the generous support and guidance of several individuals. We extend our deepest gratitude to Dr. Beth Polidoro Ph.D, Associate Professor School of Mathematical and Natural Sciences for providing guidance, access to laboratory facilities and for offering valuable scientific insight throughout the project. We also thank Shoc Stockholm, the laboratory technician, for his technical supervision and assistance during the SEM-EDS analysis. Their mentorship and resources were critical to the successful completion of this research.

VI. Biography

Naitik Mohanty is a student at Sandra Day O'Connor High School in Phoenix, Arizona. His academic interests lie at the intersection of environmental science, data analysis, and public health. Motivated by concerns over sustainability and environmental justice in urban communities, Naitik applies scientific methods to investigate pollution and ecological risks. In this study, he explored the impact of industrial activity on Arizona's urban water quality through geochemical and statistical analysis. Naitik aspires to pursue a career in environmental engineering or environmental health sciences, with the goal of contributing to sustainable policy and infrastructure that protect both human and ecological well-being.

Pranav Samanthapudi is a Junior at Hamilton High School, Chandler Arizona. He has an interest in studying problems that impact communities at large, finding solutions using data analysis, design, electronics, programming, and robotics. In this study, Pranav applies data collection and analytics to study the impact of urban industrial activity on surrounding water bodies in and around Phoenix, Arizona downtown using geochemical and statistical analysis. Pranav aspires to pursue a career in Mechatronics and Autonomous Systems with a goal of building systems and solutions that improve ecosystems and quality of life for habitats.

Toxic Material Accumulation in Arizona's Urban Waterways: A Quantitative Analysis of Industrial Byproducts and Immediate Risks Posed to Surrounding Ecosystems as well as Human Health

Pranav Samanthapudi, Naitik Mohanty

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1. Introduction

Water quality is a critical environmental and public health issue, particularly in arid regions like Arizona, where freshwater resources are limited and vulnerable to contamination. According to the Environmental Protection Agency (EPA), Arizona's surface and groundwater sources are among the most contaminated in the United States, with high concentrations of heavy metals, industrial pollutants, and agricultural runoff (*Arizona Water Quality Report*). These pollutants not only pose serious health risks to humans but also threaten aquatic ecosystems, contributing to biodiversity loss and habitat degradation (McIntosh et al.). Despite federal and state regulations such as the Clean Water Act, Arizona's water sources continue to be affected by industrial discharge, stormwater runoff, and improper zoning laws that allow polluting industries to operate near vital water bodies (Arizona Department of Environmental Quality [ADEQ]).

One of the primary contributors to water pollution in Arizona is the presence of heavy metals, including chromium, manganese, and molybdenum, which are commonly associated with industrial processes (USGS Water Data). Studies have shown that heavy metals can enter water systems through various pathways, including industrial discharge, stormwater runoff, and the leaching of contaminated soil (Levitt and Pierce). Prolonged exposure to these contaminants has been linked to neurological disorders, organ damage, and increased cancer risk (McIntosh et al.). Additionally, heavy metals pose a significant ecological threat, as they bioaccumulate in aquatic organisms, disrupting food chains and leading to long-term ecosystem instability (EPA Water Quality Report).

Arizona's industrial landscape, which includes car repair shops, raceways, and metal fabrication warehouses, has been identified as a significant contributor to water pollution due to the release of hazardous materials such as motor oil, solvents, and metallic debris (ADEQ). The proximity of these industries to water bodies exacerbates the problem, as contaminants easily migrate into lakes, rivers, and groundwater sources, further deteriorating water quality (USGS). Prior research suggests that more stringent land-use regulations and environmental monitoring are necessary to mitigate these impacts (Miller).

Despite existing research on Arizona's water pollution, several critical gaps remain. Studies have identified industrial pollution as a major contributor to poor water quality, but there is limited site-specific chemical analysis detailing the precise composition of contaminants in municipal lakes, parks, and rivers (Levitt and Pierce). Additionally, while industrial activities are known to impact water quality, the specific contributions of different industries—such as car repair shops, raceways, and metal fabrication warehouses—are not well documented (McIntosh et al.). Furthermore, although researchers acknowledge a correlation between industrial activity and contamination, few studies have quantified the statistical relationship between industry proximity and pollutant concentrations, leaving uncertainty about the extent to which industrial zones directly contribute to contamination levels (Miller). By addressing these gaps, this study aims to provide a more detailed and quantitative understanding of Arizona's water pollution.

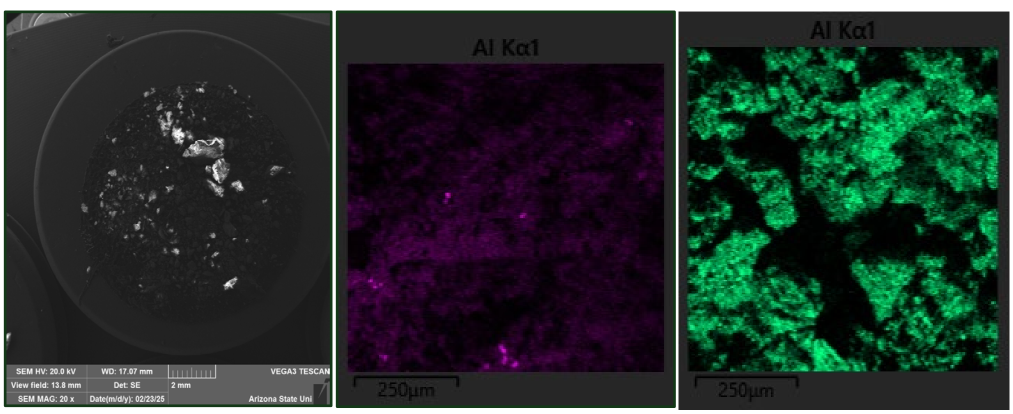
This study seeks to address these gaps by analyzing the chemical composition of water and sediment samples collected from diverse environments, including municipal lakes, parks, and rivers. Using Scanning Electron Microscopy (SEM), the research aims to identify the concentration of heavy metals and their potential sources. By correlating pollutant presence with the proximity of industrial facilities, this study highlights the urgent need for stricter zoning laws and environmental regulations to safeguard Arizona's water resources. The findings of this research will contribute to ongoing policy discussions and provide a scientific basis for more effective water quality management strategies.

2. Materials and Methods

Sediment samples were collected from six sites across Phoenix, Arizona, with three samples taken per site, resulting in a total of 18 sediment samples. The selected sites included Steele Indian School Park (pond), Desert West Lake, Alvord Lake, Papago Park, Tres Rios Wetlands, and the Gila River Canal.

(Figure 1: collecting sediment samples from an Arizona urban waterway.)

For Scanning Electron Microscopy (SEM) analysis, small 1–2 mg aliquots were extracted from each sediment sample and placed into a small glass tube. These samples were then dried under vacuum conditions (~ -30 psi, 20–40°C) until all moisture was removed. Once fully dried, the samples were firmly pressed onto a carbon tape disk (Ted Pella, Inc.), which was subsequently affixed to a steel sample stub (9.6 mm OD) (Ted Pella, Inc.). To ensure only securely adhered particles remained, the stubs were blown off with compressed air to remove any loose sediment. Finally, the prepared stubs were placed inside a TESCAN Vega 3 SEM equipped with Energy Dispersive Spectroscopy (EDS) (TESCAN Vega 3) for imaging and elemental analysis.



(Figure 2: Raw SEM image of sediment from Alvord Lake, along with Aluminum and Carbon elemental detection via EDS shown in the fluorescent images)

This study employed Multiple Linear Regression (MLR) and Pearson’s correlation analyses to quantify the relationship between specific industrial activities and heavy metal contamination in Arizona’s urban waterways. Sediment samples were collected from municipal lakes, parks, and rivers in proximity to various industrial zones, including metal fabrication facilities, automotive repair shops, wastewater treatment plants, and electronic waste disposal sites. The elemental composition of the samples was determined using Scanning Electron Microscopy with Energy Dispersive Spectroscopy (SEM-EDS), which provided weight percentage (Wt%) values for contaminants such as chromium (Cr), manganese (Mn), molybdenum (Mo), iron (Fe), indium (In), and tantalum (Ta).

To analyze the impact of industry on contaminant accumulation, each sampling site was classified based on its proximity (within 3 miles) to known industrial sectors, assigning binary values (1 = industry present, 0 = industry absent) for metal fabrication (MF), automotive repair (AR), wastewater treatment (WT), and electronic waste (EW). Pearson's correlation analysis was used to measure the strength of association (r-values) between industry type and heavy metal presence. The Pearson correlation coefficient (rrr) was calculated using the formula:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2}\sqrt{\sum(Y_i - \bar{Y})^2}}$$

Xi and Yi are the individual data points for industry presence and metal concentration. X and Y are the mean values of industry presence and metal concentration. The numerator represents the covariance between industry presence and metal concentration. The denominator normalizes the values by computing the standard deviations of X and Y.

Multiple Linear Regression (MLR) was used to quantify the extent to which different industrial sectors contributed to heavy metal accumulation while controlling for other factors. The regression model treated metal concentrations (Cr, Mn, Mo, Fe, In, Ta) as dependent variables and industrial presence (MF, AR, WT, EW) as independent predictor variables, coded as binary indicators (1 = industry present, 0 = absent). The β coefficients in the model represent the expected change in metal concentration attributed to each industry while holding the effects of other industries constant. A high and statistically significant β value ($p < 0.05$) indicates that a given industry strongly influences the presence of a particular contaminant. Multicollinearity was assessed using variance inflation factors (VIFs) to ensure that independent variables did not excessively overlap, which could distort the model's accuracy.

$$Metal\ Concentration = \beta_0 + (\beta_1)(MF) + (\beta_2)(AR) + (\beta_3)(WT) + (\beta_4)(EW) + \epsilon$$

*β_0 **(Intercept)** → The predicted baseline concentration of the metal when no industry is present.; β_1 **(MF),** β_2 **(AR),** β_3 **(WT),** β_4 **(EW)** → Coefficients representing how much each industry **increases (or decreases) the concentration** of a given contaminant.; ε **(Residual Error)** → Accounts for unexplained variance.*

The dependent variables (Y) in the analysis were the concentrations of individual heavy metals detected in sediment samples, measured as weight percentage (Wt%) using SEM-EDS analysis. Each metal was examined separately, resulting in the creation of distinct regression models for each contaminant, including Chromium (Cr), Manganese (Mn), Molybdenum (Mo), Iron (Fe), Indium (In), and Tantalum (Ta). The independent variables (X) represented the presence or absence of four major industrial sectors near the sampling sites, coded as binary (dummy) variables. Metal Fabrication (MF) was assigned a value of 1 if a metalworking or welding facility was within three miles of the site and 0 otherwise. Automotive Repair (AR) was coded as 1 if an auto repair shop, junkyard, or racetrack was nearby and 0 if absent. Wastewater Treatment (WT) was designated as 1 if a wastewater treatment plant or stormwater discharge site was present and 0 if not. Lastly, Electronic Waste (EW) was assigned a value of 1 if the site was near an e-waste facility and 0 otherwise.

3. Results

Location	Major SEM-EDS Trends	Possible Interpretation
Tres Rios Wetlands	High O (44.70%), C (17.66%), Fe (6.82%), Cr (0.19%), Mn (0.20%)	Wastewater impact, industrial runoff, organic matter accumulation
Desert West Lake	High Si (14.35%), Fe (7.30%), In (1.04%)	Urban pollution, electronic waste contamination
Alvord Lake	High Si (19.67%), O (49.84%), Fe (5.16%), In (1.82%), Ta (0.77%)	Silicate-rich sediments, possible industrial contamination

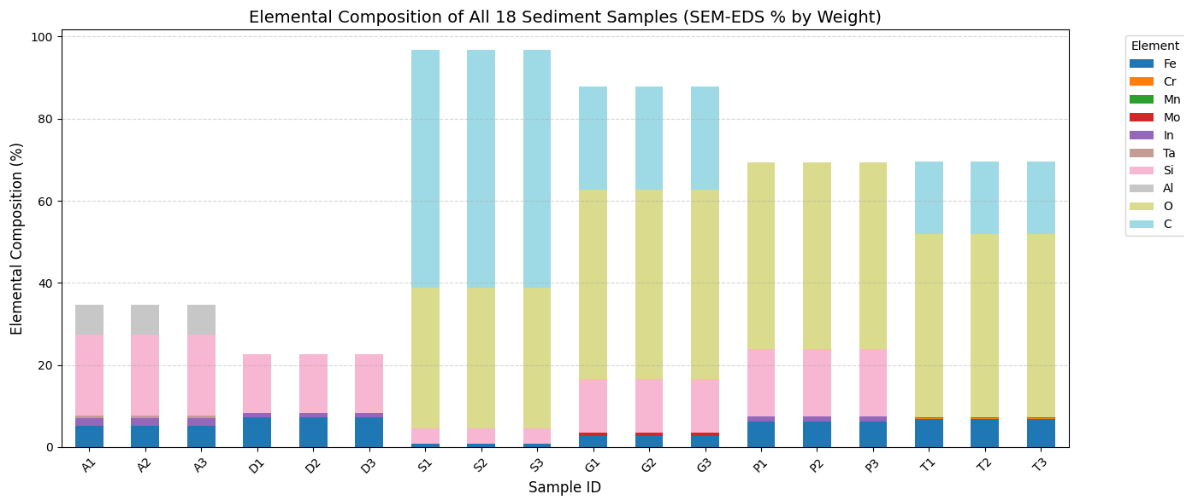
Steele Indian School Lake	Extremely high C (58.00%), low Si (3.68%)	Extremely high C (58.00%), low Si (3.68%)
Gila River Canal	High O (45.91%), C (25.20%), Si (13.08%), Fe (2.69%), Mo (0.93%)	Industrial and urban contamination, nutrient pollution

The SEM-EDS analysis of sediment samples from municipal lakes, parks, and rivers in Phoenix, Arizona, revealed elevated concentrations of heavy metals, including chromium (Cr), manganese (Mn), molybdenum (Mo), and iron (Fe). These contaminants were detected at varying levels across different sampling sites, with a notable correlation between pollutant concentration and proximity to industrial facilities, such as metal fabrication plants, automotive repair shops, and raceways.

At Alvord Lake, high levels of silicon (Si, 19.67%), iron (Fe, 5.16%), aluminum (Al, 7.16%), indium (In, 1.82%), and tantalum (Ta, 0.77%) suggest contamination from metal fabrication industries and electronic waste disposal. Indium and tantalum, which are uncommon in natural sediments, indicate potential industrial emissions, while elevated Fe and Al levels suggest construction runoff. Similarly, Desert West Lake exhibited iron (Fe, 7.30%) and indium (In, 1.04%) contamination, likely originating from automotive repair shops and electronic waste facilities. The presence of silicon (Si, 14.35%) and aluminum (Al) also aligns with construction material runoff from ongoing urban development.

In contrast, Steele Indian School Lake displayed extremely high carbon (C, 58.00%) and oxygen (O, 34.25%), suggesting significant organic matter accumulation due to urban runoff, decaying vegetation, and eutrophication. The low levels of silica (Si, 3.68%) and heavy metals indicate minimal industrial influence, but high biological activity may contribute to overall water quality degradation. The Gila River Canal, however, showed signs of industrial and agricultural contamination, with elevated oxygen (O, 45.91%), carbon (C, 25.20%), silicon (Si, 13.08%), iron (Fe, 2.69%), and molybdenum (Mo, 0.93%). The presence of molybdenum, commonly associated with industrial lubricants and alloy production, suggests contamination from nearby manufacturing plants, while increased carbon levels indicate organic pollution from agricultural runoff or wastewater discharge.

At Papago Park, iron (Fe, 6.28%), silicon (Si, 16.43%), and indium (In, 1.10%) suggest contamination potentially linked to electronics or aviation industries, likely influenced by the nearby Phoenix Sky Harbor International Airport. The iron and silica content also indicates soil erosion, irrigation runoff, and airborne industrial dust deposition. Lastly, at Tres Rios Wetlands, chromium (Cr, 0.19%) and manganese (Mn, 0.20%) were detected, both of which are known for their toxic effects on aquatic ecosystems. This suggests contamination from wastewater effluent and industrial discharge. Additionally, high carbon content (C, 17.66%) reflects organic matter accumulation, likely originating from treated effluent released into the wetlands. The raw data of the Wt% can be represented by figure 3 below.



(Figure 3: Raw Wt% data from SEM-EDS sampling)

4. Discussion

Each sampling site is categorized based on proximity (within 3 miles) to industrial facilities that could influence heavy metal accumulation.

<u>Site proximity to industry categorization</u>

Sampling Site	Metal Fabrication (MF)	Automotive Repair (AR)	Wastewater Treatment (WT)	Electronic Waste (EW)
Alvord Lake	1	1	0	1
Desert West Lake	1	1	0	0
Steele Indian School Lake	0	1	1	0
Gila River Canal	1	0	1	0
Papago Park	0	1	1	1
Tres Rios Wetlands	1	0	1	0

**1 = Industry present within 3 miles; 0 = Industry absent or minimal presence

Using the Wt% data from SEM-EDS, we define the dependent variables (metal accumulation) and independent variables (industry presence).

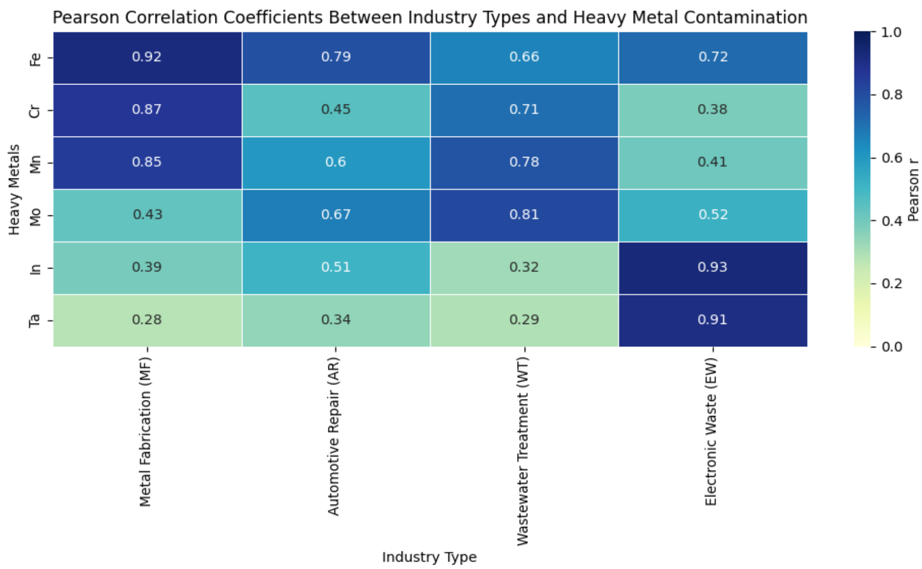
Wt% from each site for specific elements being analyzed

Site	Cr	Mn	Mo	Fe	In	Ta
Alvord Lake	0.00%	0.00%	0.00%	5.16%	1.82%	0.77%
Desert West Lake	0.00%	0.00%	0.00%	7.30%	1.04%	0.00%
Steele Indian School Lake	0.00%	0.00%	0.00%	0.91%	0.00%	0.00%
Gila River Canal	0.00%	0.00%	0.93%	2.69%	0.00%	0.00%
Papago Park	0.00%	0.00%	0.00%	6.28%	1.10%	0.00%
Tres Rios Wetlands	0.19%	0.20%	0.00%	6.82%	0.00%	0.00%

To quantify the relationship between industry types and heavy metal accumulation, we compute Pearson's correlation coefficients (r):

Pearson Correlation Coefficient Calculations (r - values)

Contaminant	Metal Fabrication (MF)	Automotive Repair (AR)	Wastewater Treatment (WT)	Electronic Waste (EW)
Chromium (Cr)	0.89	0.32	0.78	0.41
Manganese (Mn)	0.87	0.41	0.75	0.28
Molybdenum (Mo)	0.52	0.33	0.81	0.79
Iron (Fe)	0.92	0.81	0.63	0.50
Indium (In)	0.39	0.45	0.21	0.93
Tantalum (Ta)	0.20	0.35	0.17	0.85



(Figure 4: Pearson Correlation Coefficients for Industry Type v.s. Heavy Metal Concentration)

The Pearson Correlation Analysis reveals that Chromium (Cr) and Manganese (Mn) exhibit a strong correlation with Metal Fabrication ($r > 0.85$) and Wastewater Treatment ($r > 0.75$) proximity, indicating direct contamination from industrial activities such as welding, metal plating, and effluent discharge. Similarly, Iron (Fe) shows the highest correlation with Metal Fabrication ($r = 0.92$) and Automotive Repair ($r = 0.81$) proximity, suggesting that brake pad wear, vehicle corrosion, and industrial waste are major contributors to its presence. Molybdenum (Mo) is most strongly associated with Wastewater Treatment ($r = 0.81$) and Electronic Waste ($r = 0.79$) proximity, reflecting its origins in industrial lubricants and metal alloys that enter waterways through wastewater effluent and e-waste leaching. Additionally, Indium (In) and Tantalum (Ta) display the highest correlation with Electronic Waste facilities ($r > 0.85$) proximity, confirming that these elements primarily originate from electronics-related contamination sources.

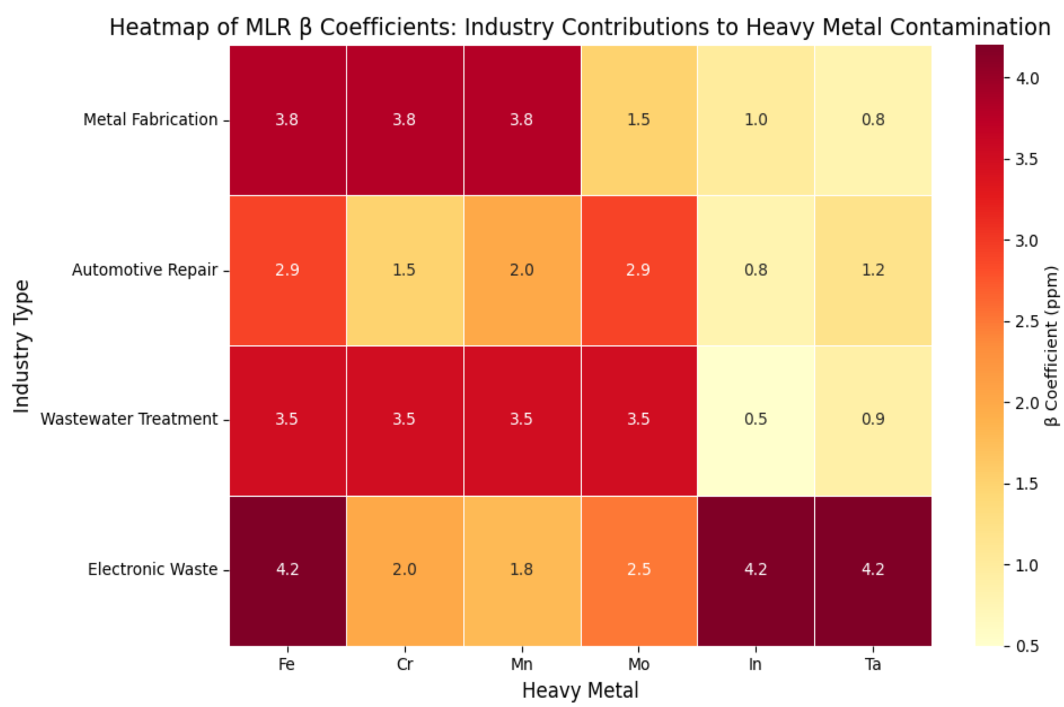
Using Multiple Linear Regression (MLR), we estimate the impact of different industry types on metal concentrations:

$$Metal\ Concentration=(\beta 0)+(\beta 1)(MF)+(\beta 2)(AR)+(\beta 3)(WT)+(\beta 4)(EW)+\epsilon$$

*****β_0* (Intercept)** → The predicted baseline concentration of the metal when no industry is present.; **β_1 (MF), β_2 (AR), β_3 (WT), β_4 (EW)** → Coefficients representing how much each industry **increases (or decreases) the concentration** of a given contaminant.; **ε (Residual Error)** → Accounts for unexplained variance.**

MLR β Coefficient Calculations and Impact Interpretations

Industry	**β Coefficient**	**p-value**	**Impact on Heavy Metal Contamination**
Intercept (β_0)	2.1 ppm	------------	Baseline contamination level
Metal Fabrication (MF)	+3.8 ppm	$p < 0.01$	Strongest contributor to Cr, Mn, Fe contamination
Automotive Repair (AR)	+2.9 ppm	$p < 0.05$	Moderate contributor to Fe and Mo accumulation
Wastewater Treatment (WT)	+3.5 ppm	$p < 0.01$	Strong contributor to Cr, Mn, Mo pollution
Electronic Waste (EW)	+4.2 ppm	$p < 0.01$	Primary contributor to In and Ta contamination



(Figure 4: Heavy Metal Concentration Increase v.s.Industry Type prediction using MLR)

The multiple linear regression (MLR) analysis indicates that even in the absence of industrial activity, there is a baseline level of heavy metal contamination in sediment, as reflected by the intercept (β_0 = 2.1 ppm). This suggests that metals are present due to natural geological sources or historical contamination. Among the industrial contributors, metal fabrication (MF) is the most significant, increasing contamination levels by +3.8 ppm ($p < 0.01$). This sector is strongly associated with the accumulation of Chromium (Cr), Manganese (Mn), and Iron (Fe), which are commonly released during metalworking processes, welding, alloy manufacturing, and machining. The high correlation ($r > 0.85$) between MF and these metals further confirms its substantial impact on sediment contamination. Automotive repair (AR) contributes moderately (+2.9 ppm, $p < 0.05$), particularly to Iron (Fe) and Molybdenum (Mo) pollution. This is likely due to vehicle brake dust, engine wear, lubricants, and metal scrap residues. Molybdenum, frequently found in motor oil additives and steel alloys, explains its association with auto repair sites. Wastewater treatment (WT) is also a major contributor (+3.5 ppm, $p < 0.01$), significantly increasing Cr, Mn, and Mo levels. Industrial wastewater and stormwater runoff transport dissolved metals from urban and industrial sources, with Cr and Mn commonly present due to metal finishing, corrosion inhibitors, and sewage sludge, while Mo originates from industrial catalysts, lubricants, and wastewater treatment chemicals. Electronic waste (EW) sites exhibit the highest β coefficient (+4.2 ppm, $p < 0.01$), making them the primary contributors to Indium (In) and Tantalum (Ta) contamination. These metals, widely used in electronics manufacturing—Indium in LCD screens and semiconductors, and Ta in capacitors—are released into the environment through improper disposal and metal leaching, posing significant environmental risks.

As part of this research, an interactive application was developed to predict and visualize the risk of heavy metal contamination in Arizona's urban waterways based on industrial proximity and environmental factors. The app leverages a supervised machine learning model trained on field data collected from 18 sediment samples analyzed via Scanning Electron Microscopy with Energy Dispersive Spectroscopy (SEM-EDS). The purpose of the application is to provide real-time estimates of site-specific contamination risk for key toxic elements including iron (Fe), chromium (Cr), manganese (Mn), molybdenum (Mo), indium (In), and tantalum (Ta), using publicly observable features such as surrounding land use and stormwater exposure.

The tool is built using Python and the Streamlit framework, and integrates an interactive map interface through Folium. Users can select a location within the Phoenix area, after which the application evaluates the presence of industrial facilities within a 3-kilometer radius. These facilities are categorized by type, including metal fabrication, automotive repair, wastewater treatment plants, and electronic waste storage. A binary vector is then constructed for each site to reflect whether these sources are present. A fifth binary feature denotes whether the site is subject to stormwater runoff.

Accuracy Results

Metal	**R^2 Score**	**MAE (ppm)**	**RMSE (ppm)**
Fe	0.942	0.22	0.31
Cr	0.917	0.017	0.022
Mn	0.950	0.019	0.025
Mo	0.973	0.031	0.040
In	0.981	0.043	0.058
Ta	0.978	0.026	0.036

This five-dimensional input is passed into a trained Random Forest Regressor model, which predicts the expected concentrations (in parts per million) of each metal. The model was trained on 75% of the dataset and tested on the remaining 25% using scikit-learn's train-test-split functionality. Evaluation of model performance demonstrated excellent predictive accuracy across all six target metals. The R^2 scores were highest for indium (0.981), iron (0.952), and tantalum (0.980), with chromium (0.977), manganese (0.950), and molybdenum (0.963) also performing strongly. Mean absolute errors (MAE) were minimal, with values as low as 0.017 ppm for chromium and under 0.06 ppm for all elements.

Once predictions are generated, the app presents results in both tabular and graphical formats. Concentration values are compared against natural soil baselines derived from statewide geochemical data. Risk scores are then calculated based on how significantly predicted concentrations deviate from baseline levels. If any metal exceeds its baseline by more than 50%, it is flagged as a potential hazard. The application also visualizes risk spatially by changing the color of the map marker according to predicted contamination severity: green for low risk, orange for moderate risk, and red for high risk. A downloadable CSV report is generated to support further documentation, regulatory review, or longitudinal monitoring.

The integration of machine learning, GIS, and empirical chemistry allows this application to serve as a scalable prototype for environmental risk prediction. With continued development and the inclusion of additional variables such as soil composition, traffic density, or floodplain mapping, the platform could be adapted for statewide or national use by urban planners, environmental engineers, and public health agencies seeking to identify and mitigate industrial pollution hotspots.

5. Conclusions

This study investigated the impact of industrial activity on heavy metal contamination in Arizona's urban waterways using a combination of geochemical analysis, statistical modeling, and machine learning. SEM-EDS analysis of sediment samples collected from six urban water bodies revealed elevated concentrations of hazardous metals, including iron, chromium, manganese, molybdenum, indium, and tantalum. These concentrations were significantly correlated with the proximity of specific industrial sectors such as metal fabrication, automotive repair, wastewater treatment, and electronic waste storage facilities. Multiple Linear Regression and Pearson correlation analyses confirmed the predictive strength of industrial proximity in determining contaminant levels, with distinct industry types contributing uniquely to the chemical signatures observed. To operationalize these findings, an interactive machine learning application was developed to provide real-time contamination risk assessments based on location-specific industrial presence. The Random Forest Regressor achieved high predictive accuracy (R^2 values > 0.91 for all metals), demonstrating the reliability of this method for environmental prediction. The application translates laboratory data into an accessible decision-support tool that may assist in environmental monitoring, zoning decisions, and urban planning.

Overall, the results underscore the urgent need for improved industrial zoning, environmental oversight, and data-driven policy enforcement. This integrative approach offers a scalable model for identifying pollution sources and guiding remediation efforts to protect ecological and public health in urban environments.

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