Scientific Research Publishing

Evaluation of Human Impacts on Bartlett Pond Ecosystem, Laredo, Southern Texas, USA, through Empirical Modeling

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Abstract

The trace elements chemistry of Bartlett Pond, a small shallow wetland pond in Laredo, Southern Texas, was sampled to evaluate the dynamics of trace elements impacts on water quality and ecosystems ecology of the pond. Two types of fish (bass and tilapia) were also sampled to see the trace element accumulation in different parts of their body. The concentrations of trace elements in water samples were found in the following order: Fe $\gg$ Sb > Pb > As $\gg$ Co > Tl > Cr > Cd within Bartlett Pond. Overall, the water quality of the pond is unacceptable for drinking and any other purposes as trace element concentrations (e.g. As, Cd, Co, Cr, Pb, Fe, Sb and Tl) are exceedingly higher (several fold) than the WHO and US EPA guidelines. Predictive and correlation analysis shows that most trace elements exhibit a strong positive correlation among them indicating the same anthropogenic sources and biogeochemical processes regulate these trace elements within the pond. Distributions of the trace elements in water exhibit different shapes mostly as positively skewed distribution for As, Cd, Co, Cr, and Tl, symmetrical distribution for Fe and almost symmetrical distribution for Pb and Sb. Concentrations of As, Co and Tl accumulated much higher in different parts of the Bass than Tilapia fish. The concentrations of As, Tl, Co, and Sb appeared significantly higher in different parts of the body of both Bass and Tilapia than the maximum SRM certified values. Accumulation of these contaminants in fish tissues pose increased health risks to humans who consume these contaminated fish although fishing is prohibited. Anthropogenic activities in the region primarily degrade the whole pond ecosystem ecology of the Bartlett Pond and waters of this pond to be not recommended for any use. These findings may be useful for

the scientific community and concerned authorities to improve understanding about these precious natural resources and conservation of the ecosystem ecology.

Keywords

Trace Elements, Bartlett Pond, Laredo, Southern Texas, Wetlands, Ecosystem Ecology

1. Introduction

Wetlands play a vital role in hydrologic cycle and regulating chemical composition of surface waters and these ecosystems constitute about 6% of total global land area [1] [2] [3]. Wetlands are the most biologically diverse of all ecosystems serving as a home to wide range of plants and animals, habitat for variety of fish and wildlife, help to purify water, flood control, shoreline stability, water recharging, ground water supply and supporting society in various ways including ecosystems services [4] [5] [6].

Natural wetlands have high and long-term capacity to filter pollutants, sediments and nutrients and keep the ecosystems ecology of any landscape healthy so they can be considered to be the kidneys of the earth [7] [8] [9]. According to Holgerson and Raymond [10], there are 547 million to 3.19 billion ponds globally based on an estimate although significant uncertainty surrounds pond numbers at national to international scales in different regions. Freshwater system is a habitat for diverse set of organisms and about 15% of all animal species that have been described today live in freshwater systems and most animal species belong to crustaceans, rotifers, insects, or oligochaetes are found in lakes and ponds [11]. Planktonic and periphytic algae as well as different life forms of macrophytes are also species in lakes and ponds [11].

Disturbances in wetlands ecosystems due to human activities reduces natural water absorbing capacity, resulting in floods and erosion in wet periods, and less water flow the rest of the year and half of the U.S. wetlands are gone primarily due to agricultural drainage [3]. The population growth of Laredo in Southern Texas has been rapidly increasing, 3.4-fold higher within five decades, so the land use change pattern is intense in the region [12] [13]. Therefore, surface water bodies receive higher amounts of sediment and chemical loads including trace elements. Trace elements are specific pollutants which do not undergo biodegradation and they creates hazardous effects on the ecological system by accumulating in water, sediments and biota across the food chain posing serious threat to the environment and the humans [14] [15] [16].

About 80% of municipal wastewater without treatment is discharged directly into water bodies and industry is mainly responsible for transporting millions of tons of heavy metals to water bodies including in coastal oceans [17]. The high nutrients loading into water bodies creates the eutrophication in ponds, lakes,

reservoirs, and coastal regions leading to algal blooms which damages the aquatic plants and animals [17] [18] and coastal ecosystems cover nearly 20% of earth's surface and more than 415 coastal areas have been experiencing eutrophic problems [19].

Surface runoff contributes tremendous amount of nutrients to water bodies and hence lead to water eutrophication causing development of blooms of algae, production of cyanotoxins, decreasing water pH, depletion of oxygen and therefore affecting aquatic biodiversity and ecology [20] [21]. Eutrophication could have an influence on the concentration of trace elements in aquatic environments [21] and the trace elements dynamics change with the variation in DOC concentration or making complexations with DOC [22]. In a natural condition, elements including trace elements enter water bodies through the chemical weathering, erosion, and dissolution of water-soluble salts and constitute the background level [23] and these elements concentrations increases in aquatic ecosystems due to anthropogenic activities [14] [16] [23]. Anthropogenic activities threaten the biodiversity of ponds and lakes, and in 30% of North American and 40% of European fish species are threatened [11]. Runoff from the urban centers primarily from road runoffs carry out pollutants such as salts, metals, polycyclic aromatic hydrocarbons (PAHs) which are toxic to aquatic organisms [24]-[29]. Heavy metals and organochlorine substances are the most common contaminants in freshwater systems and some of these chemicals accumulate in food chain with much higher concentration in top carnivores than organisms at lower trophic levels due to biomagnification and they have numerous effects on organisms including direct toxic impacts and long term various effects such as carcinogenesis, reproductive disorders, reduced growth, and neurological disorders [11] [30] and DNA damage, changes in species abundances, increased mortality and ultimately affecting the whole ecosystems ecology [28]. Human activities including industrial development altering the earth's ecosystems in various ways impacting the water resources and as a consequences aquatic ecosystems are seriously threatened primarily in urban areas [11] [31] [32] [33] and about 25% of bird species on earth have gone extinction [31].

The effects of human population density and activities on water quantity and quality primarily from rivers have been documented earlier by various authors in different landscapes but such studies on lakes and ponds are lacking (relatively less than rivers) in different regions on the earth including in Southern Texas [34]-[47]. Sometimes periodic droughts create severe regional water shortages in such a semiarid zone where moisture availability is the critical factor in plants and animal distribution and the human water use has been increasing about twice as fast as population growth over the past century globally, but its impacts vary with location [3].

The Bartlett Pond is an urban retention pond situated within the Jovita Idar's El Progreso Park complex in East Central Laredo in Texas which is about 12 km north-east of Laredo city center. Soil in the pond is classified as hydric soil type and the surrounding area is classified as Copita Soil Series [48] (UC Davis Soil

Web App) which is well drained fine sandy loam that is moderately alkaline at a pH of 8.2.

Water pollution is a major environmental problem within Southern Texas and the degradation of water quality in the Rio Grande River system, which drains through Laredo, an international boundary to Mexico. The basic water quality parameters from Rio Grande River systems and Manadas Creek, an urban tributary of Rio Grande within Laredo for antimony and arsenic distribution have been documented in earlier studies [49] [50] [51] but the water quality of lakes, ponds and groundwater has not yet been documented for the Southern Texas region. Wetlands in Laredo are considered rich in biodiversity, and play a major role in maintaining groundwater sources, preventing, and controlling loss of nutrients. More than 50% of the wetlands in the US are disappearing or degrading due to increase in human population or human activities despite the Government's policy for wetlands conservation [3]. The main objective of this study was to investigate the concentration and sources of trace elements which are responsible for changing the ecology of the pond and to evaluate the whole aquatic ecosystem ecology of the Bartlett Pond.

2. Study Area

The research was conducted in Bartlett Pond, an urban retention pond situated within the Jovita Idar's El Progreso Park complex in East Central Laredo, TX (27.554722˚N 99.473889˚W) in Southern Texas (Figure 1). The pond has historically served as a drainage basin for the Upper Zacate Creek system, which is one of the three major tributaries of the Rio Grande at Laredo, Texas. The pond, with an area of nearly three hectares is located about 12 km north-east of Downtown Laredo (27.554722˚N 99.473889˚W) and its maximum depth is about 4.26 m. Today, the pond is primarily used for recreational purposes only. Visitors frequent the park for activities such as picnics, outdoor games, running, hiking, non-motorized boating, and fishing. It's notable that fishing activities in the pond are strictly catch-and-release, aligning with the park's focus on conservation and outdoor enjoyment. Additionally, the pond is a catchment and pour point of run-off from various surrounding locations, including the Laredo International Airport, which are potential sources of nonpoint pollution. Both the park and the pond are managed by the City of Laredo Parks and Recreation Department, which oversees maintenance duties.

The Bartlett Pond is the second largest pond within Laredo after Lake Casa Blanca which is about 6 km north-east of Bartlett. The Bartlett wetland site is a habitat of many plants including algae and some flowering plants. The site is also a habitat for many animal species including several bird species and more migratory birds especially in winter season. The region around Bartlett Pond in Laredo, Texas, is renowned for its exceptional bird diversity, with hundreds of species inhabiting the area and over 650 species in Texas [52]. Laredo is situated within a rich and diverse ecosystem in Texas, recognized as part of the birdiest corridor in North America [52]. This vibrant avian community includes both
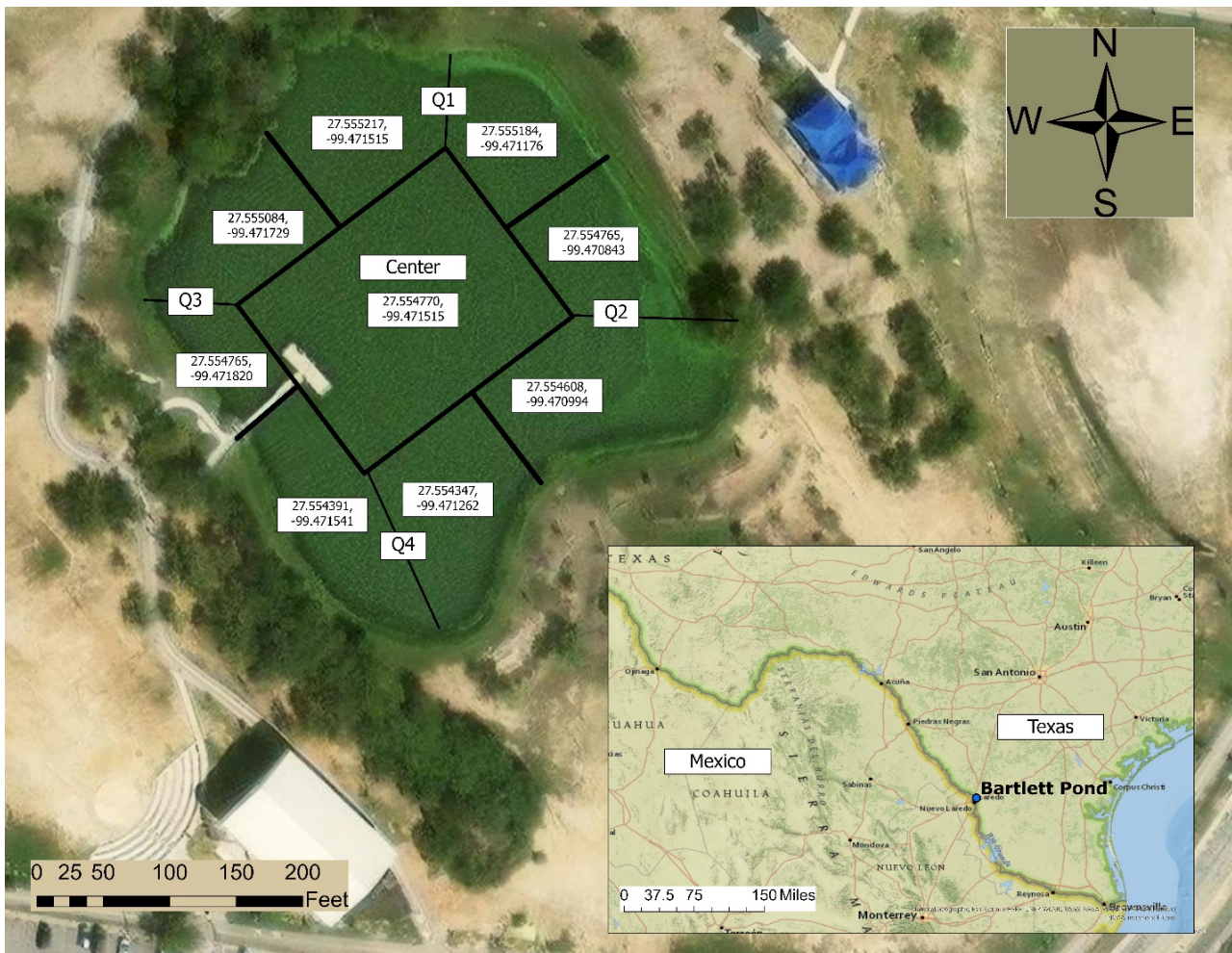
Figure 1. Locations of Bartlett Pond in Laredo, Southern Texas with four quadrants in which 24 samples collected from each quadrant, n = 96.

local and migratory bird species, contributing to the area's ecological richness. Notably, Laredo boasts the unique distinction of being the only location in the United States where four different species of Kingfisher—Ringed, Belted, Green, and Amazon—have been observed [52]. While migratory birds typically stay for only a few weeks to months during the winter around Bartlett Pond, there have been no documented reports regarding the specific situation of birds in this area. Bartlett Pond exhibits richness in terms of species diversity, largely attributed to its favorable climate, particularly during the winter months. Biodiversity plays a critical role in sustaining life on Earth, providing essential resources such as food and medicines and moreover, biodiversity contributes to a wide range of ecological benefits, including soil formation, waste disposal, air and water purification, nutrient cycling, absorption of solar energy, biogeochemical processes that nourish ecosystems, and regulation of hydrological cycles with cumulative value of these ecological services is estimated to be approximately US\$ 33 trillion per year, roughly equivalent to half of the world's gross national product (GNP) [3] (Cunningham and Cunningham 2021).

Laredo is situated at an altitude of 127.41 m asl on the Mexican border in Southern Texas with an area about 265.7 km^2 with a large area surrounded by forest. Rio Grande is the major river system in the area within Laredo, but its water neither enters Bartlett Pond nor into Lake Casa Blanca, as the river flows about 14 km south from the pond. Annual average rainfall is 500 mm, and the mean annual temperature is 23.5˚C. The average temperature ranges between 8.9˚C in December and 31.7˚C in August in the Laredo. According to US Climate, August is the hottest month of the year with a minimum of 25.2˚C to maximum of 38.2˚C.

3. Materials and Methods

3.1. Sample Collection

Bartlett Pond was divided into four quadrants: quadrant-I (Q1), quadrant-II (Q2), quadrant-III (Q3) and quadrant-IV (Q4) and each quadrant had 24 sampling points as in Figure 1. Water samples were collected from four quadrants of the pond with a total of 96 samples during summer 2018 (Figure 1). Two types of fish (bass and tilapia) were also taken from quadrant 3 site for the trace elements analysis from three different parts of their body. There are two main inlet points in the pond; one at Q2 (quadrant II), where the surface runoff enters into the pond through the pipe, and the other at Q3 (quadrant III) where more urban surface runoff enters into the pond. Samples were taken in 500 mL acid-washed polyethylene bottles, and refrigerated at the laboratory of Texas A&M International University (TAMIU) until analysis for trace elements (Fe, Sb, Pb, As, Co, Tl, Cr, Cd). In each sample, 50 µL concentrated nitric acid was added to analyze for trace elements by Inductively Coupled Plasma-Optical Emission Spectroscopy (ICP-OES), by method US EPA 3015A at the Department of Biology and Chemistry of TAMIU [53].

3.2. Analytical Methods

Acid digestion of trace metals in fishes and water was done with a CEM MARS 6 Microwave Digestion System (CEM Corporation, Matthews, North Carolina, United States). Trace metal analysis was done with an Agilent ICP-720 Inductively coupled plasma-optical emission spectrometer (Agilent Technologies, Santa Clara, California, United State) by following method US EPA 3015A [53]

For Water

Briefly, 20 mL of water sample was measured into a digestion vessel and digested using EPA method 3015A. The digested samples were filtered through a 0.45 µm polycarbonate filter and analyzed by Inductively Coupled Plasma-Optical Emission Spectrometer (ICP-OES) for metal concentrations against a standard calibration curve [53]. Replicate samples, standard reference material (SRM), field blanks and laboratory spikes were treated in the same way.

For Fish

Fish samples were taken from the freezer and allowed to thaw. They were

rinsed with Milli-Q water, separated into three parts (head, body, and tail), dried in an oven at 80˚C for 24 hours, and grinded into a fine powder to evenly mix the samples before digestion. Approximately 200 mg of dried powder sample was weighed into the Teflon digestion vessel and digested with 7 mL of HNO_3, 3 mL HF, and 2mL H_2O_2 in a CEM MARS 6 microwave digester for 30 min following EPA method 3015A. The digested fish samples were then diluted to 50 mL with Milli-Q water and filtered through a 0.45 μm polycarbonate filter and analyzed by ICP-OES for trace metals (Fe, Sb, Pb, As, Co, Tl, Cr, Cd) by following method US EPA 3015A [53]. SRM oyster tissue was subjected to the same process.

Quality Control

The accuracy of the instrument was checked by triplicate analysis of the same samples. Method blanks, spike recovery, and standard reference material (SRM) analysis were also employed. Certified SRM 1566b oyster tissue and 1643f water were analyzed in the same way as the fish and water respectively to check the accuracy of analysis. The analytical values were within the range of certified values and the overall average recovery of trace metals in standard substances was between 88 and 105%.

3.3. Statistical Tool for Data Analysis

We utilized sophisticated statistical tool, Version 29.0.0 (241) of IBM SPSS Statistics software for conducting our analyses. Our analytical approach centered around three primary programs within the software:

1) *Analyze > Compare Means*: This module was instrumental in conducting comparisons of means across different groups or conditions, providing valuable insights into the variations and trends within our dataset.

2) *Analysis > Correlate > Bivariate*: Through this tool, we explored the relationships between pairs of variables, allowing us to assess the strength and direction of associations within our data.

3) *Analyze > Regression > Linear*: Utilizing this program, we conducted linear regression analyses to model the relationships between one or more predictor variables and a dependent variable of interest, facilitating a deeper understanding of the underlying patterns and predictive factors within our dataset.

4. Results and Discussion

4.1. Spatial Variations in Trace Elements

The concentrations of trace elements in water samples were found in the following order: Fe ≫ Sb > Pb > As ≫ Co > Tl > Cr > Cd within Bartlett Pond. Variation pattern of average concentrations with standard deviations of measured trace elements (As, Cd, Co, Cr, Fe, Pb, Sb, and Tl) from each quadrant (n = 24) is presented in Table 1. Summary descriptive statistics of different trace elements in Bartlett Pond water are given in Table 2 and the standard deviations were calculated by using n = 96.

Table 1. Average trace element concentrations in different sections of Bartlett Pond within Laredo, Southern Texas during summer 2018. All values are in μg/L. The standard deviations were calculated using n=24 for each section. WHO guideline values are from WHO 2017 [54].

Trace Elements	Quadrant I	Quadrant II	Quadrant III	Quadrant IV	WHO Guideline
As	98.48 ± 56.18	200.81 ± 221.19	152.02 ± 115.29	107.94 ± 74.14	10
Cd	23.51 ± 55.26	119.49 ± 267.21	58.57 ± 101.25	42.03 ± 69.61	3
Co	49.39 ± 53.62	152.46 ± 262.56	57.11.02 ± 101.06	63.49 ± 66.34	50*
Cr	31.97 ± 57.60	143.45 ± 259.64	73.71 ± 107.25	51.30 ± 71.01	50
Fe	1764.28 ± 700.95	3255.47 ± 2561.39	2229.92 ± 984.52	1177.59 ± 444.22	1000-3000
Pb	160.65 ± 105.16	257.53 ± 239.90	267.04 ± 126.87	177.55 ± 106.74	10
Sb	281.52 ± 102.76	344.65 ± 253.97	289.53 ± 115.82	230.22 ± 71.47	20
Tl	41.53 ± 47.64	149.50 ± 243.66	80.98 ± 94.64	50.24 ± 68.47	2

*Canadian Drinking Water Guideline (2006) [55].

Table 2. Summary descriptive statistics of the different trace elements in the Bartlett Pond water. The standard deviations were calculated using n = 96. All measurements are in micrograms/Liter (μg/L).

Trace Elements	n	Minimum	Maximum	Mean	St. Deviation
Arsenic	95	34.37	561.80	130.45	102.51
Cadmium	95	0.02	379.77	48.46	90.77
Cobalt	95	10.13	449.92	78.61	93.76
Chromium	95	3.06	463.10	63.55	101.51
Iron	95	563.29	8401.27	2107.46	1613.09
Lead	95	21.08	579.36	205.19	122.80
Antimony	95	93.69	801.79	276.70	123.70
Thallium	95	0.00	475.92	69.62	92.97

Interestingly, the distributions of the trace elements in water exhibit different shapes, as shown in Table 3. A positively skewed distribution means that smaller scores are more frequent than larger scores in the sample, with a few extremely high values pulling the average towards the right side of the distribution. For each data distribution, the mean and standard deviation are provided in the top-right corner of every figure included in this section.

4.1.1. Spatial Variation of Arsenic

Arsenic concentration appeared highest (200.81 ± 221.19 μg/L) at quadrant-II followed by quadrant-III (152.02 ± 115.29 μg/L), quadrant-IV (107.94 ± 74.14 μg/L) and least at the quadrant-I (98.48 ± 56.18 μg/L) (Table 1). The arsenic concentration is much higher than the US EPA and WHO guideline values [54] [56]. The high concentration site has direct surface runoff input, and the lower concentration site has presence of vegetation close to the points that may control concentration of measured arsenic due to uptake. The spatial variation of the trace element arsenic (As) in Bartlett Pond water shows positively skewed shape

Table 3. Descriptions of the shape distributions.

Trace Elements	Shape Distribution
Arsenic	Positively Skewed
Cadmium	Positively Skewed
Cobalt	Positively Skewed
Chromium	Positively Skewed
Iron	Almost symmetrical
Lead	Almost symmetrical
Antimony	Symmetrical
Thallium	Positively Skewed

distribution as shown in histograms (Figure 2). Arsenic contamination in groundwater is high in Texas primarily in wells of southern High Plains and southern Gulf Coast may be due to role of phosphate fertilizers used in the past which might have mobilized arsenic, use of arsenical pesticides or from geological sources [57].

4.1.2. Spatial Variation of Cadmium

Cadmium concentration appeared highest (119.49 ± 267.21 μg/L) at quadrant-II followed by quadrant-III (58.57 ± 101.25 μg/L), quadrant-IV (42.03 ± 69.61 μg/L) and least at the quadrant-I (23.51 ± 56.26 μg/L) (Table 1). The cadmium concentration is much higher than the US EPA and WHO guideline values [54] [56]. The spatial variation of the trace element cadmium (Cd) in Bartlett Pond water shows positively skewed shape distribution as shown in histograms (Figure 3). The spatial variation of cadmium within the Bartlett Pond is due to variation in surface urban runoff input, vegetation, and specific sampling location within the point.

4.1.3. Spatial Variation of Cobalt

Cobalt concentration appeared highest (152.46 ± 262.56 μg/L) at quadrant-II followed by quadrant-III (97.11 ± 101.06 μg/L), quadrant-IV (63.49 ± 66.34 μg/L) and least at the quadrant-I (49.39 ± 53.62 μg/L) (Table 1). The spatial variation of the trace element cobalt (Co) in Bartlett Pond water shows positively skewed shape distribution as shown in histograms (Figure 4). The spatial variation of cobalt within the Bartlett Pond is due to variation in surface urban runoff input, vegetation, and specific sampling location within the point.

4.1.4. Spatial Variation of Chromium

Chromium concentration appeared highest (143.45 ± 259.64 μg/L) at quadrant-II followed by quadrant-III (73.71 ± 107.25 μg/L), quadrant-IV (51.30 ± 71.01 μg/L) and least at the quadrant-I (31.79 ± 57.60 μg/L) (Table 1). The chromium concentration is much higher than the US EPA and WHO guideline values [54] [56]. The spatial variation of the trace element chromium (Cr) in Bartlett Pond water shows positively skewed shape distribution as shown in histograms (Figure 5). The spatial variation of chromium within the Bartlett

Pond is due to variation in surface urban runoff input, vegetation, and specific sampling location within the point.

4.1.5. Spatial Variation of Iron

Iron concentration appeared highest (3255.47 ± 2561.39 µg/L) at quadrant-II followed by quadrant-III (2229.92 ± 984.52 µg/L), quadrant-IV (1177.59 ± 444.22 µg/L) and least at the quadrant-I (1764.28 ± 700.95 µg/L) (Table 1). The spatial variation of the trace element iron (Fe) in Bartlett Pond water shows almost symmetrical shape distribution as shown in histograms (Figure 6). The spatial variation of iron within the Bartlett Pond is due to variation in surface urban runoff input, vegetation, and specific sampling location within the point.
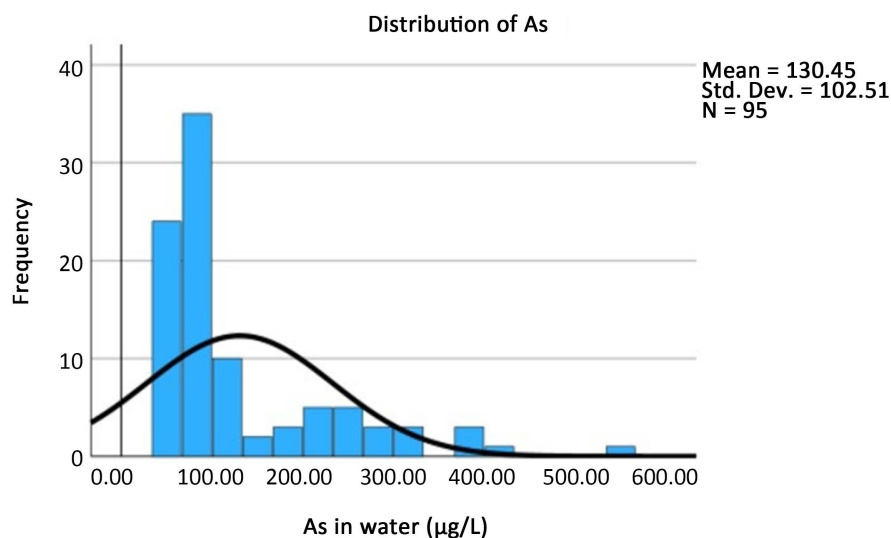

Figure 2. Histogram displaying the spatial variation of the trace element arsenic (As) in water. The distribution of arsenic is positively skewed.
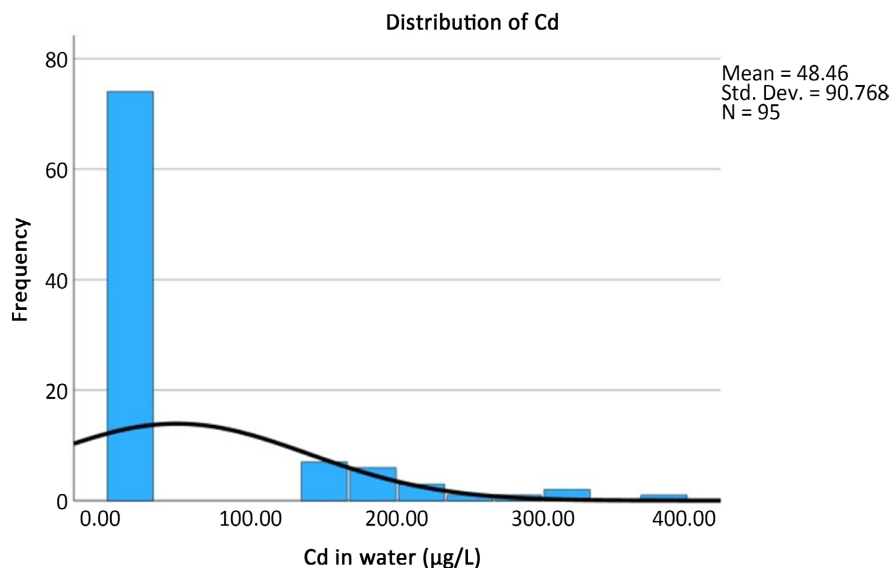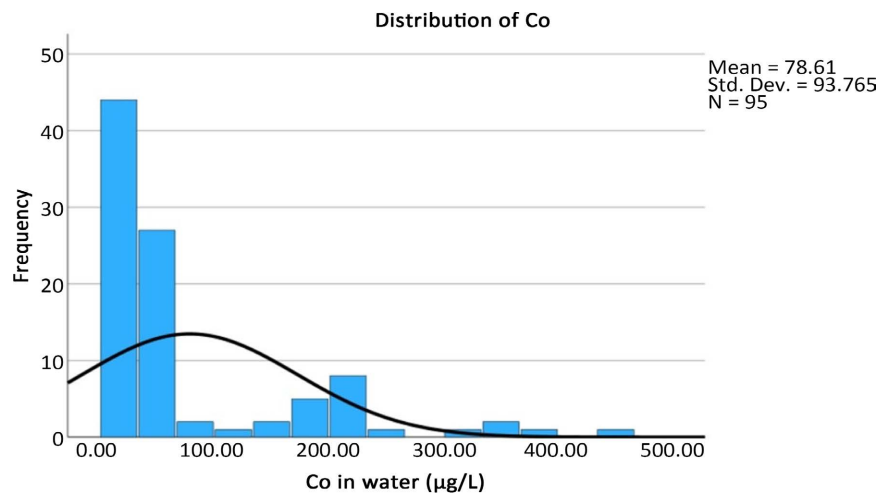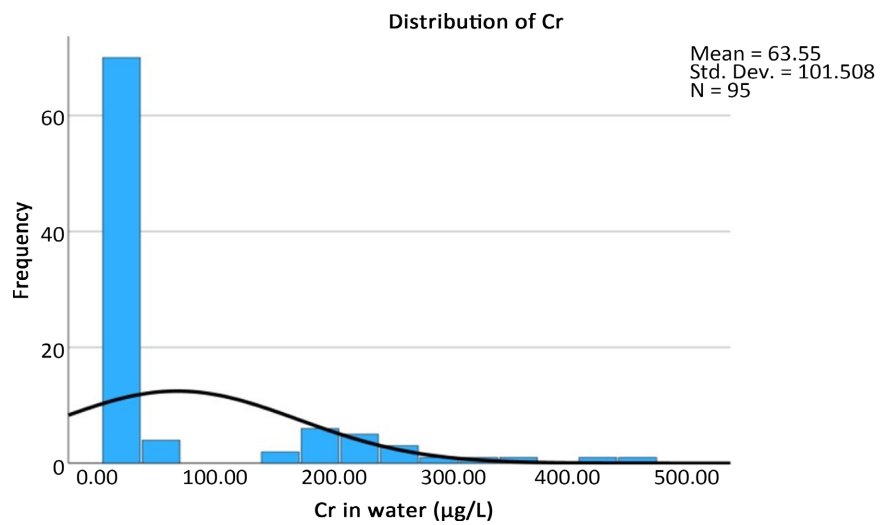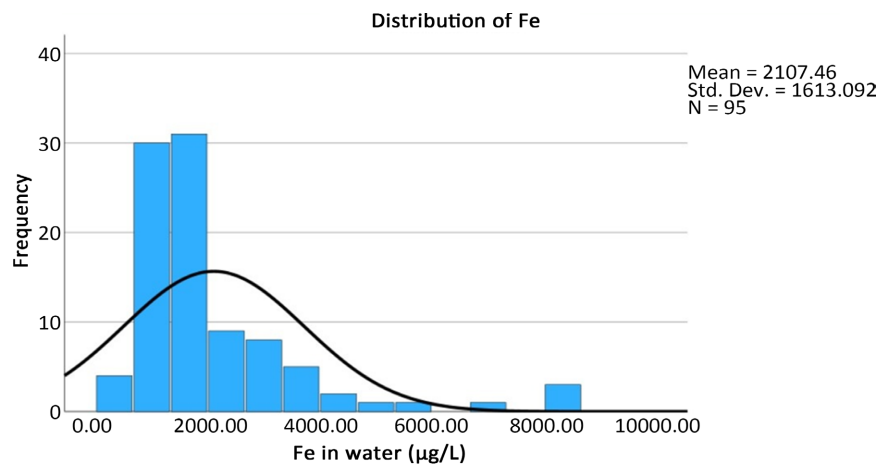

Figure 3. Histogram displaying the spatial variation of the trace element cadmium (Cd) in water. The distribution of cadmium is positively skewed.

Figure 4. Histogram displaying the spatial variation of the trace element cobalt (Co) in water. The distribution of cobalt is positively skewed.

Figure 5. Histogram displaying the spatial variation of the trace element chromium (Cr) in water. The distribution of chromium is positively skewed.

Figure 6. Histogram displaying the spatial variation of the trace element iron (Fe) in water. The distribution of iron is almost symmetrical skewed.
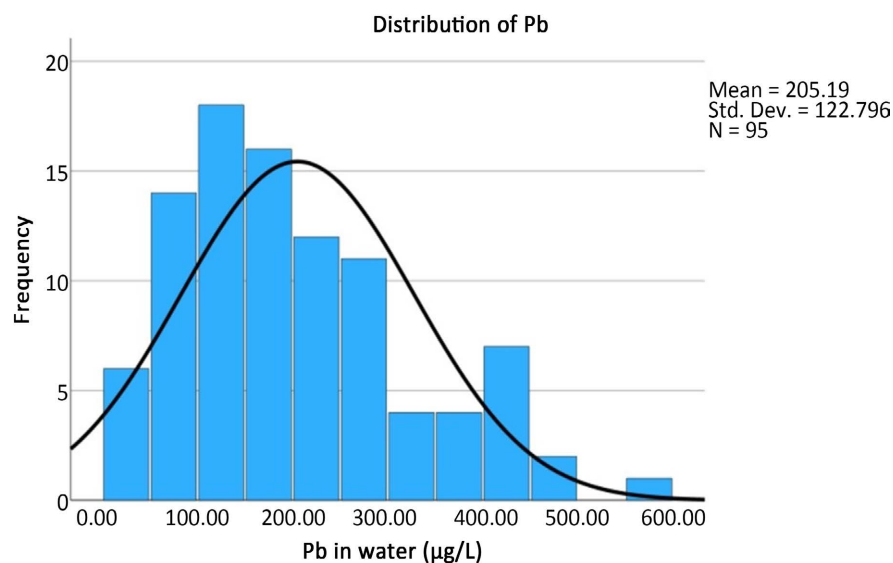
4.1.6. Spatial Variation of Lead

Lead concentration appeared highest (267.04 ± 126.87 μg/L) at quadrant-III followed by quadrant-II (257.53 ± 239.90 μg/L), quadrant-IV (177.55 ± 106.74 μg/L) and least at the quadrant-I (160.65 ± 105.16 μg/L) (Table 1). The lead concentration is much higher than the US EPA and WHO guideline values [54] [56]. The spatial variation of the trace element lead (Pb) in Bartlett Pond water shows almost symmetrical shape distribution as shown in histograms (Figure 7). The spatial variation of lead within the Bartlett Pond is due to variation in surface urban runoff input, vegetation, and specific sampling location within the point.

4.1.7. Spatial Variation of Antimony

Antimony concentration appeared highest (344.65 ± 253.97 μg/L) at quadrant-II followed by quadrant-III (289.53 ± 115.82 μg/L), quadrant-I (281.52 ± 102.76 μg/L) and least at the quadrant-IV (230.22 ± 71.47 μg/L) (Table 1). The antimony concentration is much higher than the US EPA and WHO guideline values [54] [56]. The spatial variation of the trace element antimony (Sb) in Bartlett Pond water shows symmetrical shape distribution as shown in histograms (Figure 8). The spatial variation of antimony within the Bartlett Pond is due to variation in surface urban runoff input, vegetation, and specific sampling location within the point. Earlier documented studies show that the antimony (Sb) is generally taken up by terrestrial plants, but the detailed mechanisms are still lacking [58] (Tschan *et al.* 2009; [59] Feng *et al.* 2013; [60] Vidya *et al.* 2023).

4.1.8. Spatial Variation of Thallium

Thallium concentration appeared highest (149.50 ± 233.67 μg/L) at quadrant-II followed by quadrant-III (80.93 ± 94.64 μg/L), quadrant-IV (50.24 ± 68.47 μg/L) and least at the quadrant-I (41.53.22 ± 47.64 μg/L) (Table 1). The thallium

Figure 7. Histogram displaying the spatial variation of the trace element lead (Pb) in water. The distribution of lead is almost symmetrical skewed.
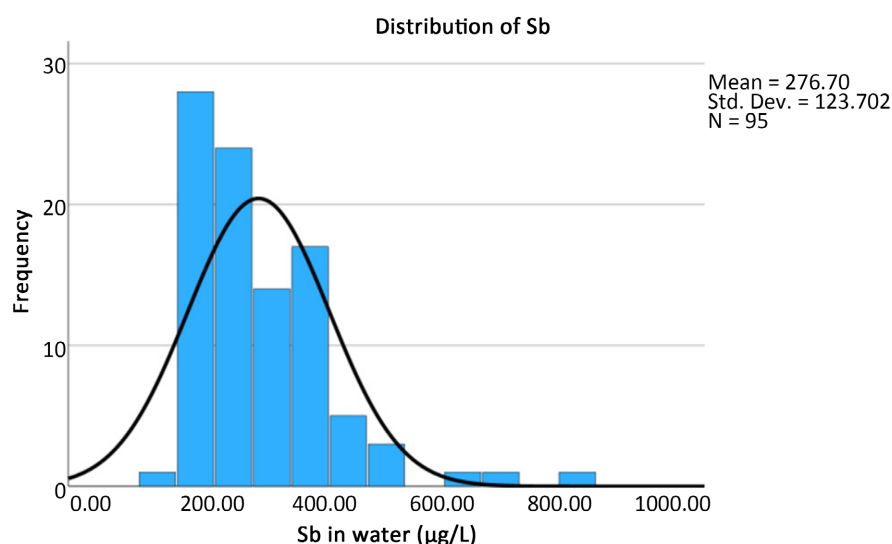
Figure 8. Histogram displaying the spatial variation of the trace element antimony (Sb) in water. The distribution of antimony is symmetrical skewed.

concentration is much higher than the US EPA and WHO guideline values [54] [56]. The spatial variation of the trace element thallium (Tl) in Bartlett Pond water shows positive skewed shape distribution as shown in histograms (**Figure 9**). The spatial variation of thallium within the Bartlett Pond is due to variation in surface urban runoff input, vegetation uptake and specific sampling location within the point.

4.2. The Predictive and Correlation Analyses

The correlation analysis of measured trace elements within Bartlett Pond yields fascinating results (see **Table 4**). It reveals that most trace elements demonstrate a strong positive correlation among themselves, with 10 pairs exhibiting a correlation coefficient exceeding 0.90. Notably, the highest correlation coefficient (0.992) is observed between cobalt and chromium, whereas the lowest (0.346) is found between lead and iron.

4.2.1. The Univariate and Multiple Regression Analyses of Arsenic in Relation to Other Trace Elements

We have established strong correlations between arsenic and various trace elements, leading us to develop predictive models specifically for arsenic in conjunction with different elements. **Figure 10** displays the regression analysis depicting the relationship between arsenic and cobalt. The regression model expressed $\widehat{As}$ = 1.07 Co + 46.59 with an R-squared value of 95%, indicates the model's effectiveness in forecasting arsenic levels based on known cobalt concentrations. The regression coefficient of 1.07 signifies that a 1 µg/L increase in cobalt in pond water results in a 1.07 µg/L increase in arsenic levels within the same water sample.

We have similarly constructed predictive models for arsenic in relation to other measured trace elements (Cd, Co, Cr, Fe, Pb, Sb, and Tl), detailed in **Table 5**.
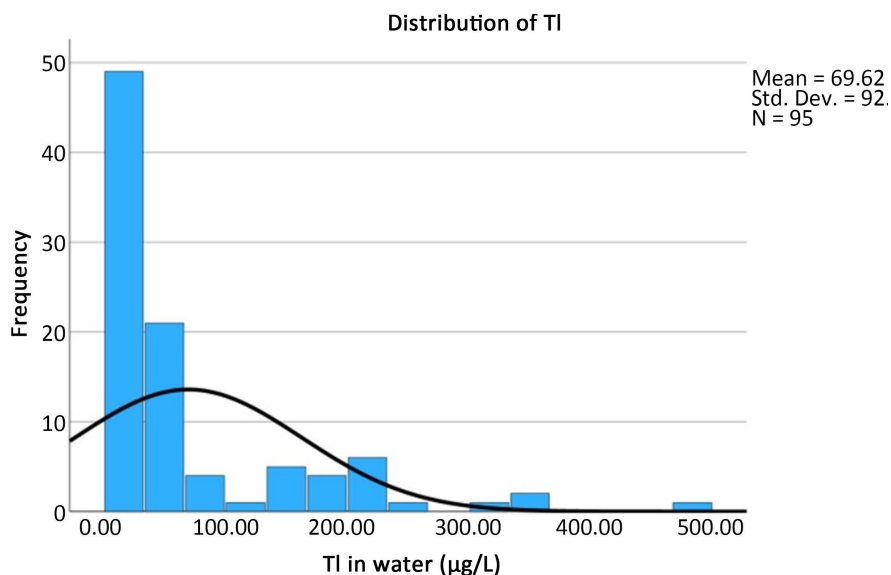
Figure 9. Histogram displaying the spatial variation of the trace element thallium (Tl) in water. The distribution of thallium is positively skewed.

Table 4. Pearson's correlation matrix of probabilities among trace elements in water samples from Bartlett Pond during summer 2018, n = 96.

Elements	As	Cd	Co	Cr	Fe	Pb	Sb	Tl
Arsenic	1	0.948**	0.976**	0.960**	0.623**	0.621**	0.800**	0.953**
Cadmium	0.948**	1	0.984**	0.992**	0.427**	0.593**	0.706**	0.961**
Cobalt	0.976**	0.984**	1	0.991**	0.554**	0.628**	0.773**	0.967**
Chromium	0.960**	0.992**	0.991**	1	0.507**	0.602**	0.743**	0.970**
Iron	0.623**	0.427**	0.554**	0.507**	1	0.346**	0.714**	0.547**
Lead	0.621**	0.593**	0.628**	0.602**	0.346**	1	0.433**	0.615**
Antimony	0.800**	0.706**	0.773**	0.743**	0.714**	0.433**	1	0.746**
Thallium	0.953**	0.961**	0.967**	0.970**	0.547**	0.615**	0.746**	1

**Correlation is significant at 1% level (2-tailed).
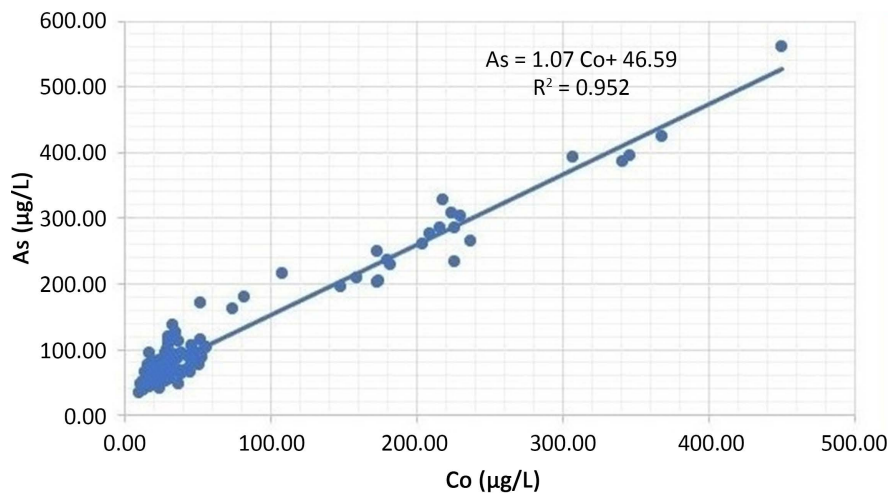
Figure 10. The bivariate distribution of arsenic and cobalt.

Table 5. Predictive models for estimating Arsenic.

Model #	Independent variable(s)	Predictive Model	R2 value
1.	Cd	$\widehat{As}$ = 1.07 Cd + 78.55	90%
2.	Co	$\widehat{As}$ = 1.07 Co + 46.59	95.2%
3.	Cr	$\widehat{As}$ = 0.97 Cr + 68.82	92.2%
4.	Fe	$\widehat{As}$ = 0.04 Fe + 47.04	38.8%
5.	Pb	$\widehat{As}$ = 0.52 Pb + 24.05	38.6%
6.	Sb	$\widehat{As}$ = 0.66 Sb − 53.07	64.1%
7.	Tl	$\widehat{As}$ = 1.05 Tl + 57.29	90.8%
8.	Cd, Co, Cr, & Fe	$\widehat{As}$ = 0.77 Cd + 0.80 Co − 0.55 Cr + 0.01 Fe + 38.00	96.4%

To derive the multivariate model (Model # 8) in Table 5, we began the process by utilizing all seven remaining trace elements as independent variables and applied the Backward Elimination Regression method. The resulting model demonstrates high significance ($F = 603.17$, $df = (4, 90)$, $p < 0.001$) with an R-squared value of 96.4%, signifying its substantial practical utility.

4.2.2. The Univariate and Multiple Regression Analyses of Cadmium in Relation to Other Trace Elements

Cadmium exhibits a strong correlation with various trace elements, and we have developed predictive models for cadmium in conjunction with several of these elements (such as As, Co, Cr, Fe, Pb, Sb, and Tl). Figure 11 demonstrates the regression analysis depicting the relationship between cadmium and chromium. The regression model, expressed as $\widehat{Cd}$ = 0.89 Cr − 7.93, with an R-squared value of 98.5%, indicates the model's effectiveness in predicting cadmium levels based on known chromium concentrations. The regression coefficient of 0.89 implies that a 1 μg/L increase in chromium in pond water corresponds to a 0.89 μg/L increase in cadmium levels within the same water sample.

Additionally, we have established predictive models for cadmium with other measured trace elements (As, Co, Cr, Fe, Pb, Sb, and Tl), as presented in Table 6.

To derive the multivariate model (Model #16) in Table 6, we initiated the process by utilizing the remaining six trace elements (As, Co, Cr, Fe, Pb, and Tl) as independent variables and employed the Backward Elimination Regression method. The resulting model demonstrates high significance ($F = 3761.55$, $df = (6, 88)$, $p < 0.001$), with an R-squared value of 99.6%, signifying its substantial utility for practical applications.

4.2.3. The Univariate and Multiple Regression Analyses of Cobalt in Relation To Other Trace Elements

Cobalt exhibits a strong relationship with all other trace elements, and we have developed predictive models for cobalt in conjunction with various trace elements such as As, Cd, Cr, Fe, Pb, Sb, and Tl. In Figure 12, the regression analysis demonstrates the relationship between cobalt and chromium. The regression

Table 6. Predictive models for estimating Cadmium.

Model #	Independent variable(s)	Predictive Model	R² value
9.	As	$\widehat{Cd}$ = 0.84 As − 61.08	90.0%
10.	Co	$\widehat{Cd}$ = 0.95 Co − 26.45	96.9%
11.	Cr	$\widehat{Cd}$ = 0.89 Cr − 7.93	98.5%
12.	Fe	$\widehat{Cd}$ = 0.02 Fe − 2.14	17.3%
13.	Pb	$\widehat{Cd}$ = 0.44 Pb − 41.56	34.5%
14.	Sb	$\widehat{Cd}$ = 0.52 Sb − 94.89	49.3%
15.	Tl	$\widehat{Cd}$ = 0.94 Tl − 16.88	92.4%
16.	As, Co, Cr, Fe, Pb, & Tl	$\widehat{Cd}$ = 0.06 AS + 0.38 Co + 0.50 Cr − 0.01 Fe − 0.02 Pb + 0.07 Tl − 4.77	99.6%
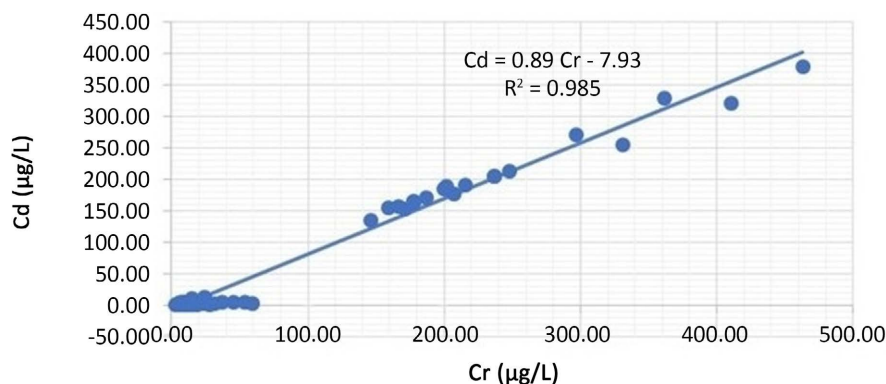
Figure 11. The bivariate distribution of cadmium and cromium.
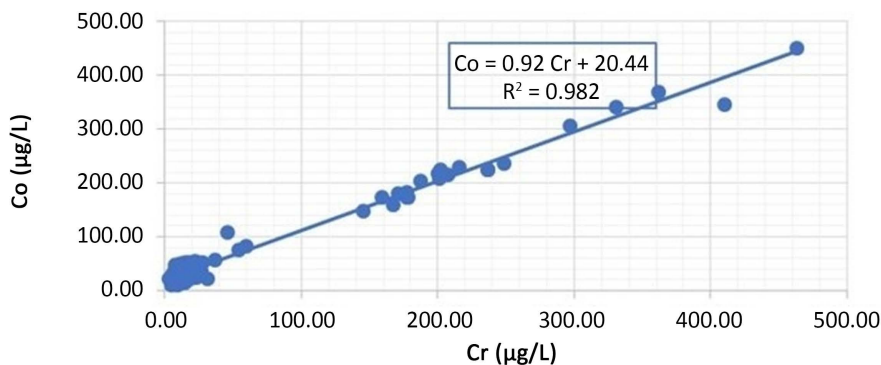
Figure 12. The bivariate distribution of cobalt and cromium.

model, expressed as $\widehat{Co}$ = 0.92 Cr + 20.44 with an R-squared value of 98.2%, indicates the model's effectiveness in predicting cobalt levels based on known chromium concentrations. The regression coefficient of 0.92 implies that a 1 µg/L increase in chromium in pond water corresponds to a 0.92 µg/L increase in cobalt levels within the same water sample.

Similarly, we have established predictive models for cobalt with other measured trace elements (As, Cd, Fe, Pb, and Sb), detailed in **Table 7**.

To determine the multivariate model (Model # 24) in **Table 7**, we initiated the process using the remaining five trace elements (As, Cd, Fe, Pb, and Sb) as independent variables and applied the Backward Elimination Regression method.

Table 7. Predictive models for estimating Cobalt.

Model #	Independent variable(s)	Predictive Model	R^2 value
17.	As	$\widehat{Co}$ = 0.89 As − 37.80	95.2%
18.	Cd	$\widehat{Co}$ = 1.02 Cd + 29.34	96.9%
19.	Cr	$\widehat{Co}$ = 0.92 Cr + 20.44	98.2%
20.	Fe	$\widehat{Co}$ = 0.03 Fe + 10.79	30.7%
21.	Pb	$\widehat{Co}$ = 0.48 Pb − 19.78	38.8%
22.	Sb	$\widehat{Co}$ = 0.59 Sb − 83.60	59.4%
23.	Tl	$\widehat{Co}$ = 0.98 Tl − 10.72	93.4%
24.	As, Cd, Fe, Pb, & Sb	$\widehat{Co}$ = 0.10 As + 0.82 Cd + 0.01 Fe + 0.03 Pb + 0.03 Sb − 0.90	99.3%

The resulting model demonstrates high significance (F = 2512.07, df = (5, 89), p < 0.001) with an R-squared value of 99.3%, indicating its considerable utility for practical applications.

4.2.4. The Univariate and Multiple Regression Analyses of Chromium in Relation to Other Trace Elements

The relationship between chromium and various trace elements has been extensively studied, leading to the development of predictive models. These models encompass chromium in conjunction with several trace elements, including arsenic (As), cadmium (Cd), cobalt (Co), iron (Fe), lead (Pb), antimony (Sb), and thallium (Tl). For instance, the predictive model relating chromium to arsenic is expressed as follows: $\widehat{Cr}$ = 0.95 As – 60, demonstrating an impressive R-squared value of 92.2%. This model effectively predicts chromium levels based on known arsenic concentrations. Specifically, a 1 µg/L increase in arsenic in pond water corresponds to a 0.95 µg/L increase in chromium levels within the same water sample.

Similar predictive models have been established for chromium in relation to other measured trace elements, such as arsenic, cadmium, and iron, as detailed in Table 8.

To derive the multivariate model (Model # 32) in Table 8, we employed a Backward Elimination Regression method, utilizing the remaining three trace elements (As, Cd, and Fe) as independent variables. The resulting model demonstrates remarkable significance (F = 4733.79, df = (3, 91), p < 0.001) and boasts an R-squared value of 99.4%. This high level of significance underscores its practical utility for real-world applications.

4.2.5. The Univariate and Multiple Regression Analyses of Iron in Relation to Other Trace Elements

Iron does not display a strong relationship with all other trace elements. We have developed predictive models for iron in conjunction with various trace elements such as As, Cd, Co, Cr, Pb, Sb, and Tl. The regression analysis model for iron concerning arsenic is represented as follows: $\widehat{Fe}$ = 9.80 As + 829.09,

with an R-squared value of 38.8%. This suggests the model's effectiveness in predicting iron levels based on known arsenic concentrations. The regression coefficient of 9.80 indicates that a 1 μg/L increase in arsenic in pond water results in a 9.80 μg/L increase in iron levels within the same water sample. Additionally, we've established predictive models for iron with other measured trace elements (As, Cd, Co, Cr, Pb, and Tl), detailed in Table 9.

To determine the multivariate model (Model # 40) in Table 9, we began by using all remaining trace elements (As, Cd, Co, Cr, Pb, and Tl) as independent variables and employed the Backward Elimination Regression method. The resulting model demonstrates high significance (F = 96.93, df = (6, 88), p < 0.001) with an R-squared value of 86.91%, signifying its substantial utility for practical applications.

4.2.6. The Univariate and Multiple Regression Analyses of Lead in Relation to Other Trace Elements

Lead demonstrates a strong moderate relationship with all other trace elements. We have developed predictive models for lead in conjunction with various trace elements (such as As, Cd, Co, Cr, Fe, Sb, and Tl). For instance, the regression analysis model depicting lead's relationship to arsenic is represented as follows: $\widehat{Pb}$ = 0.75*Arsenic (As) + 108.13, with an R-squared value of 38.6%. This

Table 8. Predictive models for estimating Chromium.

Model #	Independent variable(s)	Predictive Model	R² value
25.	As	$\widehat{Cr}$ = 0.95 As − 60.49	92.2%
26.	Cd	$\widehat{Cr}$ = 1.11 Cd + 9.77	98.5%
27.	Co	$\widehat{Cr}$ = 1.07 Co − 20.79	98.2%
28.	Fe	$\widehat{Cr}$ = 0.03 Fe − 3.75	25.8%
29.	Pb	$\widehat{Cr}$ = 0.50 Pb − 38.63	36.3%
30.	Sb	$\widehat{Cr}$ = 0.61 Sb − 105.22	55.2%
31.	Tl	$\widehat{Cr}$ = 1.06 Tl − 10.16	94.0%
32.	As, Cd, & Fe	$\widehat{Cr}$ = −0.08 As + 1.13 Cd + 0.01 Fe + 2.20	99.4%

Table 9. Predictive models for estimating Iron.

Model #	Independent variable(s)	Predictive Model	R² value
33.	As	$\widehat{Fe}$ = 9.80 As + 829.09	38.8%
34.	Cd	$\widehat{Fe}$ = 7.58 Cd + 1740.04	18.2%
35.	Co	$\widehat{Fe}$ = 9.53 Co + 1358.70	30.7%
36.	Cr	$\widehat{Fe}$ = 8.07 Cr + 1594.97	25.8%
37.	Pb	$\widehat{Fe}$ = 4.54 Pb + 1175.53	12.0%
38.	Sb	$\widehat{Fe}$ = 9.31 Sb − 469.23	51.0%
39.	Tl	$\widehat{Fe}$ = 9.50 Tl + 1446.20	30.0%
40.	As, Cd, Co, Cr, Pb, & Tl	$\widehat{Fe}$ = 11.31 As − 88.36 Cd + 38.35 Co + 35.14 Cr − 1.95 Pb + 7.52 Tl − 457.25	86.9%

model suggests its usefulness in predicting lead levels based on known arsenic concentrations. Notably, the regression coefficient of 0.75 implies that a 1 µg/L increase in arsenic in pond water results in a corresponding 0.75 µg/L increase in lead levels within the same water sample. Similarly, we have established predictive models for lead with other measured trace elements (As, Cd, Co, Cr, Fe, Sb, and Tl), which are presented in Table 10.

To derive the multivariate model (Model # 48) as shown in Table 10, we began the process by utilizing all remaining trace elements (Cd, Co, Fe, and Tl) as independent variables and employed the Backward Elimination Regression method. The resulting model demonstrates high significance (F = 20.26.17, df = (4, 90), p < 0.001) with an R-squared value of 47.6%, indicating its considerable practical utility for applications.

4.2.7. The Univariate and Multiple Regression Analyses of Antimony in Relation to Other Trace Elements

Antimony demonstrates a notably strong correlation with various trace elements, and we have developed predictive models for antimony alongside several others (such as As, Cd, Co, Cr, Fe, Pb, and Tl). For instance, the regression analysis model illustrating the relationship between antimony and arsenic is expressed as $\widehat{Sb}$ = 0.97 As + 150.72, with an R-squared value of 64.1%. This model suggests its effectiveness in predicting lead levels based on known arsenic concentrations. The regression coefficient of 0.97 indicates that a 1 µg/L increase in arsenic in pond water leads to a 0.97 µg/L increase in antimony levels within the same water sample. we have also established predictive models for antimony with other measured trace elements (Cd, Co, Cr, Fe, Pb, and Tl), as outlined in Table 11.

In order to derive the multivariate model (Model #56) found in Table 11, we initiated the process by using remaining trace elements (Co and Fe) as independent variables and employed the Backward Elimination Regression method. The resulting model demonstrates high significance (F = 116.00, df = (2, 92), p < 0.001) with an R-squared value of 71.6%, indicating its substantial practical applicability.

Table 10. Predictive models for estimating Lead.

Model #	Independent variable(s)	Predictive Model	R² value
41.	As	$\widehat{Pb}$ = 0.75 As + 108.13	38.6%
42.	Cd	$\widehat{Pb}$ = 0.80 Cd + 166.29	35.2%
43.	Co	$\widehat{Pb}$ = 0.82 Co + 140.54	39.4%
44.	Cr	$\widehat{Pb}$ = 0.73 Cr + 158.88	36.3%
45.	Fe	$\widehat{Pb}$ = 0.03 Fe +149.72	12.0%
46.	Sb	$\widehat{Pb}$ = 0.43 Sb + 86.15	18.8%
47.	Tl	$\widehat{Pb}$ = 0.81 Tl + 148.62	37.9%
48.	Cd, Co, Fe, & Tl	$\widehat{Pb}$ = −3.86 Cd + 4.04 Co − 0.04 Fe + 0.86 Tl + 93.98	47.6%

Table 11. Predictive models for estimating Antimony.

Model #	Independent variable(s)	Predictive Model	R² value
49.	As	$\widehat{Sb}$ = 0.97 As + 150.72	64.1%
50.	Cd	$\widehat{Sb}$ = 0.96 Cd + 230.08	49.8%
51.	Co	$\widehat{Sb}$ = 1.02 Co + 196.49	59.8%
52.	Cr	$\widehat{Sb}$ = 0.91 Cr + 219.14	55.2%
53.	Fe	$\widehat{Sb}$ = 0.06 Fe + 161.29	51.0%
54.	Pb	$\widehat{Sb}$ = 0.44 Pb + 187.12	18.8%
55.	Tl	$\widehat{Sb}$ = 0.99 Tl + 207.61	55.6%
56.	Co & Fe	$\widehat{Sb}$ = 0.72 Co + 0.03 Fe + 152.54	71.6%

4.2.8. The Univariate and Multiple Regression Analyses of Thallium in Relation to Other Trace Elements

Thallium demonstrates a robust correlation with various trace elements, and we have developed predictive models for thallium in conjunction with several elements (Arsenic, Cadmium, Cobalt, Chromium, Iron, Lead, and Antimony). Specifically, the regression analysis model linking thallium to arsenic is represented as $\widehat{Tl}$ = 0.85 As – 43.14, with an impressive R-squared value of 90.8%. This suggests the model's effectiveness in predicting thallium levels based on known arsenic concentrations. The regression coefficient of 0.85 indicates that a 1 µg/L increase in arsenic in pond water leads to a corresponding 0.85 µg/L increase in thallium levels within the same water sample. Similarly, we have established predictive models for thallium with other measured trace elements (Cadmium, Cobalt, Chromium, Iron, Lead, and Antimony), which are detailed in Table 12.

To determine the multivariate model (Model # 64) in Table 12, we began by using the Backward Elimination Regression method, employing all remaining trace elements (Cadmium, Cobalt, Chromium, and Iron) as independent variables. The resulting model shows high significance (F = 823.24, df = (2, 92), p < 0.001) with an R-squared value of 94.7%. This underscores its substantial practical utility and relevance for applications.

4.3. Toxicity of Trace Elements and Their Testing in Bartlett Pond

4.3.1. Hypothesis Testing and Toxicity of Arsenic (As)

Arsenic contamination in water is a significant concern globally due to its toxicity and potential health risks. Arsenic is a naturally occurring element found in soil and rocks and released into the aquatic and terrestrial landscape through the natural chemical weathering processes, and it can seep into groundwater, making its way into drinking water sources, and globally more than 200 million people are risk due to its contamination [61] [62] [63]. Anthropogenic activities contribute to exceeding high concentration in the environment. Chronic exposure to arsenic-contaminated water has been linked to various health issues, including skin lesions, cancer (skin, bladder, lung), cardiovascular diseases, and

Table 12. Predictive models for estimating Thallium.

Model #	Independent variable(s)	Predictive Model	R^2 value
57.	As	$\widehat{Tl}$ = 0.85 As – 43.14	90.8%
58.	Cd	$\widehat{Tl}$ = 0.99 Cd + 21.91	92.4%
59.	Co	$\widehat{Tl}$ = 0.96 Co – 5.76	93.5%
60.	Cr	$\widehat{Tl}$ = 0.89 Cr + 13.18	94.0%
61.	Fe	$\widehat{Tl}$ = 0.03 Fe + 3.11	30.0%
62.	Pb	$\widehat{Tl}$ = 0.47 Pb – 25.97	37.9%
63.	Sb	$\widehat{Tl}$ = 0.56 Sb – 85.51	55.6%
64.	Cd, Co, Cr, & Fe	$\widehat{Tl}$ = 0.91 Cd + 0.01 Fe + 5.07	94.7%

neurological effects [54] [56] [62].

The permissible level of arsenic in drinking water varies across countries. The World Health Organization (WHO) and the US Environmental Protection Agency (EPA) Federal recommend a maximum concentration of 10 micrograms per liter (μg/L) of arsenic in drinking water in the US.

We tested the hypotheses H0: $\mu \leq 10$ μg/L versus H1: $\mu > 10$ μg/L and concluded that we reject the null hypothesis. The sample mean and standard deviation for arsenic are 130.45 μg/L and 102.51 μg/L, respectively. These results indicate that the arsenic level in pond water exceeds the permissible limit. Therefore, pond water is considered contaminated in terms of arsenic concentration.

4.3.2. Hypothesis Testing and Toxicity of Cadmium (Cd)

Cadmium in water is a serious concern for environmental, ecosystems ecology and health issues. Cadmium is a toxic heavy metal that can enter water sources through industrial discharge, mining activities, agricultural runoff, and improper disposal of waste [55]. It poses significant risks to human health, especially when consumed through contaminated water or food grown in cadmium-contaminated soil. Exposure to cadmium in drinking water over time can lead to various health problems, including kidney damage, bone mineral density reduction, and potentially increasing the risk of certain cancers [54] [56].

The WHO has set a provisional guideline value for cadmium in drinking water at 3 μg/L to minimize health risks. The study involves hypothesis testing, where two hypotheses are proposed:

Null Hypothesis (H_0): The mean Cadmium level (μ) in pond water is less than or equal to 3 μg/L versus alternative Hypothesis (H_1): The mean Cadmium level (μ) in pond water is greater than 3 μg/L.

The study's results indicate that the sample mean Cadmium level is 48.46 μg/L, with a sample standard deviation of 90.77 μg/L. Based on these values, the researchers conclude rejecting the null hypothesis. As the sample mean Cadmium level significantly exceeds the threshold of 3 μg/L, the study asserts that the Cadmium concentration in pond water exceeds permissible limits. Consequently, pond water is deemed unsafe for drinking due to elevated Cadmium le-

vels.

4.3.3. Hypothesis Testing and Toxicity of Cobalt (Co)

The permissible levels of cobalt in water can vary based on different guidelines set by regulatory bodies. Cobalt is a naturally occurring element and can be present in water sources through various means, including industrial discharge, mining activities, and erosion of rocks and soils [56]. Internationally, the WHO doesn't have a specific guideline value for cobalt in drinking water. However, they recommend a provisional guideline value for cobalt in drinking water of 10 micrograms per liter based on health considerations. We tested the hypotheses H0: $\mu \leq 10$ µg/L versus H1: $\mu > 10$ µg/L and concluded that we reject the null hypothesis. This decision is based on the sample mean and standard deviation for Cobalt, which are 78.61 µg/L and 96.76 µg/L, respectively. The mean cobalt concentration is significantly higher than the Canadian drinking water standard (50 µg/L). These values imply that the Cobalt level in the pond water exceeds the permissible range. Consequently, regarding Cobalt levels, the pond water is considered undrinkable.

4.3.4. Hypothesis Testing and Toxicity of Chromium (Cr)

The permissible level of chromium in water varies based on the type of chromium present. There are primarily two forms of chromium: trivalent chromium (chromium-3) and hexavalent chromium (chromium-6). Chromium-3 is naturally occurring and considered essential in small amounts for human health, while chromium-6 is a toxic form often associated with industrial processes [56]. The United States Environmental Protection Agency has set a Maximum Contaminant Level (MCL) for total chromium in drinking water at 100 µg/L. This MCL includes both chromium-3 and chromium-6. We tested the hypotheses: H0: $\mu \leq 100$ µg/L vs. H1: $\mu > 100$ µg/L and concluded that we reject the null hypothesis (p-value < 0.001). This decision was based on the all sample mean and standard deviation for Chromium, which were 63.55 µg/L and 101.51 µg/L, respectively. It is interesting to note that while the sample mean is within the permissible limit, the standard deviation is notably large. The mean value of chromium at quadrant-II appeared 143.45 µg/L, which is higher than the US EPA standard. This suggests that the Chromium level in the pond water exceeds the permissible limit. Therefore, pond water is considered undrinkable.

4.3.5. Hypothesis Testing and Toxicity of Iron (Fe)

Excess iron in water can lead to issues such as a metallic taste, discoloration of water (appearing brown or reddish), and potential staining of laundry, dishes, and plumbing fixtures [56]. Additionally, high levels of iron in water can contribute to adverse health effects if consumed regularly over a prolonged period [54]. The permissible level of iron in water varies based on different standards set by various organizations. In general, the acceptable level of iron in drinking water typically ranges from 300 µg/L to 500 µg/L according to the World Health Organization guidelines although no strict value given. However, this guideline

might differ depending on regional or national standards. Having tested the hypotheses H_0: μ ≤ 500 μg/L against H_1: μ > 500 μg/L, we have concluded that we reject the null hypothesis. This decision is based on the sample mean and standard deviation for iron, which are 2107.46 μg/L and 1613.09 μg/L respectively, along with a p-value < 0.001. Consequently, the Iron level in the pond water does not meet the permissible limits, indicating contamination in the pond water due to elevated Iron levels.

4.3.6. Hypothesis Testing and Toxicity of Lead (Pb)

The permissible level of lead in water varies depending on the regulatory standards set by different countries or organizations. In the United States, the Environmental Protection Agency has set the action level for lead in drinking water at 15 μg/L. This action level means that if lead levels exceed 15 μg/L in more than 10% of sampled taps in a water system, actions must be taken to reduce lead levels. However, it's important to note that no level of lead exposure is considered safe, especially for children, as even low levels of lead exposure can have harmful effects on health, including developmental issues and damage to the brain and nervous system [56]. We tested the hypotheses H_0: μ ≤ 15 μg/L versus H_1: μ > 15 μg/L. Our conclusion is that we reject the null hypothesis due to the sample mean and standard deviation for Lead being 205.19 μg/L and 122.80 μg/L respectively, with a p-value of < 0.001. This implies that the Lead level in pond water exceeds the permissible limit, indicating contamination in the pond water concerning Lead.

4.3.7. Hypothesis Testing and Toxicity of Antimony (Sb)

The permissible level of antimony in water can vary based on different regulations and guidelines set by governing bodies. In the United States, the Environmental Protection Agency has set a Maximum Contaminant Level Goal for Antimony in drinking water at 6 μg/L. However, it's important to note that different countries or regions might have their own standards or guidelines for Antimony levels in water. These regulations are put in place to ensure public health and safety by limiting exposure to potentially harmful trace elements like Antimony.

We tested the hypotheses H_0: μ ≤ 6 μg/L vs. H_1: μ > 6 μg/L and concluded that we reject the null hypothesis. The sample mean and standard deviation for Antimony are 276.70 μg/L and 123.70 μg/L, respectively, with a p-value of < 0.001. This indicates that the Antimony level in pond water exceeds the permissible limit, suggesting contamination. Therefore, the pond water is contaminated in terms of Antimony levels.

4.3.8. Hypothesis Testing and Toxicity of Thallium (Tl)

The permissible level of Thallium in drinking water is regulated by various health authorities and standards maximum concentration limit set by different countries. Generally, the acceptable concentration levels of Thallium in water are very low due to its toxicity. In the United States, the Environmental Protection

Agency has set the maximum contaminant level goal (MCLG) for Thallium in drinking water at zero, meaning there is no safe level of exposure to Thallium. However, they have established an enforceable regulation called the maximum contaminant level (MCL) at 2 μg/L Thallium in public water systems. We tested the hypotheses H_0: $\mu \leq 2$ μg/L vs. H_1: $\mu > 2$ μg/L and concluded that we reject the null hypothesis. The sample mean and standard deviation for Thallium were found to be 69.62 μg/L and 92.97 μg/L, respectively. This indicates that the Thallium level in pond water is not within the permissible range, suggesting that the pond water is undrinkable in terms of Thallium content.

Overall, pond water contains excessive amounts of all measured trace elements beyond the permissible levels for drinking. Additionally, the standard deviations are very large. Consequently, the Bartlett Pond water is severely contaminated, and many fish were found dead during sampling. The Bartlett Pond water is not recommended for any use until we reverse its healthy water quality.

4.4. Impact of High Concentration of Trace Element on Aquatic Life

We investigated the effects of high concentration of trace elements on the aquatic animals on the pond water. For this purpose, we selected two fish species, namely Tilapia and Bass. Three specimens of each species were captured for analysis. Utilizing our standard methods, we measured the concentrations of trace elements present in different parts of the fish—namely the Head, Body, and Tail—to ascertain potential differential impacts. The data collected for this phase of the study are presented in Table 13.

We conducted small-sample t-tests for 48 different possible combinations of 2 fish types, their 3 body parts, and 8 trace elements, focusing on the right-tailed alternative hypotheses as stated in Table 13 (NB3). The analyses yielded the following results:

The concentrations of the trace elements are equivalent in both types of fish

Table 13. Average concentration (in mg/kg) of Trace Elements in the body parts of Tilapia and Bass Fish.

Fish (Body Part)	As	Cr	Pb	Cd	Tl	Co	Fe	Sb
Tilapia (Head)	5.03* (0.58)	0.67 (0.05)	0.20 (0.18)	0.13 (0.10)	1.04* (0.59)	0.77* (0.10)	60.77 (11.15)	12.47* (4.73)
Tilapia (Body)	5.51* (1.17)	0.80 (0.19)	0.67 (0.30)	0.12 (0.08)	1.49* (0.20)	0.82* (0.18)	66.61 (12.16)	17.19 * (2.94)
Tilapia (Tail)	5.58* (0.86)	0.91 (0.24)	1.18 (1.92)	010 (0.08)	1.00* (0.85)	0.94* (0.14)	94.36 (8.11)	18.96* (1.74)
Bass (Head)	6.26* (2.11)	0.81 (0.06)	2.84 (2.76)	0.14 (0.10)	1.69* (0.55)	1.04* (0.30)	64.40 (24.23)	21.9* (3.72) *
Bass (Body)	6.98* (1.19)	0.92 (0.43)	0.95 (0.68)	0.04 (0.05)	1.70* (1.11)	1.10* (0.28)	91.54 (23.97)	19.92* (5.74)
Bass (Tail)	6.59* (1.63)	0.89 (0.16)	0.64 (0.62)	0.14 (0.05)	0.24* (0.07)	1.21* (0.25)	69.65 (9.58)	20.28* (4.34)
Max. SRM Certified Value for Fish	**3.00**	**1.00**	**1.00**	**0.50**	**0.10**	**0.50**	**100.00**	**1.00**

NB 1: The numbers within the parentheses are the corresponding sample standard deviations. NB 2: Sample size (n) for each case was 3. NB 3: * = p-value < 0.001 for H_0: The Mean value = The Max. SRM Certified Value vs. H_1: The Mean value > The Max. SRM Certified Value.

and consistent across the body parts of the two types of fish. The concentrations of the trace elements such as As, Tl, Co, and Sb are significantly higher (p-value < 0.001) than the maximum SRM certified values for each fish but trace elements such as Cr, Pb, Cd, and Fe are not significantly higher than the maximum SRM certified values for each fish [64]. In summary, the study revealed that certain trace elements were found in higher concentrations than anticipated in both types of fish and their respective body parts. Conversely, other trace elements fell within the expected ranges. It is evident that the elevated levels of the toxic elements: As, Tl, Co, and Sb, which have accumulated in fish tissues, pose increased health risks to humans who consume these contaminated fish although fishing is prohibited. It is likely that the fish have accumulated these higher levels of trace elements from the contaminated pond water.

5. Conclusions

The investigation of spatial distribution of trace elements, including arsenic, cadmium, cobalt, chromium, iron, lead, antimony, and thallium, and their potential toxicity provided a detailed understanding of their distribution across different positions of the pond and shedding light on the implications for both environmental health and aquatic life. We observed distinct spatial patterns and identified potential sources of contamination primarily from anthropogenic sources such as surface urban runoff, and specific sampling locations by utilizing descriptive statistics, histograms, and regression analyses. Natural chemical weathering mechanisms appear to have a negligible contribution to the severe contamination observed within the pond. Moreover, the correlation analyses unveiled strong positive correlations among the most trace elements, indicating interconnectedness within the ecosystem.

Further analyses involved hypothesis testing to assess the toxicity of each trace element in accordance with regulatory standards. Results consistently indicated elevated concentrations of trace elements surpassing permissible limits, rendering the pond water unsuitable for drinking and posing significant risks to environment and human health. The large standard deviations observed underscored the variability within the dataset, emphasizing the severity of contamination and the urgent need for remedial action.

Moreover, the impact of high trace element concentrations on aquatic life, particularly Tilapia and Bass, was investigated. We evaluated trace element levels in different body parts of the Bass and Tilapia fish, uncovering significant findings regarding potential differential impacts through meticulous sampling and analysis. Contaminant accumulation was notably higher in Bass compared to Tilapia fish. The analysis highlighted the need for comprehensive monitoring and mitigation strategies to safeguard aquatic ecosystems and mitigate adverse effects on biodiversity.

Overall, the findings underscore the critical importance of ongoing monitoring and management of water quality in Bartlett Pond. The integration of advanced statistical techniques with field observations has facilitated a comprehensive under-

standing of environmental dynamics, informing evidence-based decision-making and guiding future research and conservation efforts. Addressing the identified contamination requires collaborative efforts from policymakers, environmental agencies, and local communities to ensure the restoration and preservation of water quality and ecosystem health for current and future generations.

Acknowledgements

Authors' Contributions

MPB conducted methodology and chemistry data analysis, and drafted, reviewed, and edited the manuscript. RA contributed to conceptualization, sampling design, and participated in writing, reviewing, and editing. GBM handled data analysis with empirical modeling, and contributed to writing, reviewing, and editing. CL, VM, EVC, DM, and OBA performed field and laboratory work, and participated in reviewing and editing. AAM was involved in methodology, conceptualization, sampling design, grant writing, funding acquisition, and participated in writing, reviewing, and editing.

Conflicts of Interests

The authors declare no conflicts of interest.

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