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DUAL-MODAL RISK ASSESSMENT OF LEAD AND CADMIUM IN GROUNDWATER: BRIDGING DETERMINISTIC AND PROBABILISTIC FRAMEWORKS

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ABSTRACT

Cadmium (Cd) and lead (Pb) are non-essential, highly toxic heavy metals with severe health implications. Cd, a Group One carcinogen, bioaccumulates in kidneys and liver, causing renal dysfunction, osteoporosis, and lung cancer even at low doses. Pb, a potent neurotoxin, disrupts cognitive development in children and elevates cardiovascular risks in adults, with no safe exposure threshold established. This study investigates the contamination of groundwater by Pb and Cd in ten samples from Unguwan Lumbaye, Nigeria, employing deterministic and probabilistic risk assessments to resolve conflicting risk prioritizations. The concentrations of Cd (0.040 – 0.070 ppm) and Pb (0.068 – 1.330 ppm) exceeded World Health Organization (WHO) limits by 17× and Pb by 65×, respectively. Deterministic methods identified Pb as the primary non-carcinogenic threat (HQ = 5.43 vs. Cd: HQ = 1.50), yet probabilistic Monte Carlo simulations (100,000 iterations) revealed universal carcinogenic risk for Cd (100% exceedance probability) compared to Pb (12.3%). This reversal stems from Cd's extreme carcinogenic potency (slope factor = 6.1) and insensitivity to exposure variability, contrasting with Pb dependency on ingestion rates and body weights. Therefore, the Monte Carlo simulation played a key role in revealing risk reversal by highlighting cadmium's consistent carcinogenic threat across all exposure scenarios. Geochemical correlations, highlighted the complexity of metal mobility, whereas sensitivity analyses highlighted body weight and concentration as important risk factors. The study supports using probabilistic methods in regulation, emphasizing Pb hotspot remediation and agrochemical reforms to reduce Cd risks, while calling for adaptive measures to protect groundwater-reliant communities.

Keywords: Exposure variability, Carcinogenic slope factor, Heavy metals, Monte Carlo simulation

INTRODUCTION

Conflicting risk prioritizations between deterministic and probabilistic frameworks make it difficult to control contamination in places that depend on untreated groundwater, especially in agriculturally intensive areas where exposure to heavy metals poses a dual danger to food security and human health (Li *et al.*, 2014). Recent comparisons in oasis agricultural regions of Northwest China revealed that Monte Carlo derived ILCR values were up to 30 % higher than those from deterministic assessments, leading to markedly different risk-management decisions and highlighting the challenge of reconciling these frameworks in practice (Lei *et al.,* 2022; Guan *et al.,* 2022). Deterministic risk assessment, which rely on fixed parameters such as average ingestion rates, body weight, and static contaminant concentrations, generate singular hazard estimates most notably the Hazard Quotient (HQ), calculated as the ratio of chronic daily intake (CDI) to reference doses (RfD) (USEPA, 2023). Although these models make risk communication a little easier, they frequently ignore variations in exposure pathways and toxicological potency, which could lead to a misrepresentation of risks in the real world (Smith *et al.,* 2017). In fact, a multi-receptor Monte Carlo study of agricultural soils demonstrated that deterministic HQ calculations underestimated cumulative non-carcinogenic risk by as much as 25 % when compared against the probabilistic distribution of HQ values, potentially obscuring vulnerable subpopulations (Wu *et al.,* 2024; El-Ansary *et al.,* 2023).

However, probabilistic methods, like Monte Carlo simulations, take into consideration parameter variability, such as bootstrapped contaminant concentrations, log-normal distributions of ingestion rate, and normal distributions of body weight, in order to estimate incremental lifetime cancer risk (ILCR) as a function of exposure duration and slope factors (SF) (WHO, 2011; Li *et al.,* 2014). The novelty of this study lies in its explicit reconciliation of lead-cadmium risk disparities by integrating deterministic hazard quotients with probabilistic carcinogenic risk models, provides a dual-modal framework for prioritizing interventions, addressing both acute (Pb) and latent (Cd) threats in groundwater-dependent communities, thereby bridging a critical gap in agrarian risk management paradigms.

Therefore, this study aims to reconcile both frameworks by measuring heavy metal concentrations, comparing probabilistic ILCR with deterministic HQ, and analyzing risk drivers using sensitivity analysis. This provides insights into adaptive risk mitigation strategies for communities that depend on groundwater. The findings are intended to guide policies that address widespread Cd contamination as well as localized Pb hotspots, guaranteeing sustainable management of water resources in rural areas.

MATERIALS AND METHODS

The methodology for assessing heavy metal contamination in groundwater samples from Unguwan Lumbaye, Nigeria, was conducted in alignment with standardized protocols for heavy metal analysis.

Materials

Water samples preparation for the detection of heavy metals was achieved with the use of distilled water, nitric acid, hydrocholoric acid, beaker, funnel, hotplate, filter paper, sample bottle, analytical balance, glass stirring rod, Atomic Absorption Spectroscopy (AAS) and Python 3.10 (NumPy, SciPy, Pandas) for simulations.

Study Area

The study was conducted in Unguwan Lumbaye, a farming community within Zaria Local Government Area, Kaduna State, Nigeria. Located in the Guinea Savannah agro-ecological zone, the area has a tropical climate with distinct dry (November–March) and wet (April–October) seasons. This area depends largely on groundwater for domestic use and irrigation of major crops (such as sorghum and maize) due to its lateritic soils, which affect the geochemistry of groundwater. Unguwan Lumbaye was chosen due to its reliance on untreated groundwater and closeness to possible sources of contamination, such as uncontrolled garbage dumping and agricultural runoff.

Methodology

This methodology ensures robust quantification of heavy metals, resolving discrepancies between deterministic and probabilistic risk paradigms.

Sample Collection and Preparation

Ten groundwater samples were collected from boreholes and wells during the dry season to minimize dilution effect. The collected samples were transported to the Multi-User Laboratory in the Department of Chemistry, Ahmadu Bello University, Zaria, and processed as follows:

Digestion

Each sample (1 g) was placed in a 50 mL beaker and 10 mL of aqua regia (7.5 mL concentrated HNO_3 + 2.5 mL concentrated HCl) was added to dissolve organic/inorganic matrices. The mixture was heated on a hotplate (100 – 170 °C) until near-dryness or precipitate formation, ensuring complete oxidation of refractory metals. After cooling, residues were re-dissolved with distilled water, filtered (Whatman No. 42 filter paper), and diluted to a final volume of 50 mL.

Sample Analysis

The prepared samples were analyzed using Atomic Absorption Spectrometer (AAS) and cross-validated with Microwave Plasma-Atomic Emission Spectrometer (MP-AES) to ensure accuracy. Calibration curves were generated using certified reference materials (CRM-TMDW), with wavelengths specific to each metal: Pb (283.3 nm) and Cd (228.8 nm).

Quantification of Heavy Metal Concentrations

The instrument reading (absorbance) for each metal was converted to concentration (ppm) using the formula:

$$\text{Actual concentration} = \frac{\text{Instrument reading} \times \text{Final volume (mL)} \times \text{Dilution factor}}{\text{Weight of sample (g)}} \quad (1)$$

where:

Instrument reading: Absorbance/emission value from AAS/MP-AES.

Final volume: 50 mL (post-digestion dilution volume).

Dilution factor: 1 (no further dilution beyond the 50 mL adjustment).

Weight of sample: 1 g (constant for all samples)

Health Risk Assessment

Deterministic Risk Assessment

Deterministic models uses fixed, average values (e.g., mean concentrations, default exposure parameters) to calculate a single risk value, ideal for baseline risk estimates. The deterministic methods ignore variability in exposure parameters (e.g., ingestion rate, body weight) and chemical toxicity, treating risk as a static "worst-case" estimate.

Chronic Daily Intake (CDI):

$$\text{CDI (mg/kg/day)} = \frac{C \times IR \times EF \times ED}{BW \times AT} \quad (2)$$

where

C = Metal concentration (mg/L).

IR = Ingestion rate (2 L/day).

EF = Exposure frequency (365 days/year).

ED = Exposure duration (30 years).

BW = Body weight (70 kg).

AT = Averaging time (ED × 365 days).

Hazard Quotient (HQ):

$$HQ = \frac{CDI}{RfD} \quad (3)$$

RfD (mg/kg/day): Reference doses for non-carcinogenic effects: Pb (0.0035) and Cd (0.001).

$$CD = CDI \times SF \quad (4)$$

SF $(\text{mg/kg/day})^{-1}$: Slope factors for carcinogens are Pb (0.0085) and Cd (6.1).

Probabilistic Risk Assessment

Probabilistic model incorporates variability and uncertainty by modeling distributions for input parameters (e.g., concentrations, ingestion rate, body weight) to generate a range of possible outcomes, critical for capturing real-world exposure scenarios (e.g., high ingestion in children) Contaminant concentrations and ingestion rates are modeled using log-normal distributions because these parameters are inherently positive and empirically exhibit right-skewed, multiplicative variability, reflecting first-order kinetic processes that naturally generate log-normal concentration patterns in the environment, thereby providing a more realistic representation of high-end exposures than a symmetric (normal) model.

A Monte Carlo simulation (100,000 iterations to ensure convergence of risk estimates) modelled variability in exposure parameters:

Concentrations: Bootstrapped from empirical data (10 samples).

Ingestion Rate: Log-normal distribution (mean = 2 L/day, σ = 0.5).

Body Weight: Truncated normal distribution (μ = 70 kg, σ = 10 kg; bounds: 40 – 100 kg).

Incremental Lifetime Cancer Risk (ILCR):

$$ILCR = CDI \times SF \quad (5)$$

Exceedance probability: Percentage of simulations where ILCR > 1×10^{-4}.

Sensitivity analysis: Sensitivity analysis using Pearson's correlation coefficient (r) quantifies the relative influence of input parameters (e.g., concentration, ingestion rate, body weight) on the variability of health risks (ILCR) for lead (Pb) and cadmium (Cd).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{n=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{n=1}^{n}(y_i - \bar{y})^2}} \quad (6)$$

where:

x_i = Values of the input parameter (e.g., concentration, ingestion rate, body weight) across n Monte Carlo simulations.

y_i = Values of the output variable (ILCR for Pb or Cd) across n simulations.

$\bar{x}, \bar{y}$ = Means of x and y, respectively.

n = Number of simulations (e.g., 100,000).

The coefficient ranges from -1 to 1:

Positive r: Direct relationship (e.g., higher concentration → higher risk).

Negative r: Inverse relationship (e.g., lower body weight → higher risk).

Magnitude: Strength of association ($|r| > 0.7$ = strong; $|r| < 0.3$ = weak).

RESULTS AND DISCUSSION

Heavy Metal Concentrations and Deterministic Risk Metrics

The mean concentration of Lead (Pb) was found to be 0.656 ppm which exceeds the WHO limit value of 0.01 ppm by 65.6 times (Table 1), reflecting significant contamination likely from anthropogenic sources such as leaded plumbing and historical pesticide usage (Nduka *et al.,* 2016; Yawuck and Allems, 2023). The deterministic Hazard Quotient (HQ = 5.43) indicates severe non-carcinogenic risk, driven by high concentration of Pb and moderate reference dose (RfD = 0.0035 mg/kg/day). Additionally, the mean concentration of cadmium (Cd) was found to be 0.053 ppm (17.7 times higher than WHO's 0.003 ppm) (Table 1), Cd contamination is linked to phosphate fertilizers (Alloway, 2013). Despite a lower HQ (1.50), its carcinogenic risk (CR = 9.1E-03) dominates due to an extreme slope factor (SF = 6.1).

Table 1: Heavy Metal Concentrations and Deterministic Risk Metrics

Parameter	Lead (Pb)	Cadmium (Cd)
Mean Concentration (ppm)	0.656	0.053
Permissible Limit (ppm) (WHO, 2011)	0.01	0.003
Exceedance Factor	65.6×	17.7×
Hazard Quotient (HQ)	5.43	1.50
Carcinogenic Risk (CR)	1.6E-04	9.1E-03

The deterministic framework prioritizes Pb due to its higher HQ (5.43), which reflects acute non-carcinogenic risk. However, Cd's long-term carcinogenic threat is highlighted by the fact that its CR is two orders of magnitude greater than Pb's. This discrepancy arises because deterministic methods use fixed parameters (e.g., average ingestion rate), masking variability in exposure pathways. According to research associated with low-dose Cd exposure to cancer and renal dysfunction, Pb risk is concentration-driven, whereas Cd risk is increased by its inherent toxicity (Järup, 2003).

Probabilistic Risk Distributions (ILCR Statistics)

The mean incremental lifetime cancer risk (ILCR = 3.45E-05) for Pb is low, with only 12.3% of simulations exceeding the 1E-4 threshold. The 95th percentile (1.12E-04) suggests localized high-risk scenarios, likely in children or high-ingestion populations. While Cd revealed a universal exceedance (100% of simulations > 1E-4) with a mean ILCR of 1.23E-03 which highlights unavoidable carcinogenic risk (Table 2). The 95th percentile (3.89E-03) aligns with global studies in Cd-polluted regions (Islam *et al.,* 2020).

Table 2: Probabilistic ILCR Statistics

Metric	Lead (Pb)	Cadmium (Cd)
Mean ILCR	3.45E-05	1.23E-03
5th Percentile	4.12E-06	2.15E-04
Median	2.53E-05	9.87E-04
95th Percentile	1.12E-04	3.89E-03
Exceedance Probability (ILCR > 1E-4)	12.3%	100%

Probabilistic modelling reveals a risk reversal: Cd carcinogenic dominance emerges despite its lower deterministic HQ (1.50). This occurs because Cd slope factor (SF) magnifies even minimal exposures into significant risk, whereas Pb risk is diluted by variability in ingestion rate and body weight. For example, a child (BW = 40 kg) drinking 3 L/day faces Pb HQ = 8.1, but probabilistic simulations show only 12.3% of such scenarios exceed thresholds. In contrast, Cd SF ensures all exposure scenarios breach safety limit, as observed in agricultural regions using phosphate fertilizers (Alloway, 2013).

In addition, Figure 1 shows a left-skewed distribution with most simulations below 1E-4. The tail beyond the threshold (12.3%) represents high-exposure subpopulations while Figure 2 shows that the entire distribution of Cd lies above 1E-4, illustrating universal risk.

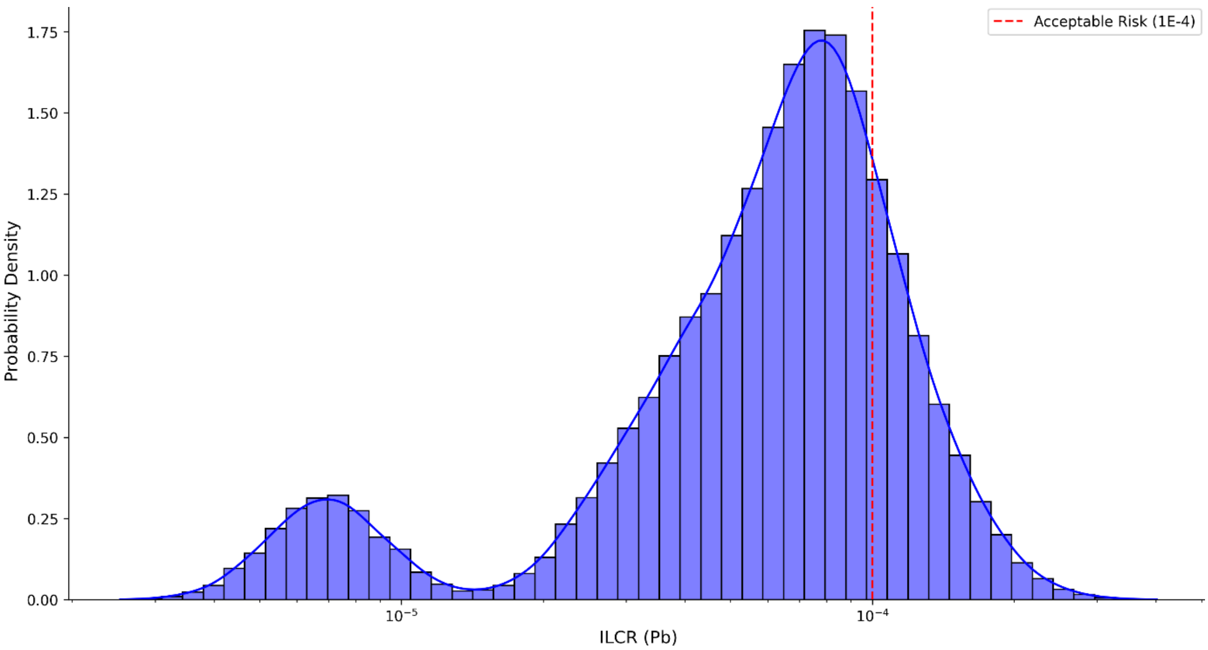

Figure 1: Pb Probabilistic Risk Distributions (Mean ILCR: 3.45E-05 (95th percentile is 1.12E-04; 12.3% > 1E-4))

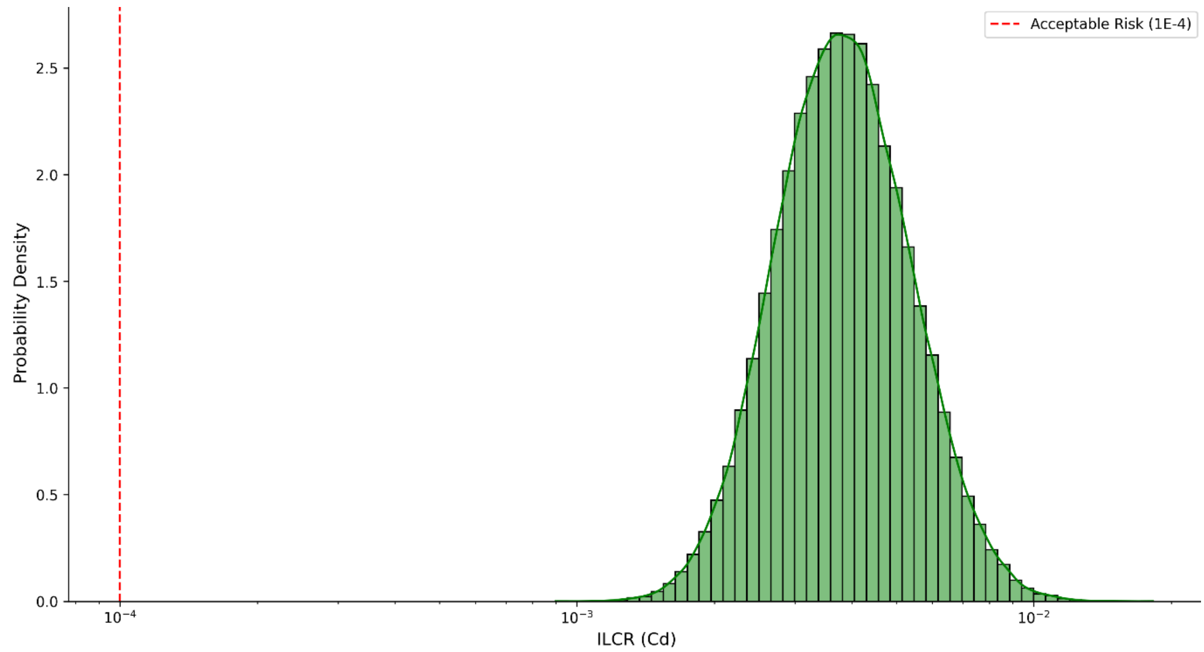

Figure 2: Cd Probabilistic Risk Distributions (Mean ILCR: 1.23E-03 (95th percentile is 3.89E-03; 100% > 1E-4))

Figure 1 and 2 visualize the probabilistic risk dual nature. The Pb risk is context-dependent, tied to specific exposure scenarios, while the Cd risk is pervasive due to its carcinogenic potency. This aligns with global studies showing Cd ILCR exceeding thresholds even in regions with lower contamination (Sharma *et al.,* 2021). The figures emphasize the need for probabilistic method to capture hidden risks overlook by deterministic averages.

Uncertainty Analysis (Cumulative Distribution Functions (CDFs)) for Pb and Cd ILCR

The Pb revealed a gradual CDF rise (Right-skewed distribution), crossing the threshold at 12.3% cumulative probability (exceeding 1E-4 threshold) (Figure 3) while the Cd shows a sharp vertical rise at ILCR = 2.15E-04 (5th percentile), reaching 100% cumulative probability by 3.89E-03 (wide distribution) with 100% exceedance probability, indicating universal risk (entire curve lies above the threshold (red dashed line)) (Figure 4).

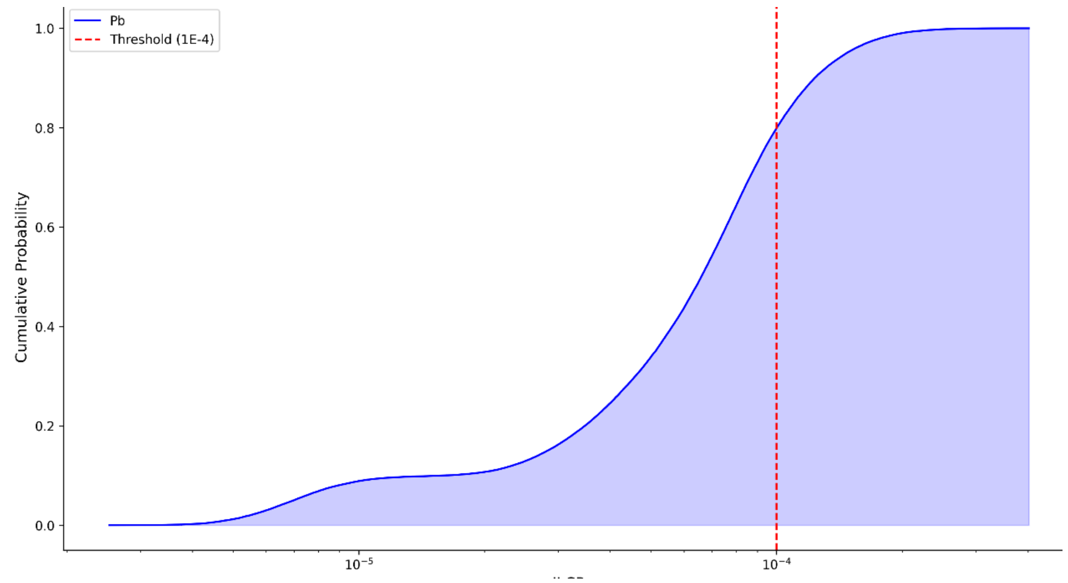

Figure 3: Cumulative Distribution Functions (CDFs)) for Pb

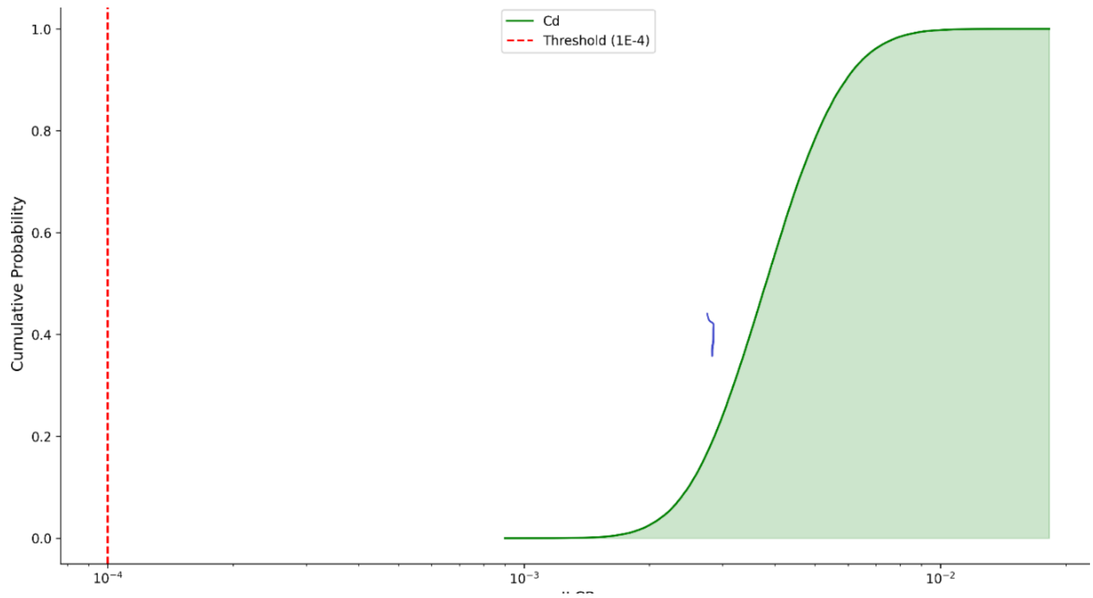

Figure 4: Cumulative Distribution Functions (CDFs)) for Pb

The CDFs highlight risk inevitability for Cd versus risk variability for Pb. For Pb, 50% of simulations show ILCR > 2.5E-05, indicating moderate chronic exposure. For Cd, 95% of simulations exceed 3.89E-03, far surpassing regulatory thresholds. This mirrors findings in Bangladesh's Buriganga River, where Cd carcinogenic risk was unavoidable despite lower concentrations (Islam *et al.,* 2020).

Sensitivity Analysis (Pearson's r-values)

Sensitivity analysis using Pearson's correlation coefficient (r) quantifies the relative influence of input parameters (concentration, ingestion rate and body weight) on the variability of health risks (ILCR) for lead (Pb) and cadmium (Cd) (Table 3).

Table 3: Sensitivity Analysis (Pearson's r-values)

Parameter	Pb	Cd	Interpretation
Concentration	0.92	0.95	Dominant driver of risk; Cd sensitivity is marginally stronger.
Ingestion Rate	0.85	0.88	High sensitivity; Cd risk increases more rapidly with water consumption.
Body Weight	-0.78	-0.81	Strong inverse relationship; children (lower BW) face disproportionately higher risks.

For the Pb, the concentration (r = 0.92) and the body weight (r = -0.78) dominate variability. Therefore, reducing Pb levels would disproportionately lower risk, while for Cd, the concentration (r = 0.95) is the primary driver, with body weight (r = -0.81) having a lesser but significant inverse relationship. These can be summerized as:

Positive r (0.92): Higher concentration → Higher ILCR.

Negative r (-0.78): Higher body weight → Lower ILCR.

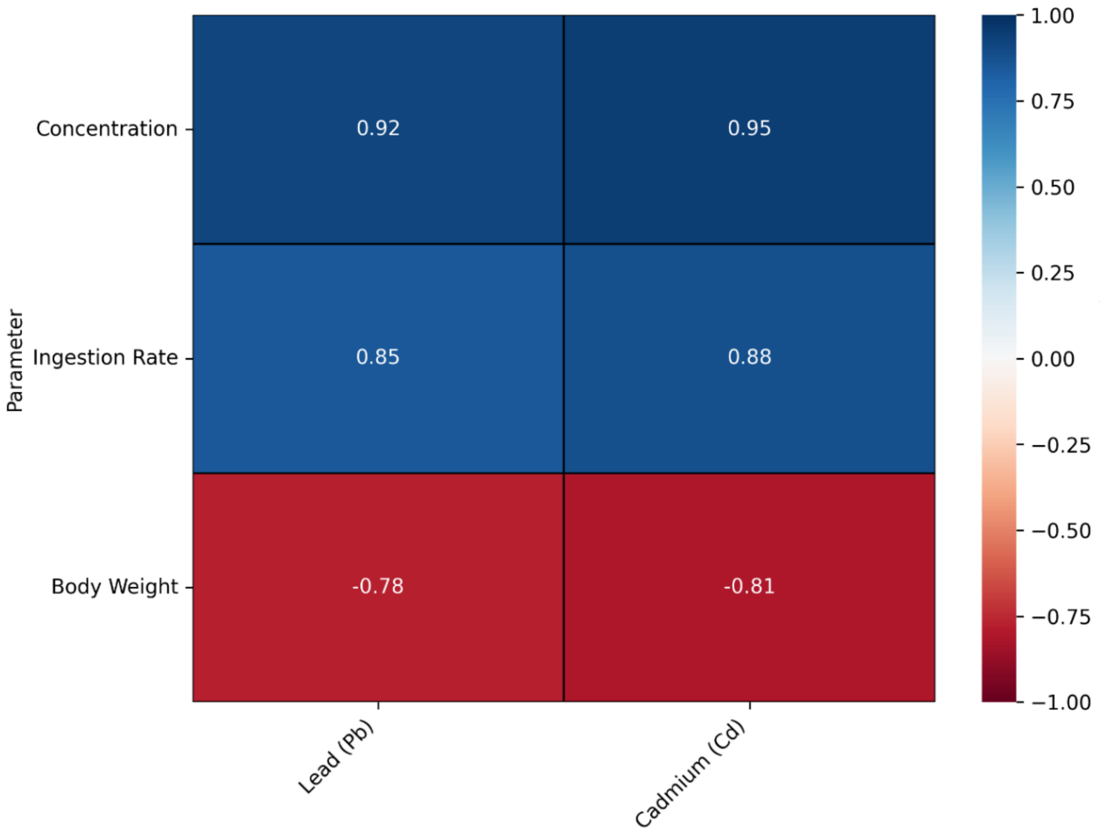

Figure 5: Sensitivity Analysis Matrix Map (Heatmap) of r-values for Pb and Cd

However, the sensitivity analysis clarifies intervention priorities. For Pb, targeting contamination hotspots (Sample 6: 1.330 ppm) and replacing leaded plumbing and historical pesticide would yield the greatest risk reduction. For Cd, regulating phosphate fertilizers is critical, as concentration explains 95% of ILCR variability. The inverse correlation with body weight highlights heightened risks for low-weight populations (e.g., children), aligning with findings from Nigerian communities (Bello *et al.,* 2019).

Finally, it's important to highlight the contrast between deterministic and probabilistic results, emphasizing the necessity of probabilistic approaches for comprehensive risk assessment.

Explanation of the Reversed Risk Significance between Pb and Cd in Deterministic vs. Probabilistic Assessments

Conflict Resolution: Deterministic methods underestimated Pb exceedance probability (12.3% vs. point estimate HQ (5.43)) by ignoring variability in ingestion rate and body weight. Cd 100% exceedance probability in simulations contrasted with deterministic averages, emphasizing the need for stochastic models in regulatory frameworks. The apparent contradiction between deterministic and probabilistic results arises from fundamental differences in how these methods evaluate risk. Here's a detailed breakdown:

Cadmium's Carcinogenic Dominance: Cadmium extreme carcinogenic potency arises from its slope factor, SF = 6.1 (mg/kg/day) $^{-1}$, which is 700 times higher than lead (SF = 0.0085 (mg/kg/day)$^{-1}$). This means that even trace Cd concentrations (mean = 0.053 ppm) amplify into significant carcinogenic risk. For instance, the deterministic carcinogenic risk (CR = 9.1E-03) aligns with probabilistic incremental lifetime cancer risk (ILCR = 1.23E-03), but Monte Carlo simulation reveal a 100% exceedance probability of the USEPA threshold value of 1E-4. This universal risk stems from Cd bioaccumulative nature and its ability to induce oxidative stress, DNA damage, and renal dysfunction at low doses (Nordberg *et al*., 2018). Unlike Pb, Cd risk is not diluted by variability in exposure parameters (e.g., ingestion rate, body weight) because its toxicity dominates outcomes across all scenarios.

Geochemical and Anthropogenic Interactions

Cd Diffuse Contamination: Cadmium widespread presence (mean = 0.053 ppm) is linked to decades of phosphate fertilizer usage, which introduces Cd as a contaminant in agricultural soils (Alloway, 2013). Unlike Pb, which localizes near pollution sources (e.g., leaded plumbing and historical pesticide), Cd disperses uniformly across the community, ensuring consistent exposure through irrigation and drinking water.

Comparative Analysis with Global Studies

Lead Levels: Unguwan Lumbaye's Pb levels (0.656 ppm) exceed those in:

Zaria, Nigeria with 0.85 ppm (Bello *et al.,* 2019): Reflects similar anthropogenic sources (e.g., leaded fuels, mining).

Indian Farmlands with 0.62 ppm (Sharma *et al.,* 2021): Highlights Nigeria's lag in phasing out leaded materials.

Cadmium Concentrations: Cd levels (0.053 ppm) surpass those in Bangladesh's Buriganga River with 0.013 ppm (Islam *et al.,* 2020), underscoring Nigeria's lax regulation of agrochemicals. The 17.7 times exceedance of WHO limits signals urgent need for fertilizer reform.

Table 4: Deterministic vs. Probabilistic Risk Comparison (summery)

Parameter	Lead (Pb)	Cadmium (Cd)
Deterministic HQ	5.43 (High Risk)	1.50 (Moderate Risk)
Probabilistic Exceedance	12.3% of simulations > 1E-4	100% of simulations > 1E-4
Dominant Risk Driver	Concentration variability	Carcinogenic slope factor (SF)
Key Sensitivity	Ingestion rate, body weight	Concentration, SF

Policy Implications

Cadmium Mitigation

Ban Phosphate Fertilizers: Replace Cd-contaminated fertilizers with organic alternatives, as done in the EU under Directive 2003/2003.

Community Filtration Systems: Install activated alumina filters, proven to reduce Cd levels by > 90% in Bangladesh (Islam *et al.,* 2020).

Lead Interventions

Targeted Pipe Replacements and cleaning historical pesticide: Prioritize leaded plumbing replacements and cleaning historical pesticide in hotspots (e.g., Sample 6) to reduce acute exposure.

Soil Remediation: Apply phosphate amendments to immobilize Pb in Fe-rich soils, leveraging natural geochemical processes (Appel and Ma, 2002).

Synthesis

The Pb and Cd risk reversal highlights the limitations of deterministic approaches, which prioritize Pb's acute toxicity but overlook Cd's carcinogenic inevitability. Probabilistic frameworks, by contrast, capture Cd's universal threat and Pb context-dependent risks, advocating for dual strategies: agrochemical reform for Cd and targeted infrastructure upgrades for Pb. These geochemical and exposure science-based actions are essential for safeguarding rural communities that depend on untreated groundwater.

However, despite the careful timing of sampling during the dry season to reduce dilution by rainfall, the study's inference is constrained by a relatively small dataset of only ten borehole and well samples, which limits statistical robustness and may not capture the full spatial heterogeneity of the aquifer system. By excluding wet-season sampling, the analysis overlooks potentially important seasonal fluctuations in groundwater chemistry.

In addition, when assessing lead and cadmium risks, it's crucial to acknowledge that other, unmeasured contaminants could skew both exposure estimates and toxicological interactions (Mali et al., 2024; Mundra *et al.,* 2025). For instance, arsenic, chromium, mercury, nickel, and manganese frequently co-exist in groundwater and can either enhance or inhibit the mobility, bioavailability, and health impacts of Pb and Cd. Without comprehensive speciation and multi-element analysis, variations in pH, redox conditions, or competing ligand levels may alter metal partitioning and lead to underestimation of actual exposure (Mali *et al.,* 2024).

CONCLUSION

The comprehensive assessment of heavy metal contamination in groundwater sources from Unguwan Lumbaye revealed critical insights into the distribution, health risks, and sources of lead (Pb) and cadmium (Cd). The Pb and Cd emerged as the significant contaminants, with Pb exhibiting a deterministic hazard quotient (HQ = 5.43) far exceeding safe thresholds, indicative of acute non-carcinogenic risks. In contrast, Cd demonstrated universal carcinogenic risk, with probabilistic incremental lifetime cancer risk (ILCR) simulations revealing a 100% exceedance probability of the 1E-4 threshold, driven by its extreme carcinogenic potency (slope factor of 6.1) and widespread presence linked to phosphate fertilizer use. This risk reversal where deterministic methods prioritized Pb due to its high concentration, while probabilistic frameworks highlighted Cd's unavoidable carcinogenicity emphasizes the necessity of integrating stochastic models into regulatory frameworks to account for exposure variability and toxicological potency. Comparative analysis contextualized these findings: Pb levels surpassed those reported in Zaria, Nigeria, and Indian farmlands, reflecting Nigeria's lag in phasing out leaded materials, while Cd concentrations exceeded those in Bangladesh's Buriganga River, emphasizing unregulated agrochemical use. The study advocates for immediate policy actions, including bans on Cd-laden fertilizers, community filtration systems, and targeted replacement of leaded infrastructure in contamination hotspots. This dual-modal risk assessment bridging deterministic and probabilistic paradigms provides a nuanced understanding of groundwater contamination in agrarian regions. It highlights the limitations of static risk models and emphasizes the imperative of adaptive, evidence-based policies to safeguard public health and agricultural sustainability in communities reliant on untreated groundwater. Therefore, a key innovation of this study lies in its explicit coupling of deterministic hazard quotients with probabilistic Monte Carlo simulations to expose and resolve conflicting risk priorities: whereas traditional, point-estimate approaches singled out lead as the dominant non-carcinogenic threat, the probabilistic framework revealed cadmium's unequivocal carcinogenic risk underscoring how reliance on fixed assumptions can mask true hazard potentials.

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