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Monte Carlo-Based Probabilistic Health Risk Assessment of Airborne Heavy Metals from a Medical Waste Incinerator in Southwestern Nigeria

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Abstract

Purpose: Incineration of medical waste may increase airborne exposure to heavy metals in nearby areas. This study integrates empirical field measurements with a Monte Carlo-based probabilistic health risk assessment (PHRA) to assess inhalation hazards surrounding a medical waste incinerator in Ido-Ekiti, Nigeria.

Method Particulate matter was collected with passive glass slide samplers from several zones over a two-month period. Ten heavy metals were measured through laboratory analysis, and their concentrations were converted into effective airborne volumetric values (C_{air}). To address variability, exposure parameters were assigned statistical distributions, and 10,000 Monte Carlo iterations were performed in MATLAB.

Results: Statistical convergence was attained after 4,000 iterations. The simulated non-carcinogenic Hazard Quotient (HQ) distribution was right-skewed, featuring a median mode near $HQ = 400$ and a 95th percentile of 850. Across scenarios, the probability of surpassing safety thresholds approached 100%, mainly due to airborne contaminant concentration (C_{air}) and exposure time (ET). Carcinogenic risk profiles (ILCR) also surpassed standard regulatory benchmarks.

Conclusion: The probabilistic method reveals critical upper-tail exposure risks that deterministic estimates fail to detect. These findings emphasize the urgent need for strict spatial buffer zones, advanced air pollution controls for local medical waste incinerators, and the incorporation of probabilistic frameworks into environmental impact assessments.

Keywords: Monte Carlo Simulation, Heavy Metals, Medical Waste Incinerator, Probabilistic Health Risk Assessment, Inhalation Exposure, Health risk.

Introduction

Medical waste management in sub-Saharan Africa, particularly Nigeria, presents interconnected environmental and public-health challenges between environmental challenges and public health predicaments [1]. Medical waste incinerators (MWIs), while providing an important means of reducing infectious waste, can emit particulate matter and trace metals when combustion and emission-control systems are inadequate [9]. In some healthcare facilities in Nigeria, medical waste incineration occurs within hospital premises, potentially exposing nearby workers and surrounding communities to combustion-derived pollutants [4].

In Nigeria, many previous studies utilized the deterministic method to assess risks associated with the exposure to emissions of heavy metals from MWIs [2,10,16]. Deterministic risk assessment is useful for screening and comparison but generally represents uncertain or variable exposure parameters using fixed point estimates. Such an approach may not adequately characterize the distribution of possible exposure conditions. Probabilistic risk assessment addresses this limitation by assigning probability distributions to uncertain and/or variable parameters and propagating these distributions through the risk model [5,14].

Medical waste incineration in Nigeria may also be accompanied by inadequate waste segregation and variable combustion conditions [7]. Under incomplete or poorly controlled combustion conditions, particulate-bound metals may be released into the surrounding environment, where they can contribute to human exposure through inhalation and other pathways [12]. A probabilistic approach is therefore necessary for to capture the full spectrum of potential health risks that are associated with the emissions of heavy metals from MWIs [3].

In Sub-Saharan Africa, medical waste incineration (MWI) continues to be a serious environmental health concern. In order to achieve UN Sustainable Development Goal (SDG 3), it is essential to

assess harmful air emissions from MWIs. Exposure heterogeneity across populations is not adequately captured by traditional deterministic risk models. Therefore, in order to detect serious tail-end dangers that susceptible subpopulations near incineration sites suffer, probabilistic risk models are required.

In this study, Monte Carlo-Based Probabilistic Health Risk Assessment (PHRA) was employed to treat exposure parameters as probability distributions rather than fix constant. In this approach, threshold exceedance was quantified, magnitude of the risk was identified, uncertainty and sensitivity of the model was also characterized which establish robust evidence for clinical and environmental policy interventions.

Although previous studies have assessed heavy-metal contamination and health risks associated with medical waste incineration in Nigeria, many assessments have relied primarily on deterministic point estimates. By using Monte Carlo simulation to characterize the variability and uncertainty related to inhalation exposure parameters and measured heavy-metal concentrations surrounding a medical waste incinerator in Ido-Ekiti, the current study adds to this body of work. In particular, the study evaluates the likelihood of surpassing particular risk thresholds, predicts the distributions of non-carcinogenic and carcinogenic risks, and uses sensitivity analysis to identify significant exposure factors. Instead of depending only on a single central-estimate risk number, this method offers a probabilistic description of possible exposure hazards.

Materials and methods

Study area

The Federal Teaching Hospital, Ido-Ekiti (FETHI), which is located at Ido-Osi local government Area of Ekiti State on latitude 7.8434° N and longitude 5.1877° E Ekiti State, Nigeria. The hospital features an incinerator for medical waste that can burn about 3,500 kg. Sampling sites representing near-source, intermediate, and comparison locations were chosen at different distances from the incinerator, such as roughly 10 m, 25-50 m, and 200-300 m. In order to account for any pollutant dispersion from the incinerator, the direction of the predominant wind during sampling was also taken into account while choosing the sampling locations [6].

Data collection

Glass slides measuring 2.54 by 4.54 cm² were placed near the hospital incinerator after being cleaned with ethanol and deionized water. Additionally, the slides were positioned in a few departments that are 100-300 meters away from the same incinerator, where its fumes are dispersed. To ascertain the degrees of exposure or vulnerability, measurements were made at the hospital's incinerator and three distinct departments/units (designated A-D). The slides were exposed for two months. Following a two-month exposure period, the slides were carefully taken out of their original positions, and diluted hydrochloric acid was used to rinse the particulate matter (PM) into a container. The samples were labeled, stored in fresh vials (five for each department and blank slides), and transported to the heavy-metal analysis lab at the Center for Energy and Research Development (CERD), Obafemi Awolowo University, Ile-Ife. The mean concentrations of particulate-associated heavy metals across the sampling locations are summarized in Table 1.

Table 1: Mean concentrations of particulate-associated heavy metals measured around the medical waste incinerator in mg/kg

Group	Cr	Cd	As	Cu	Fe	Hg	Zn	Pb	Co	Ni
A	0.232	0.136	0.12	0.272	0.32	0.056	0.36	0.08	0.08	0.136
B	0.272	0.16	0.144	0.32	0.352	0.088	0.4	0.088	0.128	0.136
C	0.208	0.16	0.128	0.296	0.296	0.056	0.32	0.064	0.112	0.12
D	0.224	0.144	0.128	0.288	0.328	0.064	0.304	0.072	0.104	0.088
Mean	0.234	0.15	0.13	0.244	0.324	0.066	0.346	0.076	0.106	0.12
SD	0.036	0.015	0.019	0.084	0.03	0.018	0.047	0.014	0.019	0.02

Particulate-bound heavy metal concentrations measured from laboratory analysis (C_{lab}), in mg/kg) were converted into effective airborne volumetric concentrations (C_{air} , in mg/m³) to serve as inputs for inhalation risk modeling. The total mass of deposited heavy metal (M_{metal} , mg) was determined by scaling C_{lab} against the total recovered particulate mass (M_{PM} , kg). This mass was subsequently standardized over the effective sampled air volume (V_{air} , m³) corresponding to the passive slide surface area ($A_{collector}$, m²) and the two-month exposure duration ($t_{sampling}$, hours) according to Equation (1).

$$C_{air} = \frac{C_{lab} \times M_{PM}}{V_{air}} \quad (1)$$

C_{air} = Effective airborne heavy metal concentration (mg/m³).

C_{lab} = Heavy metal concentration in deposited particulate matter measured via laboratory analysis (mg/kg).

M_{PM} = Total mass of particulate matter collected off the glass slides (kg).

V_{air} = Effective ambient air volume sampled over the passive deposition area (m³).

Exposure Assessment Framework

The non-carcinogenic and carcinogenic health risks via inhalation were evaluated using the standard United States Environmental Protection Agency (USEPA) risk assessment methodology. Deposition values measured on glass slides (mg/kg) were transformed into effective ambient suspended particulate concentrations (C_{air} , mg/m³) to account for airborne exposure prior to deterministic and probabilistic modeling. The non-carcinogenic Risk Hazard Quotient (HQ) and Hazard Index (HI) were calculated using Exposure Concentrations (EC) and Inhalation Reference Concentrations (RfC).

The inhalation exposure concentration (C_{air}) was evaluated using Equation (2)

$$EC = \frac{C_{air} \times ET \times EF \times ED}{AT_n} \quad (2)$$

Non-carcinogenic health hazards were characterized by calculating the Hazard Quotient (HQ) via Equation (3)

$$HQ = \frac{EC}{RfC \times 1000} \quad (3)$$

Carcinogenic risks were quantified as the Incremental Lifetime Cancer Risk (ILCR) using Equation (4)

$$ILCR = EC \times IUR \quad (4)$$

Where ET is exposure time (hours/day), EF is exposure frequency (days/year), ED is exposure duration (years), and AT_n is the average time (hours).

Non-carcinogenic Inhalation Reference Concentrations (RfC) and carcinogenic Inhalation Unit Risks (IUR) were retrieved from standard toxicological databases and are detailed in Table 3.

Table 3: Toxicological Reference Values and Target Endpoints for Inhalation Exposure

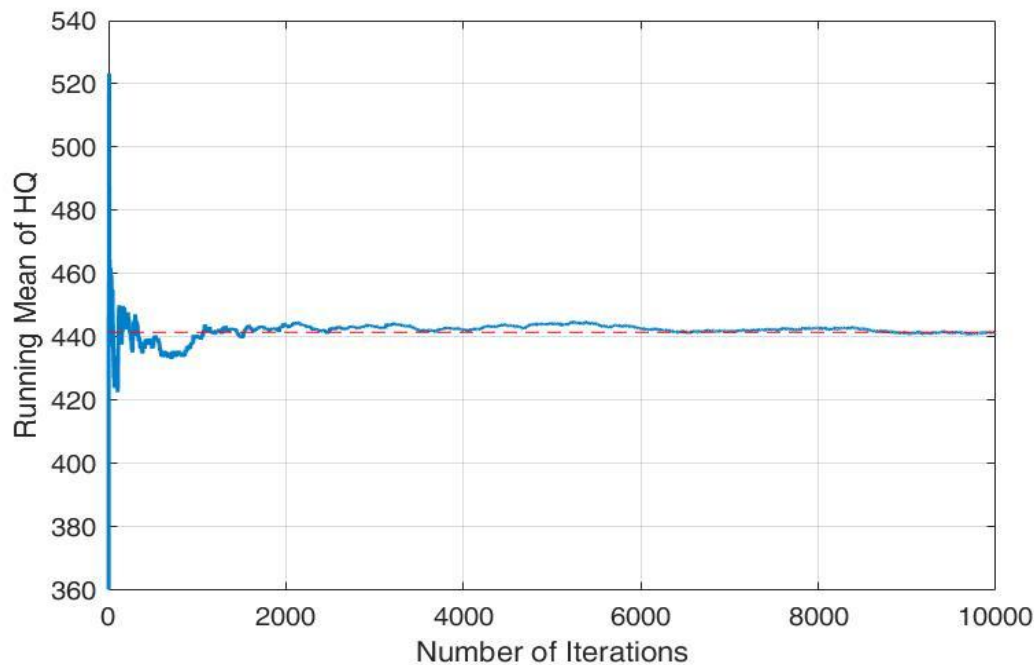
Heavy Metal	RfC (mg/m ³)	Inhalation Unit Risk (IUR) (µg/m ³) ⁻¹	Target Endpoint
Cadmium (Cd)	1.0 x 10 ⁻⁵	1.8 x 10 ⁻³	Renal / Lung
Chromium (Cr)	1.0 x 10 ⁻⁴	1.2 x 10 ⁻²	Respiratory System
Nickel (Ni)	9.0 x 10 ⁻⁵	2.6 x 10 ⁻⁴	Respiratory System
Lead (Pb)	Model IEUBKP*	N/A*	Neurological / Renal
Arsenic (As)	1.5 x 10 ⁻⁵	4.3 x 10 ⁻³	Skin / Lung

Notes: RfC = Inhalation Reference Concentration; IUR = Inhalation Unit Risk; USEPA IRIS = United States Environmental Protection Agency Integrated Risk Information System; OEHHA = Office of Environmental Health Hazard Assessment. Lead toxicity is evaluated based on Blood Lead Level (BLL) thresholds using the Integrated Exposure Uptake Biokinetic (IEUBK) model rather than a single point reference concentration.

Monte Carlo Simulation and Convergence

To assess parameter uncertainty and spatial variability, Monte Carlo simulations consisting of 10,000 iterations were run in MATLAB. Input concentrations were fitted to log-normal probability

distributions, whereas exposure parameters (exposure duration, daily exposure time, breathing rates) were modeled with standard uniform and triangular distributions. Convergence testing verified that the mean and 95th percentile estimates became stable, with a variance change of less than 0.25% after 4,000 iterations, thereby ensuring numerical stability (Figure 1)



Convergence Plot: Stability of Mean HQ

Figure 1: Convergence plot showing numerical stability of the running mean Hazard Quotient (HQ) across 10,000 Monte Carlo iterations

Ethical Approval

This research focused exclusively on environmental sampling and monitoring of heavy metal particulate deposition on passive collectors located near the medical waste incinerator. No human subjects or biological tissues were sampled or included in this stage of the study; administrative and facility access permits were obtained before the field setup began.

Table 2 outlines the exposure parameters used in the Monte Carlo simulation together with their respective statistical distribution profiles.

158 Table 2: Inhalation Exposure Parameters and Probability Distributions Used in Monte Carlo
159 Simulation

Parameter	Description	Unit	Distribution Type	Value / Distribution Parameters	Source
C _{air}	Airborne heavy metal concentration	mg/m ³	Log-normal	Metal-specific (derived from particulate conversion)	This study
ET	Exposure time	hours/day	Uniform	Uniform (8, 24)	USEPA / Regional exposure profile
EF	Exposure frequency	days/year	Constant	350	USEPA standard default
ED	Exposure duration	Years	Triangular	Triangular (10, 30, 50)	USEPA / Occupational & residential range
AT _n	Averaging time (non-carcinogenic)	Hours	Calculated	ED × 365 days/year × 24 hours/day	USEPA RAGS Part F
AT _c	Averaging time (carcinogenic)	Hours	Constant	70 years × 365 days/year × 24 hours/day	USEPA RAGS Part F
RfC	Inhalation Reference Concentration	mg/m ³	Constant	Metal-specific (see Inhalation Benchmark Table)	USEPA IRIS
IUR	Inhalation Unit Risk	(μg/m ³) ⁻¹	Constant	Metal-specific (see Inhalation Benchmark Table)	USEPA IRIS / OEHHHA

160 *Note: Parameter distributions were selected based on exposure characteristics and variable empirical*
161 *behavior. Heavy metal concentrations (C_{air}) were fitted to log-normal distributions to represent positive*
162 *skewness inherent to atmospheric environmental data. Exposure time (ET) and exposure duration (ED)*
163 *were assigned uniform and triangular distributions, respectively, to capture variability in daily*
164 *occupational and residential presence around the facility. Averaging times (AT_n and AT_c) and toxicological*
165 *benchmarks (RfC and IUR) were parameterized in accordance with USEPA RAGS Part F inhalation risk*
166 *guidelines.*

167 The features of each input variable and the relevant empirical data were taken into consideration
168 when choosing probability distributions. Because environmental contamination concentrations
169 typically show positive skewness and cannot take negative values, heavy-metal concentrations
170 were depicted using a log-normal distribution. Physiological parameters were limited to physically

meaningful values and represented using distributions suitable for their empirical variability. When there was not enough information to describe the variability of deterministic parameters, they were treated as constants. Sensitivity and convergence analysis were performed on the chosen distributions and their parameters to assess their impact on the calculated risk.

Ten thousand iterations were used in the Monte Carlo simulation. The exposure and risk equations were used to propagate random values that were independently sampled from the given input distributions for each iteration. By analyzing the stability of the estimated mean and chosen percentiles as the number of iterations grew, simulation convergence was evaluated. When further iterations resulted in minor changes in the major risk estimates, the final number of iterations was deemed sufficient. The mean and 95th percentile changed by less than 0.25% after approximately 4,000 iterations.

Parameter characterization

Exposure parameters were modeled by the use of probability distribution in order to account for the variability. The empirical concentration data were evaluated against candidate probability distributions, and the distribution providing the best statistical fit was selected for Monte Carlo simulation. Unless otherwise specified, input variables were assumed to be statistically independent because correlation coefficients between the input parameters were not available.

Results and discussion

Risk distribution and exceedance

To overcome the constraints of deterministic risk assessments based on point estimates, Monte Carlo simulations ($N = 10,000$) were carried out in order to incorporate uncertainty and population-level variability into the non-carcinogenic Hazard Quotient (HQ) and Incremental Lifetime Cancer Risk (ILCR) models. The risk distributions that emerged were markedly right-skewed, featuring prolonged upper-tail risk profiles across the exposure scenarios.

For inhalation exposure that is non-carcinogenic, the empirical probability of surpassing the statutory screening threshold was $P(HQ > 1) \approx 100\%$ (> 0.9999), showing that risk exceedance is ubiquitous throughout the target cohort. In addition, $P(HQ > 10)$ likewise produced an exceedance probability of 100 (> 0.9999). As shown in Figure 7, the log-log exceedance distribution indicated

that exceedance probabilities held a plateau close to unity (100) up to roughly $HQ \approx 100$, after which they exhibited log-linear decay at extreme tail values. The non-carcinogenic HQ distribution produced a 5th percentile of 120, a 25th percentile of 290, a median (50th percentile) of 400, a 75th percentile of 540, a 95th percentile of 850, a 97.5th percentile of 980, and a maximum of 2,560 (Figure. 2). The probability density function (PDF) reached its peak at an estimated mode of about $HQ = 400$, suggesting that a baseline exposure scenario in this population surpasses international safety thresholds by more than two orders of magnitude.

Regarding carcinogenic health effects, the simulated Incremental Lifetime Cancer Risk (ILCR) profiles showed substantial exceedances of the threshold. The cumulative probabilities of surpassing standard regulatory benchmarks, such as the de minimis threshold (10^{-6}), the intermediate threshold (10^{-5}), and the statutory mitigation threshold (10^{-4}), were all 100% (1.0). This total exceedance stems from the fact that the lowest simulated ILCR across all Monte Carlo iterations stayed well above 0.02, far exceeding acceptable risk limits. The carcinogenic risk profile was marked by a 5th percentile of 0.05, a median (50th percentile) of 0.17, and a 95th percentile of 0.42.

The pronounced gap between the simulated risk profiles and the accepted benchmark values (Figures 3 and 5) highlights serious environmental hazards associated with closeness to the incineration unit and insufficient buffer zones. Conventional deterministic risk frameworks that depend only on point estimates would hide these crucial upper-tail exposure dynamics, strengthening the case for probabilistic risk paradigms in environmental health decision-making within high-risk settings.

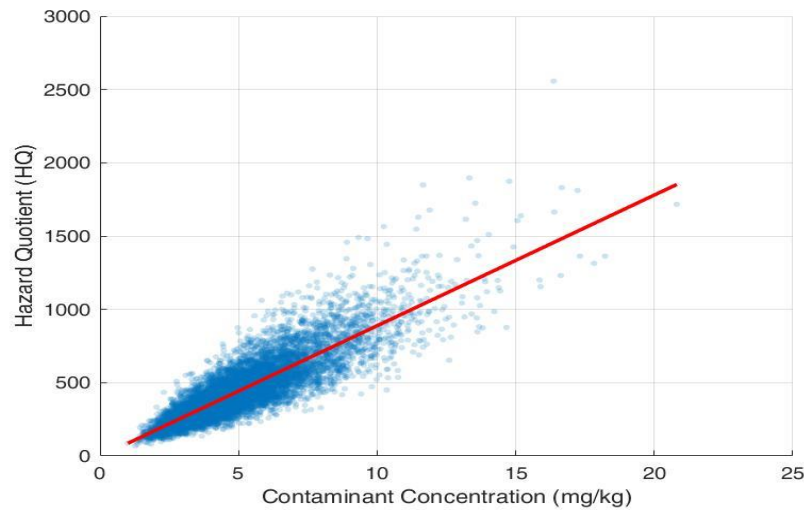


Figure 2: Scatter evaluation displaying individual Hazard Quotients relative to heavy metal concentrations across environmental sampling locations.

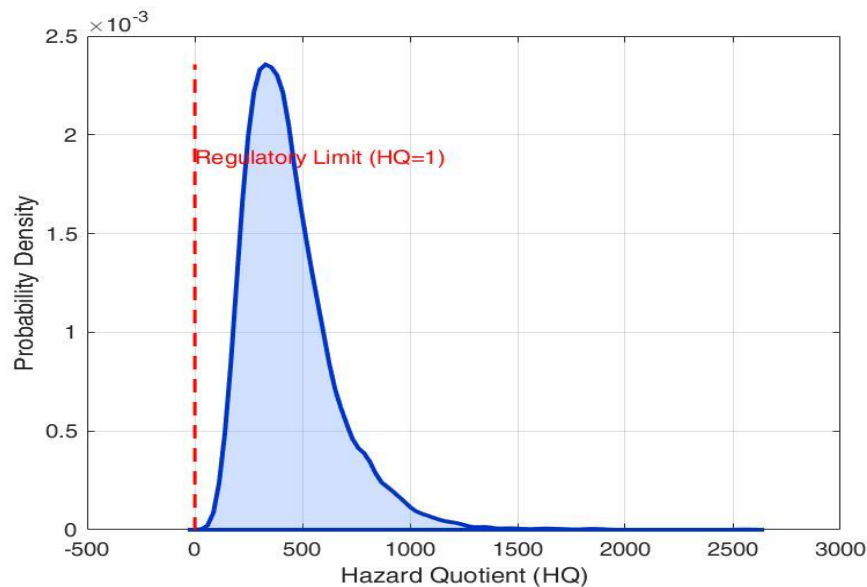


Figure 3: Probability density function (PDF) showing non-carcinogenic Hazard Quotient distributions against the USEPA regulatory safety limit (HQ = 1.0)

Distribution of health risks

The probability distribution in Figure 4 indicates a heavy-tailed distribution for both HQ and CR. In the simulated population, a substantial proportion of the simulated risk estimates exceeded the selected screening benchmark. The distribution also indicated variability in risk across simulated

exposure scenarios. Furthermore, the extreme shift and clear separation of the simulated risk profile away from acceptable levels is explicitly illustrated by the cumulative distribution function in Figure 6 and summarized in the box-and-whisker plot (Figure 5).

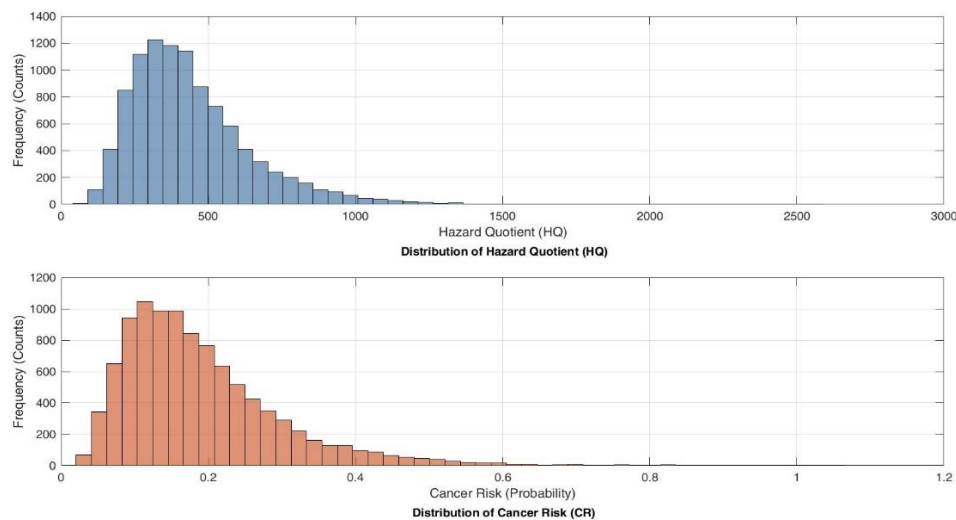


Figure 4: Frequency distribution (histograms) of simulated Hazard Quotient (HQ) and Incremental Lifetime Cancer Risk (ILCR)

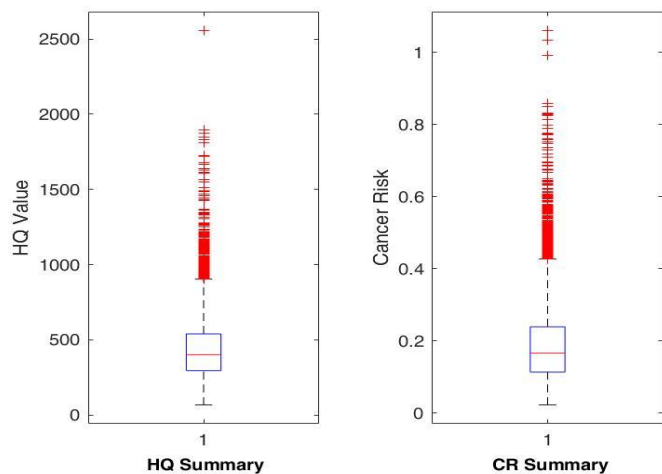


Figure 5: Box-and-Whisker Distribution of HQ and Cancer Risk (CR)

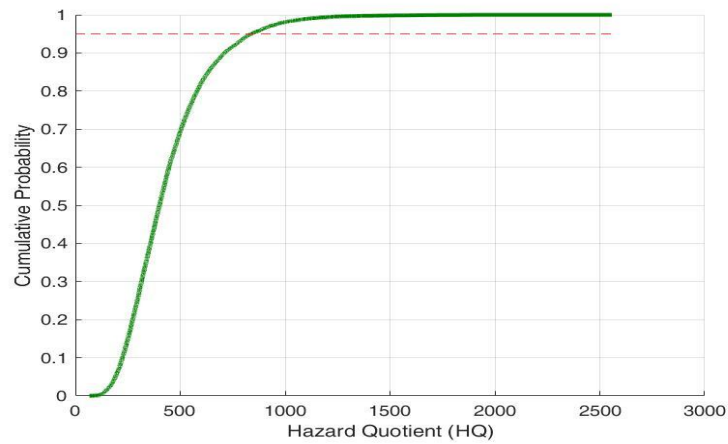
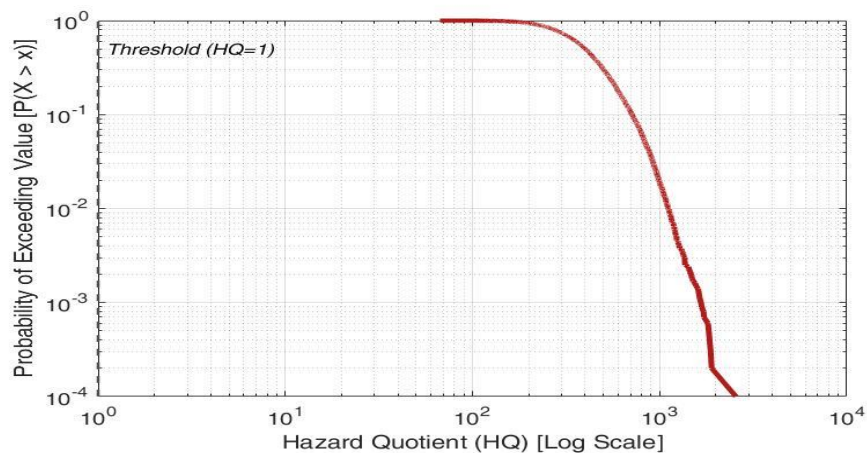


Figure 6: Empirical Cumulative Distribution Function (CDF) of non-carcinogenic Hazard Quotient (HQ) relative to the regulatory limit (HQ = 1.0)

Exceedance probability

In this study, we determined the exceedance probability using a log-log scale to visualize the possibility of exposure events that are extreme in nature as shown in Figure 7. The upper-tail observations represent simulated exposure scenarios associated with comparatively higher estimated risk. These scenarios are important for characterizing uncertainty and variability but should not be interpreted as identifying specific individuals or predicting actual clinical outcomes



Log-Log Exceedance Plot: Probability of High-Risk Scenarios

Figure 7: Logarithmic representation of risk exceedance.

Sensitivity and correlation analysis

Sensitivity analysis showed that the airborne contaminant concentration (C_{air}) was the main factor influencing estimated non-carcinogenic Hazard Quotients (HQ) and carcinogenic risk profiles, exhibiting a strong positive correlation with overall health risk (Figure 8).

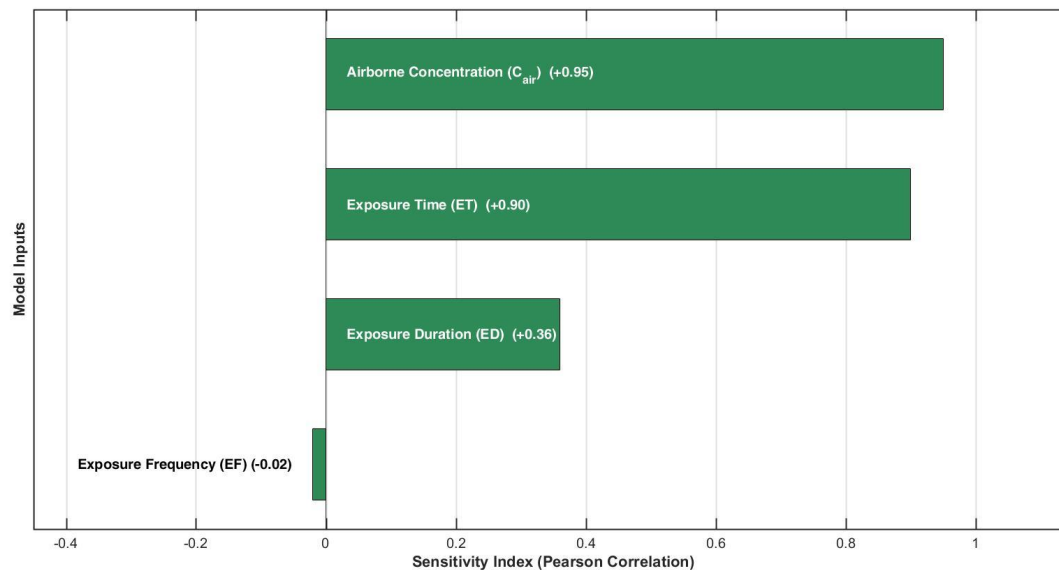


Figure 8: Tornado chart showing the rank-order sensitivity (Pearson correlation) of model parameters on cumulative inhalation risk.

This is directly consistent with the USEPA RAGS Part F inhalation framework, in which exposure concentration (EC) is determined linearly by airborne concentration. Daily exposure time (ET) and exposure duration (ED) likewise had clear positive effects on estimated risk, highlighting that extended daily presence and long-term residency or occupational duty near the incinerator substantially increase cumulative inhalation exposure. Variability in the exposure frequency (EF) parameter contributed moderately to model variance, while toxicological reference values functioned as baseline scaling constants [11,15].

Limitations of the study

When interpreting the findings, a number of limitations ought to be taken into account. Firstly, the health-risk assessment relies on measured environmental concentration data and modelled exposure parameters, rather than on direct biomonitoring of the individuals exposed. As a result,

the estimated risks reflect potential exposure scenarios and should not be taken as proof of adverse health effects within the study population. Secondly, uncertainty in the toxicological benchmarks that were selected may add considerably to the uncertainty of the risk estimates. Thirdly, this analysis concentrates on inhalation exposure and does not consider other pathways that may be relevant, including ingestion of contaminated soil or dust and dermal contact. Fourthly, the Monte Carlo model presumes specified probability distributions and, unless stated otherwise, independence among the input parameters. Lastly, the concentration dataset reflects the sampled locations and the measurement period, and it may fail to capture temporal or spatial variability outside those observations. These limitations ought to be taken into account when the findings are extrapolated to other populations or locations

Conclusion

The Monte Carlo-based assessment revealed considerable variability and right-skewed patterns in the estimated health risks linked to inhalation exposure to airborne heavy metals near the medical waste incinerator. By assessing probability distributions instead of depending only on deterministic point estimates, the probabilistic framework captured upper-tail exposure scenarios and quantified threshold exceedances that would otherwise go unnoticed. Under the USEPA RAGS Part F inhalation methodology, airborne contaminant concentration (C_{air}), daily exposure time (ET), and exposure duration (ED) emerged as the primary parameters influencing cumulative risk.

To bring local health policy into line with the UN Sustainable Development Goals (SDG 3 on Good Health and Well-being and SDG 11 on Sustainable Cities), regulatory authorities in Sub-Saharan Africa need to enforce strict spatial buffer zones, require a shift from open/uncontrolled medical waste incineration units to modern systems fitted with advanced air pollution control devices, and embed Monte Carlo-based probabilistic health risk assessments (PHRA) within standard Environmental Impact Assessment (EIA) protocols.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Clinical trial number

Not applicable.

Authors' Contributions

O.P.I.: Conceptualization, Methodology, Software (MATLAB script development), Formal analysis, Writing (Original draft). **E.E.O.:** Investigation, Validation, Visualization, Writing (review & editing). **O.O.O.:** Data curation (provision of baseline experimental datasets), Project administration. **A.E.O.:** Validation, Data curation, Writing (review & editing). **O.J.O.:** Formal analysis, Methodology support, Software validation. **K.E.A.:** Validation, Toxicological framework supervision, Writing (review & editing). **T.M.A.:** Investigation, Visualization, Writing (review & editing). All authors read and approved the final manuscript.

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