Tech-Sphere Journal of Pure and Applied Sciences (TSJPAS)
A Subsidiary of Tech-Sphere Multidisciplinary International Journal (TSMIJ)
Oghenerhoro et al. Vol 3, Issue 1, 2026 Publication Edition
ISSN: 3092-9598

Algorithmic Modeling and Simulation of Non-Carcinogenic Health Risk from Black Soot Exposure among Population Groups in Warri Metropolis, Nigeria

Research Article
https://stem.techspherejournal.com

Article Info
Revised Date: 29th August, 2026
Accepted Date: 31st August, 2026
Published Date: 5th September, 2026

Keywords
Comparative
Population
Health
Risk Algorithmisation
Modeling, Simulation

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DOI: https://doi.org/10.5281/zenodo.22341746

ABSTRACT

The study employed algorithmic modeling and simulation to assess the non-carcinogenic health risks among children, as well as adult males and females due to black soot pollution in Warri metropolis. The study was motivated by difficulties in estimating personal pollutant intake and associated health hazards, as well as limitations arising from heterogeneous study designs. These challenges were addressed by linking individual daily pollutant intake to health-risk profiles using an algorithmic approach. Human health risk assessment matrices for pollutant inhalation were adopted to develop four algorithms for the target population groups. The algorithms were simulated using average black soot concentration and human exposure-duration data obtained during the rainy and dry seasons. Dust-fall measurement techniques were used during the wet season, while a high-volume (HV) sampler was used during the dry season. The non-carcinogenic risk was evaluated based on the hazard quotient/risk-index criterion, where values greater than unity indicate potential non-carcinogenic health risk. The reported percentages represent the relative contributions of each population group to the overall modeled risk and are not hazard quotient values expressed as percentages. The simulated results showed that children below 1 year had the highest relative risk contribution (47.6%), followed by children aged 1–12 years (20.6%) and adult males (19.4%), while adult females had the lowest contribution (12.4%). The findings indicate that children, particularly infants, are more vulnerable to potential non-carcinogenic health effects associated with black soot exposure, whereas adult females had the lowest modeled risk contribution.

1 Introduction

In recent years, advances in high-resolution air quality modelling and the development of low-cost pollution monitoring technologies have brought individual exposure to air pollution into greater focus, particularly regarding inequalities in exposure and the fundamental right to breathe clean air [1, 2].

In response to this growing societal concern, environmental and health research has increasingly shifted from conventional assessments of ambient air quality towards high-resolution personal exposure assessment and individual-level risk analysis. However, the limited availability of personal data, including age, body weight, and physical activity level, continues to pose challenges for accurate dose estimation. Although wearable technologies have become increasingly available, thereby making the measurement of personal exposure to airborne pollutants more technically feasible, challenges remain in translating such measurements into reliable estimates of individual pollutant dose [3, 4]. A detailed understanding of personal exposure to air pollution is then crucial to reduce inequalities in exposure and to inform public health policies that aim to limit inequalities in exposure [5, 6].

Algorithmic modelling and simulation of individual exposure risks can be useful tools to determine the relative importance of physiological and demographic factors, such as body characteristics, physical activity, age and gender, on the health impacts of exposure to pollutants. This can also help to create more accurate, more detailed, and more personalized risk assessment methods, as suggested in earlier research [7, 8].

While it is a relatively new field in environmental health risk assessment, Algorithmic modeling, or Algorithmisation is a mathematical modelling technique that features profiling properties: matching ready-to-use models with real situations specific to those models and then assessing one's own and others' mathematical models [9,10].

In addition, algorithmisation in Environmental Health Risk Assessment (EHRA) is referred to as the use of automated, step-by-step mathematical and computational logic to evaluate human health risks from environmental hazards [11,12]. It transforms standard risk assessment frameworks—like hazard identification, dose-response, exposure modeling, and risk characterization into structured, repeatable, and data-driven computational workflows [7, 12].

While the global risks associated with exposure to black soot pollution and its attendant non-carcinogenic health effects are of serious concern, the quest for methodologies that can accurately estimate individual exposure and associated health risks has increased in recent years [13, 14]. Scientists, writers, non-governmental organizations, government agencies, and legislative bodies have increasingly identified black soot as a significant environmental and public health menace [15, 16]. Black soot, also referred to as fine black particulate matter or colloidal particles due to its small particle size, is primarily composed of impure carbon particles generated from the incomplete combustion of hydrocarbons and is commonly associated with fine particulate matter (PM_2) [16, 17].

Furthermore, the nomenclature and classification of soot are influenced by the nature of its dispersed phase and dispersion medium, which may be solid, liquid, or gaseous. When solid soot particles are dispersed in a gaseous medium, the resulting colloidal system is commonly described as smoke or an aerosol [17- 19]. Black soot contains or is associated with various hazardous air pollutants, including sulphur dioxide, nitrogen oxides, and other toxic constituents [16, 20]. Studies have also established that soot particles are often mixed with mineral components and may be coated with substances such as sulphuric acid, potentially contributing to cellular damage and corrosion of materials. These characteristics make black soot a significant air-quality concern, particularly in densely populated communities and environments where combustion-related emissions are prevalent [17-20].

Despite increasing recognition of the health risks associated with black soot exposure, accurate estimation of individual and population-specific health risks remains challenging. Existing black-soot risk assessment models largely rely on generalized exposure assumptions and physiological parameters, which may not adequately account for differences in age, sex, body weight, inhalation rate, exposure duration, and exposure frequency among population groups. Consequently, such generalized approaches may limit the precision with which non-carcinogenic inhalation risks can be estimated for specific individuals or vulnerable populations [19, 20].

To address this limitation, this study proposes an algorithmic approach for estimating non-carcinogenic inhalation risk from black soot exposure by integrating measured soot concentrations with key exposure and physiological parameters. The proposed algorithm incorporates soot concentration, inhalation rate, body weight, exposure duration and frequency, and the relevant reference concentration to systematically estimate risk across different population groups. By incorporating age- and sex-specific physiological characteristics, the approach provides a more population-specific representation of exposure and risk than generalized risk assessment methods [20, 21].

The proposed methodology complements conventional environmental health risk assessment by providing a systematic and reproducible framework for quantifying non-carcinogenic inhalation risks. It enables comparisons of risk among different population groups and can facilitate the identification of groups that may be particularly vulnerable to black soot exposure. The principal novelty of the study lies in the algorithmic integration of measured seasonal black-soot

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concentrations with age- and sex-specific physiological parameters to quantify and compare non-carcinogenic inhalation risks among children and adults. This integrated approach provides a basis for more precise population-specific risk characterization and may support evidence-based environmental health interventions and pollution-control strategies [19-21].
The International Agency for Research on Cancer (IARC) classified particulate substances or components of black soot known as mutagens as human carcinogens [20- 22].
In addition, the United States Environmental Protection Agency noted that these pollutants or substances in the form of smoke, dust, and poisonous gases tend to subject any person to the risk of premature death, fatal injury, or incurable impairment of physical and mental health due to direct or indirect inhalation [22, 23].
When black soot is inhaled, it penetrates deeply into bronchiolar tissue, resulting in oxidative stress, inflammation of the pulmonary ventilation rate, and possibly deoxyribonucleic acid damage [24, 25].
The United States Environmental Protection Agency noted that Short-term effects of soot are irritation of the eyes, nose, and throat, cough, chest tightness, wheezing, dyspnea, and acute exacerbation of asthma, while long-term effects include arrhythmias and lung cancer [26, 27].
In addition, Studies have linked exposure to black soot to an increased risk of heart disease, as the particles can enter the bloodstream and cause inflammation and oxidative stress [27,28].
Furthermore, findings have ascertained that inhaling black soot can also cause eye irritation and skin problems, and can harm the nervous system. It was, however, documented that in the Niger Delta region, the notable adverse human health effects from exposure to soot are cough, exacerbation of asthma, and skin Increase in black soot emission across Warri metropolis has resulted in dramatic environmental changes that affect the weather and human lives [26-29].
The residents of Warri, one of the hubs of hydrocarbon business activities in Nigeria, could hardly stay outside their homes without being negatively impacted by black soot pollution [29,30].
Recently, the Warri Refinery and Petrochemical Company (WRPC) was identified as a major emitter of black soot on a daily basis without concern for the environment and health of the residents. Research has shown that gas flaring, petroleum processing, increased vehicular emissions, and open burning of industrial and domestic wastes are major contributors of back soot pollution in Warri metropolis [30, 31].
It is, however, imperative to assess the health-related risks to exposed children, adult females, and males across the Warri metropolis in accordance with the definition of risk analysis. Risk analysis is defined as a detailed examination of possible scenarios involving risk assessment, risk evaluation, and risk management alternatives, undertaken to understand the nature of unintended negative consequences to human life, health, property, or the environment [30-32].

2 Materials and Methods

The study adopted algorithmisation and data simulation methodology. It involved algorithmic reconstruction and integration of documented and adopted environmental health risk assessment indicators in dose – response matrices. However, particulate samples collected during the study were quantitatively analyzed to determine the concentrations of fine particulate pollution. Quality control measures included standardized sampling procedures, routine instrument checks, and the maintenance of consistent sampling conditions to ensure the reliability and accuracy of the measurements. This approach was adopted because of its proven flexibility, global acceptability, and wide range of applicability. Simulated data were obtained using a high- volume air sampler for dry samples, and the dust fall method was directly employed for wet samples [33-35].

2.1 Modeling Approach

The study acknowledged the three major human exposure routes: dermal, oral, and inhalation, which serve as the critical bridge that transforms environmental pollution into effective internal doses as documented [32, 33].

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However, the inhalation route was considered because it has been established by various studies that inhalation exposure varies as a function of age, weight, gender, activity level, and physical condition and enables rapid transfer of pollutants into systemic circulation [12,13]. Hence, a triangular matrix of human health risk assessment involving inhalation was developed in accordance with the targeted population. The matrices include the screening index, hazard quotient, and contaminant reference dose or concentration limits $\left(Rf_c\right)$.

Screening Index method: Risk is a function of contaminant dose intake, while dose intake or dose rate is a function of C implies *pollutant concentration; and t is time; IR implies inhalation rate,* as expressed in (1) with reference to [25].

$$D = m\sum c_t \times t_i \times IR_i \tag{1}$$

where D implies dose; C implies micro-environmental pollutant concentration; t implies time spent in the m and IR implies inhalation rate.

Human exposure to black soot contaminant was taken as an integral function of dose intake and body weight over time as reported in (2). Thus,

$$\int_0^t \frac{p_r(t)CV_Y(E)}{BW_{(t)}}dt = \frac{p_r(t)C_b \times V_Y \times E_d}{BW \times (t_a)}. \tag{2}$$

Hazard quotient, as widely employed and expressed as a determinant metric for chronic health effects due to human exposure to one chemical, was reconstructed as given in equation (3). The reconstruction was based on a human health risk assessment context for non-carcinogenic effects, as expressed in the risk index (SI). Mathematically, we have:

$$HQ_{black\ soot} = \int_0^t \frac{P_r(t)C_bV_y(E)}{BW_{(t)}Rf_c}dt = \frac{P_r(t) \times C_b \times V_y \times E_d}{BW \times (t_a)Rf_c}, \tag{3}$$

where C_b implies ambient concentration of black soot $\left(\mu g / m^3\right)$, P_r implies pulmonary vent rate (m³/day), E_d implies Duration of exposure (yr), V_y implies exposure frequency(day/year/365day), BW implies body mass (kg), Rf_c implies Reference concentration $\left(\mu g / m^3 / day\right)$ and t_a implies average time for non -carcinogenic risk $\left(E_d \times 365 days / year\right)$. A regional reference concentration guideline was adopted in accordance with Nigerian national Environmental air quality control guidelines.

2.1.1. Population-Specific Risk Formulation

The above general risk formulation was used for 4 population groups: Children under 1 year; children 1-12 years; adult females; and adult males. The mean body weights and inhalation rates were 9.2 kg and 4.5 m^3/day for children under 1 year, 41.1 kg and 8.7 m^3/day for children aged 1-12 years, 78.1 kg and 11.3 m^3/day for adult females, and 80.1 kg and 15.2 m^3/day for adult males, respectively. The same reference value was used throughout the population groups. The population-specific risk indices were then used to produce the numerical results that appear in Tables 1–3. Reference is made to the following equation:

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$$\left.\begin{aligned} THQ_{blacksoot} &= \frac{4.5m^3 perday \times C \times V_y \times E_d}{BW \times (t_a) \times 40\mu / m^3 / day} \\ &= \frac{4.5m^3 perday \times C \times V_y \times E_d}{9.2kg \times (t_a) \times 40\mu / m^3 / day} \\ &= \frac{4.5m^3 perday \times C \times V_y \times E_d}{9.2kg \times E_d \times 40\mu / m^3 / day} \\ &= \frac{4.5m^3 perday \times C(\mu g / m^3) \times V_y (day / year / 365days) \times E_d}{9.2kg \times E_d \times 365days / year \times 40\mu / m^3 / day} \\ &= \frac{4.5 \times C \times V_y}{9.2 \times 40} \times \frac{perday \times \mu g / m^3 \times day / year / 365days \times E_d}{E_d \times 365days / year \times \mu g / m^3 / day} \\ &= 0.0122 \times 10^{-3} \times C \times V_y \end{aligned}\right\} \quad (4)$$

2.1.2. Algorithmisation Model For Children Between 1-12 years

Algorithmisation was done using the respective default average age, inhalation values, and regional reference concentration for black soot for the short term of an $41.1kg, 8.7m^3$ and $40\mu g / m^3 / day$ in (3) with reference to [30,-36], as a result:

$$\left.\begin{aligned} THQ_{blaksoot} &= \frac{8.7m^3 perday \times C \times V_y \times E_d}{BW \times (t_a) \times 40\mu / m^3 / day} \\ &= \frac{4.5m^3 perday \times C \times V_y \times E_d}{41.1 \times (t_a) \times 40\mu / m^3 / day} \\ &= \frac{8.7 \times C \times V_y}{41.1 \times 40} \times \frac{perday \times \mu g / m^3 \times day / year / 365days \times E_d}{E_d \times 365days / year \times \mu g / m^3 / day} \times 10^{-3} \\ &= 0.005 \times 10^{-3} \times C \times V_y \end{aligned}\right\} \quad (5)$$

2.1.3. Algorithmisation Model for Adult Females

Algorithmisation was done using the respective default average age, inhalation values, and regional reference concentration for black soot for short term, of, $78.1kg, 11.3m^3$ and $40\mu g / m^3 / day$ with reference to [30- 35] in (3).

Accordingly, short-term inhalation rates for children (>1year), children (1 – 12 years), adult females, and males are, respectively, and $4.5m^3, 8.7m^3, 11.3m^3$ and $15.2m^3$ per day on average. However, average human body weights for children under one year, children between 1- 12 years, adult females, and adult males are, respectively $9.2kg, 41.1kg, 78.1kg,$ and $80.1kg$ .Then, the following is obtained:

ISSN: 3092-9598

$$\left.\begin{aligned} THQ_{blaksoot} &= \frac{11.2m^3 perday \times C \times V_y \times E_d}{BW \times (t_a) \times 40\mu g / m^3 / day} \\ &= \frac{11.2m^3 perday \times C \times V_y \times E_d}{78.1 \times (t_d) \times 40\mu g / m^3 / day} \\ &= \frac{11.2 \times C \times V_y}{79.1 \times 40} \times \frac{perday \times \mu g / m^3 \times day / year / 365days \times E_d}{E_d \times 365days / year \times \mu g / m^3 / day} \times 10^{-3} \\ &= 0.00353 \times 10^{-3} \times C \times V_y \end{aligned}\right\} \quad (6)$$

2.1.4. Algorithmisation Model for Adult Males

Algorithmisation was done using the respective default average age, inhalation values, and regional reference concentration for black soot for a short term of 80.1kg, 15.2 m^3 per day, and $40\ \mu g/m^3/day$ in equation (3) as documented [29,36].

Accordingly, short-term inhalation rates for children $(>1 year)$, children $(1-12\ years)$, adult females, and males are respectively 4.$5m^3$, $8.7m^3$, 11.3m^3, and 15.2 m^3 per day on average.

However, average human body weights for children under one year, children between 1- 12 years, adult females, and adult males are respectively 9.2kg, 41.1kg, 78.1kg, and 80.1kg. As a result:

$$\left.\begin{aligned} THQ_{black-ssot} &= \frac{15.2m^3 perday \times C \times V_y \times E_d}{BW \times (t_a) \times 40\mu g / m^3 / day} \\ &= \frac{15.2m^3 perday \times C \times V_y \times E_d}{80.1kg \times (t_d) \times 40\mu g / m^3 / day} \\ &= \frac{15.2 \times C \times V_y}{80.1 \times 40} \times \frac{perday \times \mu g / m^3 \times day / year / 365days \times E_d}{E_d \times 365days / year \times \mu g / m^3 / day} \times 10^{-3} \\ &= 0.00473 \times 10^{-3} \times C \times V_y \end{aligned}\right\} \quad (7)$$

2.2 The Area of Study

The study area is Warri Metropolis, Nigeria. Like many other African countries, Nigeria has experienced significant population growth, urbanization, and industrialization, particularly over the past few decades. However, the rapid expansion of these activities has not always been matched by adequate environmental management frameworks for analysing and understanding the risks associated with black soot pollution. This imbalance has contributed to the occurrence and worsening of black soot pollution events, with the major oil-producing cities being Warri and Port Harcourt.

Even more problematic is the fact that Nigeria is an integral part of the sub-region in West Africa known as one of the world's most polluted regions in terms of the concentration of aerosols and soot present in the atmosphere. Particulate pollution in Nigeria also comes from a significant source of dust transported from the Sahara Desert and biomass

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burning, which are important contributors to atmospheric particulate matter and black and organic carbon (black soot). It is reported that these sources contribute more than 75% of the pollution in Nigeria [38]. As a result, these pollutants and their effects on human health, protection of natural resources, and socio-economic development are of increasing concern and need scientific and technological attention.

In this context of risk management, environmental risks and their associated impacts cut across various aspects of human life and development, underscoring the need for concerted research and effective risk-management strategies [39-44].

The city of Warri has grown and is still growing significantly in size due to industrialization and economic activities. The metropolis is one of the hubs of hydrocarbon activities in Nigeria in particular and West Africa in general. By all standards, Warri is the fastest-developing city in Delta State, Nigeria, with a population projection of about 9,100,000 in 2021. It has attained urban center status. An increase in petrochemical and oil activities, coupled with other economic activities such as construction, painting, etc., has led to unforeseen black soot pollution [44,45].

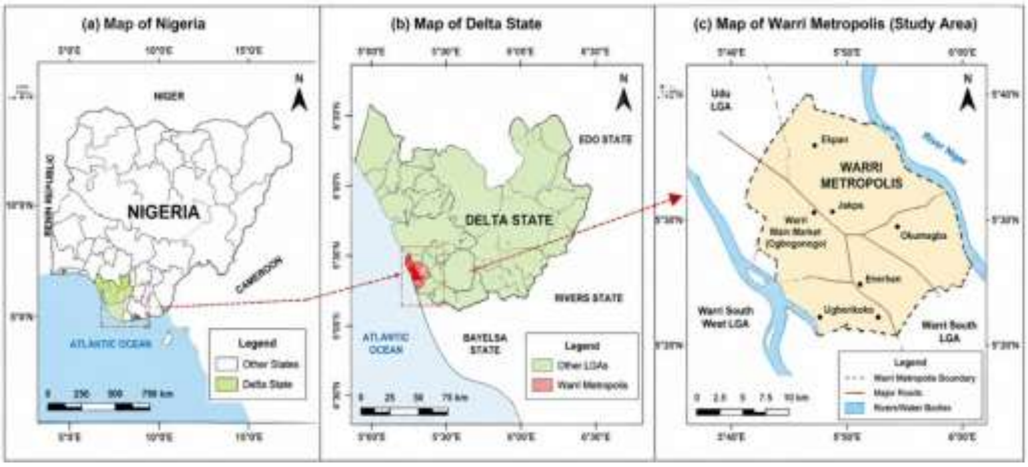

Figure 1: Location of Warri Metropolis within Delta State, Nigeria

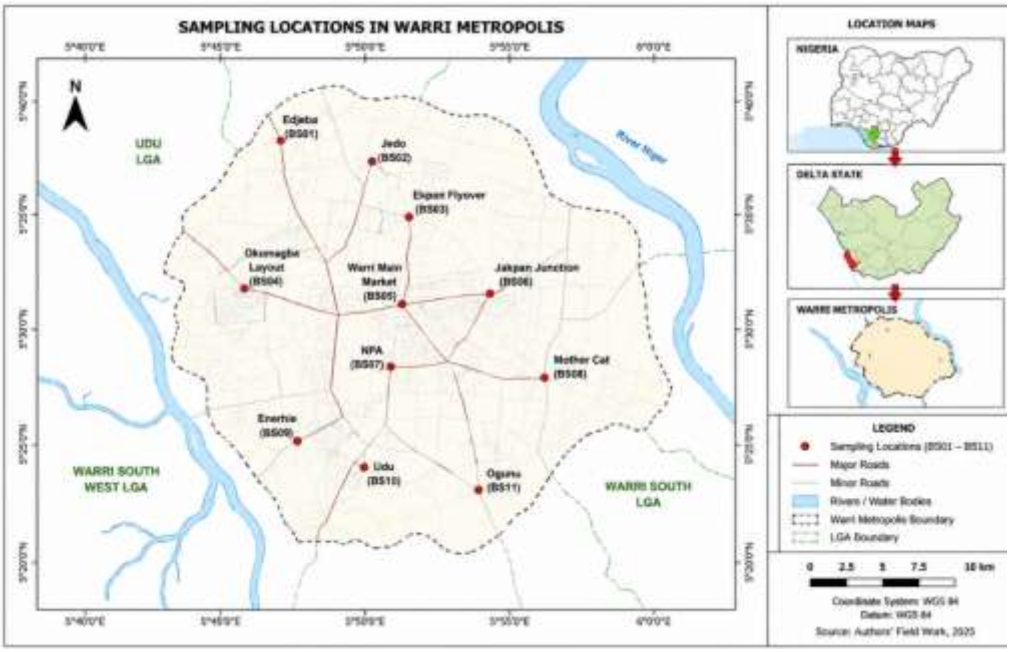

Figure 2: Spatial Distribution of the Eleven Sampling Locations in Warri Metropolis

2.3 Sampling and Simulation

The study period consisted of 12 calendar months: the dry season (October 2025 to March 2026) and the wet season (April 2026 to September 2026). A total of 11 sampling points were used to sample 269 environmental samples in Warri Metropolis. The sampling points were numbered BS01 to BS11 (Figure 2). The sampling sites were chosen to be close to main roads and areas of high commercial and human activity.

During the dry season, direct sampling was carried out using the high-volume air sampler, and the dust-fall method was used during the wet season. Climatic information such as temperature, relative humidity, wind direction, and wind speed was collected with the environmental samples taken in both seasons. The 269 environmental samples were all samples observed from the eleven sample locations over the observation period; an additional breakdown of these observations by individual sampling location or individually by season was not available from the records. The measured black-soot concentrations were then fed into the non-carcinogenic health-risk assessment. The proposed algorithms were used to compute the risk indices for various population groups, and the percentage contribution was calculated in MS-Excel.

2.4 Spatial Distribution and Analysis of Non-Carcinogenic Risk

In Table 1, the sample codes are given for the eleven spatial points throughout the metropolis, ranging from BS01 to BS11. The simulated non-carcinogenic risk index for the various population groups at the various locations is given in Table 1. The simulated risk indices for ambient black-soot exposure of 25.00 $\mu g/m^3$ are shown in Table 2 for different exposure times. The percentage distribution of the non-carcinogenic risk indices among population groups is shown in Figure 3, and the parametric ranking of the factors that influence the risk assessment is shown in Figure 4. The results for the non-carcinogenic risk indices are also graphically presented in Figure 5 for the different population groups.

Table 1: Non-Carcinogenic Risk Indices for Different Population Groups at the Sampling Locations

Sampling Location	Code	Black-Soot Concentration ($\mu g/m^3$)	Exposure Duration (h/day)	Children <1 year	Children 1–12 years	Adult Female	Adult Male
Edjeba	BS01	25.00	18	0.305	0.133	0.089	0.188
Jedo	BS02	29.00	18	0.354	0.154	0.010	0.137
Ekpan Flyover	BS03	30.00	18	0.366	0.159	0.106	0.142
Okumagba Layout	BS04	16.00	18	0.195	0.085	0.057	0.076
Warri Main Market	BS05	21.00	18	0.256	0.111	0.074	0.100
Jakpan Junction	BS06	26.00	18	0.317	0.138	0.092	0.123
NPA	BS07	18.00	18	0.230	0.095	0.064	0.085
Mother Cat	BS08	31.00	18	0.387	0.164	0.109	0.147
Enerhie	BS09	10.00	18	0.122	0.053	0.035	0.047
Udu	BS10	27.00	18	0.329	0.143	0.095	0.128
Ogunu	BS11	36.00	18	0.439	0.190	0.127	0.171
Total				3.300	1.426	0.858	1.344

Note: HQ denotes the non-carcinogenic hazard quotient. The total row represents the aggregate risk index across the eleven sampling locations.

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Table 2: Effect of Exposure Duration on Non-Carcinogenic Risk Indices at a Constant Black-Soot Concentration of 25.00 μg/m³

Exposure Duration (h/day)	Children <1 year	Children 1–12 years	Adult Female	Adult Male
0	0.000	0.000	0.000	0.000
2	0.034	0.015	0.010	0.021
4	0.068	0.030	0.020	0.042
6	0.102	0.044	0.030	0.063
8	0.136	0.059	0.040	0.084
10	0.169	0.074	0.049	0.104
11	0.186	0.081	0.054	0.115
12	0.203	0.089	0.059	0.125
14	0.237	0.104	0.069	0.146
16	0.271	0.118	0.079	0.167
18	0.305	0.133	0.089	0.188

Note: The simulations were conducted at a constant black-soot concentration of 25.00 μg/m³. The risk indices were calculated using the same population-specific parameters and governing exposure-risk relationship used for the 18 h/day values in Table 1. HQ denotes the non-carcinogenic hazard quotient.

At a fixed black-soot concentration of 25.00 μg/m³, the simulated risk index increases proportionally with exposure duration. At the reference exposure duration of 18 h/day, the simulated values correspond to those reported for the 25.00 μg/m³ sampling location in Table 1. This consistency confirms that the same exposure-risk relationship and population-specific parameters were applied in both tables.

Table 3: Non-Carcinogenic Health Risk Index and Percentage Contribution by Population Group

Population Group	Aggregate Non-Carcinogenic Risk Index	Percentage Contribution (%)
Children below 1 year	3.300	47.6
Children between 1–12 years	1.426	20.6
Adult Female	0.858	12.4
Adult Male	1.344	19.4
Total	6.928	100.0

Note: Percentage contributions represent the relative contribution of each population group to the total non-carcinogenic risk index. Percentages may not sum exactly to 100% because of rounding.

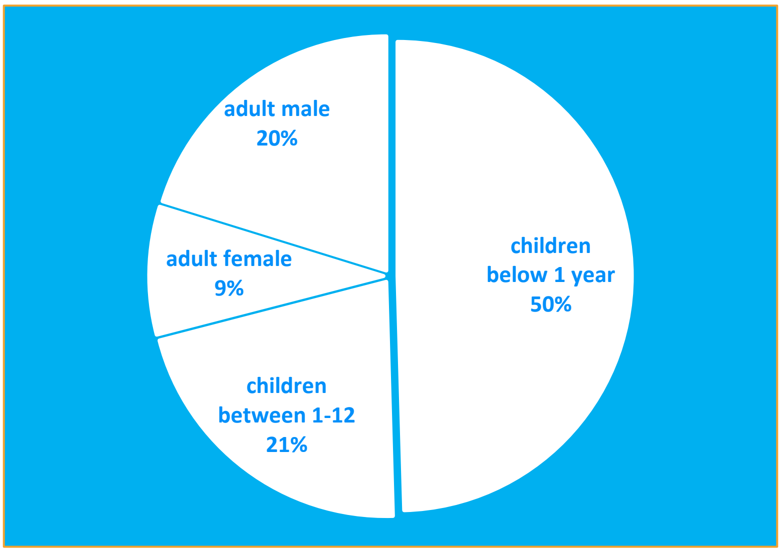

Figure 3: Percentage Distribution of Non-Carcinogenic Risk among Population Groups

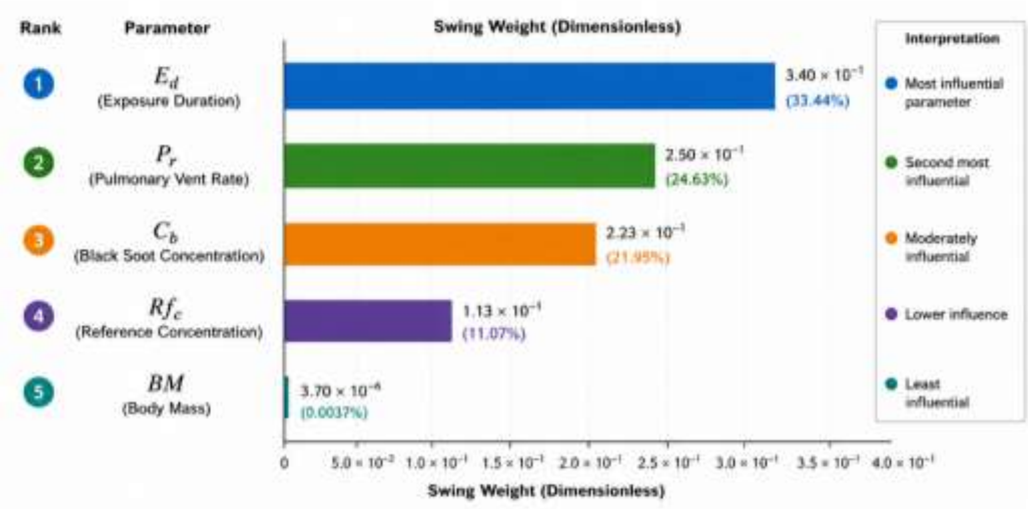

Figure 4: Parametric Ranking of Non-Carcinogenic Risk Factors- Swing Weight Method

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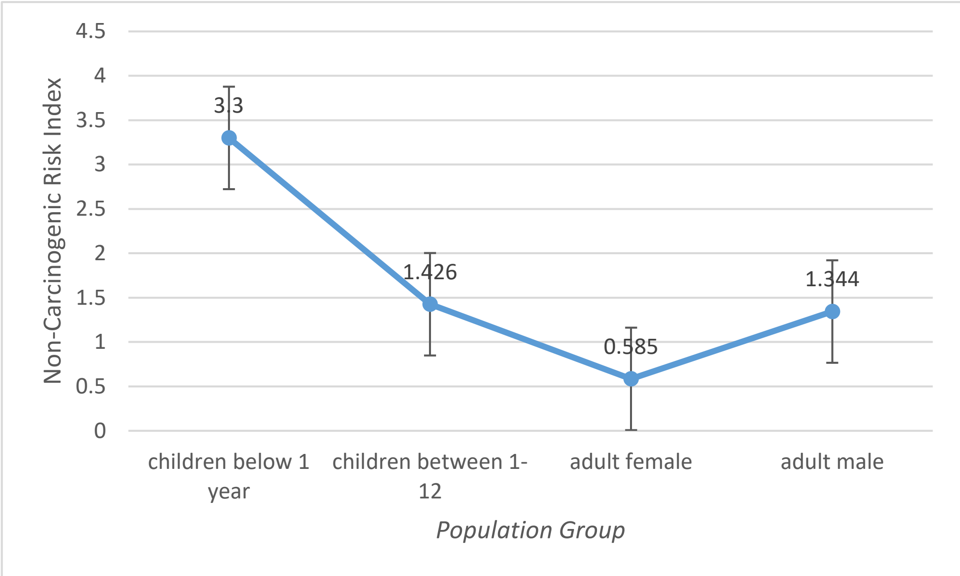

Figure 5: Non-Carcinogenic Risk Index by Population Group

3 Discussion

The results show that children below one year of age account for the largest proportion of the estimated non-carcinogenic health risk (47.6%), followed by children aged 1–12 years (20.6%), adult males (19.4%), and adult females (12.4%). However, adult females and males have probabilities of 19% and 12%, respectively, while children between the ages of 1-12 have a probability of 21%.and below 1 year have probabilities of 48% This finding is consistent with previous studies on the vulnerability of children to air pollution and their higher inhalation rates compared with adults. Allergic inhalations rates differ significantly between children and adults because there are differences in body size, physiology, behaviour and activity level. The infants and children have higher oxygen and resting metabolic rates per kg body weight than adults because their lung SA per kg body weight is relatively larger and their growth rate is higher. For example, at rest, an infant from 1 week to 1 year will have an oxygen consumption of about 7 mL/kg/min, whereas an adult at rest will have an oxygen consumption of 3-5 mL/kg/min.

Therefore, adults breathe more absolute amounts of air and pollutants during the same amount of time, but the amount of air passing through the lungs of a sleeping baby may be as much as twice the amount of air passing through the lungs of a sleeping adult. Other factors affecting lung volume include body height, and people in higher altitudes may have larger lung capacities than people at sea level.

The inhalation dosimetry and health effects of children have been studied at a U.S. Environmental Protection Agency workshop [16]. When evaluating health risks resulting from inhalation exposure, age-related variations in lung structure and function, breathing patterns and particle deposition should be taken into account. Children, also more likely than adults, tend to breathe through the mouth, especially during sleep and exercise, decreasing the role of nasal filtering of breathing. In addition, particle uptake by the nasal airways may be less efficient in children, potentially resulting in greater deposition of particles in the lower respiratory tract.

In addition, the deposition rate of fine particles has been reported to be significantly associated with increased body mass index (BMI), an important factor as childhood obesity is on the rise [16, 17].

4 Conclusion

The study has proven the effectiveness of an algorithmic modelling approach for evaluating the individual non-carcinogenic health risk of exposure to black soot in Warri metropolis. The results showed that there was a significant difference in risk index among the various population groups, with the highest risk index among children under 1 year of age (47.6%), children aged 1-12 years (20.6%), and adult males (19.4%), while the lowest risk index was in adult females (12.4%).

The increased risk in younger children is due to several physiologic and behavioral differences that affect inhalation and particle deposition rates, such as increased inhalation rate per unit of body weight and differences in respiratory development. The outcomes thus underscore the vulnerability of children to Black soot pollution and highlight the importance of the consideration of age-specific exposure characteristics in an environmental health risk assessment.

The study also shows that the ambient black soot concentration and exposure time can substantial affect non-carcinogenic risk. Therefore, minimizing pollutant levels and exposure to these pollutants over extended periods is critical in the study area to minimize potential health effects, especially for sensitive population groups.

The overall algorithmic framework developed is helpful for comparative and population-specific assessment of the risk of exposure to black soot. Its use can contribute to the monitoring of the environment, public-health planning and the creation of interventions to reduce exposure to black soot pollution in Warri metropolis and other affected urban and industrial environments.

Acknowledgement

The authors wish to express their sincere gratitude to their respective institutions throughout the conduct of this research. The authors would like to thank the reviewers and editors for their constructive comments, valuable suggestions, and careful evaluation of the work, which has helped to improve the quality of the work.

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Tech-Sphere Journal of Pure and Applied Sciences (TSJPAS)
A Subsidiary of Tech-Sphere Multidisciplinary International Journal (TSMIJ)
Oghenerhoro et al. Vol 3, Issue 1, 2026 Publication Edition
ISSN: 3092-9598

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