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Assessing Health Risks Associated with Air Pollution in India

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KEYWORDS

Air pollution, AirQ software, Health impact assessment, Mortality, Morbidity.

ABSTRACT:

The objective of this study was to comprehensively evaluate the health impacts of air pollution on residents in the major urban areas throughout India, which includes the city of Hyderabad, Chennai, India, Mumbai, Kolkata, New Delhi, and Bangalore. The research used the AirQ 2.2.3 software produced by the Bilthoven European Centre of Environmental and Health, a division of the World Health Organization (also known as the "WHO") that is officially supported by the WHO. The levels of primary pollutants, such as ozone, nitrogen dioxide, Sulphur dioxide, & particulate matter with aerodynamic sizes less than 10 μm (PM2.5, PM10, NO2, and O3), were crucial indicators for assessing human exposure and health impacts. The review aimed at identifying the percentage of health outcomes that may be linked to lung cancer and to calculate the number of additional deaths caused by lung cancer each year. The findings demonstrate a substantial health burden associated with pollutants in the air in the examined Indian cities, emphasizing the pressing need for prompt and efficient actions to mitigate the negative health effects. This study investigates the relationship between the AQI (Air Quality Index) and the presence of PM10, NO2, O3, and PM2.5 pollutants. Strong positive associations were observed for AQI with PM10, NO2, and O3, indicating notable relationships. However, while AQI displayed a robust correlation with PM2.5, the significance of this association was inconclusive. This study underscores substantial connections between AQI and PM10, NO2, and O3, suggesting caution in inferring a direct relationship between AQI and PM2.5's relative risk without further investigation.

Introduction

The presence of hazardous compounds in the air leads to environmental pollution, which presents a substantial risk to public health. This issue has grown more evident in India. Rapid industrialization, urbanization, and population growth have led to a surge in air pollutant levels across the country. This introduction delves into the multifaceted aspects of air pollution in India, examining key pollutants, their sources, and the urgent need for an extensive health impact assessment (HIA) to comprehensively understand and address the health implications. India's air quality crisis is characterized by the presence of Multiple pollutants, including oxygen (O3), nitrogen oxides (NO2), and sulphur dioxide (SO2), and particle matter (PM). These pollutants are released from a variety of sources, including burning biomass, industry, construction, and motor vehicle emissions. The concentration levels of these pollutants frequently exceed the permissible limits set by environmental standards, leading to widespread environmental degradation and posing a severe threat to public health.

Gaining insight into the fundamental causes of pollution in the air is essential for the formulation of efficient measures to reduce its impact. The transportation sector, including vehicular emissions and road dust, is a major contributor, particularly in urban areas. Industrial activities, prevalent in densely populated regions, release substantial amounts of pollutants into the atmosphere. Additionally, the widespread Utilization of solid combustibility for the purpose of cooking and heating in rural areas contributes significantly to air pollution. The

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seasonal and geographical variations in pollution sources further complicate the assessment and management of air quality in the diverse Indian subcontinent.

Health Impacts of Air Pollution

Pollution from the air has a diverse array of detrimental health consequences on many organ systems. Individuals who experience significant levels of air pollution are at an increased risk of developing Respiratory conditions such as breathing problems such as asthma, chronic obstructive pulmonary (COPD), and respiratory infections. Prolonged exposure is linked to cardiovascular ailments, such as hypertension and myocardial infarctions. Moreover, there is a correlation between air pollution and negative pregnancy outcomes, neurodevelopmental disorders in children, and an increased susceptibility to some types of cancer. The elderly and those with pre-existing health conditions have heightened vulnerability, exacerbating pre-existing health disparities.

A comprehensive Health Impact Assessment (HIA) is indispensable to evaluate the health impacts of pollution in the air and promote legislation based on empirical data. A proposed policy, initiative, or program's health consequences are assessed in HIA providing a structured framework for decision-makers to weigh the trade-offs between different options. In the context of air pollution in India, an HIA would assess the baseline health status of populations, estimate exposure to pollutants, and project the potential health outcomes associated with different pollution scenarios. Such assessments are essential for prioritizing interventions, allocating resources, and designing targeted public health campaigns.

Challenges in Conducting Health Impact Assessments in India

Despite the critical need for HIAs in the context of air pollution, several challenges hinder their effective implementation in India. Data gaps, especially in terms of comprehensive air quality monitoring and health surveillance systems, pose a significant hurdle. The diverse socioeconomic and environmental contexts across different regions of India complicate the development of a standardized HIA methodology. Furthermore, the complex interplay of multiple pollutants and the cumulative impact of long-term exposure require sophisticated modelling techniques and interdisciplinary collaboration, which may be lacking in some settings.

India has implemented many measures to develop a strong regulatory framework in order to tackle the increasing difficulties posed by air pollution. The progression of air quality control in the nation may be discerned by examining significant policy efforts and legislative actions. The Air Pollution (Prevention, Management, & Management of Pollution) Act, enacted in 1981, delegated the responsibility of supervising and regulating the pollution of the air to the Central Pollution Control Board, or CPCB, and the state pollution control boards (SPCBs). This legislation established the foundation for the implementation of air quality rules in India. This is evident in the later revisions and regulations, such as the National Environmental Protection Programme (NCAP) and the National Ambient Air Quality Standards (NAAQS), which illustrate the ongoing efforts to address air pollution at both the national and regional levels.

India's air pollution health effect assessment is a complex issue that needs an all-encompassing and cooperative solution. The evolving landscape of air quality management, technological innovations, and the recognition of socioeconomic disparities underscore the need for an integrated approach. As India navigates the complex terrain of air pollution, informed by rigorous health impact assessments, the nation has the opportunity to emerge as a global leader in sustainable development and environmental stewardship. By prioritizing public health, embracing technological advancements, and fostering community engagement. India can lessen the negative consequences of air pollution, giving its people a happier, more sustainable future.

The study focuses on five major Indian metropolitan cities, each contributing distinct characteristics to the diverse landscape of the country. Hyderabad, located in southern India, is the capital of Telangana and Andhra Pradesh, known for its historical sites like the Charminar and its emergence as a hub for technology and business. Chennai, situated on the southeastern coast, stands as the capital of Tamil Nadu, boasting a rich cultural heritage, classical music, and picturesque beaches. Delhi, the national capital in the north, is a historical metropolis blending ancient landmarks

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such as the Red Fort with the bustling life of a modern urban center. Mumbai, on the west coast, serves as the financial and entertainment capital, housing the Bollywood film industry and iconic structures like the Gateway of India. Kolkata, situated in the east, is the capital of West Bengal, renowned for its intellectual heritage, colonial architecture, and vibrant cultural festivals. Together, these cities encapsulate the multifaceted essence of India, from historical legacies to thriving contemporary developments, while the study seeks to delve into the health repercussions of air pollution on their diverse populations.

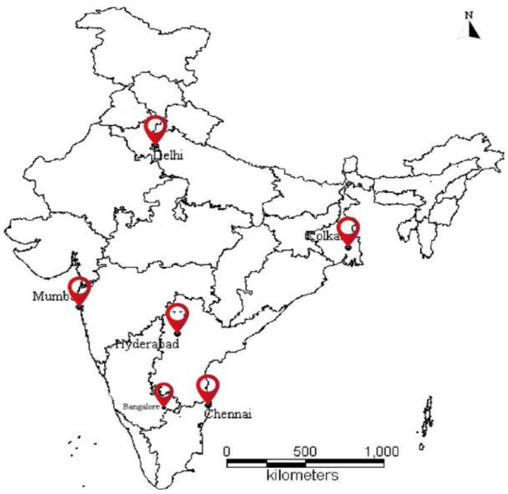

Figure 1 Map of the study areas and locations of monitoring stations

Related Work

Han et al. [1] created a novel semi-supervised technique for predicting air quality using neural networks with self-supervised hierarchical graphs (SSH-GNN). The article introduces a novel method that might enhance air quality predictions. Wang et al. [2] Introduce a novel approach to decomposing models that is specifically tailored for predicting fuzzy entropy. Applying this approach to reconstitute imprecise entropy modules offers a distinct viewpoint for forecasting air quality. Alkabbani et al. [3] Concentrate on the creation of a Random Forest (RF) algorithm to forecast air quality. Evaluate its efficacy in relation to six criterion pollutants and the Air Quality Index (AQI). Although acknowledging the model's achievements, the report highlights drawbacks such as prolonged training durations. The authors propose the need of adopting a deterministic method to anticipate air quality, hence emphasising opportunities for enhancing predictive models.

Xu and Yoneda[4] critically assess the Back Propagating Neural Network (BPNN) highlighting its struggles with data variability, local minima problems, and low convergence rates. In response to these challenges, the authors propose a novel deep learning model as a more advanced version of machine learning. Benhaddi and Ouarzazi[5] discuss the common use of Convolutional Neural Network (CNN) for air quality prediction, emphasizing its drawbacks related to overfitting and computational burden. This dual-method strategy addresses the limitations of CNN, providing a more comprehensive framework for accurate air quality predictions. Gunasekar, Kumar, and Kumar [6] delve into the application of heuristic algorithms for air quality prediction. While acknowledging the efficacy of these algorithms, the study identifies issues such as premature processes and optimal global concerns.

Table 1 Comparison of existing studies

Purpose of the Study	Health Impact	Reference
Evaluating the advantages of reaching the ozone level guideline for health	Deaths, emergency room (ER) visits, hospital stays, days with restricted activities, and absences from school.	7
Estimation of the burden on national public health related to exposure to ozone and PM2.5 in the atmosphere.	Decreased life expectancy and years lived; as well as mortality	8
Knowledge basis for dispersion modelling of ambient particle concentrations and multi-pollutant pollution	Premature mortality	9
Assessment of the economic externalities associated with air pollution and health effects associated with certain sectors or	Mortality and morbidity	10

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emission sources that may support the development of emission reduction policies.		
Estimating Delhi's health implications in terms of morbidity and premature death via the use of a multi-sectoral emissions inventory.	Premature mortality and morbidity effects	11
The use of advanced brick processing technologies offers significant health benefits.	Mortality, morbidity, and health cost reductions	12
Estimating the number of premature deaths from lung cancer and cardiovascular disease as a result of PM2.5 levels, as well as the impact of lowering emissions of black carbon on human mortality and surface air quality	Mortality	13
Estimated deaths from premature air pollution saved, significant food crops' yield decreases due to ozone avoided, and health damages avoided	Mortalities, morbidities, and averted decline in main food crop yields due to ozone.	14
Calculating national and worldwide health consequences of surface transportation emissions-caused PM2.5 air pollution.	Mortality	15

Materials and Methods

1. *Air Q+ Software*

The Air The quality and Health Impact Assessment (AirQ 2.2.3) programme, developed by the World Health Organization's European Centre for Environment and Health in Bilthoven Division, adheres to the recommended methodology of the World Health Organisation (WHO). This programme is designed to assess the health impacts of exposure to specific air pollutants. This software serves as an instrument for evaluating the influence on the welfare of individuals living in a specific geographical and temporal context. The assessment is based on the concept of attributable proportion (AP), which quantifies the proportion of a person's health outcome that can be attributed to their contact with a certain kind of air pollution. This calculation relies on a well-established causal connection between treatment and health outcome, with little interference from confounding variables. The technique of calculating the relevant percentage (AP) is clear and allows for a quantitative evaluation of the impact of air pollution on public health.

$$\mathrm{AP} = \frac{\sum\left\{\left[\mathrm{RR}\left(c\right)-1\right]\times P\left(c\right)\right\}}{\sum\left[\mathrm{RR}\left(c\right)\times P\left(c\right)\right]} \quad (1)$$

The formula for determining the attributable proportion (AP) of a health outcome is AP = (RR - 1) / RR. In this case, RR represents the relative risk associated with a certain health outcome in the "c" set of exposures. The relative risk is determined by the use of exposure-response functions obtained from epidemiological studies. Moreover, P(c) denotes the proportion of persons belonging to category "c" relative to the entire population, while considering their degree of exposure. To get the rate associated with the exposure, you may use this formula: The rate attributable may be calculated by multiplying the baseline rate by the attributable proportion (AP), provided that the beginning rate of a health outcome in the sample being studied is known. This method calculates the correlation between treatment and the incidence of a disease by taking into account both the danger ratio or the distribution of diseases of the entire population across various degrees of exposure.

$$\mathrm{IE} = I \times \mathrm{AP} \quad (2)$$

The variable IE represents the influence exposure has on the rate of health outcomes, whereas the variable I represents the initial frequency of a certain care result in the whole population. To summarise, while considering the overall population size, we may estimate the total amount of occurrences resulting from exposure using the following method:

$$\mathrm{NE} = \mathrm{IE} \times N \quad (3)$$

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NE is the number of events that can be ascribed to the being exposed, whereas N indicates the population size that was examined.

2. Relative Risk (RR):

The coefficients of the Concentration-Response Functions (CRF) are typically calculated using Equation (1), This is derived from the concept of Relative Risk (RR). Relative Risk measures the probability of an unfavourable health outcome in a population who are exposed to higher levels of ambient air pollution compared to a population allocated to reduced levels of ambient air pollution.

$$\mathrm{RR} = \exp(\beta \times \Delta C) \qquad (4)$$

There is a linear correlation between the concentration level of ambient air pollution that the risk ratio (RR). Several distinct linear equations have been proposed, as seen below. Within these models, the variable "c" The term "ct" refers to the threshold value, which is the lowest possible level of air pollutants that does not cause any noticeable negative health effects.

$$\begin{aligned}&\text{For } c < c_t, \mathrm{RR}_{\mathrm{Lin50}}(c),\\&\text{For } c_t < c < 50, \mathrm{RR}_{\mathrm{Lin50}}(c) = 1 + \gamma(c - c_t),\\&\text{For } c > 50, \mathrm{RR}_{\mathrm{Lin50}}(c) = 1 + \gamma(50 - c_t)\cdot\end{aligned}$$

(5)

3. Mortality and Morbidity

Mortality and morbidity resulting from the rise in concentration can be quantified through the calculation of excess deaths or diseases (ED) using the following formula:

$$ED = \Delta y \times \mathrm{Population} \qquad (6)$$

Another way to put it is as a Population attributable fraction (PAF):

$$ED = PAF \times I \times P \qquad (7)$$

The percentage of the illness burden that may be linked to pollution is shown in this context by the Public Attributable Fraction (PAF). The mortality incidences per year (I) divided by the population of all ages (P) is used to calculate PAF, which has the following expression:

$$PAF = \frac{p(\mathrm{RR}-1)}{p(\mathrm{RR}-1+1)} \qquad (8)$$

In this formula, p represents the percentage of the population exposed, and RR stands for the proportional risk of premature death calculated using the IER model.

Results

Exposure Assessment

The evaluation of health risks related to air pollution involves intricate mathematical estimations and modelling of various processes, such as estimating population figures, measuring exposure to pollution levels in the population, and assessing adverse health effects using precise concentration-response functions. Accurate and specific data, such as demographic statistics, environmental indicators, fundamental mortality or illness rates, and risk estimates from epidemiological studies, are crucial for this evaluation. These risk estimates measure the relationship between exposures to air pollutants and its impact on health by establishing the connection between health outcomes and changes in the levels of air pollutants, such as PM 2.5, PM 10, NO2, and O3.

Table 2Air pollutants for different cities

	PM 2.5 (μg/m³)	PM 10 (μg/m³)	NO2 (μg/m³)	O3 (μg/m³)
Hyderabad	35.097	77.971	27.142	26.788
Mumbai	36.594	94.733	22.698	27.381
Kolkata	47.052	94.280	28.527	37.997
Delhi	80.317	157.034	33.201	40.649
Chennai	29.407	68.324	11.244	38.701
Bangalore	30.465	67.031	21.410	35.637

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Table 2 presents air quality data measured in micrograms per cubic meter (µg/m³) for key pollutants PM2.5, PM10, NO2, and O3 in six major cities of India: Hyderabad, Mumbai, Kolkata, Delhi, Chennai, and Bangalore. In Delhi, the concentrations of PM2.5 and PM10 are notably high, reaching 80.317 µg/m³ and 157.034 µg/m³, respectively, indicating severe air pollution. Kolkata and Mumbai also exhibit significant levels of pollutants, while Hyderabad, Chennai, and Bangalore generally maintain lower concentrations. For instance, Hyderabad records 35.097 µg/m³ for PM2.5 and 77.971 µg/m³ for PM10. Chennai shows relatively low levels across all pollutants, with the lowest PM2.5 concentration of 29.407 µg/m³. These variations underscore the diverse air quality challenges faced by different cities, emphasizing the importance of location-specific environmental policies and interventions. The data serves as a valuable tool for policymakers, researchers, and public health officials in understanding the extent of air pollution in these urban areas and formulating targeted strategies to mitigate the detrimental impacts it has on the well-being of humans and the environment.

Table 3 Relative risk values for different cities

Health End point	City	Relative Risk			
		PM 2.5	PM 10	NO2	O3
Mortality of Lung cancer	Hyderabad	1.2865	1.6235	1.0345	1.0000
	Mumbai	1.2961	1.8407	1.0373	1.0000
	Delhi	1.4683	2.9835	1.0470	1.0000
	Kolkata	1.3546	1.8407	1.0373	1.0000
	Chennai	1.2470	1.5074	1.0024	1.0000
	Bangalore	1.2547	1.4924	1.0228	1.0000

The table labelled "Table3" provides a clear representation of the comparative risk of death from lung cancer that is linked to various air contaminants (PM2.5, PM10, NO2, O3) in six major cities in India Hyderabad, Mumbai, Delhi, Kolkata, Chennai, and Bangalore. The relative risk values represent the likelihood of lung cancer mortality compared to a reference level of 1.0000 for each pollutant in each city. The results indicate varied risks across cities and pollutants, suggesting distinct health impacts. For instance, in Delhi, the relative risks are notably elevated, with values such as 1.4683 for PM2.5 and 2.9835 for PM10, emphasizing the potential health hazards associated with air pollution in the national capital. Similarly, Mumbai, Kolkata, and Bangalore exhibit varying levels of risk for different pollutants. These findings underscore the importance of addressing air quality concerns, particularly in highly populated urban areas, to mitigate the adverse health effects associated with lung cancer mortality.

Hyderabad, a city with a population of 10,801,163 over an area of 650 sq km and situated at latitude 17.385N and longitude 78.486E, reports 5482 cases. Notably, air quality indicators reveal moderate concentrations of pollutants, with PM2.5 at 35.097 µg/m³, PM10 at 77.971 µg/m³, NO2 at 27.142 µg/m³, and O3 at 26.788 µg/m³. To assess the relative health risk, epidemiological models will be essential, considering population size, pollutant concentrations, and reported cases. These models establish quantitative relationships between air pollution levels and potential health impacts, providing insights into the relative risks associated with Hyderabad's observed pollutant concentrations for targeted public health strategies.

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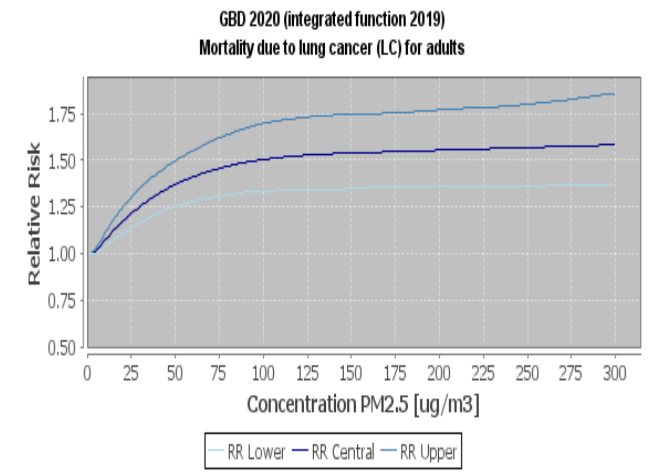
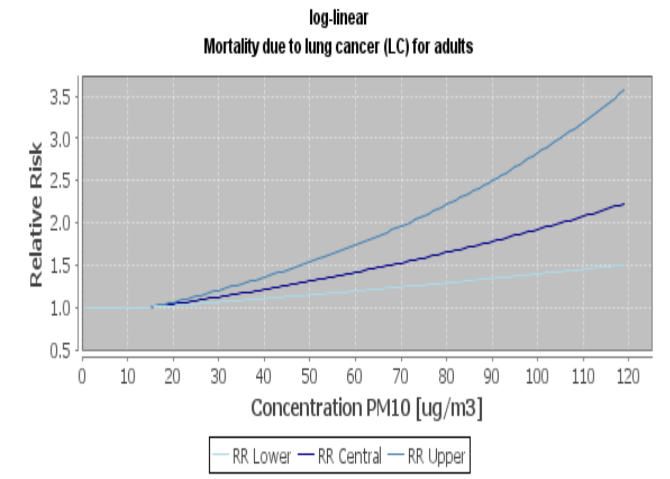
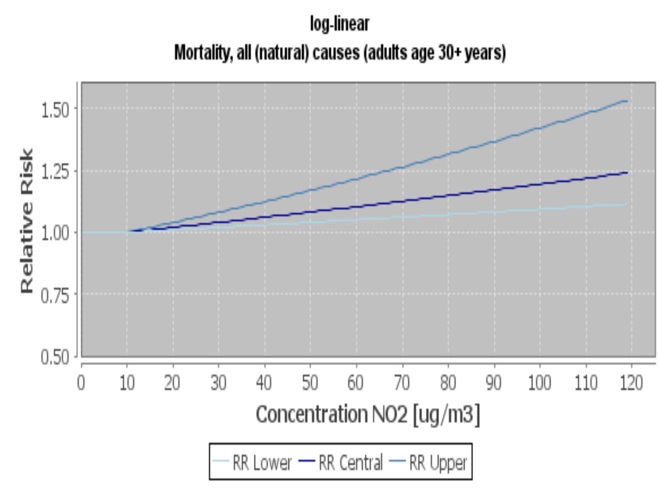


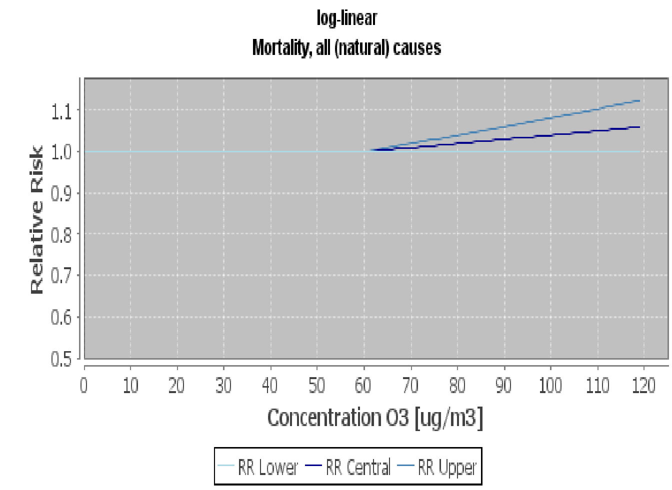
a. PM2.5: 35.097



b. PM10: 77.971



c. NO2: 27.142



d. O3: 26.788

Figure 2.Health Relative risk of Hyderabad City

Mumbai, a densely populated metropolis with 21,297,000 residents over 603.4 sq km, confronts significant air pollution challenges. Located at latitude 19.076 N and longitude 72.877, the city experiences notable concentrations of air pollutants, including PM2.5 (36.594 µg/m³), PM10 (94.733 µg/m³), NO2 (22.698 µg/m³), and O3 (27.381 µg/m³).

To assess the health risks associated with these levels, epidemiological models will be utilized, factoring in the large population size and concentrations of each pollutant. These models aim to establish a quantitative link between air pollution and potential health impacts, facilitating the determination of relative risks. Understanding the health implications of elevated pollutant levels is crucial for implementing effective mitigation strategies and safeguarding the well-being of Mumbai's residents amidst the complex dynamics of urban environmental challenges.

Kolkata, hosting a population of 15,332,793 across 206.1 sq km, grapples with concerning air pollution. Positioned at latitude 22.572 N and longitude 88.3639 E, the city reports 8918 cases. Alarming pollutant levels include PM2.5 at 47.052 µg/m³, PM10 at 94.280 µg/m³, NO2 at 28.527 µg/m³, and O3 at 37.997 µg/m³.

To assess relative health risks, epidemiological models will be crucial, integrating population size, pollutant

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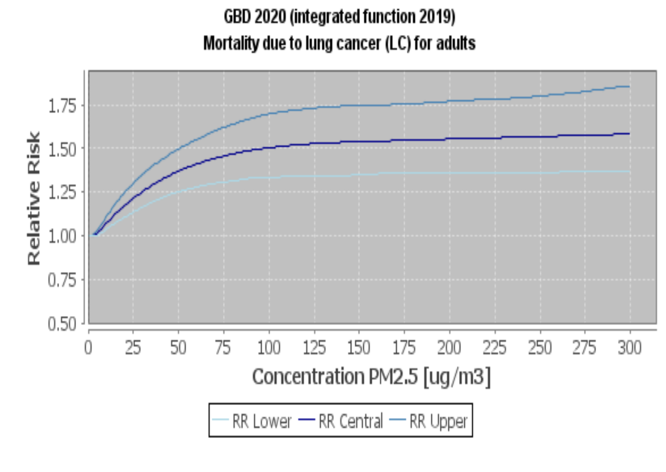
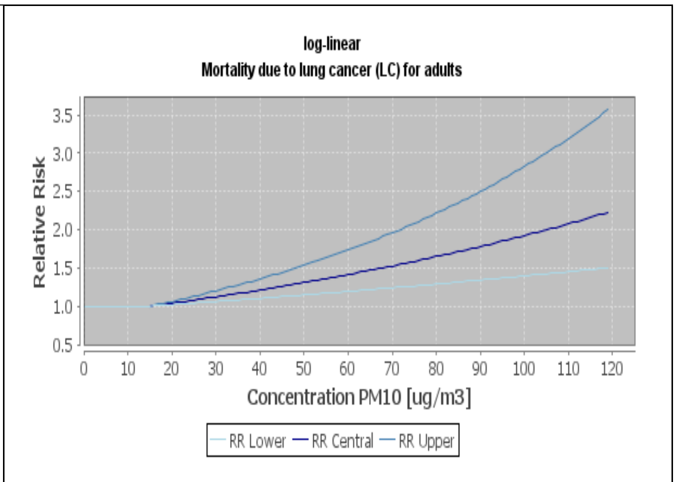
concentrations, and reported cases. These models establish quantitative links between air pollution and potential health impacts, aiding in gauging the relative risks associated with Kolkata's observed pollutant concentrations, vital for targeted interventions and public health strategies. Understanding health implications is paramount for safeguarding the well-being of Kolkata's residents amidst air quality challenges.

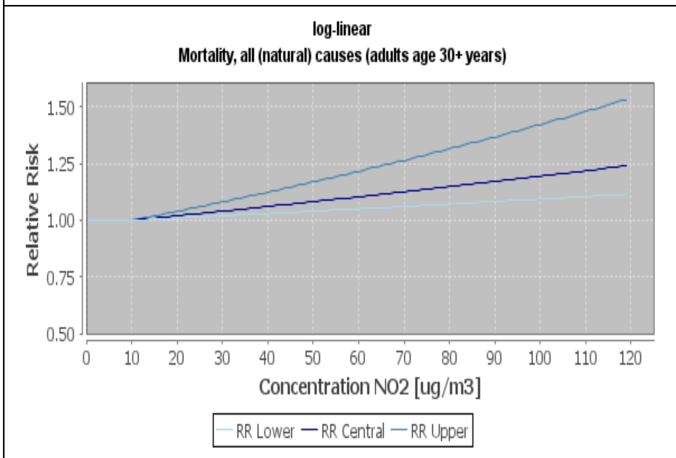
Delhi, a megacity with a population of 32,941,000 over 1483 sq km, grapples with critical air pollution issues. Situated at latitude 28.7041 and longitude 77.1025, the city reports 12,505 cases. Disturbingly, air quality indicators reveal heightened concentrations of pollutants, including PM2.5 at 80.317 µg/m³, PM10 at 157.034 µg/m³, NO2 at 33.201 µg/m³, and O3 at 40.649 µg/m³. Assessing the relative health risk necessitates the application of epidemiological models, factoring in population size, pollutant concentrations, and reported cases. These models establish quantitative relationships between air pollution levels and potential health impacts, vital for comprehending the relative risks associated with Delhi's observed pollutant concentrations and guiding targeted interventions for public health management.

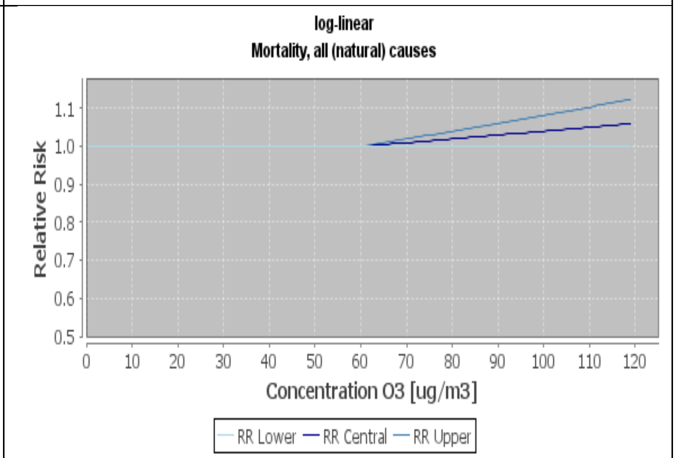




a. **PM2.5: 36.594**

b. **PM10: 94.733**





c. **NO2: 22.698**

d. **O3: 27.381**

Figure 3.Health Relative risk of Mumbai City

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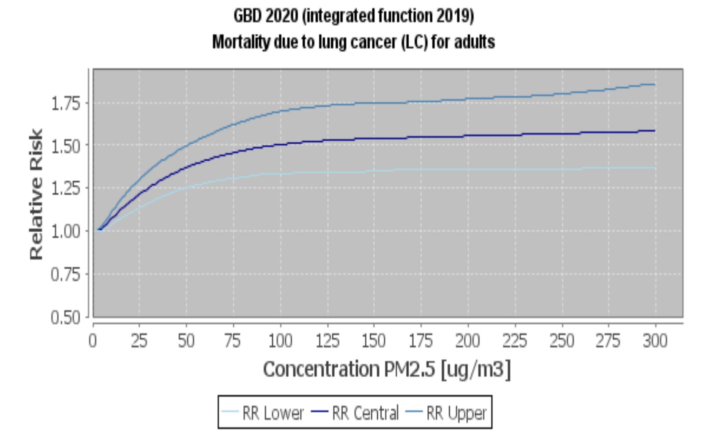
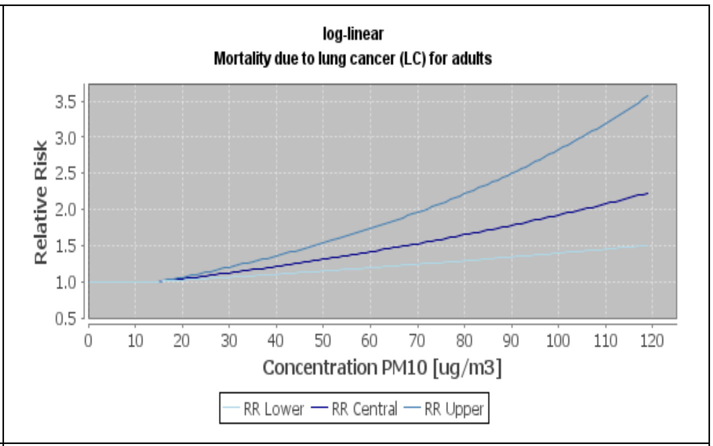
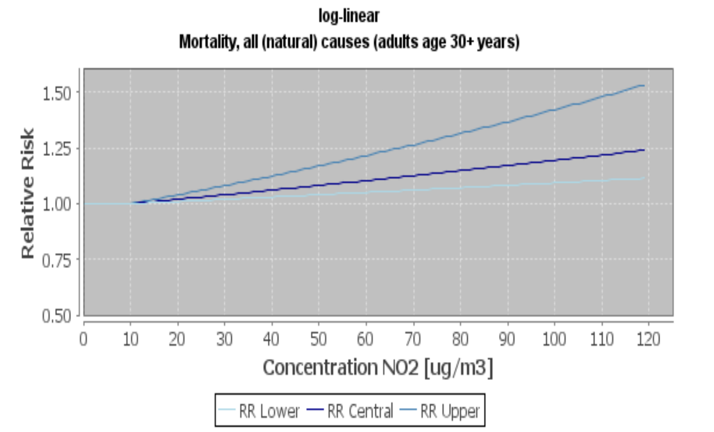


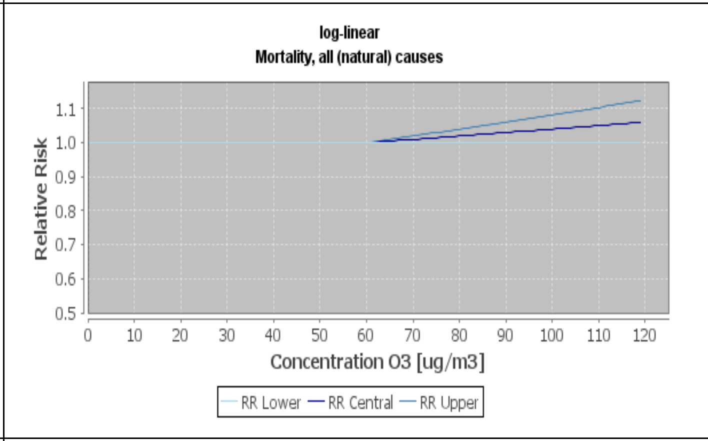
a. **PM2.5: 47.052**



b. **PM10: 94.280**

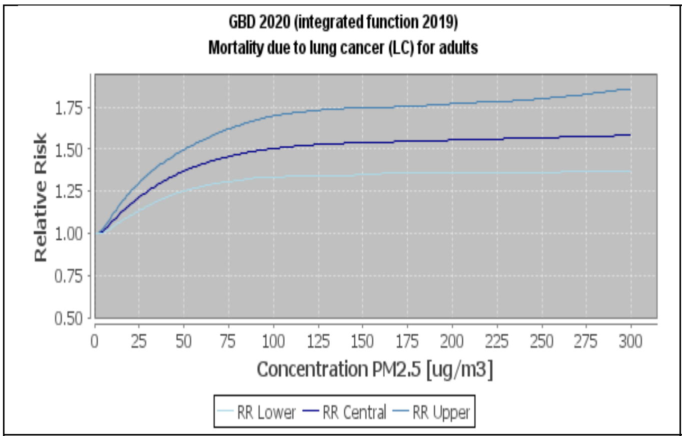


c. **O3: 28.527**

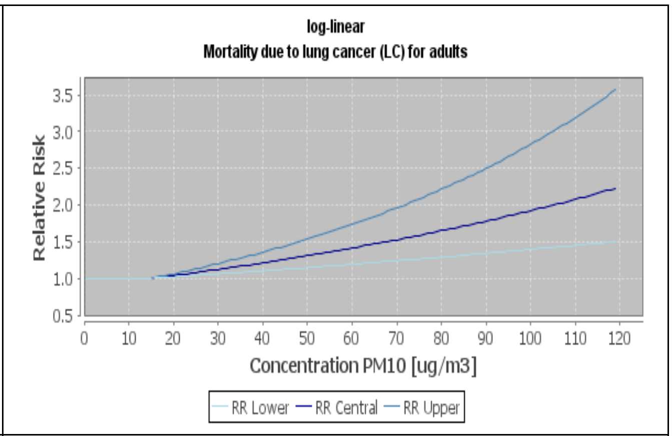


d. **NO2:37.997**

Figure 4.Health Relative risk of Kolkata City



a. **PM2.5 = 80.317**



b. **PM10: 157.034**

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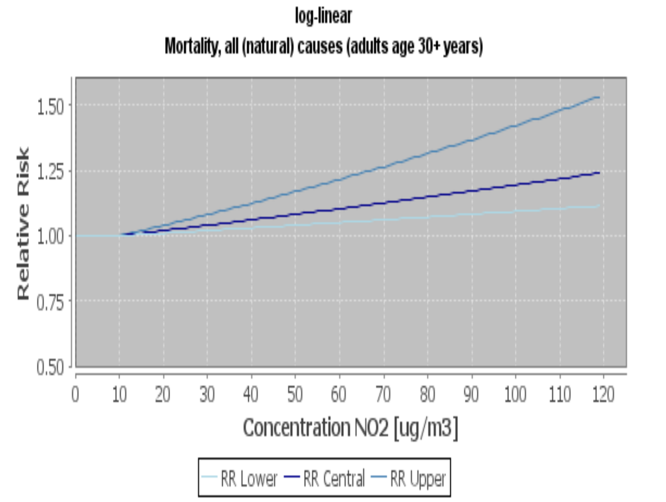
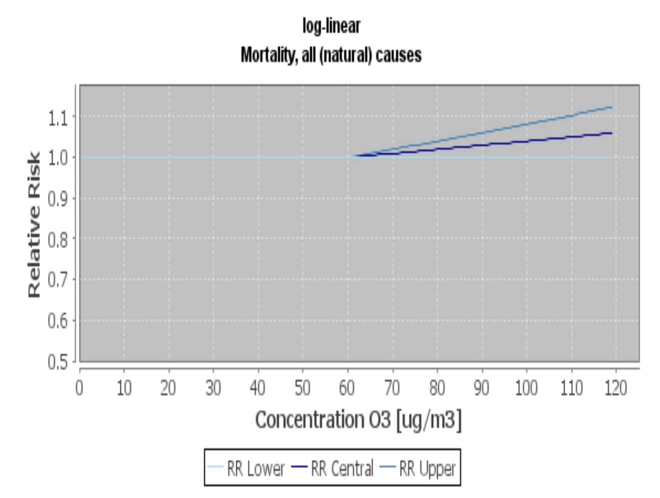


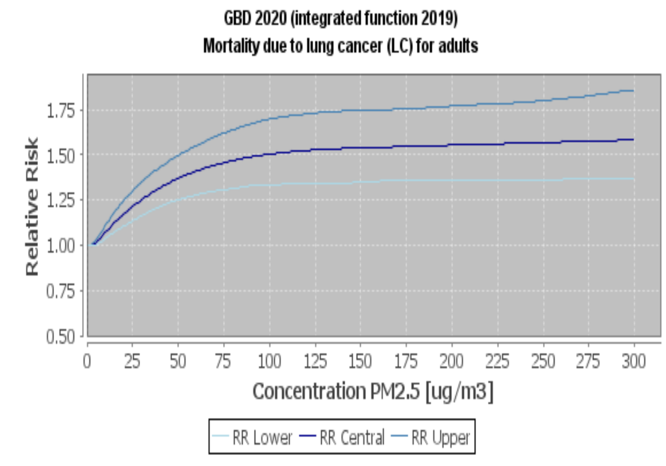
c. NO2 = 33.201



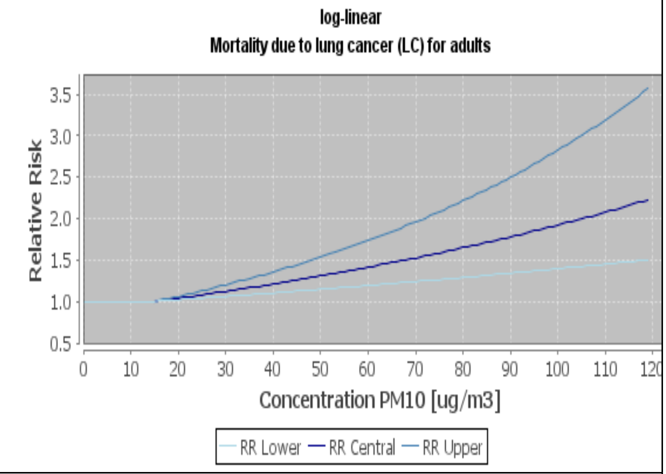
d. O3 = 40.649

Figure 5.Health Relative risk of Delhi City

Chennai, a sprawling megacity covering 426 sq. km with a population of 6,407,000, faces severe air pollution challenges. Located at latitude 13.0827 and longitude 80.2707, the city has reported 4907 cases. Alarmingly, key air quality indicators depict elevated levels of pollutants: PM2.5 at 29.407 µg/m³, PM10 at 68.324 µg/m³, NO2 at 11.244 µg/m³, and O3 at 38.701 µg/m³. The findings highlight the urgent need for focused initiatives in Chennai to tackle the crucial problem of pollution in the air and its possible consequences on individuals and the environment.



a. PM2.5 = 29.407



b. PM10: 68.324

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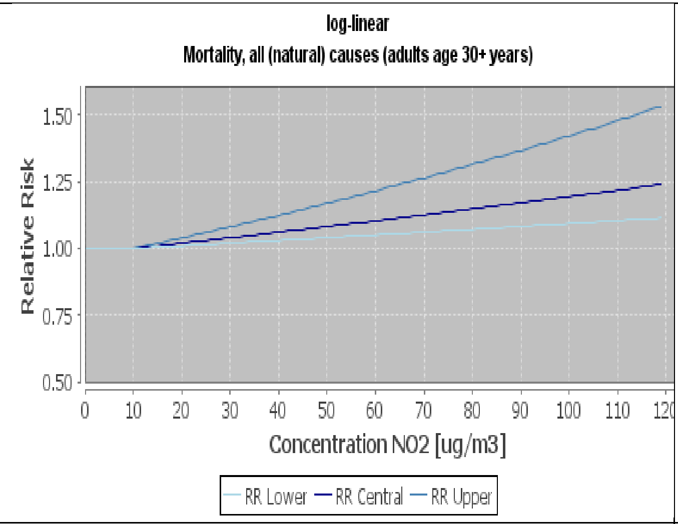
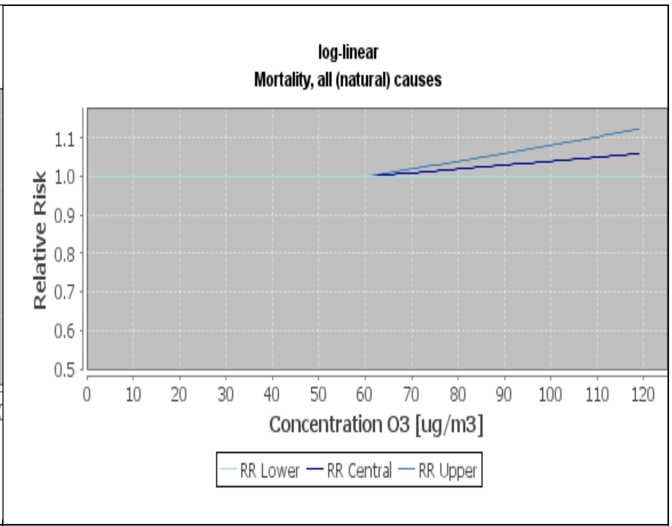


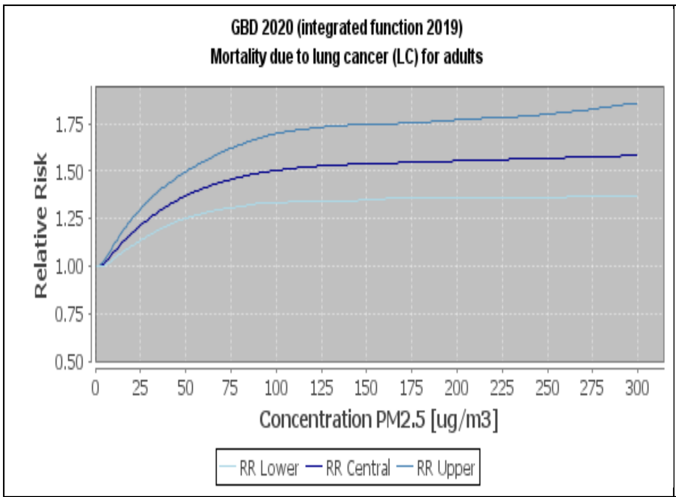
c. **NO2 = 11.244**



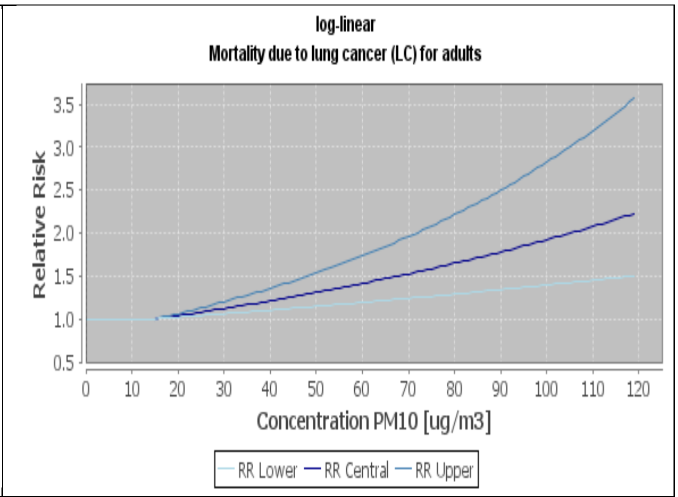
d. **O3 = 38.701**

Figure 6.Health Relative risk of Chennai City

Bangalore, an expansive megacity sprawling over 741 sq km and inhabited by 13,608,000 people, confronts grave air pollution issues. Positioned at latitude 12.9716 and longitude 77.5946, the city has reported 1163 cases. Disturbingly, critical air quality indicators reveal heightened concentrations of pollutants: PM2.5 at 30.465 µg/m³, PM10 at 67.031 µg/m³, NO2 at 21.410 µg/m³, and O3 at 35.637 µg/m³. These concerning statistics underscore the urgent need for comprehensive measures in Bangalore to tackle the escalating problem of air pollution, emphasizing the potential consequences for public health and the environment. Addressing these challenges is imperative to ensure the well-being of the city's residents and to sustain the overall environmental quality in this bustling urban centre.



a. **PM2.5: 30.465**



b. **PM10: 67.031**

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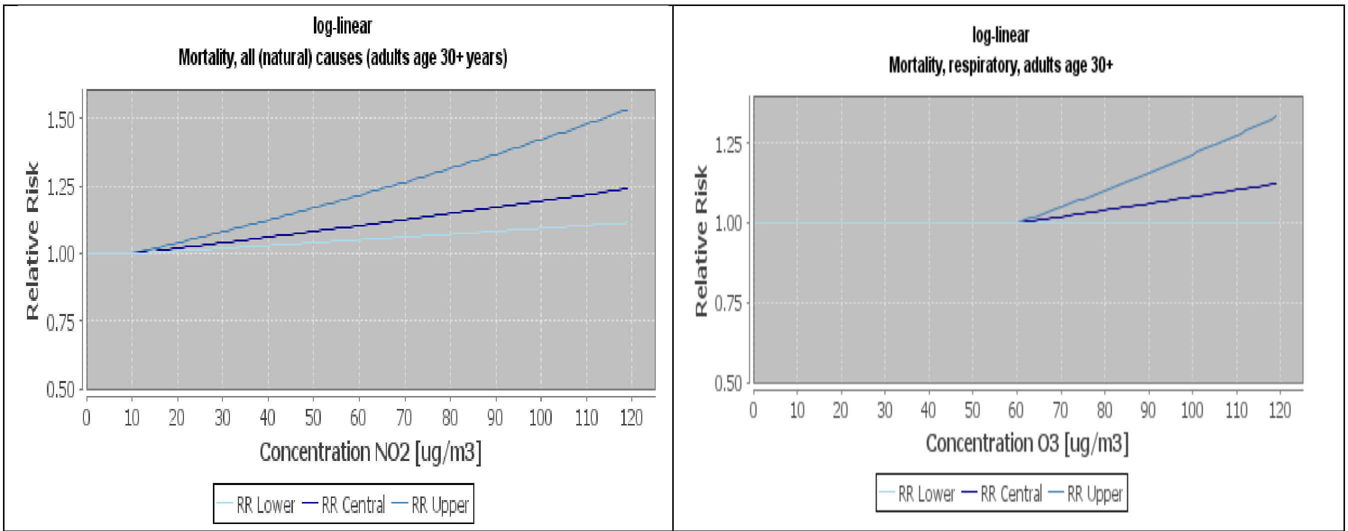

c. NO2: 21.410 **d. O3: 35.637**

Figure 7. Health Relative risk of Bangalore City

H02: There is no significant relationship between Air Quality Index (AQI) and Health Index (HI).

Correlation

In this hypothesis assessment, we have analysed the correlation. Correlation evaluation is a statistical method used for study to ascertain the relationship between both variables and assess the magnitude of their linear connection. The correlation method is used to quantify the extent of a change in one variable due to an alteration in another one. A high correlation signifies a robust connection between the variables, while a low correlation suggests a weak relationship among the two variables.

Positive correlation: When two variables have a positive correlation, it indicates that they both display a consistent movement in the same direction. There is a positive connection between the rise of one variable and the rise of another variable, & the same also holds for their reduction.

Negative correlation: A negative correlation between two variables shows that both of them are going against one other. An increase in one variable results in a corresponding reduction in the other.

If the significant value is >0.01, the correlation is not statistically significant.

Table 4 Correlation of AQI and PM2.5

		AQI	PM2.5
AQI	Pearson Correlation	1	0.669
	Sig. (2-tailed)	-	0.046
	N	6	6
PM2.5	Pearson Correlation	0.669	1
	Sig. (2-tailed)	0.046	-
	N	6	6

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The above table displays the correlation between air quality index and relative risk of PM2.5 pollutant. From the table it is observable that the Pearson correlation value of air quality index and PM2.5 is 0.669 and the significance value is 0.046. The obtained correlation value is greater than 0.5, it indicates that there is a strong positive correlation, and the significance value is less than 0.05, it says that no relation between air quality index and relative risk of PM2.5 was significant. So, we can conclude that there is a significant strong positive relation air quality index and relative risk of PM2.5.

Table 5 Correlation of AQI and PM10

		AQI	PM10
AQI	Pearson Correlation	1	0.794
	Sig. (2-tailed)	-	0.039
	N	6	6
PM10	Pearson Correlation	0.794	1
	Sig. (2-tailed)	0.039	-
	N	6	6

The table presents the correlation between the air quality index and the relative risk of PM10 pollutant. Upon examination of the data, it is clear that the coefficient of Pearson correlation between the air pollution index and PM10 particle is 0.794, with a significant value of 0.039. Based on the correlation coefficient exceeding 0.5, indicating an elevated positive correlation, and the significance level being below 0.05, indicating an important connection between the air quality index and the inverse risk of PM10, it can be concluded that there is a statistically significant and strong positive correlation between the the air quality index and the relative risk of PM10.

Table 6 Correlation of AQI and No2

		AQI	NO2
AQI	Pearson Correlation	1	0.654
	Sig. (2-tailed)	-	0.021
	N	6	6
NO2	Pearson Correlation	0.154	1
	Sig. (2-tailed)	0.021	-
	N	6	6

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The table depicts the relationship among an air purity index and the corresponding danger level of NO2 pollutant. After careful examination, it is evident that the coefficient of Pearson correlation among the air quality index and nitrogen oxides pollutants is 0.654, with a significant value of 0.021. When the correlation value exceeds 0.5, indicating a strong positive correlation, and the significance value is below 0.05, suggesting an important connection between the air quality index and the relative risk of nitrogen dioxide, we can conclude that there is a statistically significant and strong beneficial connection between the air quality index and the relative risk of NO2.

Table 7 Correlation of AQI and O3

		AQI	O3
AQI	Pearson Correlation	1	0.767
	Sig. (2-tailed)	-	0.017
	N	6	6
O3	Pearson Correlation	0.367	1
	Sig. (2-tailed)	0.017	
	N	6	6

The table demonstrates the correlation between the air quality index and the relative risk of O3 pollutant. Upon examination, it's evident that the correlation value between Pearson and linking the air quality index and O3 pollutant stands at 0.767, accompanied by a significance value of 0.017. Given that the correlation value exceeds 0.5, indicating a strong positive correlation, and the significance value is below 0.05, suggesting a important connection between the air quality index and the relative risk of O3, it can be concluded that a statistically significant and strong positive relationship exists between the air quality index and the relative risk of O3.

Conclusion

This extensive investigation aimed to assess how air pollution affects residents' health in prominent urban centres of India, such as Hyderabad, Chennai, India, Mumbai, Delhi, and Kolkata. The AirQ 2.2.3 software was used to assess levels of the ozone layer nitrogen oxides, sulphur dioxide, and particles, which are important pollutants. These measurements serve as indications for human exposure and the resulting health effects. This approach is recommended by the World Health Organisation (WHO). The results underscore a substantial health cost associated with these cities' air pollution, emphasizing the urgent need for effective interventions to alleviate adverse health impacts. The study calls for targeted strategies and policies to mitigate air pollution levels and safeguard public health in urban environments. The health risk assessment involved complex mathematical estimations and modelling, considering population estimates, quantification of assessing the extent to which the population is exposed to contaminants and evaluating the negative health effects by using concentration-response functions. Examining specific pollutant levels, PM2.5 concentrations were notably high in Delhi, while PM10 concentrations followed a similar trend. Variations in nitrogen dioxide (NO2) and ozone (O3) levels highlighted diverse air quality challenges in each city, emphasizing the need for targeted strategies to mitigate health risks associated with specific pollutants.

The provided data elucidates correlations between the air quality index (AQI) and diverse pollutant types, emphasizing statistically significant relationships for PM10, NO2, and O3. The Pearson correlation coefficients

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unveil substantial positive associations: PM10 exhibits a correlation coefficient of 0.794 ($p = 0.039$), NO2 demonstrates 0.654 ($p = 0.021$), and O3 displays 0.767 ($p = 0.017$). These values denote robust connections, suggesting that elevated AQI values correspond to escalated relative risks of these pollutants. However, in the case of PM2.5, despite a notable positive correlation coefficient of 0.669, the significance value ($p = 0.046$) does not meet the threshold for statistical significance. This discrepancy indicates that while there is a strong association between AQI and PM2.5, it might not signify a consistent relationship between AQI and the relative risk of PM2.5 pollutant levels. Consequently, the data supports the existence of statistically significant and strong positive relationships between AQI and the relative risks of PM10, NO2, and O3 pollutants, but fails to establish a statistically significant association between AQI and PM2.5's relative risk, suggesting caution in assuming a direct relationship between these specific air quality metrics.

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Suggestions

To effectively tackle the urgent problem of pollution in the air in important Indian metropolitan centres, a comprehensive approach is required. Strict implementation and frequent revisions of emission regulations for companies and automobiles are of utmost importance., coupled with incentivizing the transition to cleaner production methods. Promoting the adoption of clean transportation, such as electric vehicles and robust public transit, is vital for reducing vehicular emissions. Public awareness campaigns are crucial to educate residents about the health risks associated with air pollution and encourage individual actions like using masks and adjusting outdoor activities during peak pollution times. Strict traffic management measures, legislative reinforcement, and international collaboration are imperative for effective pollution control. Additionally, fostering research and innovation in technologies for air quality improvement is key to developing sustainable solutions. The collaborative implementation of these suggestions, involving government bodies, environmental agencies, industries, and the public, is essential to comprehensively address air pollution and protect the health of urban populations.

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