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Mapping Pollution and Health Risk Based on Income in Major Indian Cities

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ABSTRACT

Air pollution has become one of the most pressing environmental and public health challenges in urban India, with far-reaching consequences for both human health and socioeconomic well-being. Rapid urbanization, industrial activity, vehicular emissions, and construction have led to a sustained rise in pollutant levels, particularly PM10, PM2.5, NO_2, SO_2, CO, and O_3. These pollutants degrade air quality and contribute to respiratory illnesses, cardiovascular diseases, hospital admissions, and premature mortality. However, the impacts are not uniformly distributed across the population. People from low-income groups, who often reside in densely populated and underserved neighborhoods, bear a disproportionate burden due to limited healthcare access, higher exposure levels, and inadequate living conditions. Understanding the combined effects of pollution, health risks, and income disparity is essential for developing effective and inclusive public health and environmental policies.

This study presents a data-driven visual analysis of air quality, health indicators, and socioeconomic factors across major Indian cities. Using Tableau as the primary visualization tool, multiple interactive dashboards were developed to explore pollutant concentration, hospitalization patterns, and mortality rates. The analysis revealed that PM10 is the most dominant pollutant in terms of average concentration across cities, highlighting the pervasive presence of particulate matter in the urban environment. A donut chart of hospital admissions further demonstrated that cities such as Kolkata and Delhi experience the highest pollution-related healthcare burden, indicating a direct correlation between deteriorating air quality and rising medical cases.

A critical finding emerged when analyzing hospital admissions per unit of pollutant exposure: Carbon Monoxide (CO), although less concentrated compared to other pollutants, resulted in the highest number of hospitalizations per unit exposure, underlining its acute toxicity and underestimated health impact. Mortality analysis through grouped bar charts emphasized that low-income populations consistently face higher mortality rates than middle- and high-income groups, confirming the intersection between environmental pollution and social inequality. To further contextualize localized risks, the study examined Kolkata's pollutant profile, which revealed dangerously high levels of particulate matter combined with significant gaseous pollutants, reinforcing its position as a high-risk city.

This project provides a comprehensive integration of environmental, health, and socioeconomic data to uncover critical insights into urban air pollution and its unequal health impacts. The findings underscore the need for policy frameworks that go beyond generalized pollution control, instead focusing on equity-driven interventions that target high-risk cities and vulnerable income groups. By employing visual analytics, the study demonstrates how complex datasets can be translated into accessible, actionable insights for policymakers, healthcare authorities, and urban planners. Ultimately, this research advocates for a people-centered approach to environmental governance where clean air and good health are recognized as universal rights rather than privileges.

Keywords: Air Pollution, PM10, PM2.5, Carbon Monoxide Toxicity, Public Health Risk, Respiratory Illnesses, Hospital Admissions, Mortality Analysis, Socioeconomic Disparity, Income-Based Vulnerability, Data Science, Data Visualization, Tableau Dashboards, Urban Health Analytics, Environmental Inequality, Policy-Oriented Insights, Health Risk Mapping, Pollution Hotspots, Sustainable Urban Development, India.

Introduction

With the accelerating pace of urbanization in India, air pollution has become one of the most pressing environmental and public health challenges. Metropolitan cities such as Delhi, Kolkata, and Mumbai frequently record hazardous levels of particulate matter (PM10 and PM2.5), which are capable of penetrating deep into the human respiratory system and triggering chronic respiratory and cardiovascular diseases. The consequences are severe, leading to increased hospital admissions, rising cases of asthma and bronchitis, and premature mortality.

Beyond the environmental dimension, social and economic factors further intensify the health burden. Income inequality, poor access to healthcare services, overcrowded housing, and high population density disproportionately affect low-income groups, making them more vulnerable to the effects of poor air quality. These populations often live in underserved urban zones where pollution levels are higher and healthcare support is limited, thereby amplifying health risks and widening inequality.

This study focuses on how pollution levels vary across major Indian cities and how they correlate with health outcomes and income disparities. Unlike traditional studies that analyze pollutants in isolation, this research integrates multiple dimensions—pollutant concentrations, hospital admissions, respiratory illness cases, mortality rates, literacy levels, income groups, and access to healthcare—to build a comprehensive understanding of urban health risk.

The study is guided by four central research questions:

1. Which pollutants are most dominant in major Indian cities?
2. How do these pollutants influence hospital admissions and mortality rates?
3. Are low-income populations disproportionately vulnerable to pollution-related health issues?
4. Which cities face the highest combined environmental and health burden?

To address these questions, we employ data visualization techniques in Tableau, developing interactive dashboards such as treemaps, bar charts, donut charts, and grouped comparisons. These tools simplify complex datasets into clear visual patterns, enabling deeper understanding of relationships between pollution, health outcomes, and socioeconomic conditions.

Ultimately, this project is not only an environmental analysis but also a people-centered investigation that highlights the unequal distribution of health risks. By identifying the most vulnerable populations and high-risk cities, the study provides valuable insights for policymakers, healthcare officials, and urban planners to design equitable interventions that address both pollution control and public health improvement.

Literature Review

Air-pollution research spans geospatial mapping, temporal trend analysis, exposure/risk modeling, and—less commonly—equity-focused assessments. Across this body of work, particulate matter (PM10/PM2.5) consistently emerges as the dominant pollutant, with mounting evidence for the health relevance of ozone (O_3) and carbon monoxide (CO). Below, we synthesize five representative studies and position the contribution of this work.

A. Geospatial and Temporal Characterization

Waheed et al. [1] analyzed PM2.5, PM10, NO_2, SO_2, and CO across urban Northeastern Pakistan and found persistent exceedances of standards, strong winter seasonality, and a high PM2.5/PM10 ratio (0.74), indicating substantial fine particulate burden and associated risk. Their GIS-led hotspot mapping is powerful for urban planning, yet it omits socioeconomic vulnerability layers that determine who is most exposed and least protected. Bian et al. [4] advanced spatial-temporal exposure assessment by fusing census data with Location-Based Service (LBS) mobility, revealing daytime shifts of exposure toward urban cores and highlighting O_3's outsized contribution to annual mortality. While methodologically innovative, the approach is data- and computation-intensive, which can limit uptake by public agencies lacking similar data infrastructure.

B. Health Risk Assessment and Source Dynamics

Sui et al. [2] conducted a five-year assessment in Jinan (2013–2017), showing PM10/PM2.5 as primary health-risk drivers while flagging O_3 as an emergent threat in urban and suburban areas. Using time-series, spatial maps, back-trajectory, and PSCF, they linked seasonal risk peaks (especially winter) to regional transport. However, health risks were summarized at population level without segmenting by income or access to care—an increasingly critical dimension for policy.

Kaushik et al. [3] assessed eight Haryana cities (1999–2000) and reported PM10/TSPM exceedances across residential, commercial, industrial, and sensitive zones, with winter peaks and hospital admissions rising in tandem with pollution. The Indian context and hospital-linkage are notable strengths; nonetheless, the short sampling window and limited city size constrain generalizability to today's fast-growing metros.

C. Socio-environmental Vulnerability and Equity

Morandeira et al. [5] integrated hazard indices (air, water, vectors) with socioeconomic vulnerability in Buenos Aires using GIS, Moran's I, and GWR. Over 83% of residents were exposed to at least one high-level hazard, and socially vulnerable groups faced the greatest risks. Although not air-pollution-exclusive, this study exemplifies how equity-aware spatial analytics can guide interventions toward the most affected communities.

D. Comparative Insights and Gaps

Across studies, four convergent insights stand out:

1) PM10/PM2.5 dominance and winter seasonality are consistent, with exceedances linked to combustion and meteorology [1], [2], [3].

2) O_3 and CO merit heightened attention—O_3 for its rising contribution to mortality [2], [4], and CO for acute toxicity despite lower concentrations (often underexplored).

3) Visualization is central—GIS maps, trend plots, back-trajectory/PSCF communicate risk patterns effectively [1], [2], [5].

4) Equity remains underrepresented—few studies jointly analyze pollution, health outcomes, and socioeconomic vulnerability; when they do, they're often outside the Indian metropolitan context [5].

This reveals three actionable gaps our study addresses:

- Integrated equity lens: Bringing income group, literacy, and health-care access into the same frame as pollutant trends.

- Per-unit toxicity framing: Comparing hospital admissions per unit concentration foregrounds pollutants like CO.

- Accessible visual analytics: Using Tableau delivers interactive dashboards beyond static GIS/statistical outputs.

E. Positioning of the Present Study

Building on geospatial and temporal characterizations [1], [2], [3] and exposure-aware designs [4], while adopting the equity sensibility of [5], this work contributes a multi-dimensional, interactive visualization framework for Indian metros. It triangulates

(i) pollutant dominance (PM10/PM2.5), (ii) per-unit health impact highlighting CO toxicity, and (iii) income-stratified hospital admissions and mortality, to surface high-risk cities and most-affected populations—outputs directly actionable for targeted mitigation and equitable health planning.

Table 1. Summary of Representative Literature and Relation to This Study

Study	Geography / Period	Methods & Visuals	Key Findings	Limitations vs. This Work
Waheed et al. [1] (2025)	Urban NE Pakistan; seasonal	GIS hotspot mapping; standards comparison	PM2.5/PM10 exceedances; winter peaks; ratio=0.74	No income/health-care layers; limited equity framing
Sui et al. [2] (2021)	Jinan, China; 2013–2017	Time-series, spatial maps, back-trajectory, PSCF	PM drives risk; O_3 emerging; AQI understates winter risk	No socioeconomic segmentation; static visuals
Kaushik et al. [3] (2006)	8 Haryana cities; 1999–2000	Seasonal trends; site-type comparisons; hospital linkage	PM exceedances; winter peaks; respiratory admissions rise	Short study window; smaller cities
Bian et al. [4] (2024)	Nanjing, China; annual	LBS mobility + census; exposure maps	O_3 dominates annual mortality; exposure shifts by day	High data/compute needs; limited policy translation
Morandeira et al. [5] (2019)	Buenos Aires district; cross-sectional	GIS hazards + vulnerability; Moran's I; GWR	83% exposed to ≥1 hazard; vulnerability concentrates risk	Not air-only; outside Indian metro setting

Methodology

1. Data Collection and Preparation

Air quality, health, and socioeconomic data were collected from reliable sources such as CPCB, hospitals, government health portals, and census records. Major pollutants included PM2.5, PM10, NO_2, SO_2, CO, and O_3. Health data included hospital admissions, asthma cases, and mortality rates, while socioeconomic data covered income groups, literacy, and population density.

The collected datasets were cleaned to remove missing, duplicate, and inconsistent values. Data were aggregated by city and income group. New calculated indicators were created, such as hospital admissions per pollutant unit and mortality by income group, to make the data ready for analysis.

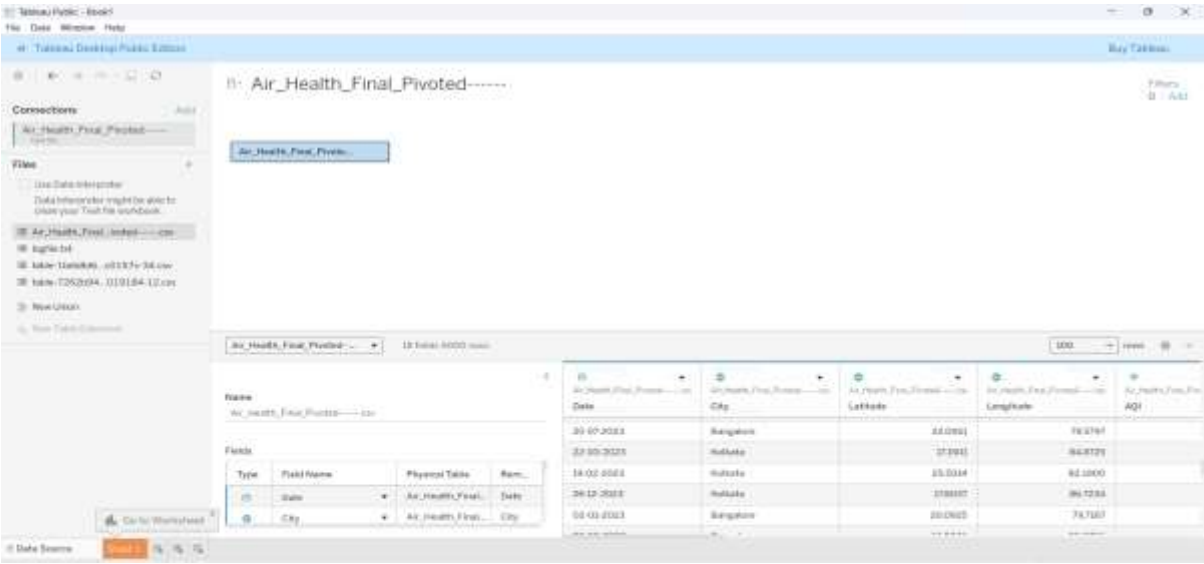
Date	City	Latitude	Longitude	AQI	Temperat	Humidity (	Asthma Ca	Respirator	Hospital A	Mortality I	Literacy R	Population	Househol	Access to	Slum Popu	Pollutant	Pollutant Value
########	Bangalore	24.88056	88.03809	192	33.59694	61.40011	25	23	14	0.36	79.36	9982	Low	95.8	42.9	PM2.5	151.7417
########	Bangalore	13.28847	74.52724	341	17.48205	80.08166	41	12	61	0.78	93.77	6107	High	49.9	21.8	PM2.5	140.6891
########	Delhi	13.24955	79.39176	161	39.71941	53.65186	44	33	29	1.22	88.3	3341	Middle	63.4	33.4	PM2.5	72.64987
########	Hyderabac	18.01304	73.45558	255	35.31304	20.20739	30	22	60	0.9	84.97	13855	Low	83.8	9.3	PM2.5	218.9397
########	Mumbai	20.62056	84.3425	180	20.96752	36.9961	9	52	42	1.35	73.9	10407	High	92.9	9.7	PM2.5	178.927
########	Ahmedaba	25.07244	87.12199	159	17.39216	42.66383	45	38	65	0.99	73.9	2338	High	80.3	7.2	PM2.5	214.3398
########	Mumbai	23.69607	77.16858	116	40.11066	87.61961	25	81	51	1.07	71.45	7895	Middle	55.5	31.1	PM2.5	218.9281
########	Kolkata	19.94526	86.19013	135	17.36705	83.82413	21	60	58	1.03	91.65	14254	Low	80.5	24.2	PM2.5	194.6383
########	Pune	17.2233	77.3586	324	17.74062	86.44194	11	51	50	0.73	85.03	4708	Low	57.8	29.7	PM2.5	126.6263
########	Mumbai	28.65457	87.00801	276	27.82225	77.80309	31	40	8	1.07	87.7	13344	Low	83.1	28.4	PM2.5	164.3203
########	Chennai	19.63366	84.56181	374	19.04393	44.61534	26	72	47	0.2	70.51	3750	Middle	97.2	20.8	PM2.5	65.28039
########	Mumbai	20.03191	85.35655	59	42.41009	83.41135	32	35	66	1.3	94.25	7604	Low	83.3	35.5	PM2.5	178.202
########	Kolkata	15.48526	73.0809	337	29.10852	88.71792	19	27	8	1.19	90.81	4421	Middle	91.8	39.1	PM2.5	69.43572
########	Ahmedaba	25.45799	87.81984	161	32.07453	44.50499	38	91	69	0.44	75.31	9119	Middle	40.1	5.7	PM2.5	182.6689
########	Mumbai	23.86018	84.13607	73	42.84318	38.23892	40	66	66	1.18	74.55	10901	Middle	83.1	14.3	PM2.5	80.5116
########	Chennai	16.38816	77.55412	340	30.9079	58.28414	39	16	6	0.12	74.59	7319	High	89.8	37.1	PM2.5	55.86129
########	Delhi	14.20162	85.73856	388	25.60773	33.10065	12	57	13	0.4	77.61	8609	Low	42.4	22.4	PM2.5	66.36259
########	Pune	23.65189	77.19173	375	38.91465	22.2837	13	89	61	0.19	83.12	7387	Low	92.3	34.8	PM2.5	30.43827
########	Kolkata	23.24128	86.41496	217	28.28551	86.20818	43	69	49	1.19	80.8	13918	Middle	55.4	20.6	PM2.5	188.1227
########	Delhi	17.2175	74.55625	158	24.55408	84.80184	39	42	22	1.16	77.28	13834	Middle	79.9	22.6	PM2.5	191.1282
########	Delhi	27.92364	83.7775	239	36.69688	31.38577	21	12	52	1.24	85.3	5993	Low	88	12.1	PM2.5	143.2853
########	Delhi	15.28671	81.2349	245	39.04817	48.54182	17	13	46	0.11	73.49	10680	Middle	79.8	16.6	PM2.5	65.49982
########	Bangalore	19.73089	74.30594	82	38.75149	78.17254	47	13	45	0.8	77.3	10044	Low	45.5	32.2	PM2.5	48.38195
########	Pune	27.80913	76.57354	254	44.33023	66.27002	28	51	62	1.09	79.16	10238	High	75.8	24.5	PM2.5	34.20837
########	Ahmedaba	19.53169	72.9935	361	38.60001	47.63513	42	18	46	0.32	81.4	13551	Middle	73	39.8	PM2.5	66.4646

2. Data Integration, Connection, and Analysis

After cleaning, the data from pollution, health, and socioeconomic sources was combined into a single dataset. This integration helped match pollution levels with hospital records and income groups, making it easier to find patterns.

The integrated data was then connected to Tableau for further study. In Tableau, calculated fields were created, such as hospital admissions per pollutant unit and mortality by income group.

Finally, different types of analysis were done, including comparing pollution across cities, studying mortality trends, and checking how income groups are affected. These steps prepared the data for creating clear dashboards and visual results.



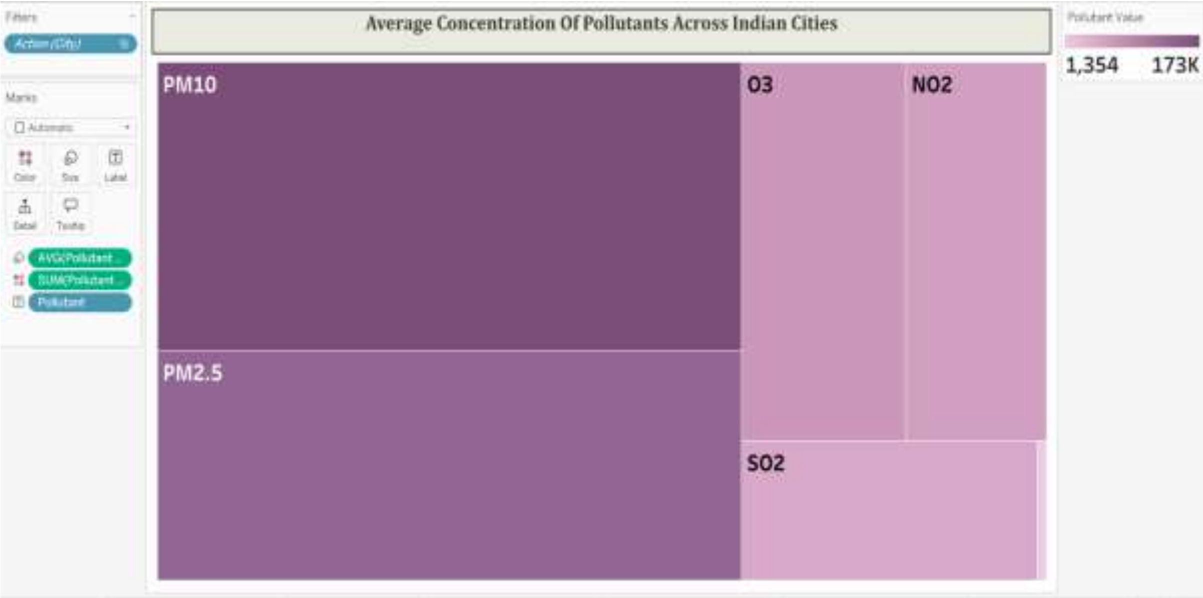
3. Data Visualization

1. **Treemap of average pollutant concentration** – Shows pollutant distribution intensity across cities in compact block visualization.
2. **Donut chart of hospital admissions by city** – Highlights city-wise hospital admission proportions linked to pollution exposure.
3. **Bar charts of mortality by city and income group** – Compares deaths across cities and income levels due to pollution.
4. **Comparative chart of hospital impact per pollutant** – Evaluates health admissions impact caused by each specific pollutant type.
5. **City-wise pollution profiles** – Displays pollutant levels and patterns for individual cities comprehensively.

6. **Grouped bar chart of income-based health risk** – Compares pollution-related health risks across different population income categories.

Results:

Tree chart



Purpose: To identify which pollutant has the highest average concentration across all cities.

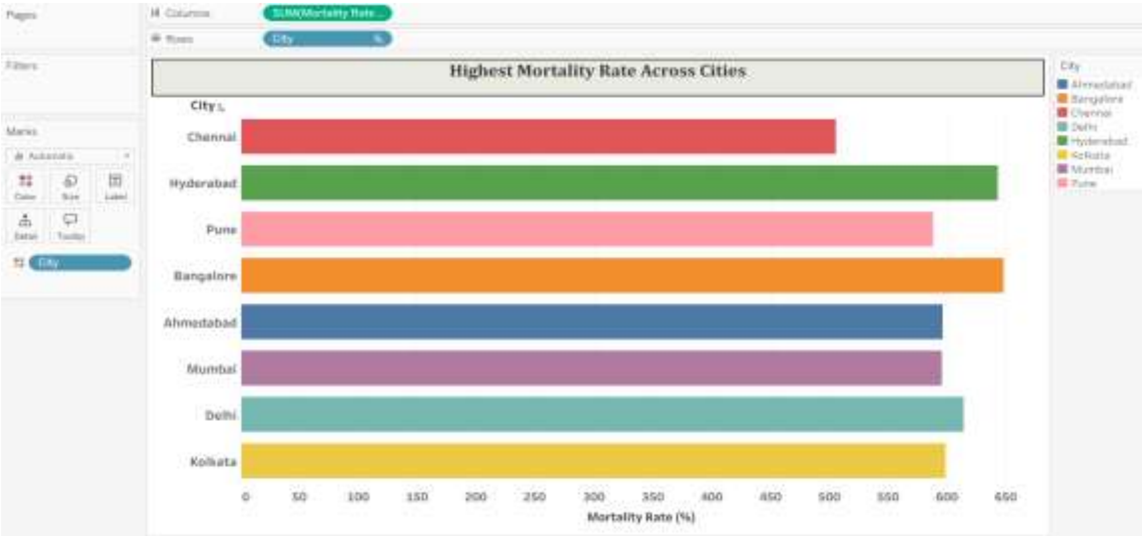
This chart shows that PM10 has the largest presence in urban air, followed by PM2.5, indicating that particulate matter is the most dominant type of pollution. Gaseous pollutants like O_3, NO_2, SO_2, and CO are present in lower concentrations. However, their health impact may still be high despite smaller volumes. The chart helps prioritize which pollutants need the most urgent attention in terms of regulation.

Donut Chart

Purpose: To compare the total number of hospital admissions due to pollution-related illnesses in different cities.

Kolkata has the highest number of hospital admissions, suggesting a greater health burden due to environmental factors. Delhi and Mumbai also report high admissions, indicating their exposure to harmful air quality. In contrast, cities like Hyderabad and Chennai show relatively fewer cases. This chart highlights where pollution is translating into significant healthcare demand.

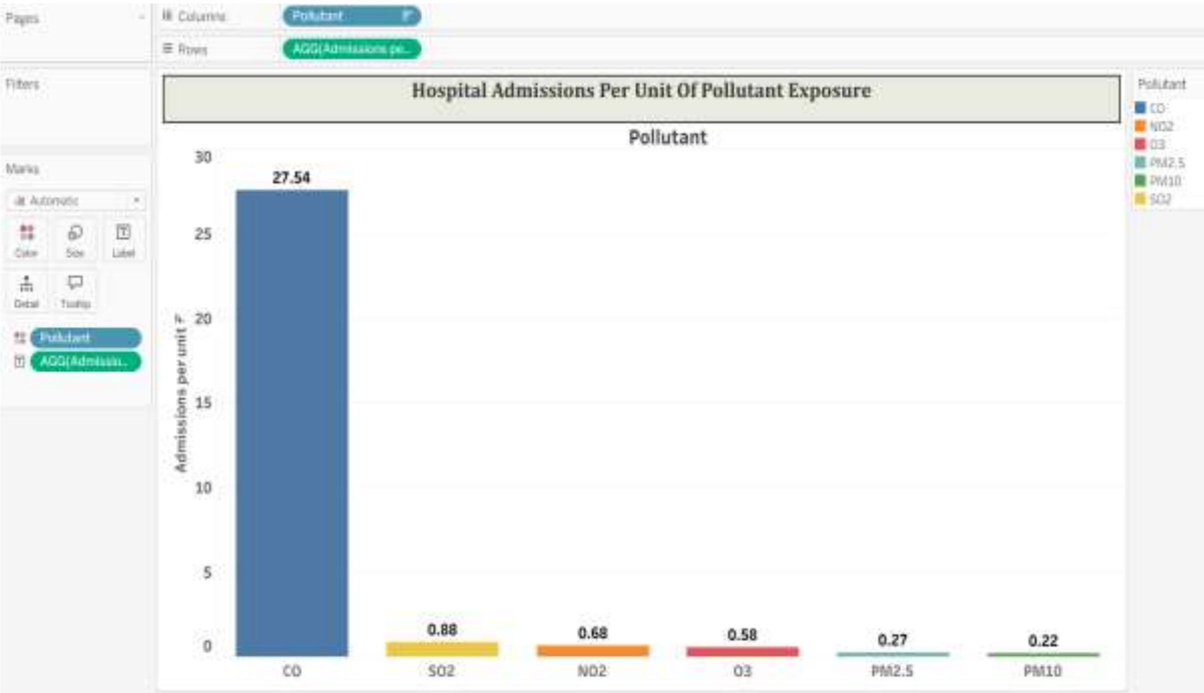
Horizontal Bar Chart



Purpose: To show which cities report the highest death rates caused by pollution-related issues.

Bangalore, Hyderabad, and Delhi exhibit the highest mortality rates, pointing to severe long-term health impacts of pollution in these areas. Mortality goes beyond hospital visits and shows the ultimate consequence of poor air quality. This chart emphasizes cities where pollution is life-threatening, not just health-threatening. It also signals where urgent intervention may be needed to reduce fatalities.

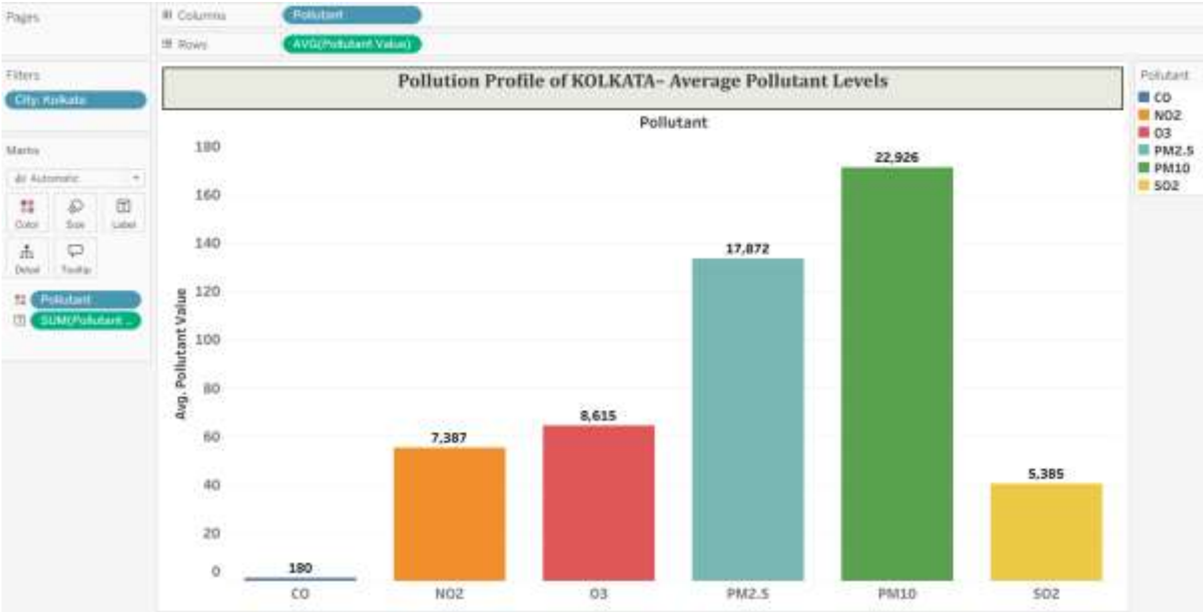
Vertical Bar Chart



Purpose: To determine which pollutant causes the most hospital admissions per unit of its concentration.

Carbon Monoxide (CO) causes the highest admissions per unit, indicating it is highly toxic even in smaller quantities. Though PM10 and PM2.5 are more abundant, their per-unit impact is lower. This chart helps in understanding not just how much of a pollutant is present, but how dangerous it is relative to its concentration. It shifts the focus from volume to intensity of health risk.

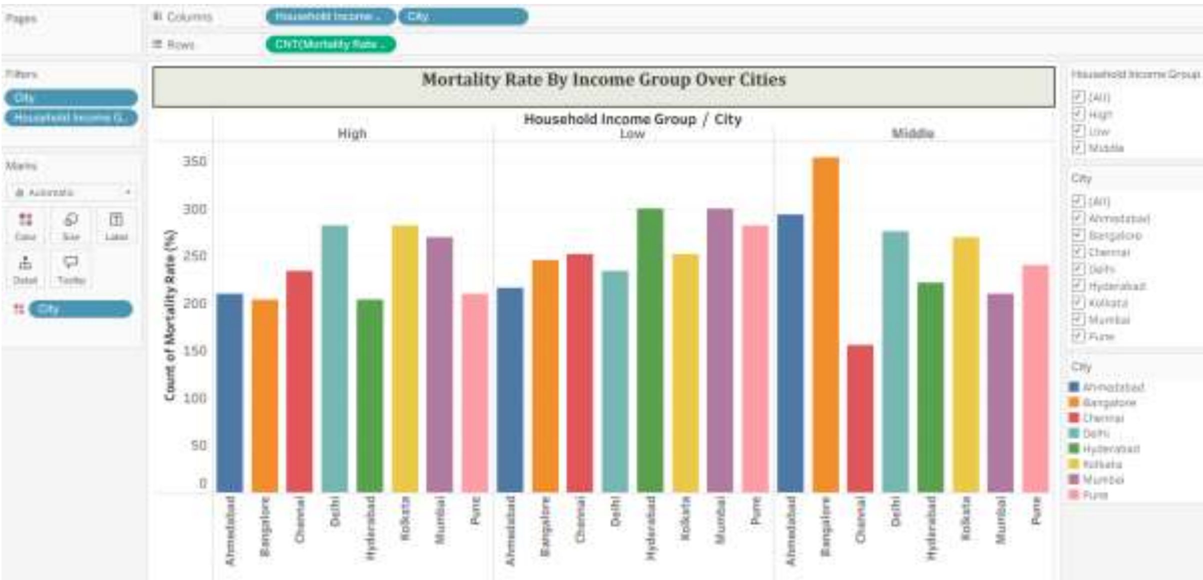
Vertical Bar chart



Purpose: To give a detailed view of which pollutants are most prominent in Kolkata specifically.

PM10 and PM2.5 are the most concentrated pollutants in Kolkata, followed by gases like NO_2 and O_3. Though CO has a low presence, its health risk remains significant. This city-specific analysis helps local authorities target the right pollutants for control measures. It also explains why Kolkata sees high hospital admissions as shown in previous chart

Grouped Bar Chart



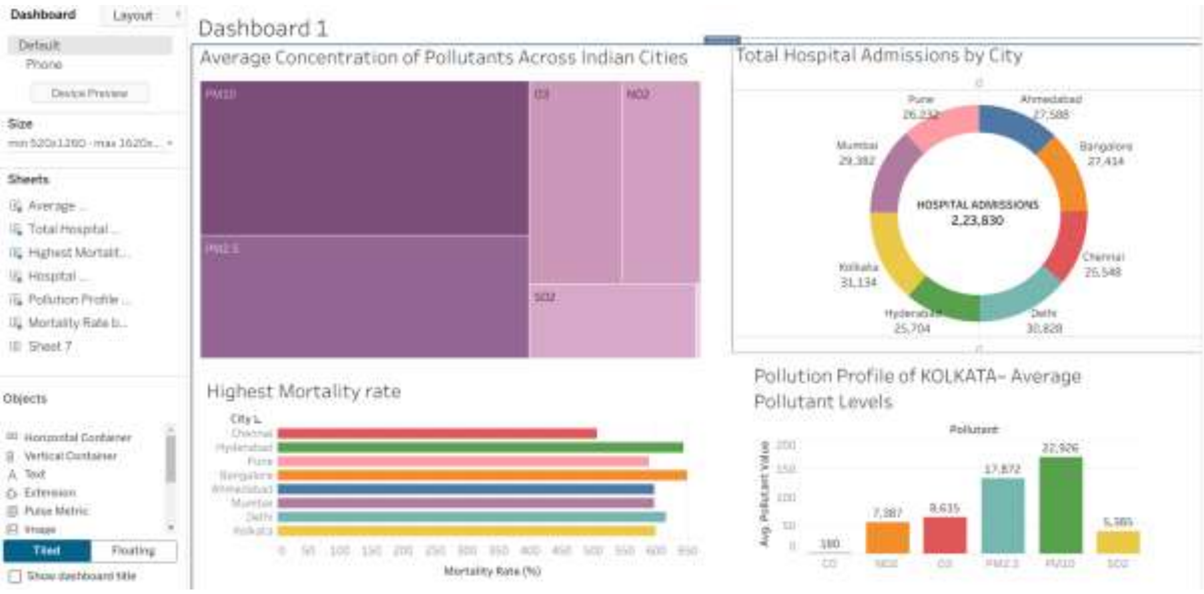
Purpose: To assess how mortality rates due to pollution differ across income groups in various cities.

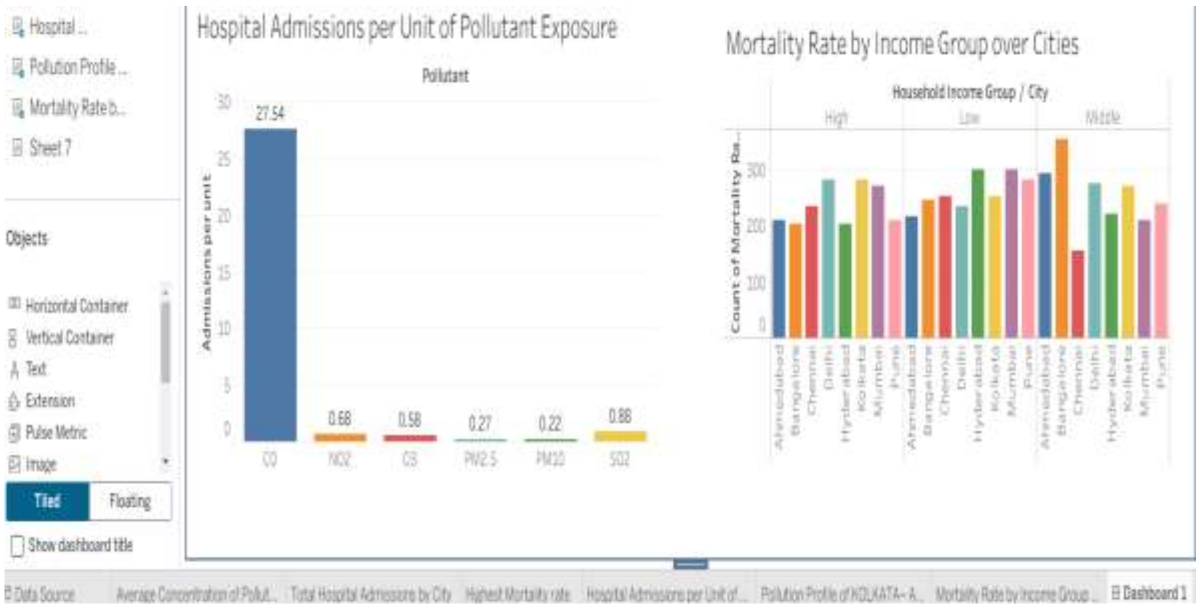
Low-income groups show the highest mortality in most cities, revealing their vulnerability to pollution due to weaker healthcare access and living conditions. Middle-income groups have moderate risk, while high-income groups are least affected. Bangalore's middle-income group stands out with unexpectedly high mortality. This chart proves that health impacts of pollution are deeply tied to socioeconomic status.

Building Dashboard.

One dashboards were developed by organizing series of charts:

Dashboard 1: This dashboard shows how much each pollutant (PM2.5, PM10, NO_2, SO_2, CO, O_3) is present in different cities. The bigger the block, the higher the pollution level. It helps quickly identify which pollutant is most dominant in each city.





Discussion

This project offers a comprehensive analysis of how air pollution affects public health across major Indian cities, with a special focus on income-based health disparities. By combining air quality data with health and socioeconomic indicators, we were able to visualize not just the extent of pollution, but also its real-world consequences on different populations.

The analysis revealed that **PM10 and PM2.5** are the most widespread pollutants across cities, contributing significantly to the overall pollution load. However, gases like **CO**, despite their lower concentrations, were found to be **more harmful per unit**, causing a higher number of hospital admissions relative to their presence. This insight highlights the need to pay attention not just to the volume of pollutants, but to their **health impact per unit exposure**.

At the city level, **Kolkata, Delhi, and Bangalore** stood out for their high hospital admissions and mortality rates, indicating a **severe public health burden**. The deep-dive into Kolkata's pollution profile confirmed that it suffers from dangerously high levels of particulate matter, explaining its leading position in hospital cases.

Most importantly, the income-based analysis showed that **low-income groups suffer the highest mortality**, proving that pollution's effects are not equally distributed. People in poorer communities are more exposed and less equipped to deal with health crises, making them the most vulnerable.

Overall, this project demonstrates how data visualization tools like Tableau can help **translate raw data into actionable insights**, aiding urban planners, policymakers, and health officials in designing **targeted interventions** to reduce pollution and protect the most at-risk populations.

COMMUNITY IMPACT

The insights from this project can be **directly applied** in various real-world contexts to improve urban living conditions and protect public health. By highlighting which pollutants are most harmful and which cities and income groups are most affected, the analysis serves as a powerful tool for **targeted policy-making, urban planning, and community health programs**.

Where It Can Be Used:

1. **Urban Policy & Government Planning:**

   Authorities can use these findings to identify pollution hotspots and implement stricter air quality regulations in high-risk cities like Kolkata, Delhi, and Bangalore.

2. **Public Health Interventions:**

   Health departments can focus resources such as mobile clinics, awareness drives, and preventive care in low-income areas with high mortality and hospital admission rates.

3. **NGO & Community Outreach:**

   Environmental and health NGOs can use the data to advocate for clean air initiatives, distribute masks or air purifiers, and educate residents about pollutant-specific health risks.

4. **City Infrastructure & Housing Projects:**

   Urban planners can design better living spaces by reducing exposure to pollution through green zones, better traffic flow, and pollution-monitoring systems in vulnerable communities.

5. **Academic & Research Use:**

   This project can support further studies on environmental justice, income inequality, and urban health, encouraging more data-driven research in policy and planning.

Why It Matters:

By focusing not just on pollution levels but also on health outcomes and income disparities, the project helps **bridge the gap between data and action**. It promotes equity, empowers communities, and ensures that clean air becomes a **shared priority and basic right**—not a privilege.

Conclusion

This project set out to explore the relationship between air pollution, health outcomes, and income-based disparities across major Indian cities. By combining environmental data with hospital admission records and socioeconomic indicators, we were able to present a comprehensive analysis of how different pollutants affect different segments of the population. The goal was not just to study pollution levels, but to understand who is suffering the most and why.

The analysis revealed that **PM10** is the most dominant pollutant in terms of concentration, while **Carbon Monoxide (CO)**, though less abundant, causes the highest number of hospital admissions per unit of exposure. Cities like **Kolkata**, **Delhi**, and **Bangalore** showed the highest health burdens, including both hospital visits and mortality rates. These findings help prioritize which pollutants and which cities require immediate attention for pollution control efforts.

A particularly significant insight from the study is the **disproportionate impact on low-income groups**. The grouped bar chart analysis showed that people in low-income categories suffer from the highest mortality rates in nearly every city. This highlights the intersection between environmental issues and social inequality, emphasizing the need for inclusive health and environmental policies that protect vulnerable populations.

In conclusion, this project not only brings out key patterns and risk factors but also demonstrates the power of data visualization in making complex issues easier to understand. It provides a strong foundation for city planners, health officials, and policymakers to design targeted interventions. Most importantly, it reinforces the message that **clean air and good health must be accessible to everyone—regardless of where they live or how much they ear**

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The following references were highly useful in supporting the analysis and approach of this project, offering insights into pollution exposure, health risk assessment, and socio-environmental impacts:

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