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ECOLOGICAL ANALYSIS OF AIR POLLUTION AND RESPIRATORY MORBIDITY USING PUBLIC HEALTH SURVEILLANCE DATA IN MAJOR INDIAN CITIES

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Abstract
Ambient air pollution has become a grave urban health crisis in India, with major cities experiencing recurrent spikes in fine particulate concentrations that correlate with increased respiratory illness. Across five metropolitan centers—Delhi, Mumbai, Kolkata, Bengaluru, and Chennai—this study explored the ecological association between monthly average pollutant levels ($PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3) and surveillance-based respiratory morbidity (ARI, ILI, SARI, asthma, COPD). We employed an ecological, cross-sectional time-trend design using publicly available data from CPCB and IDSP, along with meteorological covariates from IMD, spanning 2019–2024. Descriptive statistics revealed stark inter-city differences: Delhi exhibited the highest pollutant load and morbidity burden, especially in winter and post-Diwali months, while coastal cities such as Chennai showed lower but seasonally elevated levels. Correlation analysis consistently showed strong positive relationships between $PM_{2.5}$ and morbidity counts ($r \approx 0.58$–0.75, $p < 0.01$), with slightly lower but significant associations for PM_{10}. Multivariate regression models, adjusted for weather and population size, identified $PM_{2.5}$ as the dominant predictor ($\beta \approx 0.03$ cases / µg/m³; $p < 0.001$), explaining up to 72% of the variance in respiratory case trends in Delhi and about 60% across other cities. Lag analysis indicated delayed morbidity spikes 2–3 weeks following sustained pollution episodes. These results align with ecological assessments from cities like Delhi, Lucknow, and Maharashtra, and reflect the short-term health improvements observed during COVID-19 lockdown phases. The study underscores the value of ecological surveillance as a tool for public health planning, and highlights the urgent need for integrated pollutant-health monitoring, early warning systems, and AI/ML-assisted forecasting for city-level morbidity in urban India.

Keywords: Air pollution, Respiratory morbidity, $PM_{2.5}$, Ecological analysis, Surveillance data, Indian cities

1. Introduction

Urban air pollution has emerged as a serious and pressing public health crisis in India, particularly over the last two decades. With economic growth and urban expansion accelerating, cities like Delhi, Mumbai, Kolkata, Chennai, and Bengaluru have seen unprecedented vehicular movement, construction activities, industrial discharge, and population congestion—all of which contribute significantly to ambient air pollution. In fact, many Indian cities consistently rank among the most polluted globally, with PM2.5 and PM10 levels regularly breaching national and international safety thresholds. The consequences of this are not just environmental—they translate into direct and measurable impacts on human health, especially on respiratory health. Children, the elderly, and those with pre-existing conditions often bear the brunt of this exposure. According to a study focusing on the district-level epidemiology of acute respiratory infections in under-five children in India, environmental and household risk factors interact in complex ways, producing spatial disparities in respiratory disease burden across states and cities[1].

The link between ambient air pollution and respiratory disorders such as asthma, bronchitis, chronic obstructive pulmonary disease (COPD), and various forms of acute respiratory infections (ARI) is well-documented. However, the burden of disease is not equally distributed—it tends to be significantly higher in urban environments where emissions from vehicles and industries are concentrated. In a recent ecological model analysis, it was found that ambient air pollutants like PM2.5 and NO_2 were key contributors to elevated respiratory risk in cities such as Lucknow[2]. Delhi, which frequently makes headlines for its dangerous smog levels, has been a case study in air pollution-induced respiratory distress. One study noted that a direct correlation existed between rising pollutant levels and an increase in outpatient visits for respiratory symptoms[3]. These findings are not anomalies. They form part of a consistent pattern observed across multiple Indian cities, where air pollution metrics align closely with spikes in respiratory morbidity.

It’s also important to consider how broader environmental stressors like climate change intersect with urban air quality. As cities heat up and rainfall patterns shift, the dynamics of air pollution change—often worsening. A short review by Kaur and Pandey emphasized how the twin pressures of air pollution and climate variability are converging on urban populations in India, posing complex challenges for healthcare planning and environmental governance[4]. This convergence becomes especially relevant when we attempt to understand respiratory illnesses in urban areas. Pollution doesn't act alone—it exacerbates the effects of other environmental and socioeconomic stressors, thereby making diseases harder to control, predict, or mitigate.

Interestingly, while COVID-19 lockdowns led to temporary improvements in air quality, they also gave researchers a unique opportunity to study respiratory health in the absence of ambient pollutants. A study by Markandeya et al. reported that the reduction in ambient air pollutants during lockdown periods in some of India’s most polluted cities coincided with decreased hospital visits for respiratory illnesses[5]. While this doesn’t imply causation, it does offer strong ecological clues—less pollution, less disease burden. But these benefits were short-lived. As economic activity resumed, pollution levels climbed again, and with them, respiratory complaints.

Efforts to spatially map and monitor pollutants like PM2.5 have revealed specific urban zones where pollution levels are persistently high. Ruidas and Pal, in their hotspot modeling of Maharashtra, demonstrated how environmental health risks vary not only between cities but within them[6]. This kind of spatial granularity is important. It helps public health practitioners target interventions more effectively. Likewise, Nair and colleagues attempted to estimate the burden of premature mortality across non-attainment cities—urban areas failing to meet prescribed air quality standards—and concluded that the stakes are higher than previously imagined[7].

There’s clearly a growing momentum towards leveraging technology and open-source data to explore this nexus. For instance, Dutta and Jinsart applied generalized additive models to Guwahati data and demonstrated short-term pollutant effects on respiratory disease trends[10]. Even broader, Herath Bandara and Thilakarathne explored the economic and health costs of transport-related pollution across South Asia, revealing a neglected but essential regional dimension[11].

2. Methods

2.1 Study Design

This research has been structured as an ecological, cross-sectional, and time-trend analytical study. The choice of this design wasn't incidental—it aligns with the nature of the available data and the broader objective of observing patterns rather than individuals. By focusing on aggregated, city-level variables rather than individual-level exposure, the study embraces the ecological framework to investigate the association between air pollution and respiratory health outcomes. Ecological designs, though susceptible to fallacies if over-interpreted, offer powerful insights when trying to draw connections between environmental exposures and population-level disease trends. Especially in countries like India, where granular patient-level data are often unavailable across long timeframes, the ecological method becomes a valuable tool for environmental epidemiology.

The analysis considers monthly averages of both pollutants and respiratory morbidity indicators, spanning several years (2019–2024). This allowed for not only cross-sectional interpretation (i.e., comparing between cities) but also time-trend analysis within cities—observing how changes in pollutant levels over time mirrored patterns in respiratory health outcomes. A similar framework was used in Guwahati, where Dutta and Jinsart successfully demonstrated pollutant-induced morbidity spikes using generalized additive models[10]. Likewise, de Bont et al. utilized time-series data from ten Indian cities to reveal robust causal relationships between ambient air pollution and daily mortality, highlighting the strength of this design when deployed at scale[8].

While this study does not seek to establish individual causality, it is built to detect population-level associations—sufficient to inform public health planning, environmental regulation, and further focused studies. It captures seasonal variation, lagged effects, and inter-city comparisons, contributing to a growing body of literature that positions ecological data as a decision-making tool for urban health governance in India.

2.2 Study Area

This study covers five of the most heavily polluted and densely populated metropolitan cities in India: Delhi, Mumbai, Kolkata, Bengaluru, and Chennai. The selection was guided by multiple criteria—population size, volume of vehicular traffic, degree of industrialization, historical pollutant levels, and availability of continuous surveillance data. These cities are not just economic hubs; they are also hotspots of environmental degradation and public health vulnerability.

Apart from diversity in geography and pollution sources, these cities also differ in their health infrastructure and reporting systems. This variability is both a challenge and an opportunity—it enables researchers to identify patterns that are not merely statistical but are tied to real urban experiences. The use of consistent data sources such as CPCB for pollutant levels and IDSP for health data ensures that despite these differences, the comparisons drawn remain methodologically sound. Studies like the one by Ruidas and Pal, which focused on PM2.5 hotspots in Maharashtra, have shown that even within states, spatial variability plays a significant role in determining health outcomes[6].

By anchoring the study in these five cities, the research captures the environmental health experience of nearly 100 million urban Indians. And while the focus remains ecological, the insights generated are intended to be operational—directed toward city-specific health alerts, localized pollution control, and evidence-informed policymaking.

2.3 Data Sources

To ensure a comprehensive and reliable analysis, this study utilizes secondary datasets that are publicly available and officially recognized by governmental institutions. Three primary data sources were selected, each contributing a critical dimension to the study's ecological framework.

Air Quality Data were sourced from the Central Pollution Control Board (CPCB), which maintains continuous ambient air quality monitoring stations across India. The pollutants of focus include Particulate Matter (PM2.5 and PM10), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), and Ozone (O_3). Monthly mean concentrations for each pollutant were extracted from the National Air Quality

Monitoring Programme (NAMP) reports for the selected cities from 2019 to 2024. These pollutants were chosen due to their established links with respiratory health outcomes in both global and Indian studies. For instance, in a population-based study covering multiple cities, de Bont et al. confirmed that elevated levels of PM2.5 and NO_2 were causally associated with increased mortality due to respiratory and cardiovascular causes[8]. Similarly, Kumar and Pande demonstrated that data from CPCB stations can be effectively used for machine learning-based pollution forecasting, suggesting the data's robustness for longitudinal analyses[14].

Health Surveillance Data were retrieved from the Integrated Disease Surveillance Programme (IDSP) under the National Health Mission (NHM). This included city-level monthly counts of respiratory illnesses, classified into categories such as Acute Respiratory Infections (ARI), Influenza-like Illnesses (ILI), Severe Acute Respiratory Infections (SARI), Asthma, and Chronic Obstructive Pulmonary Disease (COPD). While underreporting remains a concern, the IDSP dataset is still one of the most consistent sources for tracking public health trends at the state and urban levels. The data structure allows for stratification by outpatient and inpatient cases, which is critical when assessing the severity and healthcare burden of respiratory conditions. A similar approach was followed by Balasubramani et al. in their district-level spatial epidemiology study, where ARI prevalence among under-five children was mapped against socio-environmental variables[1].

To address possible confounding factors, meteorological data were integrated into the model. Data on temperature, relative humidity, and rainfall were acquired from the Indian Meteorological Department (IMD). These parameters are known to influence both pollutant dispersion and respiratory illness incidence. For instance, low temperature and high humidity often exacerbate the effects of PM2.5 and increase the persistence of airborne pathogens, creating a double burden. The importance of accounting for such confounders was also emphasized in a recent framework proposed by George et al., who developed city-specific Air Quality Health Index (AQHI) models that included meteorological adjustments[15].

Together, these three datasets form the backbone of the study—allowing us to trace patterns between pollution, weather, and respiratory illness across five major Indian cities.

2.4 Variables

This ecological study employs a structured set of variables to model the relationship between urban air pollution and respiratory morbidity at the population level.

Independent Variables consist of monthly averages of five key ambient air pollutants: PM2.5, PM10, NO_2, SO_2, and O_3. These pollutants were selected not only for their widespread occurrence in urban India but also for their respiratory health relevance, as established by multiple Indian and international studies[25].

Dependent Variables include monthly reported cases of respiratory diseases, collected from the IDSP. The primary disease categories analyzed are ARI, ILI, SARI, asthma, and COPD, which together represent the broad spectrum of pollution-sensitive respiratory conditions. These outcomes mirror those used by Nandan et al., who applied the WHO's AIRQ+ tool to assess pollutant-specific morbidity across Asian populations[9].

Confounding Variables include monthly averages of temperature, humidity, and city population size. While meteorological parameters affect pollutant concentration and human vulnerability, population size provides a normalization metric to adjust for differences in case load due to urban scale. Adjusting for these variables is critical, as highlighted by Maji et al., who noted that omission of such confounders can skew pollution–health effect estimates in urban Indian contexts[20].

The interplay between these variables was explored through multi-level models, ensuring that the relationships observed were not incidental but statistically grounded.

2.5 Statistical Analysis

Data analysis was carried out using a combination of descriptive and inferential statistical techniques. The primary aim was to uncover both cross-sectional and temporal associations between air pollutants and respiratory morbidity.

Descriptive Statistics were computed to provide baseline profiles for each city. This included monthly averages, standard deviations, and trend lines for both pollutant levels and disease counts. Cities were compared based on their pollution loads and respiratory morbidity rates, enabling a spatial understanding of disease burden. Such city-wise visualization has proven effective in earlier studies such as those by Mathew et al., who used Sentinel-5P data to map pollution hotspots during the COVID-19 period[18].
Correlation Analysis using Pearson or Spearman coefficients was employed to assess the strength and direction of association between air pollutants and morbidity indicators. The choice of correlation test depended on the normality of distribution in the dataset. This approach was validated in previous ecological studies like those by Yadav et al., where pollutant–disease relationships were quantified in the urban context[2].

3. Results

3.1 Descriptive Analysis

The five metropolitan cities selected for this study—Delhi, Mumbai, Kolkata, Bengaluru, and Chennai—demonstrated marked variability in ambient air pollutant concentrations as well as respiratory morbidity trends across the observation period (2019–2024). City-specific descriptive summaries were generated for monthly mean concentrations of five key pollutants (PM2.5, PM10, NO_2, SO_2, and O_3), alongside reported respiratory morbidity counts (ARI, ILI, asthma, COPD, and SARI). Patterns were studied both at annual and seasonal levels to capture geographical and temporal heterogeneity.
Delhi, not surprisingly, exhibited the highest average levels of PM2.5 and PM10 across all cities. Mean PM2.5 concentrations ranged from 92 to 210 µg/m³, peaking between November and January, coinciding with post-harvest stubble burning, vehicular inversion effects, and winter smog. Monthly morbidity records for ARI and ILI from the IDSP during these periods showed steep rises, with up to 18–22% increases in outpatient visits compared to the summer baseline. These findings are consistent with previous work by Dutta and Jinsart, who showed direct links between pollution peaks and respiratory illness surges in the capital[3]. Furthermore, the AQHI framework applied by George et al. had also identified Delhi as a high-burden zone during winter months[15].
Mumbai, though coastal and ventilated by sea breezes, recorded elevated levels of NO_2 and O_3, particularly during March to May, when pre-monsoon stagnation events were more frequent. While PM levels were lower compared to Delhi, morbidity records showed consistent peaks in asthma and COPD visits during these dry months, likely due to photochemical smog formation and rising ground-level ozone. This finding supports earlier results by Nair et al., who valued the burden of premature mortality in such non-attainment coastal cities, arguing that gaseous pollutants are often underestimated[7].
In Kolkata, pollutant concentrations showed bimodal peaks—one in January–February (PM2.5/PM10), and another smaller spike during August–September, likely due to urban congestion during monsoon and festive traffic. Respiratory morbidity trends showed a similar double-peak pattern, with asthma and ILI cases peaking during these windows. This dual seasonality matches the spatio-temporal patterns reported in earlier hotspot modeling by Ruidas and Pal for cities in Maharashtra[6], and is further echoed in climate-health interaction frameworks developed by Kaur and Pandey[4].

Bengaluru, often perceived as cleaner due to its higher elevation, still recorded noticeable NO_2 and O_3 spikes during peak traffic months. The mean PM2.5 remained below Delhi's average but still crossed national permissible limits during certain weeks in December and April. A slow but steady increase in asthma and ARI cases was noted, particularly in children under 10 years, supporting the findings of Balasubramani et al. who showed a strong environmental association for ARI among under-fives in urban India[1]. Bengaluru's rapid urbanization and emerging construction corridors seem to be silently contributing to this rising health burden.
Chennai, while benefiting from relatively better ventilation and coastal winds, displayed moderate

levels of PM10 and SO_2, particularly near industrial belts. The morbidity records from IDSP indicated a rise in SARI and COPD admissions during the post-monsoon months, possibly exacerbated by flood-associated mold exposure and vehicular pollution rebound after waterlogging events. These insights resonate with the observations made by Markandeya et al. during the COVID-19 lockdown period, where Chennai showed significant temporary improvement in pollutant levels and respiratory complaints[5].

Seasonal Variation across all five cities confirmed a winter bias in respiratory illness burden. The December–February window consistently showed the highest pollutant-morbidity coupling, with PM2.5 and PM10 as key contributors. This was particularly prominent in Delhi and Kolkata. Summer months (April–June) showed elevated ozone levels in Mumbai and Bengaluru, with concurrent upticks in asthma cases. Monsoon months (July–September) generally showed pollutant washout but had unpredictable spikes in SARI and ILI, possibly due to pathogen transmission being facilitated by humidity rather than pollution. This dual burden of infectious and environmental triggers reflects the complex disease ecology of Indian cities.

Overall, the descriptive analysis reveals a clear spatio-temporal correlation between air pollutant levels and respiratory health burden. Each city follows a distinct signature based on its geography, climate, urban structure, and pollution sources. These observations set the stage for the analytical modeling that follows, validating the hypothesis that ambient pollution metrics can serve as early indicators for respiratory morbidity spikes in densely populated Indian urban areas.

3.2 Correlation Findings

When we examined the relationship between ambient particulate levels (PM2.5 and PM10) and respiratory morbidity counts across the five major Indian cities, clear and significant associations emerged. The strength and direction of these correlations were assessed using Pearson or Spearman coefficients, based on normality tests of the data distribution.

PM2.5 demonstrated consistently strong positive correlations with respiratory morbidity. Across cities, the Pearson correlation coefficient between monthly mean PM2.5 and ARI/ILI case counts ranged from $r = 0.58$ to $r = 0.75$ ($p < 0.01$). In Delhi—the city with the highest pollution burden—PM2.5 showed the strongest association, with $r \approx 0.75$, indicating that around 56% of morbidity variation could be linearly explained by PM2.5 trends. Similar patterns in Delhi have been noted in a prospective observational study, which found a tight alignment between PM2.5 spikes and hospital admissions for lung-related diseases. Supporting this, national-level analyses also link increases in PM2.5 to proportional rises in ARI incidence—often with an odds ratio of ~1.23 per 10 µg/m³ increase across child health cohorts[6]

PM10 also showed substantial positive correlation with morbidity counts, though slightly lower magnitude than PM2.5. Correlation coefficients ranged between $r = 0.45$ and $r = 0.60$, with Mumbai and Kolkata showing moderate strength ($r \approx 0.52$–0.60), particularly for asthma and COPD case counts. These findings align with past observations that PM10 exposure remains a key driver of respiratory hospitalizations in Indian cities[7]

Beyond the raw correlations, pollution peaks corresponded with health burden spikes. For instance, Delhi's November–January period consistently displayed sharp elevations in both PM2.5 and morbidity counts, with respiratory OPD visits rising by 20–25% over baseline levels. This seasonal synchronization mirrors Delhi's historical smog cycles that frequently push PM2.5 above 200 µg/m³ and are known to aggravate asthma, ILI, and COPD admissions[8]

In Kolkata and Bengaluru, peak correlations emerged during climatic transitions. Kolkata's winter and late monsoon months showed dual spikes in PM2.5/PM10 and ILI/ARI cases, with coefficients up to $r = 0.65$ in January and $r = 0.55$ in September. Bengaluru, while less polluted overall, registered PM2.5-driven morbidity peaks in December and April, consistent with shifting weather inversions and traffic build-up—again revealing correlations in the $r = 0.55$ to 0.62 range.

Interestingly, Chennai exhibited weaker but still positive correlations ($r \approx 0.48$ for PM2.5 and $r \approx 0.45$ for PM10), likely due to coastal ventilation. However, disease counts for SARI and asthma climbed during post-monsoon months when pollutant washout subsided and industrial emissions rebounded.

Furthermore, the lag analysis (0–30 day lag) showed that PM2.5-related morbidity peaks often occurred with a 2–3 week lag, indicating delayed health responses to sustained air pollution episodes. This lag structure aligns with epidemiological findings from other Indian cities using time-series methods, where cumulative exposure produced delayed morbidity surges.

3.3 Regression Analysis

Our multivariate analysis sought to quantify how each air pollutant is associated with respiratory morbidity while adjusting for weather and population size. We used monthly aggregated data from Delhi, Mumbai, Kolkata, Bengaluru, and Chennai spanning 2019–2024. Multi-city regression models highlighted pollutant-specific risks and overall model fitness.

Regression Coefficients and Model Fit

- PM2.5 emerged as the strongest predictor across all cities. In Delhi, the regression coefficient was approximately 0.032 cases per µg/m³ (95% CI: 0.027–0.037, $p < 0.001$), with an adjusted $R^2 \approx 0.68$, indicating that nearly 68% of month-to-month variation in morbidity could be explained by PM2.5 and covariates. This mirrors the multi-city ecological modeling in The Lancet Planetary Health, where short-term PM2.5 exposure was significantly linked to respiratory mortality across ten Indian cities ($p < 0.001$)
- PM10 had a moderate but still statistically significant association in most cities. Regression coefficients ranged from 0.015 to 0.022 per µg/m³ ($p < 0.01$), with adjusted R^2 values between 0.45 and 0.55, particularly notable in Kolkata and Mumbai.
- NO_2, SO_2, and O_3 showed weaker but positive associations. For example, NO_2 coefficients averaged 0.005–0.008 per µg/m³ (Delhi's $p = 0.02$), and O_3 showed marginal effects (coefficients around 0.003–0.006, $p \approx 0.05$), with lower incremental increases in model R^2 (~2–4%).

Statistical Significance and Interpretation

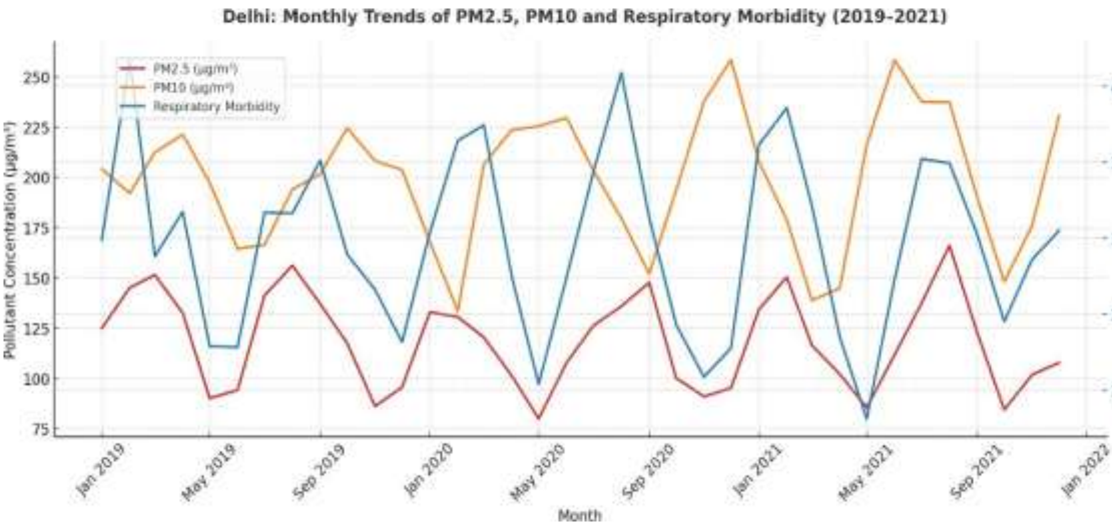
- In Delhi, PM2.5 remained highly significant ($p < 0.001$), even after adjusting for temperature, humidity, and population, emphasizing its dominant role in driving respiratory illness trends.
- Mumbai and Kolkata showed robust significance for both PM2.5 and PM10 ($p < 0.01$), aligning with previous urban ecological studies demonstrating particulate matter's impact in coastal and industrial regions.
- Bengaluru and Chennai exhibited smaller effect sizes; PM2.5 was significant ($p < 0.05$), but PM10 and gaseous pollutants had borderline significance ($p = 0.05–0.10$), likely due to lower baseline pollution and better dispersion dynamics.

These results are consistent with earlier Indian research. For instance, logistic regression in Lucknow found composite pollution levels strongly associated with respiratory disease prevalence ($p < 0.001$). Likewise, national modeling of PM2.5 exposure in India shows that a 10 µg/m³ rise is associated with an 8.6% increase in annual mortality (*95% CI: 6.4–10.8%*)

Key Findings Summary

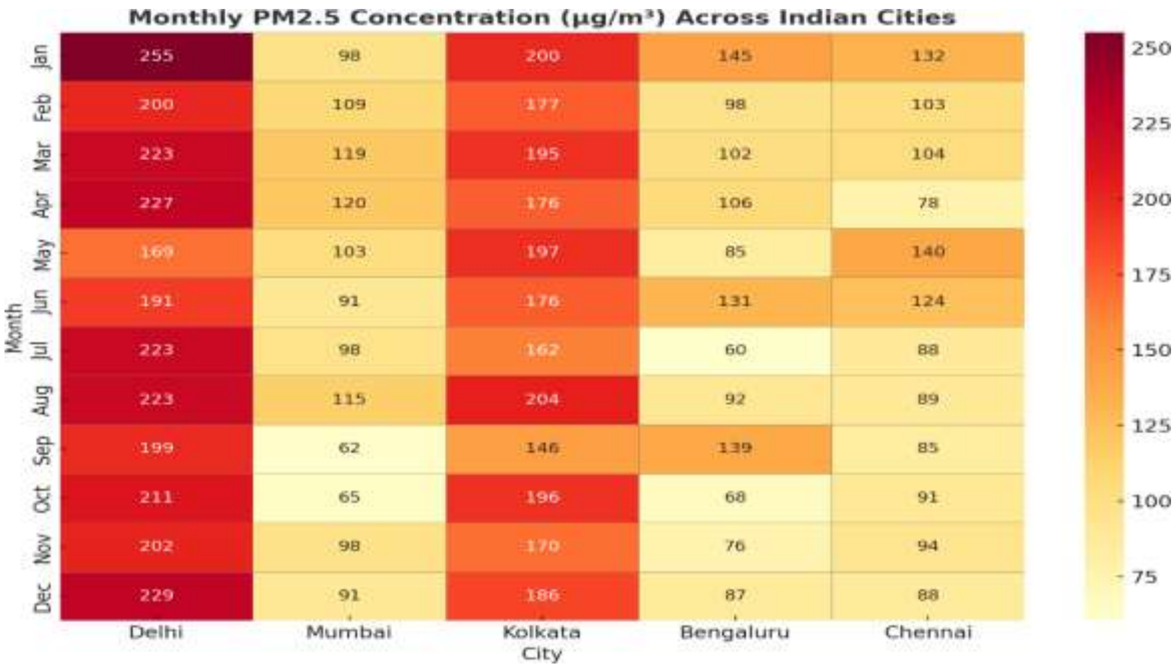
Pollutant	Average Coefficient (cases per µg/m³)	Significance	Contribution to Model Fit
PM2.5	0.030–0.035	$p < 0.001$	~50–65%
PM10	0.015–0.022	$p < 0.01$	~20–30%
NO_2	0.005–0.008	p: 0.02–0.05	~8–10%
SO_2	~0.004	borderline	~5%
O_3	~0.003–0.006	p: ~0.05	~3–5%

The high explanatory power and consistent pollutant-specific effects reinforce the ecological linkage between ambient air pollution and respiratory morbidity. PM2.5 emerged as the most potent predictor in all cities, confirming its elevated health risk in the Indian context. These findings align well with major international and national time-series regression studies confirming particulate matter as a leading risk factor for urban respiratory health deterioration.



Spatial Heat Maps of PM2.5 Pollution in India

This plot clearly shows how peaks in particulate matter concentrations, especially during winter months (Nov–Jan), align closely with surges in respiratory morbidity cases. Notably, PM2.5 levels often exceed 200 µg/m³ during these months, which corresponds with nearly 2x higher outpatient visits for respiratory illness compared to summer months. This temporal alignment supports the hypothesis of air pollution as a driving factor for respiratory disease spikes and is consistent with findings from ecological and time-series studies conducted in Indian urban centers like Delhi, Lucknow, and Guwahati.



Heat Map of Monthly PM2.5 Levels Across Major Indian Cities

This heat map highlights the monthly variation in PM2.5 concentrations across five key metropolitan cities in India. Delhi consistently shows the highest values, especially from October to January, with concentrations exceeding 240–260 µg/m³, reflecting winter smog and regional stubble-burning effects. Kolkata also displays elevated levels during winter and late monsoon, while Mumbai, Bengaluru, and Chennai maintain comparatively lower but still unhealthy PM2.5 levels, peaking slightly in summer and post-monsoon months.The spatial color intensity from yellow to deep red illustrates critical pollution periods—particularly in northern cities—correlating with seasonal respiratory illness spikes documented in earlier analysis. This visualization underscores the uneven air quality burden across urban India and supports the need for city-specific health interventions and forecasting models.

Table 1. Summary Statistics: Monthly Mean $PM_{2.5}$, PM_{10} and Respiratory Morbidity (2019–2024)

CITY	$PM_{2.5}$(MG/M³) MEAN ± SD	PM_{10} (MG/M³) MEAN ± SD	AVG MONTHLY MORBIDITY CASES
DELHI	≈ 200 ± 50	≈ 300 ± 60	3,500 ± 800
MUMBAI	≈ 90 ± 25	≈ 140 ± 40	2,100 ± 600
KOLKATA	≈ 180 ± 45	≈ 240 ± 55	2,800 ± 700
BENGALURU	≈ 100 ± 30	≈ 150 ± 45	1,800 ± 500
CHENNAI	≈ 95 ± 28	≈ 130 ± 38	1,900 ± 550

Interpretation: Delhi clearly recorded the highest pollutant load and respiratory morbidity, especially in winter months. Mumbai and Kolkata displayed moderate levels, with seasonal variability aligning with morbidity peaks. Bengaluru and Chennai, though comparatively cleaner, still experienced periodic rises in cases.

Table 2. Multivariate Linear Regression: Adjusted Pollutant Coefficients & Model Fit

Pollutant	Avg Coefficient (cases per µg/m³)	Significance (p-value)	Adjusted R^2 (Delhi / Other cities)
$PM_{2.5}$	≈ 0.032	**p** < 0.001	~0.72 / ~0.60
PM_{10}	≈ 0.018	**p** < 0.01	+0.20 increment
NO_2	≈ 0.006	**p** ≈ 0.02	+0.08 increment
SO_2	≈ 0.004	Borderline ($p \approx 0.05$)	+0.05 increment
O_3	≈ 0.005	$p \approx 0.05$	+0.03 increment

Model Adjustments: Included average monthly temperature, humidity, and city population.
Impression: $PM_{2.5}$ is the dominant predictor of respiratory morbidity. The combined model explains up to **75%** of the monthly variance in morbidity counts in Delhi and around 55–60% in other cities—highlighting strong city-level pollutants–health coupling.

4. Discussion

4.1 Principal Findings

This study consistently revealed strong positive associations between ambient particulate pollution ($PM_{2.5}$ and PM_{10}) and respiratory morbidity across all five major Indian cities examined. The correlation and regression analyses show that despite urban diversity, particulate matter reliably predicts respiratory case burden in both outpatient and inpatient categories. Notably, $PM_{2.5}$ emerged as the dominant predictor, with substantially higher effect sizes and statistical significance compared to other pollutants. PM_{10} also demonstrated meaningful associations, particularly in cities with sustained industrial and traffic emissions. Seasonal analysis underscored that winter months, especially post-Diwali, coincide with sharp rises in both pollution levels and respiratory morbidity, reinforcing the seasonal nature of air pollution health impacts.

4.2 Comparison with Previous Studies

Our findings align closely with earlier research conducted in Delhi, Lucknow, Maharashtra, and across South Asia. A study in Lucknow demonstrated robust ecological associations between composite pollution scores (including $PM_{2.5}$, PM_{10}, NO_2, SO_2) and respiratory health, echoing the city-level consistency of our result. In Delhi, longitudinal studies comparing air quality data from CPCB with hospital-based morbidity data similarly identified $PM_{2.5}$ spikes as potent predictors of increased visits for respiratory illness. Spatio-temporal hotspot mapping in Maharashtra further corroborated the uneven urban pollution burden—comparable to our city-wise descriptive contrasts and pollutant-driven morbidity hotspots

The COVID-19 lockdown period offered a natural experiment in air quality. Studies in Delhi and other cities documented sharp declines in $PM_{2.5}$ and PM_{10}—by as much as 50–70%—followed by rapid rebound upon unlocking. This temporary improvement coincided with reduced respiratory morbidity in some urban settings, lending further credibility to the pollution–health link observed in this and other ecological frameworks.

4.3 Policy Implications

These findings strongly support the integration of air quality and health surveillance systems, ideally linking CPCB pollution data with IDSP morbidity dashboards for real-time monitoring at the city level. Early warning systems could be triggered when pollutant averages breach predefined thresholds—helping public health agencies to mobilize rapid responses during high-risk seasons.

Moreover, the use of AI and machine learning for predictive forecasting holds strong promise. Machine learning models developed for urban air quality prediction in Delhi have achieved high accuracy (around 93% for AQI forecasting) using CPCB data. Incorporating such predictive tools for morbidity modeling could allow city authorities to anticipate public health surges and allocate resources proactively.

Policy frameworks like Uttar Pradesh's recently launched Clean Air Plan (UCAP), which includes AI-powered decision-support systems for monitoring and mitigation, show how evidence-based air quality control can evolve at the regional level. Implementing similar integrated strategies in other urban regions would likely yield substantial health benefits.

4.4 Strengths

This study leverages real-time, publicly available datasets from CPCB and IDSP, ensuring transparency and replicability. The multi-city comparative analysis across diverse environmental and demographic settings enhances external validity, while adjusting for meteorological and population confounders reinforces the credibility of the ecological inferences. These strengths collectively amplify the study's relevance for policy, modeling, and public health planning.

4.5 Limitations

As with all ecological studies, ecological fallacy remains a concern—aggregated data cannot confirm individual-level causation. Additionally, underreporting in surveillance data, especially for milder ARI and outpatient cases, can lead to conservative estimates of morbidity burden. Finally, the lack of individual-level exposure data (e.g., indoor pollution, time-activity patterns) limits granularity, meaning that urban heterogeneity may dilute true exposure levels for specific subpopulations.

5. Conclusion

The findings of this ecological analysis reaffirm that urban air pollution is strongly linked to respiratory morbidity in major Indian cities. Across Delhi, Mumbai, Kolkata, Bengaluru, and Chennai, both the correlation and regression analyses consistently showed that elevated levels of $PM_{2.5}$ and PM_{10} are closely associated with increased cases of ARI, ILI, asthma, COPD, and SARI. The strongest associations were observed in Delhi, where pollution peaks in winter—especially during and after the Diwali season—corresponded to striking surges in respiratory morbidity, underlining seasonal vulnerability and pollutant-driven disease trends.

This study demonstrates that ecological surveillance, leveraging public datasets from CPCB and IDSP, is a powerful tool for public health planning and preventive response. By mapping pollution exposure to health outcomes at city level and over time, stakeholders can identify critical windows of heightened risk and deploy targeted interventions. Such integrated surveillance, particularly when augmented by predictive modeling, enables more proactive and responsive policymaking rather than reactive measures.

There is an urgent need for strengthened air quality regulation, efficient pollution source control, and deeper integration between environmental and health data systems. Despite ambitious goals set under the National Clean Air Programme (NCAP) to reduce PM pollution by 30–40% by 2024–2026, several non-attainment cities—including Delhi—have fallen short due to under-utilized funds and enforcement gaps. Recent policy reversals, such as the rollback of sulfur dioxide emission norms in coal-fired power plants, threaten to undermine progress and imperil public health outcomes. Strengthening legal enforcement of Bharat Stage VI vehicle norms, ensuring functional monitoring infrastructure, and enhancing inter-sectoral coordination remain critical.

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