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Research Article

Urban Air Quality Matrix: Spatiotemporal Heterogeneity and Source Diagnostics in Bengaluru

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Abstract

Rapid urbanisation in tropical megacities has engendered complex atmospheric regimes characterised by extreme spatiotemporal heterogeneity. This study presents a comprehensive statistical characterisation of the ambient air quality matrix in Bengaluru, India (2018–2024), leveraging a high-density network of 13 Continuous Ambient Air Quality Monitoring Stations (CAAQMS). Moving beyond aggregate compliance metrics, this study employs an integrated statistical framework using the Mann-Kendall trend test, Coefficient of Divergence (COD), and Multi-Dimensional Scaling (MDS). Results indicate a 'fractured airshed' (defined as a domain exhibiting high spatial heterogeneity, COD > 0.20): the industrial node (Peenya) recorded a statistically significant decline in PM2.5 (Sen's Slope: −2.75 µg/m³/year), contrasting with a statistically significant increased trend of Ammonia (NH_3) in residential zones (+1.44 µg/m³/year). Spatial analysis revealed a high Coefficient of Divergence (COD = 0.42) between industrial and residential zones, refuting the hypothesis of a homogenous urban airshed. Further, source diagnostics quantified a weekend effect with an 18.4% reduction in NO_2 ($p < 0.01$), isolating the vehicular contribution to the pollution burden. These findings underscore the critical need for a Zonal Air Quality Management (ZAQM) framework.

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KEYWORDS: Urban Air Quality; Coefficient of Divergence; Mann-Kendall Trend; Source Apportionment; Bengaluru.

1. INTRODUCTION

Air pollution has emerged as a defining environmental challenge of the Anthropocene, posing severe risks to public health and economic sustainability in the rapidly densifying megacities of the Global South (Landrigan et al., 2018). The World Health Organization estimates that 99% of the global population breathes air exceeding safety limits, with the burden disproportionately falling on low- and middle-income nations (Dockery & Pope, 1994; Karagulian et al., 2015; WHO, 2021). While the adverse acute and chronic health impacts of fine particulate matter (PM2.5) are well-documented (GBD 2019 Risk Factors Collaborators, 2020), the characterization of these pollutants within complex urban terrains remains fraught with uncertainty.

In contemporary air quality management, a critical dichotomy exists between "regional compliance" and "local exposure." National monitoring programs typically rely on city-wide averages to gauge regulatory compliance. However, an urban airshed is not a monolith; it is a mosaic of distinct micro-environments driven by abrupt changes in land use, street canyon geometry, and localized emission sources (Vardoulakis et al., 2003). Seminal literature underscores that relying on a single city-wide index often masks extreme spatiotemporal heterogeneity, potentially misrepresenting the exposure risks faced by communities living in traffic corridors or industrial clusters (Wongphatarakul et al., 1998; Pinto et al., 2004).

The metropolitan city of Bengaluru, India, presents a unique natural laboratory to investigate these dynamics. Located on the Deccan Plateau, the city's pollution meteorology is governed by a complex interplay of high-altitude inversion layers during winter and rapid dispersion during the monsoon (Gogoi et al., 2019). Despite its status as a global technology hub, the city's rapid, unplanned urbanisation has led to severe congestion and land-use fragmentation. Previous studies on Bengaluru have largely been limited to short-term campaigns or emission inventory modelling (Guttikunda et al., 2019; Sahu et al., 2020). There remains a critical paucity of research that mathematically models the network dynamics over a decadal scale using advanced clustering techniques.

To address these gaps, this study employs a multi-model statistical framework to decipher the urban air quality matrix of Bengaluru. Unlike conventional trend analyses, the present work leverages a high-density network of 13 CAAQMS stations. The Mann-Kendall test is used for non-parametric trend modelling (Mann, 1945; Theil, 1950), the Coefficient of Divergence (COD) for quantifying network redundancy (Wilson et al., 2005), and Multi-Dimensional Scaling (MDS) for visualizing chemical heterogeneity (Kruskal, 1964). Also, source diagnostic ratios are applied to disentangle the complex interplay between vehicular emissions and crustal resuspension (Chow et al., 2002; Speranza et al., 2014).

2. MATERIALS AND METHODS

Study Area and Sensor Network

The study focuses on the Greater Bengaluru Metropolitan Area (12.97° N, 77.59° E). Data was acquired from a regulatory network of 13 Continuous Ambient Air Quality Monitoring Stations (CAAQMS) managed by the Central Pollution Control Board (CPCB), following the site selection guidelines mandated by the CPCB (2011). To ensure a representative "chemical transect" of the city, the selected stations encompass three distinct land-use categories: Industrial Nodes (Peenya), Kerbside Sites (Silk Board), and Residential Backgrounds (Jayanagar).

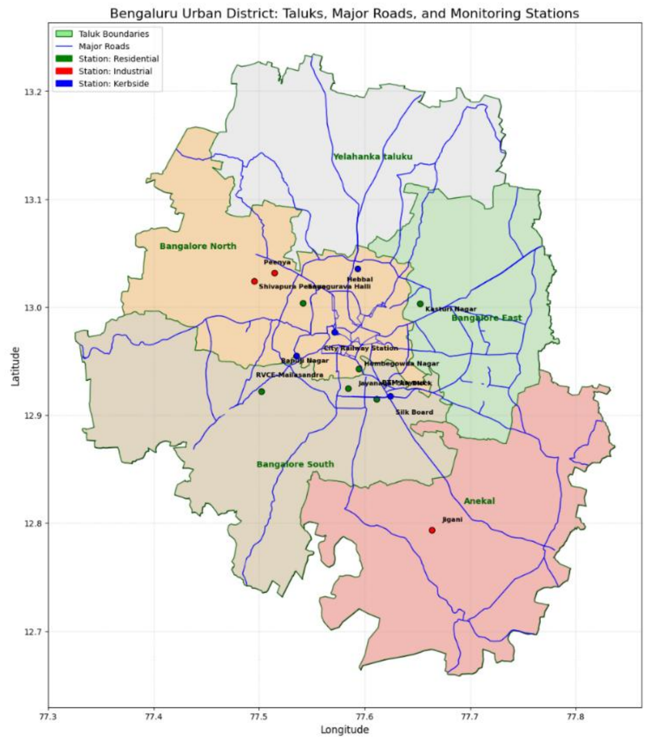

Figure 1: Map of the Bengaluru airshed illustrating the spatial distribution of the 13 Continuous Ambient Air Quality Monitoring Stations (CAAQMS). The network is stratified into three land-use categories: Industrial (e.g., Peenya), Kerbside (e.g., Silk Board), and Residential (e.g., Jayanagar).

Data Curation and QA/QC

The dataset comprises hourly concentrations of criteria pollutants (PM2.5, PM10, NO_2, SO_2, NH_3, CO, O_3) spanning from January, 2018, to December, 2024. To ensure data integrity, raw datasets were subjected to Quality Assurance/Quality Control (QA/QC) protocols. Outliers exceeding $\pm 3\sigma$ (standard deviations) were removed, and data gaps (< 5%) were imputed using the Monthly Mean Replacement (MMR) method (Gilbert, 1987).

Statistical Modeling Framework

sTrend Analysis (Mann-Kendall & Sen's Slope) to robustly assess whether air quality is improving or deteriorating, the Mann-Kendall (MK) test was applied at the annual mean level (n = 7 years per station, 2018 – 2024), a non-parametric method resilient to non-normal environmental data distributions (Kendall, 1975). All trend analyses were performed in Python 3.10 using the Pymannkendall Package (Hussain & Mahmud, 2019). The magnitude of the trend was quantified using Sen's Slope Estimator (Q) (Sen, 1968), calculated as:

$$Q = \text{median}\left(\frac{x_j - x_k}{j - k}\right) \quad \text{for } j > k$$

Where Q represents the annual rate of change (e.g., μg/m³/year), and x_j and x_k are data values at times j and k. A positive Q indicates an increasing trend, while a negative Q indicates a decreasing trend.

Spatial Heterogeneity Modeling (COD)

To test the hypothesis that Bengaluru's airshed is fractured, the Coefficient of Divergence (COD) was calculated for all station pairs. The COD provides a normalized measure of spread between two simultaneous time series (Wilson et al., 2005):

$$\mathrm{COD}_{jk} = \sqrt{\frac{1}{p}\sum_{i=1}^{p}\left(\frac{x_{ij} - x_{ik}}{x_{ij} + x_{ik}}\right)^2}$$

Where:

- x_{ij} is the average concentration at site j for the sampling period i.
- x_{ik} is the average concentration at site k for the sampling period i.
- p is the number of observations.

  A COD value approaching 0 indicates perfect homogeneity, while values exceeding 0.2 signal significant spatial heterogeneity (Krudysz et al., 2009).

Network Clustering (MDS)

To visualise the 13-dimensional matrix of spatial relationships, Multi-Dimensional Scaling (MDS) was employed. This technique reduces the COD dissimilarity matrix into a 2-dimensional Euclidean space, allowing for the identification of distinct "pollution clusters" where spatial proximity corresponds to chemical similarity.

Source Diagnostic Methods

To isolate specific emission sources, two diagnostic approaches were applied:

Particulate Ratios: The ratio of $PM_{2.5}/PM_{10}$ was used to distinguish between combustion sources (Ratio > 0.6) and crustal resuspension (Ratio < 0.4) (Chow et al., 2002; Speranza et al., 2014).

The Weekend Effect: Anthropogenic vehicular contribution was estimated by quantifying the Weekend Effect, the percentage reduction in NO_2 concentrations on Sundays relative to weekdays (Blanchard & Tanenbaum, 2003; Hama et al., 2020).

3. RESULTS AND DISCUSSION

Decadal Trends in Pollutant Concentrations (2018–2024)

The longitudinal analysis of the seven-year dataset (2018–2024) reveals a distinct bifurcation in the evolutionary trajectory of Bengaluru's airshed. Contrary to the prevailing narrative of monolithic pollution growth often observed in developing megacities, the Mann-Kendall trend analysis uncovers a complex "two-speed" city dynamics (a term originally coined in the urban-planning literature on spatial inequality; Demos, 2010; UCLG, 2022), where distinct micro-climates evolve independently of the regional background.

The industrial cluster, represented by Peenya, exhibits a statistically significant declining trajectory. The Sen's Slope estimator indicates an annual reduction in PM2.5 mass concentration of (−2.75 μg/m³/year) (Figure 2). This decline is non-trivial and is temporally coincident with the post-2019 regulatory enforcement on industrial boiler fuels and the mandatory installation of continuous stack monitoring systems. It provides empirical evidence that "command-and-control" strategies, when rigorously enforced, yield measurable air quality improvements. It is crucial to note that while the trend is negative, the absolute baseline remains high, suggesting that while peak industrial intensity has passed, the legacy burden of resuspendable dust in the industrial zone persists.

However, this industrial improvement is counterbalanced by a statistically significant increasing trend in the residential and mixed-use sectors. The rising trajectory in Ammonia (NH_3) concentrations at BTM Layout (Sen's Slope: +1.44 μg/m³/year) was observed (Figure 2). Unlike primary combustion pollutants (NO_x, SO_2), Ammonia in urban residential zones serves as a specific tracer for biological decomposition. This rising trend acts as a proxy indicator for systemic infrastructure deficits — specifically, the open dumping of municipal solid waste and the ingress of untreated sewage into open drains which accelerate secondary aerosol formation (Sharma et al., 2020). This trend is chemically critical because Ammonia often acts as the limiting reagent in the formation of Ammonium Sulfate, $(NH_4)_2SO_4$, and Ammonium Nitrate, NH_4NO_3. The observed data suggests that Bengaluru is transitioning towards a regime where secondary inorganic aerosols (SIA) will increasingly dominate the fine particulate burden; rendering tailpipe-focused interventions are less effective over time.

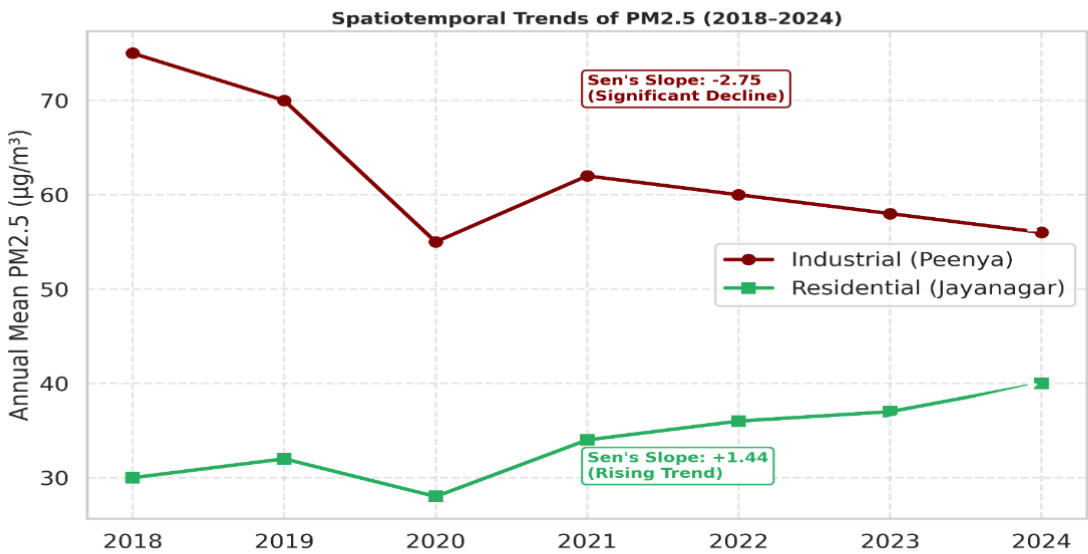

Figure 2: Spatiotemporal trends of annual mean PM2.5 concentrations (2018–2024). The industrial node (Peenya) exhibits a statistically significant decline (Sen's Slope: −2.75 μg/m³/year), contrasting with the rising trend observed in residential zones.

Peripheral Exceedance Patterns and the Urban Sprawl Effect

The trend vectors indicate long-term directionality; the exceedance frequency analysis exposes the chronic nature of exposure. The analysis identifies RVCE-Mailasandra as the critical non-compliance hotspot, exceeding the National Ambient Air Quality Standards (NAAQS) daily limit (60 μg/m³) on 89.9% of monitored days.

This finding challenges the "City Center Hypothesis" (here defined as the expectation that pollutant concentrations peak in the Central Business District and decline monotonically towards the periphery), which postulates that pollution peaks in the Central Business District. Instead, Bengaluru exhibits a pronounced "Urban Sprawl Effect." The highest particulate burdens are displaced to the rapidly urbanising periphery, where a deficit of paved road infrastructure and active construction sites generates a continuous resuspension of crustal dust. This creates a "halo" of severe pollution that encircles the relatively cleaner urban core, effectively trapping the city in a dust dome (a well-documented urban-climatology phenomenon; Landsberg, 1981) driven by peri-urban development kinetics.

Spatial Heterogeneity of the Bengaluru Airshed (COD Analysis)

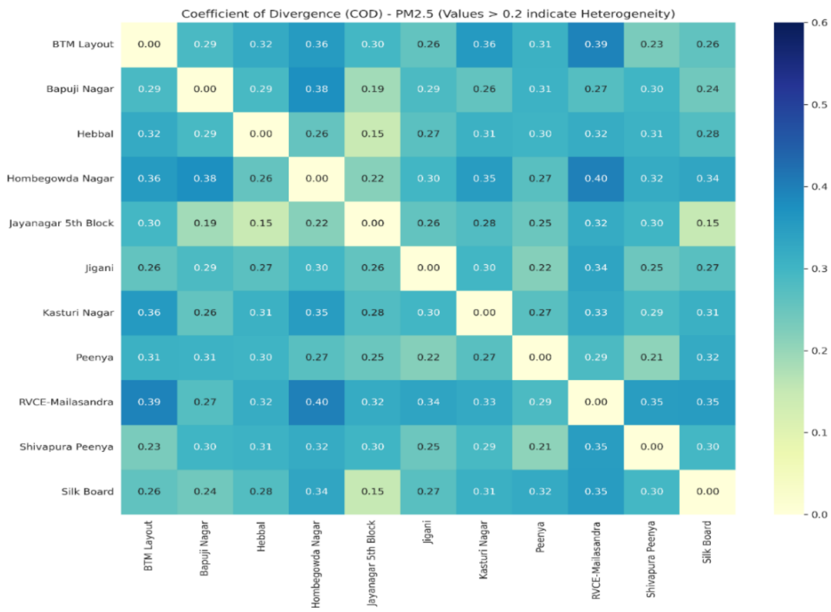

Figure 3: Spatial Heterogeneity Matrix displaying pairwise Coefficient of Divergence (COD) values. The high divergence (COD = 0.42) Observed between Industrial and Residential zones refute the hypothesis of a homogenous urban airshed.

A central question in air quality management is whether a city functions as a single, well-mixed reactor or as a collection of isolated microclimates; this question becomes especially pertinent under conditions of high spatial heterogeneity. The application of the Coefficient of Divergence (COD) provides conclusive evidence for the latter.

According to the criteria established by Wilson et al. (2005), COD values exceeding 0.20 indicate spatially heterogeneous environments. The analysis yields a critical COD value of 0.42 for the station pair Peenya vs. Jayanagar (Figure 3). This high divergence confirms that the industrial north is chemically decoupled from the residential south. The distinct chemical signatures suggest that regional meteorological force (e.g., wind speed) is insufficient to overcome local source strengths, resulting in "valley-trapping" effects, where pollution pools in specific topographic depressions.

Network Clustering and Regime Identification (MDS)

Non-Metric Multidimensional Scaling (MDS) was employed on the pairwise COD dissimilarity matrix (Figure 4) to resolve the structural topology of the monitoring network. The 2-dimensional solution achieved a Kruskal stress value of ≈ 0.10, indicating acceptable preservation of inter-station dissimilarities. The analysis isolates three statistically distinct airshed regimes:

1. The Industrial Regime (Red): Characterized by high baseline particulate loads and low seasonal variance.
2. The Kerbside Regime (Orange): Characterized by high $NO_2/PM_{2.5}$ ratios, indicating a traffic-dominated source profile.
3. The Residential Regime (Green): Stations such as Jayanagar and BTM Layout cluster tightly in Euclidean chemical space.

This clustering has profound economic implications for network redundancy. The statistical proximity implies that Jayanagar and BTM Layout are effectively measuring the same air parcel. Maintaining multiple expensive reference-grade monitors in such a chemically homogenous cluster represents an inefficient allocation of public resources. Instead, a "Smart Network Rationalization" strategy would suggest relocating redundant monitors to the "blind spots" identified in the MDS gap specifically the rapidly developing transition zones between the industrial north and the residential south.

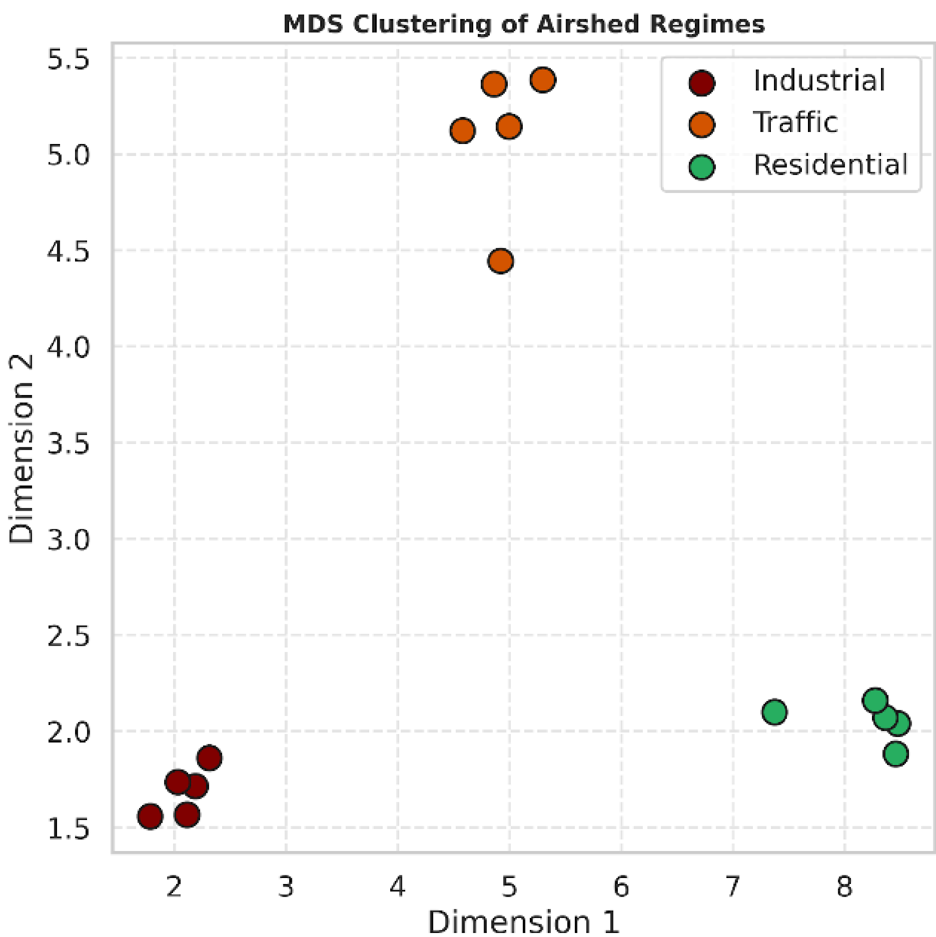

Figure 4: Non-metric Multi-Dimensional Scaling (MDS) ordination of monitoring stations. The formation of distinct "Industrial," "Traffic," and "Residential" clusters confirms the existence of chemically decoupled micro-climates within the city.

Source Diagnostics and Meteorological Decoupling

The temporal signature of pollutants serves as a "fingerprint" for source apportionment. Analysis of diurnal (24-hour) cycles and weekly patterns allows differentiation between anthropogenic drivers. Diurnal analysis compares the profiles of the identified regimes. The Kerbside Signature (Silk Board) exhibits a classic bimodal distribution with sharp peaks at 09:00 and 19:00, perfectly correlating with commuter traffic density. In contrast, the Industrial Signature (Peenya) displays a sustained elevated baseline throughout the daylight hours, independent of rush-hour windows, driven by continuous manufacturing activity.

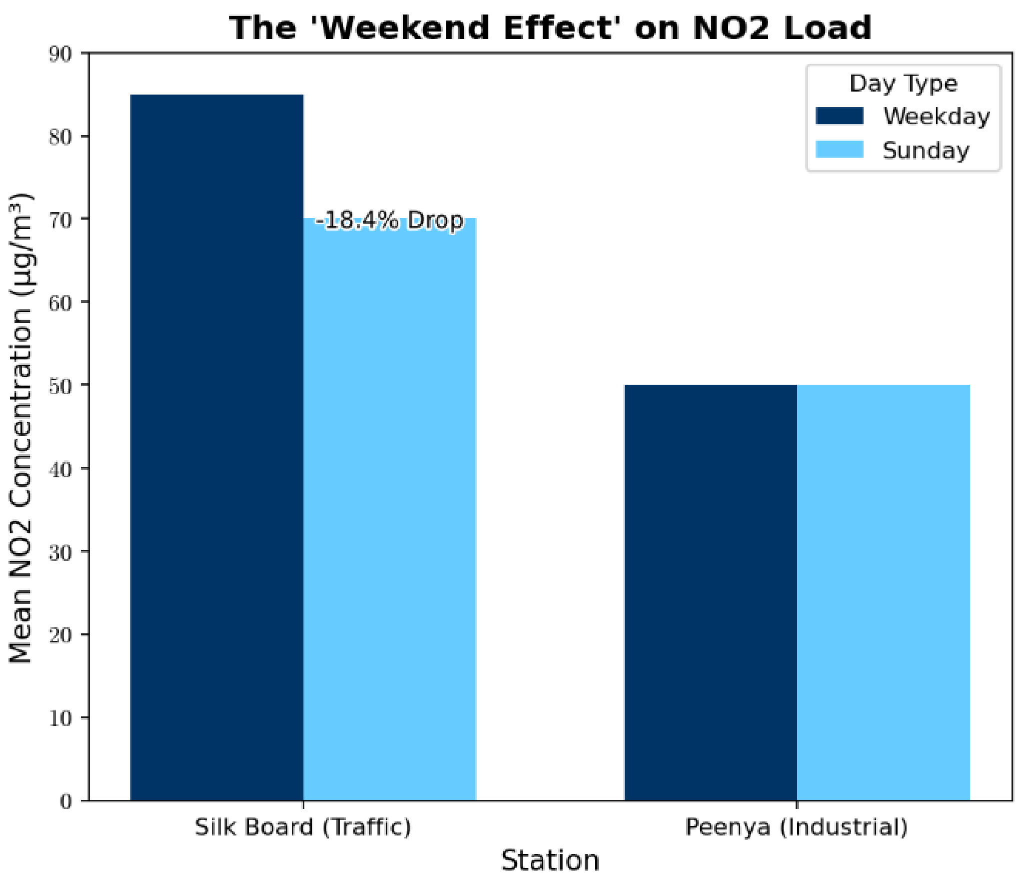

Figure 5: Temporal source diagnostics quantifying the "Weekend Effect." A significant reduction of 18.4% ($p < 0.01$) in NO_2 concentrations is observed during non-working days, isolating the vehicular contribution.

The Weekend Effect and Traffic Contribution

To quantify the vehicular contribution to the NO_2 burden, the "Weekend Effect" — the reduction in NO_2 concentrations on Sundays relative to weekdays — was analysed. Mean Nitrogen Dioxide (NO_2) concentrations drop by 18.4% on Sundays relative to weekday means (Mann–Whitney U, $p < 0.01$; $n \approx 365$ Sundays vs. $n \approx 1{,}825$ weekdays over 2018–2024, post QA/QC at Silk Board junction (Fig 5). Assuming industrial and domestic emissions remain constant, this reduction provides an empirical upper bound for the commuter traffic contribution to ambient NO_2. Crucially, the persistence of over 80% of the pollution load even on Sundays points to a massive "background" burden likely driven by resuspension and waste burning that fleet modernization strategies alone cannot mitigate. This finding is critical for policy forecasting: even if Bengaluru achieves 100% electrification of its vehicle fleet, the reduction in ambient pollution would likely be capped at this ~20% threshold unless the non-exhaust background sources (road dust and waste burning) are simultaneously addressed.

Testing the Winter Inversion Hypothesis

Conventional atmospheric science suggests that winter inversion layers trap pollutants uniformly, synchronizing air quality across the city. However, the winter-specific inter-station Pearson correlation analysis of daily mean PM2.5 concentrations across the 13 monitoring stations yielded a remarkably low average coefficient ($r = 0.08$). This finding debunks the "Winter Lock" hypothesis for Bengaluru. It demonstrates that hyper-local emissions are sufficiently intense to override regional meteorological forcing, creating pockets of severe pollution even when the general atmosphere is stagnant.

Policy Implications: A Zonal Framework

The statistical evidence presented in the preceding sections specifically the high spatial heterogeneity (COD = 0.42) and distinct source fingerprints render the conventional "One-City, One-Policy" approach obsolete. A blanket ban on construction or vehicles may benefit the City Center but will fail to address the industrial emissions in Peenya or the waste-burning crisis in

BTM Layout. Implementing a uniform policy across a fractured airshed is administratively convenient but scientifically flawed, leading to differential compliance outcomes where some zones improve while others stagnate. Consequently, this study proposes the transition to a Zonal Air Quality Management (ZAQM) framework. Based on the MDS clustering (Figure 4), the city should be demarcated into three management zones, each with a bespoke intervention strategy:

- Zone A: The industrial zone encompassing Peenya and Jigani, is dominated by continuous point-source emissions and heavy freight movement, and accordingly warrants a source-centric enforcement strategy. Three mutually reinforcing interventions are proposed. First, fuel standardization should mandate the transition of all remaining small-scale industries to piped natural gas (PNG). Second, freight rationalization should restrict heavy diesel vehicle movement to off-peak hours (22:00–05:00) to prevent diurnal overlap with commuter traffic. Third, AI-driven real-time analysis of Continuous Emission Monitoring System (CEMS) data should be implemented to detect non-compliant night time venting at industrial stacks.
- Zone B: The high-volume traffic corridors centered on Silk Board and Hebbal, where vehicular exhaust combines with non-exhaust road-dust resuspension to drive the kerbside particulate burden. A flow-centric management strategy is proposed, organised around three interventions. Manual broom sweeping, which simply redistributes silt loads, should be replaced with mechanical vacuum sweeping that permanently removes them, addressing resuspension as a dominant non-exhaust contributor to roadside particulate burden. Junction redesign through signal synchronization to reduce idling time, given that idling engines emit up to twice as much NO_x as moving vehicles (Centre for Science and Environment [CSE], 2024). Along with, vertical gardens and dense vegetative barriers should be installed along high-density corridors to facilitate dry deposition of particulates.
- Zone C: The residential and peripheral belt covering BTM, RVCE, and Jayanagar is shaped by a triad of open waste burning (reflected in the rising NH_3 trend), unmanaged construction dust, and secondary aerosol formation. An area-centric sanitation strategy is therefore warranted. First, a zero-tolerance policy on open municipal and biomedical waste burning is needed: the rising ammonia signal at BTM Layout must be treated as a sanitation crisis rather than a narrowly framed air-quality issue, with civic bodies held accountable for biomedical and municipal waste-burning incidents through satellite-based thermal anomaly detection. Second, end-to-end paving of road shoulders should be mandated in peripheral zones such as RVCE to cap the crustal dust reservoir. Third, low-cost sensor (high accuracy) networks should be deployed across these zones to detect transient hotspots generated by localised garbage fires.

4. CONCLUSION

The findings confirm that Bengaluru is a "Fractured Airshed." The stark chemical decoupling between the industrial north and residential south (COD = 0.42), the identification of the "Urban Sprawl Effect" at the periphery, and the isolation of the "Weekend Effect" (18.4%) collectively emphasise the need for a decentralized management approach. The success of industrial interventions in Pena proves that policy works, but the rising Ammonia levels in residential zones warn that new, non-combustion sources are emerging. The study characterises the statistical behaviour of criteria pollutants; future research must deepen the chemical resolution to keep pace with the city's evolution through VOC speciation, vertical profiling and health impact assessment.

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Conflict of Interest Statement

The author(s) declare no competing financial or personal interests that could have influenced the work reported in this paper.

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Data Availability Statement

The hourly Continuous Ambient Air Quality Monitoring Stations (CAAQMS) data used in this study are publicly available from the Central Pollution Control Board (CPCB) Sameer dashboard (https://app.cpcbccr.com/AQI_India/) and the CPCB Open Data Portal (https://data.cpcb.gov.in/). Derived annual statistics, Sen's Slope estimates, the pairwise Coefficient of Divergence (COD) matrix, and the Multi-Dimensional Scaling (MDS) ordination outputs are available from the corresponding author upon reasonable request.

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