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## Research Article

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# Spatio-temporal assessment of PM<sub>2.5</sub> and PM<sub>10</sub> pollution in core and peripheral municipalities of the Kathmandu valley using regulatory and low-cost sensor data

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## Abstract

Rapid urbanization within the complex Himalayan topography in Kathmandu, Nepal has led to significant air quality degradation, creating serious risks to public health. This study assesses the spatio temporal dynamics of particulate matter pollution across core and peripheral municipalities of the Kathmandu Valley by integrating regulatory monitoring data with a high-resolution network of low cost sensors. Daily mean PM<sub>2.5</sub> and PM<sub>10</sub> concentrations were analyzed from 2023 to 2024 to quantify seasonal variability spatial amplification and compliance with international safety guidelines. The results indicate a sustained air pollution problem, with annual mean PM<sub>2.5</sub> concentrations of 40.71 µg/m<sup>3</sup> in the urban core and 27.22 µg/m<sup>3</sup> in peripheral areas. Seasonal analysis shows that the core zone exceeds World Health Organization (WHO) guidelines on nearly all days during the winter and pre-monsoon seasons, largely due to meteorological stagnation and local emission sources. A clear spatial gradient was observed, with the urban core exhibiting a pollution amplification factor of up to 1.60 during the dry season, alongside contrasting particle size dominance and evidence of long-range pollutant transport during extreme pollution events. These results demonstrate that hybrid monitoring networks are effective in capturing intra-urban air pollution variability that is often overlooked by sparse regulatory stations. The study enhances understanding of exposure inequality in valley environments and provides a strong empirical foundation for air quality management in data-limited regions.

**Keywords:** *Urban air quality; hybrid monitoring network; exposure inequality; himalayan valley; particulate matter; seasonal variability*

## 1. Introduction

Ambient particulate matter pollution is one of the most severe threats to global public health and environmental sustainability in the 21<sup>st</sup> century. Fine particulate matter with an aerodynamic diameter of less than 2.5 micrometers or PM<sub>2.5</sub> and coarser particles with a diameter of less than 10 micrometers or PM<sub>10</sub> are linked to adverse health outcomes including respiratory infections cardiovascular diseases and lung cancer (Bhatta et al., 2025; Neupane et al., 2024; Zhou et al., 2025). Recent estimates indicate that the burden of chronic obstructive pulmonary disease attributed to PM<sub>2.5</sub> exposure continues to rise globally with significant economic implications projected to reach trillions of dollars by 2050 (Zhou et al., 2025). The World Health Organization guidelines provide the main reference for air quality safety, but many people live in areas without formal standards or where existing limits are not met (Nazarenko et al., 2021). The exposure inequality is most severe in rapidly developing regions where urban growth and industrial expansion advance faster than environmental regulation.

South Asia has become a major global hotspot for particulate pollution, with air quality concentrations often exceeding international safety guidelines by ten to fifteen times (Sriram & Adhikari, 2025). The Indo Gangetic Plain faces frequent pollution episodes caused by anthropogenic emissions and unfavorable meteorological conditions. Research indicates that persistent atmospheric stagnation and shallow boundary layers during winter months exacerbate

pollutant accumulation across the region (Ojha et al., 2020). Transboundary transport complicates air quality control as pollutants from India move across national borders and degrade air quality in neighboring countries such as Nepal and Bangladesh (Islam et al., 2023; Rana et al., 2016). Satellite based studies show that dust and sea salt related PM<sub>2.5</sub> pollution has expanded across South Asia over the past two decades, increasing the number of people exposed to health risks (Yue et al., 2020).

The Kathmandu Valley in Nepal illustrates the severe difficulty of managing air quality in a complex topographic setting. The bowl shaped valley topography restricts air mass ventilation and facilitates the trapping of pollutants particularly during winter temperature inversions (Aryal et al., 2009; Sah Telee et al., 2024). PM<sub>2.5</sub> concentration in the Kathmandu Valley show strong seasonal variation, with hazardous concentrations in winter and temporary reduction during the monsoon due to wet deposition (Bhatta et al., 2025). Recent analyses suggest that annual mean PM<sub>2.5</sub> concentrations have increased systematically over the last two decades (Becker et al., 2021). The primary emission sources within the valley are well documented and include vehicular exhaust biomass burning for cooking and heating and industrial emissions from brick kilns (Islam et al., 2020; Werden et al., 2022). Brick kilns specifically have been identified as major contributors to black carbon and particulate matter loads with emissions significantly higher than those from alternative fuel sources (Pokhrel & Lee, 2014). Additionally uncontrolled refuse burning and road dust resuspension further degrade the urban airshed (Neupane et al., 2020; Werden et al., 2022). Effective air quality management requires robust monitoring networks to characterize spatio temporal pollution patterns and identify hotspots. Traditional regulatory grade monitoring stations are costly to install and maintain. This constraint limits network coverage in resource constrained settings and creates major data gaps, especially in peripheral and fast growing urban areas. Recent advances in sensor technology have positioned low cost sensors as a practical complement to conventional air quality monitoring. Studies in comparable settings, including India and South Africa, have shown that calibrated low cost sensor networks can effectively capture local pollution variability and identify specific emission hotspots that may be overlooked by sparse regulatory monitoring systems (Aniyikaiye et al., 2023; Madhwal et al., 2024; Shrestha et al., 2025). Such high-resolution datasets are critical for examining fine-scale patterns of pollution exposure and for validating satellite-based estimates, which may underestimate near-surface concentrations in regions with complex terrain (Bhatta & Yang, 2023).

This study addresses these gaps through a comprehensive spatio temporal analysis of PM<sub>2.5</sub> and PM<sub>10</sub> across the Kathmandu Valley by integrating regulatory monitoring data with an expanded network of low cost sensors. By examining seasonal and diurnal variability in both core and peripheral municipalities, the study provides novel evidence on spatial inequality in particulate matter exposure and supports the development of targeted air quality management strategies beyond the urban center.

## 2. Materials and methods

### 2.1 Study Area

The study was conducted in the Kathmandu Valley, an intermontane basin of about 583 km<sup>2</sup> located in central Nepal. The valley is characterized by a bowl-shaped topography with an average elevation of 1400 m, surrounded by mountains rising to 2800 m (Gautam et al., 2004). This topographic configuration restricts proper airflow and traps pollutants, especially during winter temperature inversions (Aryal et al., 2009). During the last three decades, rapid and unregulated urban growth along with demographic change, has increased population density due to large-scale internal migration (Shrestha et al., 2024). As a result, the Kathmandu valley often ranks among Asia most polluted urban areas, with air quality index (AQI) repeatedly reaching hazardous levels during the dry season (Becker et al., 2021; Islam et al., 2020). Various mitigation efforts have been carried out, but it remains a major public health concern. This study stratified monitoring sites into two zones. The Urban Core represents the dense commercial and historic center. Peripheral areas represent rapidly urbanizing municipalities along the valley margins (Figure 1). Table 1 summarizes site specific characteristics of the sensor placement area and other details.

### 2.2 Data Collection and Processing

A two-way approach was used, combining data from official government stations and a network of low-cost sensors. Hourly PM<sub>2.5</sub> and PM<sub>10</sub> concentration data for 2023 were taken from the official site of Department of Environment (DoE), Ministry of Forests and Environment, Nepal. This dataset is from six AQMS, which serve as the benchmark for air quality monitoring with proper data curation and maintenance of quality control (USEPA, 2013).

To improve the spatial resolution in peripheral unmonitored areas, four Blue Sky (Model 8143) sensors data were taken from large monitoring cohort all over Nepal. These sensors use lasers to measure different parameters like PM<sub>2.5</sub>, temperature, and humidity at the same time (Das & Ramachandran, 2020). Sites were chosen in four nearby peripheral municipalities using purposive sampling method (Ahmed, 2024; Campbell et al., 2020). This is a non-probability method that was chosen to intentionally fill in missing data gaps in the existing regulatory network (Abou Jaoude & Muñoz Sanz, 2025). This technique allows for gathering of information on specific topics. The

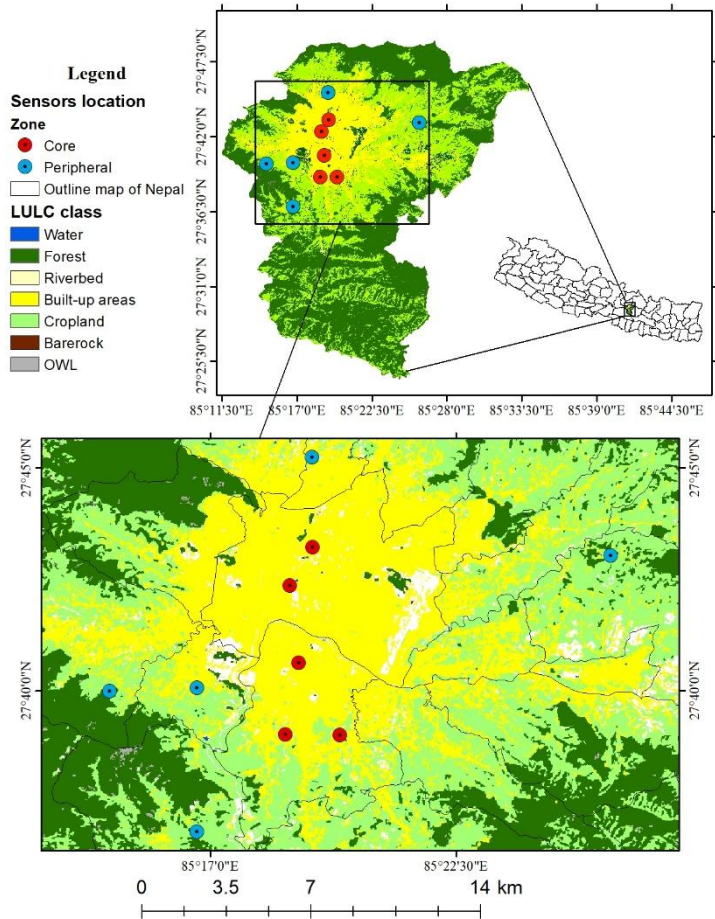


Figure 1: Study area of present study with Urban core and Peripheral areas represented by red and green color respectively along with monitoring sensor locations

sensors send data right away to the TSI Link™ cloud platform via WiFi. This allows us to manage and analyze the data remotely.

Table 1: Air quality monitoring site locations and Zones

| Site Name     | Site id with sensors | Municipality  | Zone       | Remarks |
|---------------|----------------------|---------------|------------|---------|
| Chandragiri   | LCS_Chandra01        | Chandragiri   | Peripheral | LCS     |
| Dakshinkali   | LCS_Dakshin01        | Dakshinkali   | Peripheral | LCS     |
| Changunarayan | LCS_Changu01         | Changunarayan | Peripheral | LCS     |
| Tokha         | LCS_Tokha01          | Tokha         | Peripheral | LCS     |
| Kirtipur      | AQMS_Kirtipur        | Kirtipur      | Peripheral | DoE     |
| Bhaisepti     | AQMS_Bhaisepti       | Kathmandu     | Urban Core | DoE     |
| Ratnapark     | AQMS_RatnaPark       | Kathmandu     | Urban Core | DoE     |
| Khumaltar     | AQMS_Khumaltar       | Lalitpur      | Urban Core | DoE     |
| Sankhapark    | AQMS_Sankhapark      | Kathmandu     | Urban Core | DoE     |
| Pulchowk      | AQMS_Pulchowk        | Kathmandu     | Urban Core | DoE     |

The study utilized hourly particulate matter concentrations ( $PM_{2.5}$  and  $PM_{10}$ ) obtained from two distinct monitoring stations representing the urban core and peripheral zones of the Kathmandu Valley. The raw time series data underwent rigorous quality control procedures to remove outliers and instrument errors. Then we collocated the sensor data with reference GRIMM instrument harmonization value (Shrestha et al., 2025). We aggregated valid hourly records into daily mean concentrations to facilitate the assessment of long-term trends and seasonal variability. We categorized the study period into four distinct seasons: Winter (December – February), Pre monsoon (March-May), Monsoon (June – September), and Post monsoon (September – November), to align with the local meteorological cycle.

### 2.3 Statistical and Temporal Analysis

We evaluated the temporal dynamics of pollution using the Theil Sen slope estimator, a non-parametric method robust against outliers, to quantify the rate of change in  $PM_{2.5}$  concentrations over time (Sen, 1968). To assess the statistical significance of differences in pollution levels across the four seasons, we employed the Kruskal Wallis H test (McKight & Najab, 2010). We further analyzed diurnal and weekly patterns by comparing mean concentrations between weekdays and weekends to isolate the influence of anthropogenic activities such as traffic and industrial operations.

### 2.4 Spatial Assessment and Compliance

We quantified the spatial heterogeneity of pollution by calculating an amplification factor, defined as the ratio of the mean concentration in the Core zone to that of the Peripheral zone. Additionally, we computed the ratio of  $PM_{2.5}$  to  $PM_{10}$  to characterize the particle size distribution and infer potential sources. We evaluated regulatory compliance by calculating the frequency of days exceeding the National Ambient Air Quality Standards (NAAQS) of Nepal and the 2021 World Health Organization (WHO) air quality guidelines (WHO, 2021). Cumulative Distribution Functions (CDF) were generated to visualize the probability of exposure to varying pollution levels.

### 2.5 Trajectory Modeling

To investigate the influence of regional transport during extreme pollution episodes, we utilized the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model developed by the National Oceanic and Atmospheric Administration (NOAA) (Stein et al., 2015). We computed

backward trajectories for selected high pollution days using meteorological data from the Global Forecast System (GFS). This modeling allowed us to trace the path of air masses arriving at the study site and identify potential transboundary contributions to local air quality degradation.

### 3. Results and discussion

#### 3.1 Temporal Variations of PM<sub>2.5</sub> Concentrations

The assessment of ambient particulate matter in the Kathmandu Valley shows a persistent air quality crisis, with concentrations consistently above global health guidelines. The daily mean PM<sub>2.5</sub> concentration show a proper temporal pattern, with annual mean concentrations of 40.71  $\mu\text{g}/\text{m}^3$  in the core zone and 27.22  $\mu\text{g}/\text{m}^3$  in the peripheral zone (Figure 2). These values indicate chronic exposure risk because they far exceed the WHO annual guideline of 5  $\mu\text{g}/\text{m}^3$ . Time series data show a proper seasonal cycle, with high pollution during dry months and lower concentrations during the wet season.

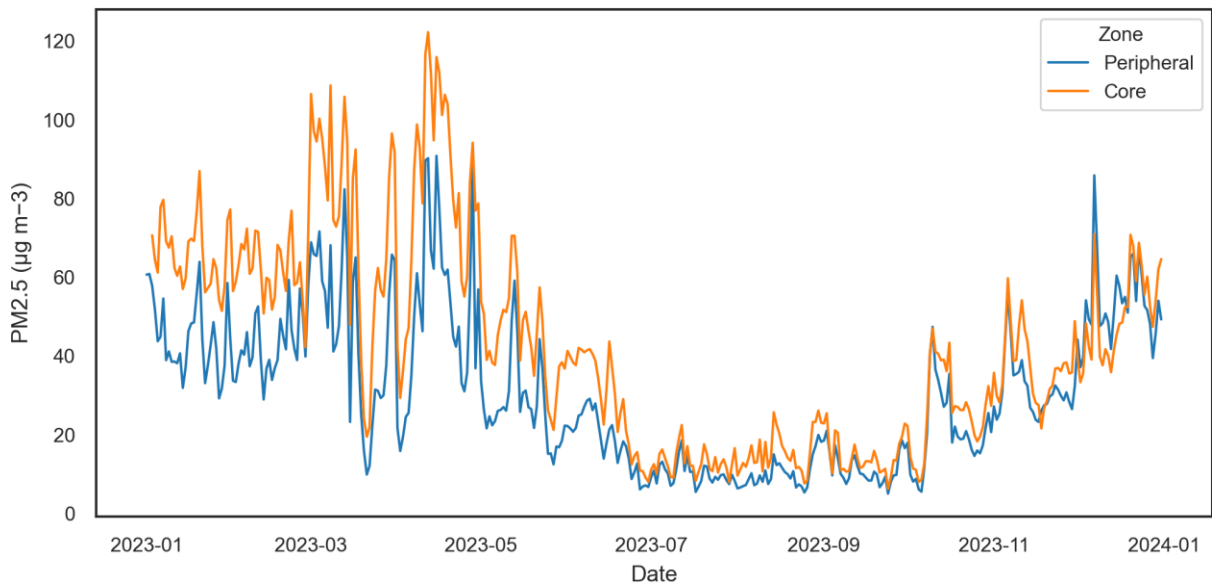


Figure 2: Daily mean PM<sub>2.5</sub> concentrations trends comparing core (orange) and peripheral (blue) zones from 2023 to 2024 showing distinct seasonal cyclicality and higher baseline pollution in the urban core.

Statistical analysis of daily trends shows a significant decline in PM<sub>2.5</sub> concentrations over the study period (Table 2). The decline is steeper in the core zone at 0.132  $\mu\text{g}/\text{m}^3/\text{day}$  than in the peripheral zone at 0.051  $\mu\text{g}/\text{m}^3/\text{day}$ . This statistically significant decline does not indicate clear improvement in air quality. The trend likely reflects yearly meteorological variation and the shift from dry to wet seasons during the study period rather than the effect of emission control measures.

Table 2: Theil-Sen Slope analysis of daily PM<sub>2.5</sub> concentration trends

| Zone       | Slope ( $\mu\text{g}/\text{m}^3/\text{day}$ ) | p-value | Significance |
|------------|-----------------------------------------------|---------|--------------|
| Core       | -0.132                                        | < 0.001 | Significant  |
| Peripheral | -0.051                                        | < 0.001 | Significant  |

### 3.2 Seasonal and Monthly Variability

PM<sub>2.5</sub> concentration change over time due to interactions between local meteorology and valley topography. As shown in Figure 3, pollution concentration is higher in winter and the pre monsoon season, with a pre monsoon mean of 65.13  $\mu\text{g}/\text{m}^3$  in the core zone, while the monsoon records the lowest mean of 17.72  $\mu\text{g}/\text{m}^3$ . The Kruskal Wallis test confirmed significant differences in PM<sub>2.5</sub> distributions across seasons ( $H = 928.06$ ,  $p < 0.001$ ). Monthly analysis corroborates these findings with peak concentrations occurring in January and April followed by a sharp decline during the monsoon months of July and August (Figure 4).

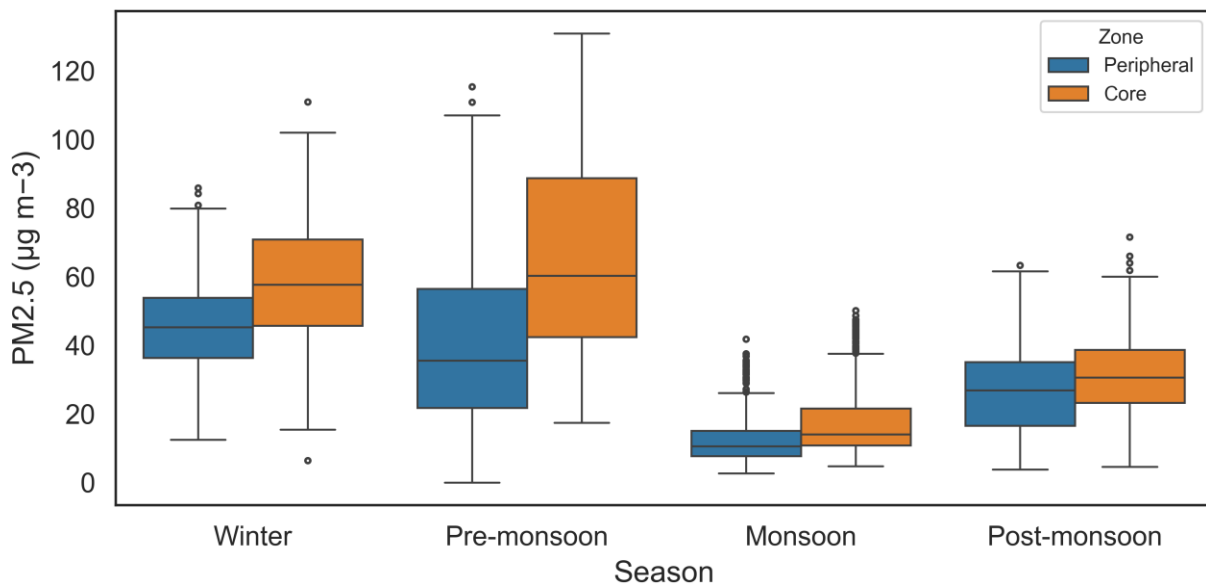


Figure 2: Boxplot distribution of PM<sub>2.5</sub> concentrations stratified by season and zone highlighting the extreme variability and elevated medians during winter and pre monsoon periods.

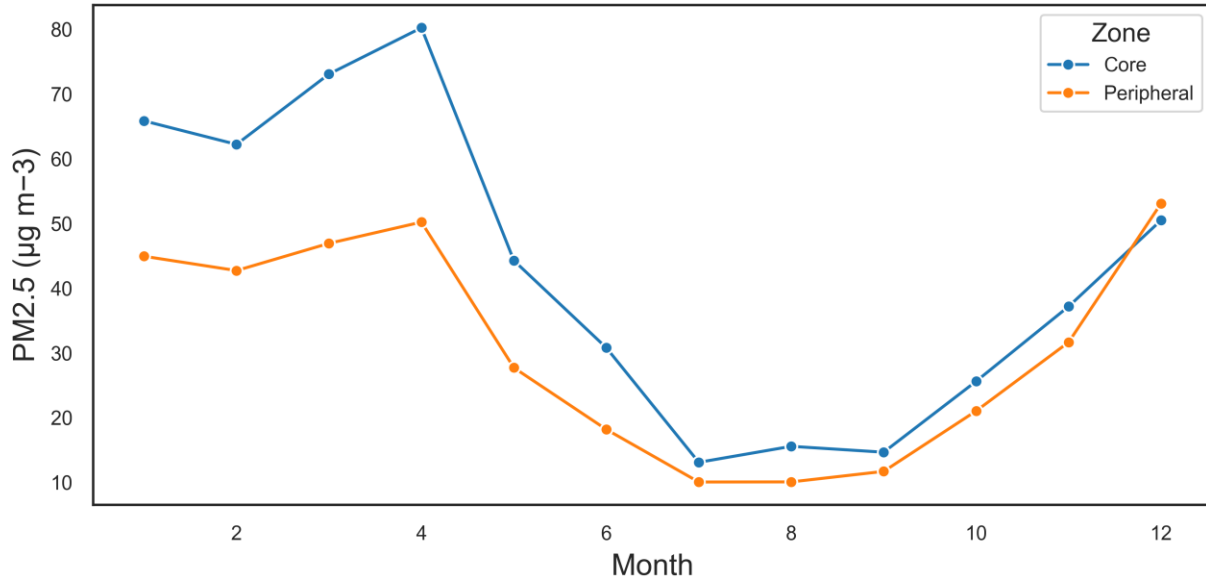


Figure 3: Monthly mean PM<sub>2.5</sub> variations indicating peak pollution levels in winter and pre monsoon months followed by monsoon washout.

This seasonal pattern matches earlier studies by Aryal et al. (2009) and Sah Telee et al. (2024), who link high winter PM<sub>2.5</sub> concentrations to strong temperature inversions that trap pollutants within the bowl shaped valley. During the pre monsoon season, dry conditions, forest fires, and regional transport increase pollution and produce annual peaks. Monsoon rainfall lowers particulate concentrations through washout, but recent evidence shows PM<sub>2.5</sub> concentration during this season often remain above health based guidelines (Bhatta et al., 2025).

### 3.3 Spatial variability and amplification

This study quantifies proper spatial divergence between the core and peripheral zones using an amplification factor (Table 3). The core zone shows higher particulate matter concentrations in all seasons, with the size of the difference changing by season. The pre monsoon period records the highest amplification factor of 1.60, which means pollution in the urban core is 60% higher than in the periphery. This gradient indicates regional meteorology sets the background pollution concentration, while dense local emission sources in the urban core further worsen air quality.

Table 3: Seasonal amplification of pollution quantifying the ratio of core to peripheral PM<sub>2.5</sub> concentrations.

| Season       | Core Mean (µg/m <sup>3</sup> ) | Peripheral Mean (µg/m <sup>3</sup> ) | Amplification Factor |
|--------------|--------------------------------|--------------------------------------|----------------------|
| Pre-monsoon  | 65.13                          | 40.77                                | 1.6                  |
| Monsoon      | 17.72                          | 12.37                                | 1.43                 |
| Winter       | 58.61                          | 45.27                                | 1.29                 |
| Post-monsoon | 31.44                          | 26.9                                 | 1.17                 |

The spatial variability index shows high seasonal fluctuations, reaching a maximum in August (Figure 5), indicating that although pollutant concentrations decline during the monsoon, relative differences between zones become more variable due to uneven washout processes. Previous work has shown that rapid expansion of built up areas and land consumption in the Kathmandu Valley

has reduced urban sustainability and likely increased emission densities in the urban core (Shrestha et al., 2024). In contrast, the lower amplification factor of 1.17 observed during the post-monsoon season suggests a more uniform distribution of pollutants, potentially driven by enhanced atmospheric mixing or changes in dominant emission sources during the transition toward winter.

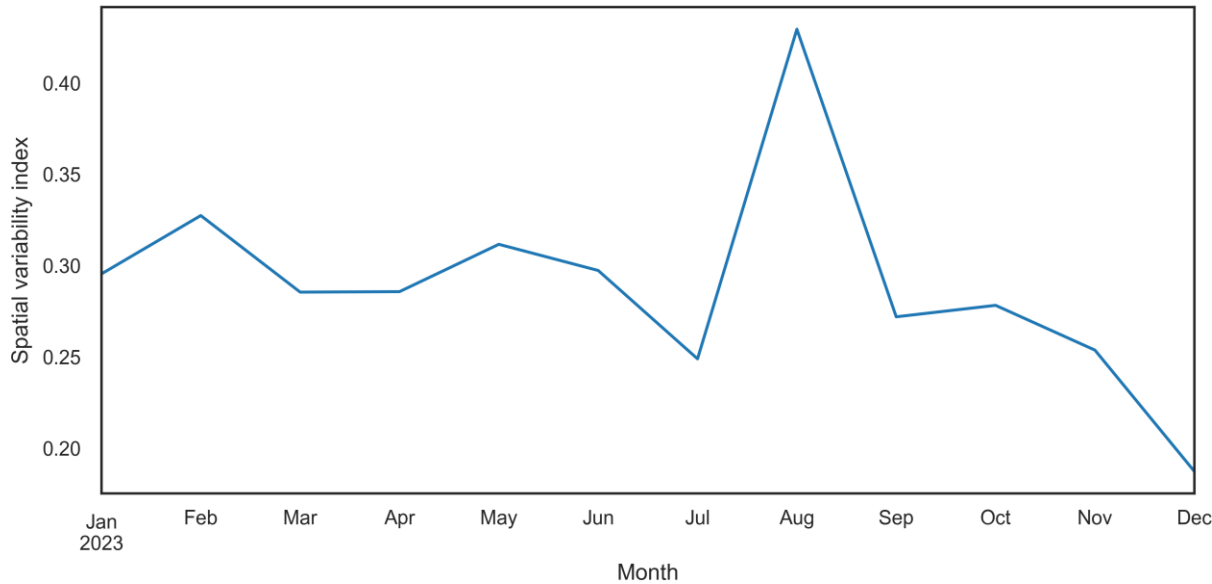


Figure 5: Monthly spatial variability index illustrating the fluctuating divergence between core and peripheral zones with maximum heterogeneity observed during the monsoon.

### 3.4 Particulate composition and day type analysis

The  $PM_{2.5}$  to  $PM_{10}$  ratio exhibits clear spatial variation along the urban–rural gradient, with the core zone showing a broader distribution and a peak around 0.6–0.7, while the peripheral zone displays a sharper peak near 0.9 (Figure 6). This pattern indicates a higher contribution of coarse dust particles in the urban core, likely from road dust resuspension and construction activities (Neupane et al., 2020), whereas fine combustion-related aerosols dominate in peripheral areas (Werden et al., 2022).

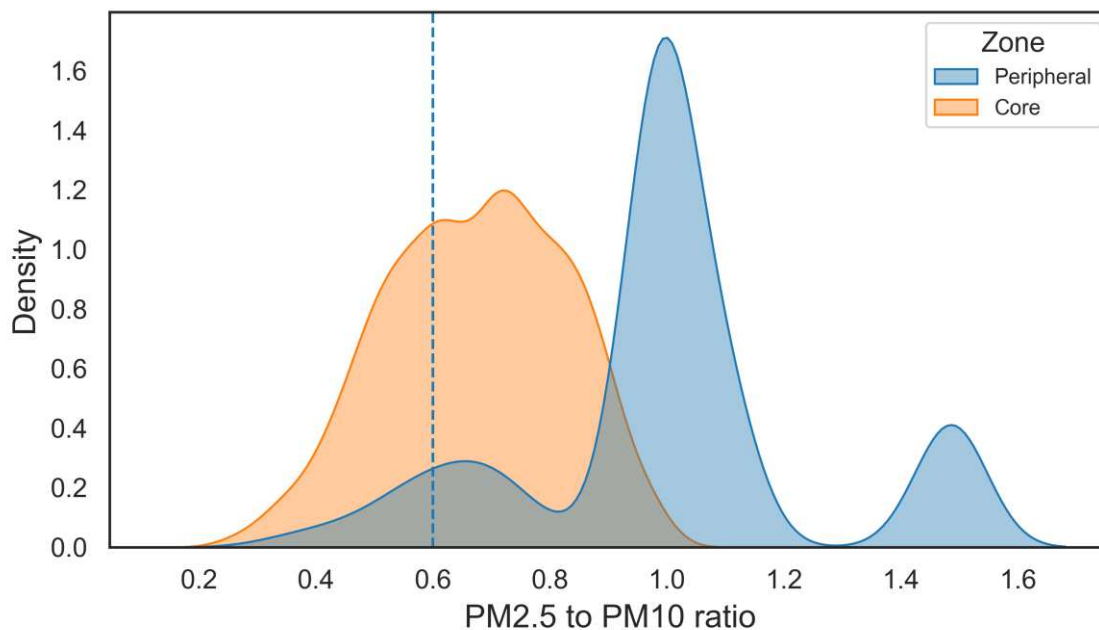


Figure 6: Density plot of PM<sub>2.5</sub> to PM<sub>10</sub> ratios showing differences in particle size composition with coarser fractions dominant in the core and finer fractions in the periphery.

Analysis of day type variability showed minimal differences between weekday and weekend PM<sub>2.5</sub> concentrations (Figure 7). Mean concentrations in the core zone remained around 40  $\mu\text{g}/\text{m}^3$  on both weekdays and weekends, which shows a continuous emission sources rather than weekday patterns. This absence of a weekend effect aligns with brick kiln operations in the valley, which run continuously throughout the week and sustain high background pollution concentration independent of traffic variation (Pokhrel & Lee, 2014; Werden et al., 2022).

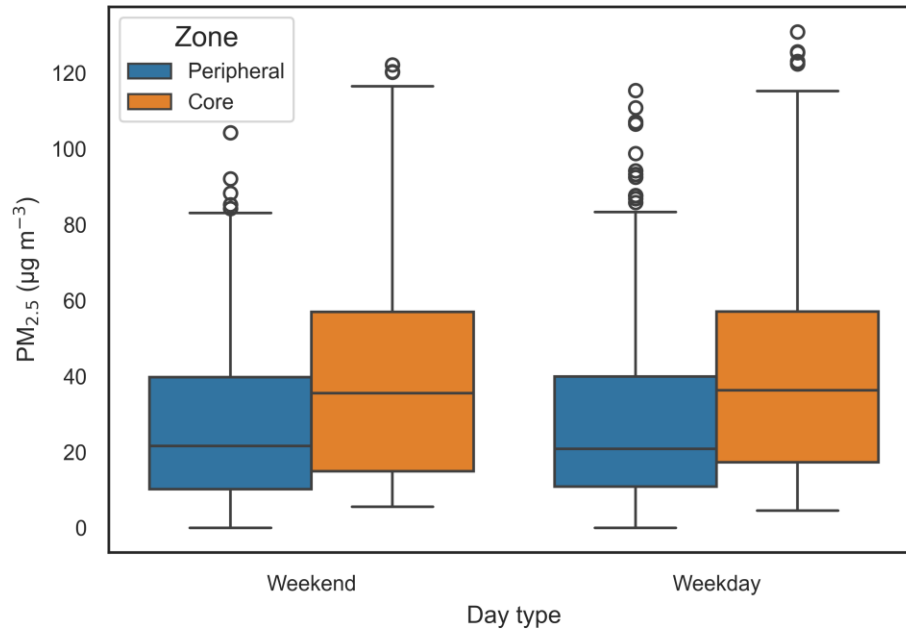


Figure 7: Comparison of PM<sub>2.5</sub> concentrations between weekdays and weekends across zones.

### 3.5 Regulatory Compliance and Public Health Implications

The exceedance analysis comparison with NAAQS and WHO standards indicates serious concerns regarding regulatory compliance and public health. Cumulative Distribution Function analysis shows that PM<sub>2.5</sub> concentrations below the WHO 24 hour guideline of 15  $\mu\text{g/m}^3$  occur rarely, especially in the core zone (Figure 8).

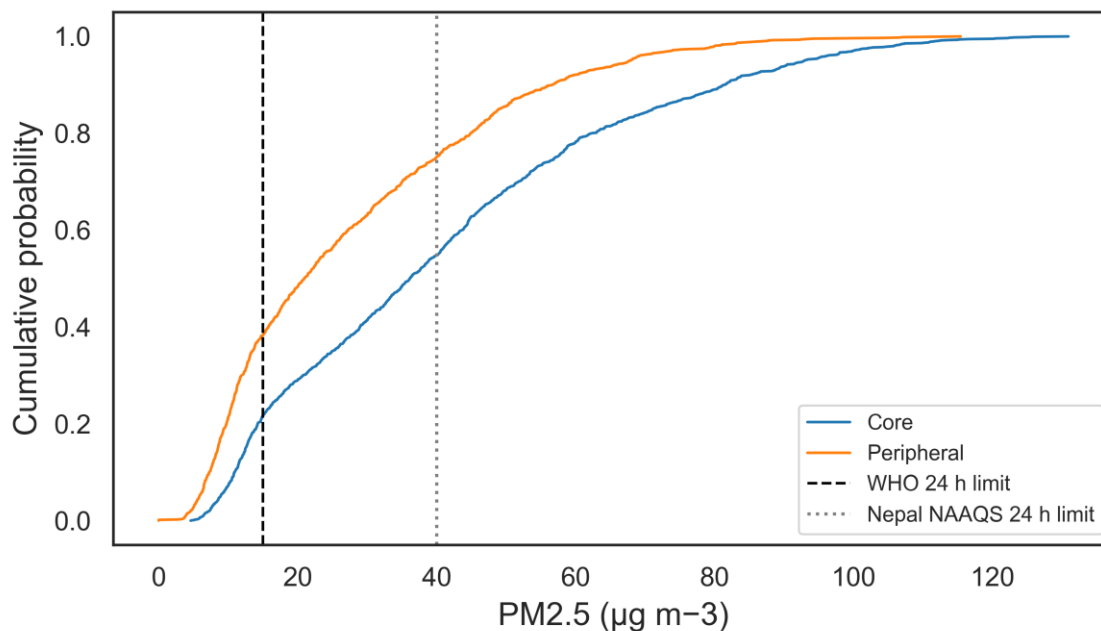


Figure 8: Cumulative Distribution Function of PM<sub>2.5</sub> concentrations relative to WHO 15  $\mu\text{g/m}^3$  and Nepal NAAQS  $\mu\text{g/m}^3$  standards.

The core zone exceeded WHO limits on almost all days during the winter and pre-monsoon seasons (Figure 9) and remained non-compliant with Nepal's NAAQS for about 87.5 percent of

the winter period. The severity of air quality degradation is further illustrated by the high frequency of violation days relative to compliant days (Figure 10; Table 4).

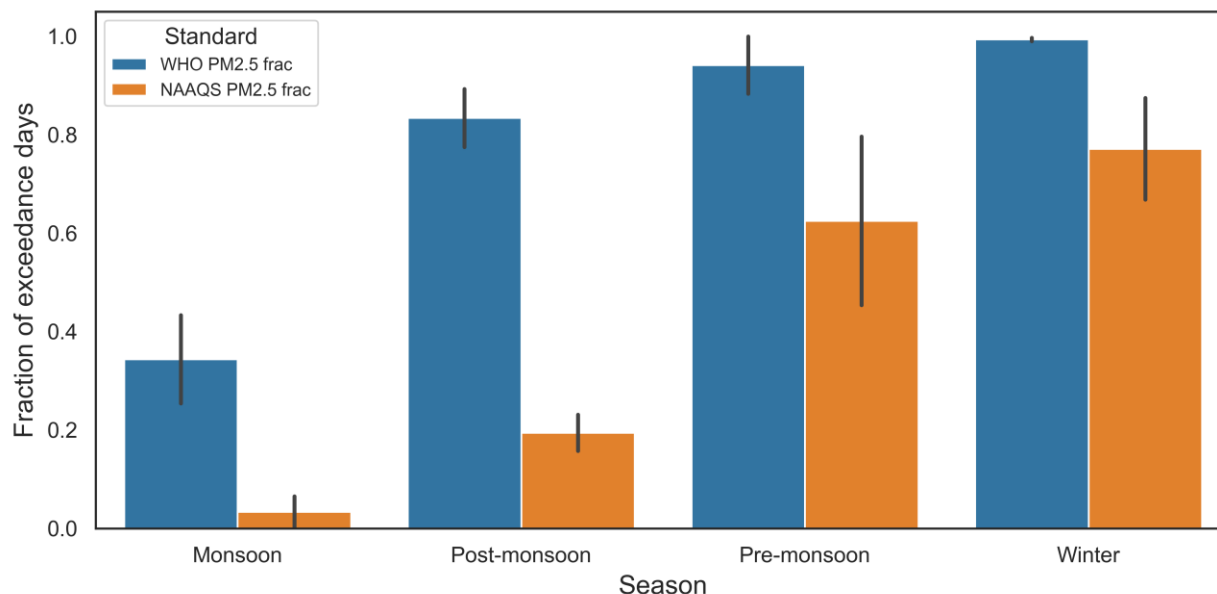


Figure 9: Fraction of days exceeding WHO and NAAQS limits stratified by season showing near total non compliance during dry seasons.

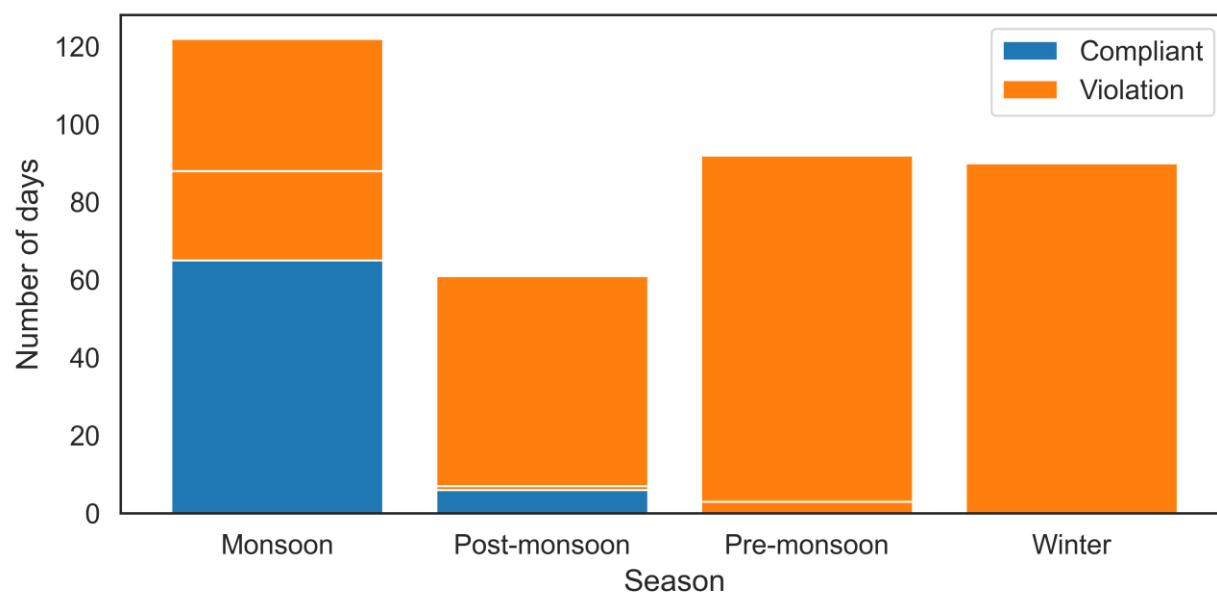


Figure 10: Number of days classified as compliant or violation based on WHO PM<sub>2.5</sub> guidelines, stratified by season.  
Table 4: Seasonal frequency of WHO guideline compliance and violations highlighting compliance rates as low as 0 percent in the core zone.

| Season       | Zone       | Total Days | Compliant Days | Violation Days | Compliance Rate (%) |
|--------------|------------|------------|----------------|----------------|---------------------|
| Monsoon      | Core       | 122        | 65             | 57             | 53.30%              |
|              | Peripheral | 122        | 88             | 34             | 72.10%              |
| Post-monsoon | Core       | 61         | 6              | 55             | 9.80%               |
|              | Peripheral | 61         | 7              | 54             | 11.50%              |
| Pre-monsoon  | Core       | 92         | 0              | 92             | 0.00%               |

|        |            |    |   |    |       |
|--------|------------|----|---|----|-------|
| Winter | Peripheral | 92 | 3 | 89 | 3.30% |
|        | Core       | 88 | 0 | 88 | 0.00% |
|        | Peripheral | 90 | 0 | 90 | 0.00% |

The monsoon season offered the only period of partial improvement in air quality, although the core zone achieved a compliance rate of just 53.3 percent (Table 4). Pollution persistence is further reflected in the frequency of extreme events, with 24 extreme pollution days recorded in the core during the pre-monsoon season compared to only 3 in the peripheral zone (Figure 11). These results are consistent with Becker et al. (2021), who classified most winter days in Kathmandu as unhealthy. Prolonged exposure to such elevated PM<sub>2.5</sub> concentrations poses serious health risks, including increased rates of chronic obstructive pulmonary disease and lung cancer (Neupane et al., 2024; Zhou et al., 2025).

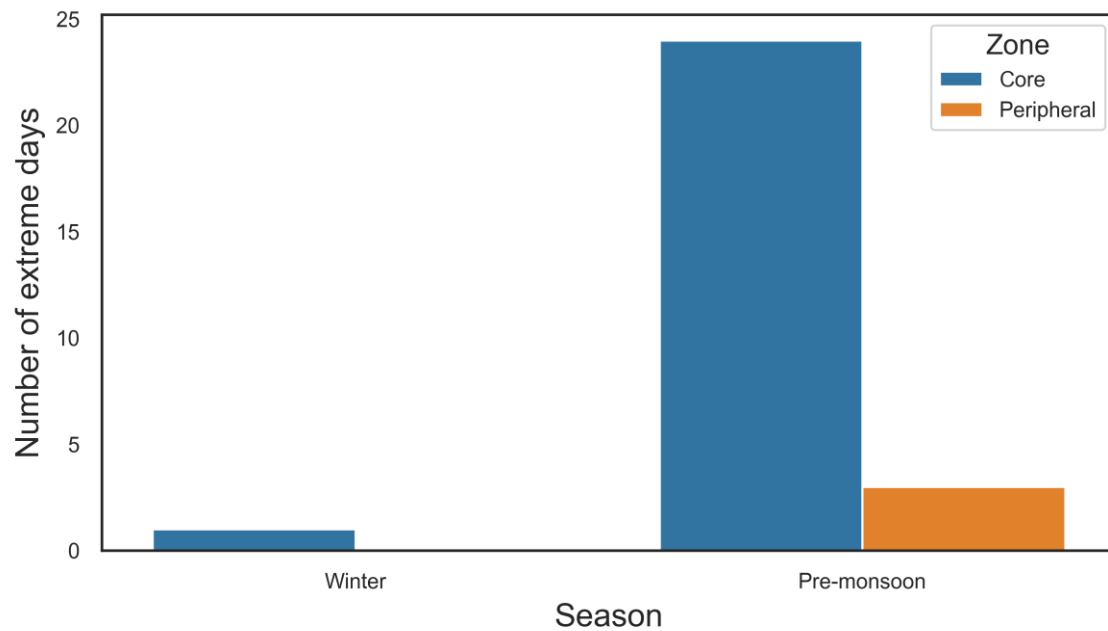


Figure 11: Count of extreme pollution days observed in pre-monsoon and winter seasons.

### 3.6 Influence of Regional Transport

The backward trajectory analysis using the HYSPLIT model for a representative high pollution event on March 15 2023 indicates that long range transport plays a pivotal role in the extreme exceedances observed during the pre monsoon season (Figure 12). Air masses reaching the study area originated from the west traversing the Indo Gangetic Plain before arriving in the Kathmandu Valley.



#### 4. Conclusion and recommendations

This study presents a comprehensive spatio-temporal evaluation of particulate matter pollution in the Kathmandu Valley by integrating regulatory monitoring data with observations from a low-cost sensor network. Results show that PM<sub>2.5</sub> and PM<sub>10</sub> concentrations consistently exceed international health guidelines across the valley, with the highest pollution levels occurring during the winter and pre-monsoon seasons. A clear spatial gradient was identified, with substantially higher particulate concentrations in the urban core than in peripheral municipalities, particularly during dry periods, reflecting the combined effects of dense traffic, dust resuspension, and valley topography. The use of low-cost sensors successfully captured pronounced intra-urban air quality heterogeneity that is not resolved by sparse regulatory stations. Overall, the findings enhance understanding of how urbanization patterns shape pollution exposure in complex valley environments and underscore the importance of integrated monitoring approaches.

Future studies should prioritize detailed chemical characterization of particulate matter using receptor modeling and speciation analysis to accurately identify dominant sources and assess zone specific toxicity. Expanded evaluation of low cost sensor performance is recommended to ensure calibration stability and data reliability across varying elevations and seasonal humidity conditions. High resolution spatio temporal pollution data should be used to estimate population weighted exposure. Also, the analytical framework should be applied to other valleys and urban centers in Nepal to enable comparative analyses and support the development of robust regional air quality management strategies.

**Consent to Participate declaration:** not applicable

**Ethics declaration:** not applicable.

**Data Availability:** The data supporting the findings of this study are available from the corresponding author upon reasonable request. Data obtained from publicly available sources are accessible through their respective monitoring platforms.

#### Author Contributions Statement

Charan Bhattarai: Conceptualization, methodology, data collection, data curation, formal analysis, visualization, and writing-original draft. Enna Mool: Data collection, data curation, investigation, formal analysis, and writing-review and editing. Rejina Maskey Byanju: Conceptualization, methodology, supervision, validation, interpretation of results, writing-review and editing.

**Competing Interests:** The authors have no competing interests.

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