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Air quality and meteorological drivers in Kathmandu Valley, Nepal: A 2021–2023 observational study

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Abstract

Air pollution in Kathmandu Valley threatens public health. Using 2021–2023 data from two urban monitoring stations (Ratna Park and Kirtipur), we analyzed associations between particulate matter ($PM_{2.5}$, PM_{10}, and total suspended particles [TSP]), temperature, and precipitation using descriptive statistics, correlation analysis, regression analysis, analysis of variance, and cluster analysis. At Ratna Park, $PM_{2.5}$ concentrations were highest in winter (December–February), with a monthly mean peak of 95.8 μg/m³ in January, driven by temperature inversions and stagnant conditions. Seasonal mean $PM_{2.5}$ was highest during the pre-monsoon season (60.6 μg/m³), followed by winter (52.5 μg/m³), with no statistically significant difference ($p = 0.34$). PM_{10} and TSP peaked in the pre-monsoon season (March–May) due to resuspension of dust from dry, bare surfaces and increased convective activity. $PM_{2.5}$ showed strong negative correlations with minimum temperature ($r = -0.57$) and precipitation ($r = -0.60$). Meteorological factors significantly affect pollutant concentrations; however, unmeasured emission sources are likely to play an important role as well. PM_{10} and TSP drove poor Air Quality Index (AQI) levels during the pre-monsoon period, while $PM_{2.5}$ was the primary contributor to winter AQI. Multiple linear regression at Ratna Park explained 68% of the variance in $PM_{2.5}$, while ridge regression confirmed the negative influence of minimum temperature and precipitation, with a stable coefficient despite multicollinearity. The study provides evidence-based insights to support air quality enhancement, public health planning, and policy-making for Kathmandu Valley and similar topographically characterized urban regions. These findings have a direct impact on the health of over 2.5 million valley residents, mostly during winter and the pre-monsoon period.

Keywords: Air quality; Precipitation; Particulate matter; Seasonal variation; Ridge regression

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1. Introduction

Kathmandu is the capital and largest city of Nepal, located in a bowl-shaped valley at an elevation of approximately 1,400 m above sea level. It is a culturally and historically

important city and one of Nepal's major tourist destinations. Despite being a major tourist destination, Kathmandu faces severe air pollution challenges due to urbanization, rising vehicle numbers, and rapid construction. The unique topography and meteorological conditions of Kathmandu Valley also play a significant role in trapping pollutants, especially during periods of atmospheric stability.[1]

Over the past few decades, air pollution has become a major environmental challenge for both the government and the public. Fine particulate matter ($PM_{2.5}$), coarse particulate matter (PM_{10}), and total suspended particles (TSP) are key indicators of air pollution in Kathmandu. $PM_{2.5}$ refers to particles with a diameter of 2.5 microns or less, and PM_{10} consists of particles with diameters less than or equal to 10 microns. Air pollution, especially $PM_{2.5}$, remains a leading global environmental risk factor, contributing to increased mortality and chronic disease burden. TSP includes particles of all aerodynamic diameters, encompassing $PM_{2.5}$, PM_{10}, and its larger particles, and has traditionally been used as a broad indicator of particulate pollution. The Environmental Protection Agency suggests that $PM_{2.5}$ is more dangerous than other pollutants because it can enter the lungs and bloodstream. These particulates directly affect human health, causing respiratory disease, cardiovascular morbidity, and premature mortality.[2] Visibility often falls below 500 m, increasing hospital admissions for respiratory illness. Exposure disparities are found in low- and middle-income countries, arising from rapid urbanization, weaker emission controls, and growing industry.[3]

Meteorological conditions play a significant role in framing air pollutant concentrations. During winter (December–February), frequent temperature inversions cause a layer of warm air to sit above cooler air near the surface. These layers trap cooler air near the surface beneath a layer of warmer air, limiting vertical mixing and allowing pollutants to accumulate.[4] Conversely, during the monsoon period, heavy, regular rainfall improves air quality.[5]

Despite growing awareness, the level of air pollution in Kathmandu consistently crosses the national ambient air quality standards of Nepal and the World Health Organization (WHO), placing increasing pressure on the government and relevant agencies to implement sustainable measures to control air pollution and maintain pollutant levels within the Air Quality Index (AQI). Nepal's National AQI standards set a 24-h $PM_{2.5}$ limit of 40 $\mu g/m^3$, a level frequently exceeded in datasets.[6] Although several studies have examined air pollution using pre-COVID-19 data, there is a need for updated analyses based on post-COVID-19 conditions. This study focuses on the 2021–2023 period to provide a contemporary assessment following the post-COVID-19 period, a time characterized by changes in human activity and emission patterns. This is essential for understanding contemporary trends and the efficacy of existing interventions. Furthermore, a detailed statistical analysis linking multiple pollutants across different urban zones for meteorological studies is lacking. Understanding these interrelated and complex interactions is critical as the success of any intervention—such as stricter emission standards or expanded public transportation—depends on local evidence. Evidence from other developing economies indicates that policies must be adapted to specific urban and meteorological contexts; for instance, studies from China have demonstrated the importance of context-sensitive public transportation strategies in improving air quality.[7]

This study analyzes recent monthly environmental data (2021–2023) from two representative monitoring stations in Kathmandu. The main pollutants are $PM_{2.5}$, PM_{10}, TSP, and climatic variables (temperature and precipitation). Analyzing pollutants and climatic variables provides a deeper understanding of their relationships, helping identify trends, seasonal variations, and other hidden aspects of air pollution and weather. We also examine the influence of seasonal climatic variations on air quality, public health, and urbanization in the city. Rising temperatures and increasingly unpredictable rainfall patterns are creating significant challenges for environmental management. Additionally, the study aims to investigate the relationship between climatic factors (maximum temperature, minimum temperature, and precipitation) and pollutant concentrations using statistical modeling techniques, such as ridge regression, to address multicollinearity among meteorological variables.

The findings are expected to contribute to the literature on air pollution and climatic conditions in Kathmandu and support the development of Kathmandu and similar topographically affected cities in South Asia. This study supports evidence-based policymaking by enabling the analysis of long-term environmental patterns and their implications for public health. However, it is essential to mention that the analysis is based on aggregated monthly data, which may smooth short-term pollution extremes. Hence, the results primarily reflect long-term patterns rather than daily variability—an important distinction when interpreting results, particularly in relation to public health implications.

2. Literature review

Air pollution is a major global environmental risk factor. According to the WHO, around 99% of the world's

population breathes air that exceeds the WHO guideline limits, causing approximately 7 million premature deaths annually.[8] Exposure to fine particulate matter allows particles to enter deep into the lungs and bloodstream, resulting in ischemic heart disease, obstructive pulmonary disease, and lung disease. Recent epidemiological studies strengthen the evidence associating particulate exposure with increased mortality risk.[9] In South Asia, approximately 60% of the population is exposed to hazardous pollution levels and is home to 37 of the world's 40 most polluted cities. With rapid economic growth, air pollution has become a major concern in South Asia, ranking the region at the top of global rankings.[10] The number of deaths is projected to increase by 36.6% in South Asia from 2045 to 2049.[11] Substandard vessels with inadequate pollution prevention measures are a major source of emissions in Southeast Asia, posing serious risks to local communities and marine environments and warranting close attention.[12] Regional modeling studies revealed strong spatial clustering of major pollution regions associated with urban emissions, topographic confinement, and seasonal meteorological variability.[13]

As Nepal is a landlocked South Asian country, its climate change, culture, social phenomena, and environmental changes are strongly influenced by neighboring countries, particularly India. Many studies in South Asia, particularly from Bengaluru[14], Delhi[15,16], and Bihar[17], report that air pollution is a key issue to be addressed. During the dry winter monsoon, the fumes disperse toward the Indian Ocean, creating a vast pollution haze, but their fate during the wet summer monsoon has been unclear.[18] In South Asia, $PM_{2.5}$ concentrations often exceed WHO guidelines by up to 20-fold.[19] Between 1990 and 2020, carbon dioxide (CO_2) emissions increased substantially across South Asia, with India showing the largest absolute rise (578.5 to 2,441.8 million tons [MT]), followed by Pakistan, Bangladesh, and Nepal. Similarly, greenhouse gas emissions between 1990 and 2018 nearly tripled in India (1,990.4 to 3,346.6 MT of CO_2-equivalents), Nepal (20.6 to 54.6 MT of CO_2-equivalents), increased markedly in Pakistan, and approximately doubled in Bangladesh. Methane emissions rose most sharply in Pakistan (70.4 to 151 MT of CO_2-equivalents), followed by Nepal (17 to 31 MT of CO_2-equivalents) and India (524.8 to 669.3 MT of CO_2-equivalents).[20] Comparable studies from Dhaka, Bangladesh, have also reported significant seasonal and meteorological influences on air pollution.[21,22] Comparing our findings with these contexts will help to generalize the observed patterns to other urban valleys in the region.

In 2004, the annual average PM_{10} concentrations in major Chinese cities were 102 μg/m^3 in southern cities, 140 μg/m^3 in northern cities, and 121 μg/m^3 in cities nationwide.[23] Additionally, the annual average concentrations of sulfur dioxide and nitrogen dioxide nationwide were 66 μg/m^3 and 38 μg/m^3, respectively. $PM_{2.5}$ is generally used as an indicator of anthropogenic air pollution: average annual concentrations range from below 10 μg/m^3 to over 100 μg/m^3 worldwide.[24] Available data from China indicate that annual average exposure to $PM_{2.5}$ among solid fuel-using populations is within the range (100–400 μg/m^3).[25] During the past decade, sulfur dioxide and nitrogen dioxide emissions have declined throughout China, and concentrations of $PM_{2.5}$ and PM_{10} have considerably decreased in most cities; however, the annual 90th percentile of maximum daily 8-hour average ozone increased.[26] Developing countries, particularly those in Asia, are rapidly adopting industrial pollution control standards similar to those in developed countries.[27] For example, Bhutan's Environmental Act addresses the principles of reduce, reuse, and recycle, and the polluter pays principle, while policies in India and Nepal emphasize the protection of property and heritage.[28]

2.1. Air quality in Kathmandu Valley: A persistent crisis

Kathmandu has faced a significant air pollution challenge for an extended period. Studies over the past two decades regularly report high pollutant levels exceeding national and international standards, particularly during the dry winter season.[29] During 85% winter days, Kathmandu is categorized as "unhealthy" according to the AQI[30] with $PM_{2.5}$ concentrations beyond 200 μg/m^3. In winter, air quality worsens due to low temperatures, weak winds, and limited rainfall, which hinder the dispersion of pollutants.[24] The primary sources of emission have been identified as vehicular traffic, road dust, outdated technologies, growing population, limited area, and urbanization.[31]

2.2. Role of meteorology and topography

Pollution concentrations are strongly influenced by the interaction between emissions and meteorology. The valley's topography is a critical factor that restricts horizontal dispersion. During the winter season, temperature inversions created by local meteorological conditions lead to high concentrations of pollutants.[32] Temperature inversions form and persist until late morning, developing a confined layer smaller than 500 m deep, leading to pollutant accumulations.[4] This creates low wintertime wind speeds, resulting in characteristic winter pollution haze. The summer monsoon has a cleansing effect, lowering $PM_{2.5}$ and PM_{10} deposition levels by 50–70% during the rainy season.[5] In addition to meteorological factors, winter emission sources also become high during

this period. Increased biomass combustion for heating, increased vehicular emissions, and open burning of agricultural waste contribute to winter pollution. These activities integrate the effects of temperature inversions, resulting in a dual challenge: an increase in emissions reduces dispersion capacity.[32] The meteorological and topographical constraints make Kathmandu a good case for studying pollution–weather interactions, yet integrated studies based on post-2020 data from multiple stations remain scarce. Recent continuous monitoring in Kathmandu states that the concentration of coarse particulate matter increases during the pre-monsoon season due to low relative humidity and increased dust resuspension.[33]

2.3. Pollution–meteorology relationship studies

In environmental research, statistical modeling of air quality data is very common. In South Asia, Delhi[15] and Dhaka[17] have shown strong negative correlations between pollutants and both temperature and precipitation. Observational and modeling studies have proposed that the boundary layer height, wind speed, humidity, and temperature significantly influence pollutant dispersion, aerosol formation, and chemical transformations.[34] In Kathmandu, similar approaches were also applied. The regression model quantified a 5% reduction in PM_{10} for each 1°C increase in temperature.[1] Recently, novel statistical probability distribution models applied to Kathmandu's air quality data confirmed peak pollution during winter and least during monsoon.[35,36]

2.4. Research gap and contribution

However, although several studies have investigated air pollution in Kathmandu to date, important gaps remain in the existing literature:

(i) Temporal gap: Only a few studies have discussed air quality data broadly from the post-COVID-19 period, especially 2021 onward.
(ii) Pollution and spatial coverage: There are limited studies representing more than one urban landscape with integrated analysis of $PM_{2.5}$, PM_{10}, and TSP.
(iii) Detailed statistical results: Statistical results of the discussion for underlying atmospheric physics, such as inversion strength and boundary layer height, are described qualitatively, but quantitative statistical assessments linking these parameters to pollutant levels are lacking.
(iv) Policy translation: Few studies offer specific, actionable, and seasonally targeted results

Despite important groundwork by previous studies, such as Shrestha[1], who quantified meteorological effects using pre-pandemic data, and Chaudhary *et al.*[35,36], who used advanced statistical distributions, a critical gap remains in the integrated analysis of $PM_{2.5}$, PM_{10}, and TSP using post-2020 data from multiple stations. Very few studies integrate such an analysis with a clear indication of how to translate robust statistical results into seasonally targeted policy recommendations. In this study, we directly address that gap by applying a multi-method statistical approach to a recent three-year dataset of two distinct urban stations. By explicitly integrating statistical findings with meteorological mechanisms such as temperature inversions and monsoon cleaning, this study aims to provide a grounded mechanistic understanding of air quality variations that can inform public health management and policy-making for Kathmandu Valley.

3. Methodology

3.1. Study area and data sources

This study focused on the Kathmandu Valley. Air quality data for $PM_{2.5}$, PM_{10}, and TSP were obtained from the Department of Environment, Nepal, under the Kathmandu Valley Air Quality Monitoring Network. Two stations were selected from a total of eight based on data completeness and their representation of different urban environments during the study period (2021–2023): Ratna Park station (27.7054° N, 85.3145° E), which is located in the center of Kathmandu with dense urban core as well as with high traffic density and business activity, and Kirtipur station (27.6786° N, 85.2774° E), which is situated in a moderate-urban, residential area. Kirtipur station is on a hill southwest of the center and has comparatively lower traffic volumes.

Meteorological data (daily precipitation, minimum and maximum temperatures) were obtained from the Department of Hydrology and Meteorology, Nepal. These data were collected from automated weather stations operating under established calibration and quality control protocols. For analytical consistency, all hourly data were aggregated into monthly averages, yielding 36 monthly observations for each variable and station. To minimize the impact of instrument calibration errors, hourly pollutant concentration data were first checked. Subsequently, the hourly values were averaged. Finally, monthly mean concentrations were calculated from daily values. Although aggregation to monthly averages supports consistency across variables, short-term variability and extreme pollution events may be obscured. Therefore, the analysis is better suited to identifying seasonal trends than to capturing episodic pollution peaks. Similarly, meteorological data (minimum and maximum temperatures) were converted to monthly averages for temperature and monthly totals for precipitation to align

with the temporal resolution of the air quality data. This aggregation ensures temporal consistency across all variables and stations. Data sources and characteristic summary are given in Table 1.

3.2. Statistical methods and analytical framework

All statistical analyses were performed using R software (version 4.3.1)[37], while initial data handling was employed using Microsoft Excel.

(i) Descriptive statistics: To understand the central tendency and dispersion of all the pollutants for both stations, mean, median, standard deviation, coefficient of variation, skewness, and kurtosis were calculated.

(ii) Comparisons of stations: To compare pollutant levels between Ratna Park and Kirtipur stations, paired *t*-tests (accounting for temporal matching), *F*-tests for equality of variances, and paired Cohen's *d* effect sizes were used.

(iii) Correlation analysis: To measure the linear relationship between pollutant concentrations and meteorological variables, Pearson's correlation coefficients were calculated as a preliminary step to quantify the linear relationship.

(iv) Regression modeling: Multiple linear regression (MLR) was employed for modeling the effect of maximum temperature (tem_max), minimum temperature (tem_min), and precipitation (precip) on each pollutant. The general form of the model is shown in **Equation 1**:

$$\text{Pollutants} = \beta_0 + \beta_1(\text{tem_max}) + \beta_2(\text{tem_min}) + \beta_3(\text{precip}) + \epsilon \quad (1)$$

We tested the key assumptions of the multiple regression to ensure its validity. The Durbin–Watson statistic was used to check for autocorrelation in residuals. The Shapiro–Wilk test was used to check the normality of residuals. Furthermore, visual inspection of fitted-value plots vs. residuals indicated homoscedasticity. Minor deviations from normality were observed, although most model assumptions were satisfied. These deviations are noted in the limitations. These diagnostic steps improve the reliability of the regression estimates.

(i) Analysis of variance: This test was used to test for significant differences in pollutant concentrations across predefined seasonal or temperature bins. When significant differences were found, Tukey's honestly significant difference test post-hoc test was used for pairwise seasonal comparisons ($\alpha = 0.05$).

(ii) Cluster analysis: Cluster analysis (*k*-means clustering; $k = 3$) was employed to standardize monthly data and group months with similar pollution and weather profiles.

(iii) Ridge regression: Ridge regression (L2 penalty) was used with shrinkage parameter λ selected via 10-fold cross-validation (λ_min). Separate models were fitted for each pollutant with tem_max, tem_min, and precipitation as predictors. We compared ordinary least squares and ridge models using adjusted R^2 and root-mean-square error.

3.3. Air Quality Index calculation

It is important to note that AQI values are conventionally analyzed using 24-h pollutant concentrations. This study used monthly mean concentrations due to data aggregation, which may substantially underestimate peak AQI levels and short-term health risks. For TSP, which lacks official AQI breakpoints, we used breakpoints scaled from the Nepal National Ambient Air Quality Standard ratio of TSP to PM_{10}. The adopted scaling approach introduces substantial uncertainty and should not be interpreted as equivalent to standard AQI metrics. Therefore, these AQI results presented should be considered as indicative of broad seasonal patterns, not precise measures of population exposure or health risk. This is a limitation of the study that should be considered when comparing AQI values across pollutants. The maximum of three pollutant-specific indices was used as the overall monthly AQI (**Equation 2**):

$$\text{AQI} = \max(\text{AQI_PM}_{2.5}, \text{AQI_PM}_{10}, \text{AQI_TSP}) \quad (2)$$

Table 1. Data sources and characteristics

Data type	Source	Temporal coverage	Spatial coverage	Original data	Analysis data
$PM_{2.5}$, PM_{10}, and total suspended particles	Department of Environment, Nepal/ Kathmandu Valley Air Quality Monitoring Network	Jan 2021–Dec 2023	Ratna Park, Kirtipur	Hourly	Monthly average
Precipitation and temperature	Department of Hydrology and Meteorology, Nepal	Jan 2021–Dec 2023	Kathmandu Valley	Daily	Monthly average

4. Results and discussion

4.1. Descriptive statistics and spatial comparison

Table 2 presents the summary statistics for pollutants and meteorological variables at the Ratna Park station. The highest mean concentration was for PM_{10} (68.67 μg/m³), followed by TSP (135.48 μg/m³) and $PM_{2.5}$ (42.72 μg/m³). Variability of all components was high (coefficient of variation > 50%), with positive skewness indicating frequent periods of very high concentrations. Similarly, the mean high and low temperatures were 25.73 °C and 13.63 °C, respectively, while the mean monthly precipitation was 4.69 mm.

Table 3 presents the summary statistics for pollutants at the Kirtipur station. The maximum concentrations recorded at Kirtipur were 159.06 μg/m³ for PM_{10}, 275.81 μg/m³ for TSP, and 101.66 μg/m³ for $PM_{2.5}$.

Table 4 presents a comparative analysis of the Ratna Park and Kirtipur stations. Paired *t*-tests showed no statistically significant differences in mean concentrations for $PM_{2.5}$ (t [34] = − 0.94, p = 0.35), PM_{10} (t [34] = −0.40, p = 0.70), or TSP (t [34] = 1.19, p = 0.24). Additionally, the effect sizes were negligible for $PM_{2.5}$ (Cohen's d = −0.17) and PM_{10} (Cohen's d = −0.08) and small for TSP (Cohen's d = 0.23). These results show that, during the study period, pollutant levels were approximately uniform across the valley. This is most probably due to regional-scale atmospheric trapping rather than isolated local hotspots. Two months (one in 2021 and one in 2023) had missing pollutant data at a single station, reducing the paired comparisons to 34 months.

Table 2. Descriptive summary statistics for pollutants and meteorological variables at the Ratna Park station (2021–2023)

Pollutants	Min	Q_1	Median	Mean	Q_3	Max	SD	CV (%)	Skewness
$PM_{2.5}$ (μg/m³)	11.72	22.27	42.76	42.72	59.22	95.76	23.20	54.30	0.51
PM_{10} (μg/m³)	17.79	33.93	66.67	68.67	87.29	165.03	38.05	55.41	0.78
TSP (μg/m³)	35.20	73.50	122.09	135.48	184.50	351.96	75.65	55.84	0.83
Max temperature (°C)	16.86	22.54	27.93	25.73	28.71	31.05	4.17	16.0	−0.75
Min temperature (°C)	4.41	8.79	14.47	13.63	19.59	20.78	5.78	42.0	−0.21
Precipitation (mm)	0.00	0.16	2.37	4.69	8.83	19.60	5.20	111	0.95

Abbreviations: CV: Coefficient of variation; SD: Standard deviation; TSP: Total suspended particles.

Table 3. Descriptive summary statistics for pollutant variables at the Kirtipur station (2021–2023)

Pollutants	Min	Q_1	Median	Mean	Q_3	Max	SD	CV (%)	Skewness
$PM_{2.5}$ (μg/m³)	12.85	22.80	34.97	46.83	68.94	101.66	27.09	57.85	0.40
PM_{10} (μg/m³)	16.78	35.48	55.65	71.41	94.00	159.06	40.25	56.36	0.49
TSP (μg/m³)	24.58	62.12	93.64	118.49	155.64	275.81	66.42	56.10	0.62

Abbreviations: CV: Coefficient of variation; SD: Standard deviation; TSP: Total suspended particles.

Table 4. Comparative analysis between Ratna Park and Kirtipur (paired by month)

Test	$PM_{2.5}$	PM_{10}	TSP
Paired *t* test	t = −0.94; df = 34; p = 0.35; 95% CI: −13.71–5.02	t = −0.40; df = 34; p = 0.70; 95% CI: −18.17–12.25	t = 1.19; df = 34; p = 0.24; 95% CI: −11.54–44.30
F test (variances)	F = 0.73; df_1 = 35; df_2 = 34; p = 0.37; 95% CI: 0.37–1.44	F = 0.74; df_1 = 35; df_2 = 34; p = 0.45; 95% CI: 0.45–1.76	F = 1.30; df_1 = 35; df_2 = 34; p = 0.45; 95% CI: 0.66–2.55
Cohen's *d* (paired)	d = −0.17 (negligible); 95% CI: −0.535–0.193	d = −0.08 (negligible); 95% CI: −0.454–0.304	d = 0.23 (small); 95% CI: −0.158–0.614

Notes: Paired *t*-tests account for temporal matching of monthly observations. Since the effect sizes are negligible for $PM_{2.5}$ and PM_{10}, and small for TSP, there are no significant differences between the two stations.
Abbreviations: CI: Confidence interval; df: Degrees of freedom; TSP: Total suspended particles.

4.2. Seasonal patterns and temporal trends

The monthly boxplots for Ratna Park station, shown in Figure 1, demonstrate a clear seasonal cycle with different patterns for fine and coarse particles. Plots show that $PM_{2.5}$ concentrations start to rise in October, remain elevated through winter (December–February) and the pre-monsoon (March–May), with the highest monthly peak in January (95.8 μg/m³), and a sharp decline after the onset of monsoon rains. The highest monthly $PM_{2.5}$ level in January (95.76 μg/m³) was approximately four times the WHO annual guideline (25 μg/m³). In contrast, PM_{10} and TSP had a more pronounced peak in the pre-monsoon season (March–May). This may be due to rising temperatures, bare surfaces, dry soils, and increased convective activity, which enhance dust resuspension. Although both coarse pollutants remain elevated, the spring maximum is distinctly visible in the boxplots. During the monsoon period (from July to September), all pollutants dropped to their lowest levels, with $PM_{2.5}$ falling to 11.72 μg/m³. The $PM_{2.5}$ winter peak corresponds with low minimum temperature.

The monthly boxplots for Kirtipur station (Figure 2) show a clear seasonal cycle, with distinct patterns for fine and coarse particles.

This seasonal variation is especially driven by meteorological conditions in Kathmandu. In winter, low temperatures, weak wind circulation, temperature inversions, and limited precipitation restrict dispersion, leading to the accumulation of pollutants near the surface. In contrast, increased rainfall and improved atmospheric mixing reduce particulate matter concentration during the monsoon season. Seasonal differences in pollutant concentrations for both stations are illustrated in Figure 3.

Statistical comparison of seasonal differences using one-way analysis of variance at Ratna Park showed significant variations for all the pollutants ($p < 0.01$). Mean concentration for $PM_{2.5}$ differed across seasons (F [3,32] = 7.91, $p < 0.001$). Furthermore, Tukey's honestly significant difference test showed that $PM_{2.5}$ concentrations in winter (52.5 μg/m³) and the pre-monsoon season (60.6 μg/m³) did not differ significantly ($p = 0.34$), although both were significantly higher than during the monsoon season (24.0 μg/m³; $p < 0.01$). For PM_{10}, concentrations during the pre-monsoon season (102.2 μg/m³) were higher than the monsoon season (41.2 μg/m³; $p < 0.001$) and winter (78.3 μg/m³; $p = 0.046$). A similar pattern was found for TSP (pre-monsoon: 199.1 μg/m³ vs. monsoon: 87.6 μg/m³; $p = 0.002$).

Similar patterns emerged at Kirtipur: $PM_{2.5}$ (F [3,31] = 31.56, $p < 0.001$), PM_{10} (F [3,31] = 22.5, $p < 0.001$), and TSP (F [3,31] = 15.23, $p < 0.001$). All results showed significant seasonal variation. For all pollutants, winter and postmonsoon had the highest concentrations, while monsoon had the lowest ($p < 0.01$ for all relevant Tukey honestly significant difference comparisons).

Given that the paired t-tests showed no significant differences between stations for any pollutant (Table 4), Ratna Park was considered representative of the valley-wide pollution levels for regression analysis.

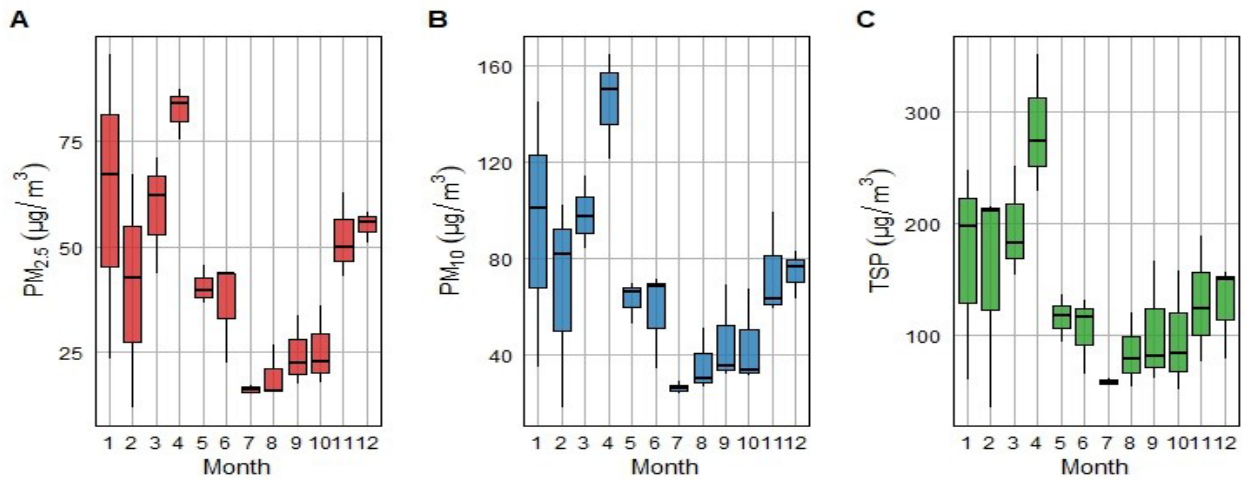


Figure 1. Monthly boxplots of (A) $PM_{2.5}$, (B) PM_{10}, and (C) total suspended particle (TSP) concentrations at the Ratna Park station. $PM_{2.5}$ peaked in winter (December–February), while PM_{10} and TSP had the highest concentration during the pre-monsoon season (March–May).

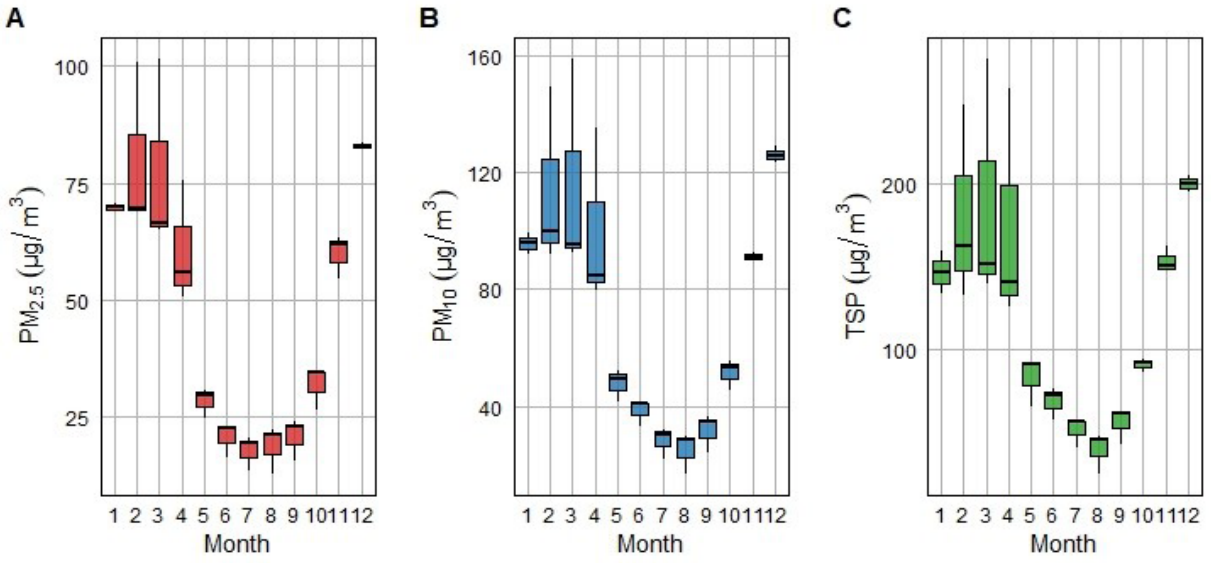


Figure 2. Monthly boxplots of (A) $PM_{2.5}$, (B) PM_{10}, and (C) total suspended particle (TSP) concentrations at the Kirtipur station. $PM_{2.5}$, PM_{10}, and TSP had the highest concentration during the winter and pre-monsoon season.

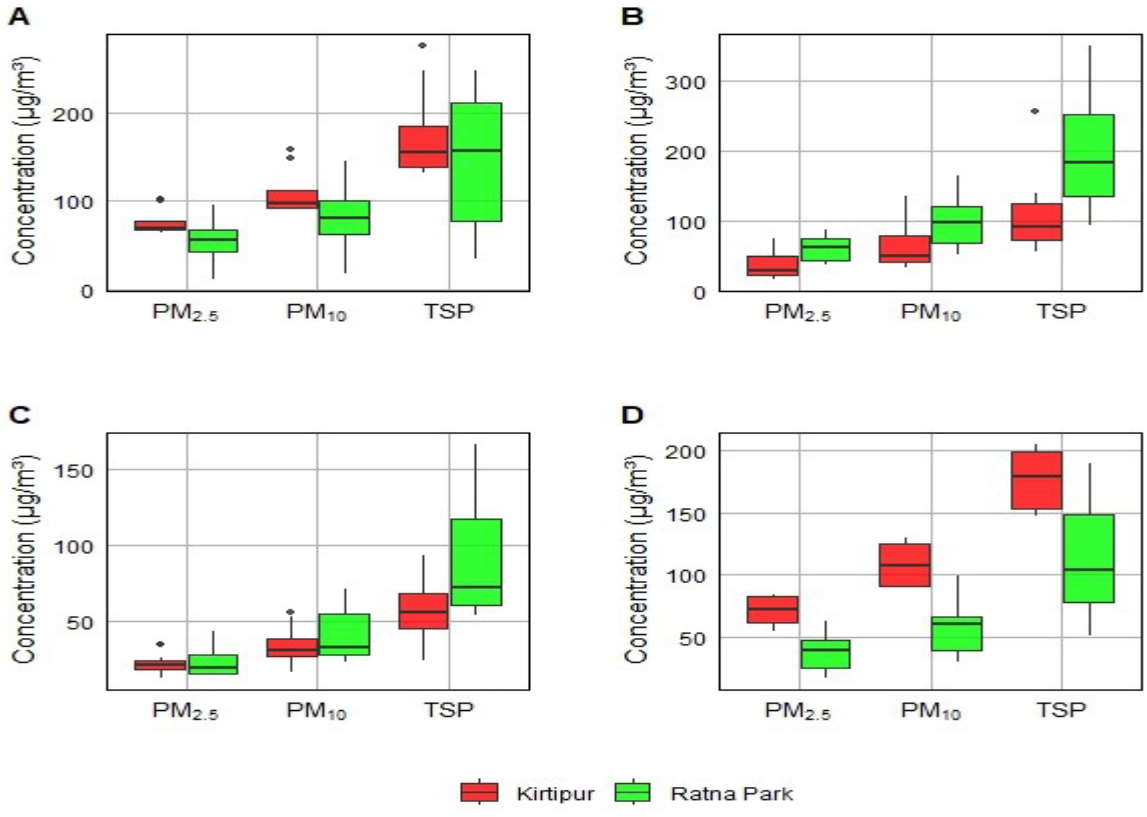


Figure 3. Seasonal differences in pollutant concentrations at Ratna Park and Kirtipur Stations. (A) Winter. (B) Pre-monsoon. (C) Monsoon. (D) Post-monsoon.
Abbreviation: TSP: Total suspended particles.

4.3. Relationships between pollutants and meteorological variables

Pearson correlation coefficients (Table 5) were calculated between all three pollutants and meteorological variables. The strongest negative correlation was between $PM_{2.5}$ and precipitation (r = −0.60), followed by minimum temperature (r = −0.57) and maximum temperature (r = −0.27), underscoring the critical role of cold, stable conditions for pollution accumulation during the night. [15]

The minimum temperature showed a stronger negative correlation (r = −0.57) than the maximum temperature (r = −0.27), which is particularly insightful. The minimum temperature typically occurs during nighttime and early morning hours. This serves as a proxy for persistence and strength of nocturnal temperature inversion. Very low minimum temperatures indicate clear skies and calm conditions. This fosters the development of strong ground-based inversions trapping the pollutants near the surface, leading to high early-morning concentrations that heavily influence the monthly average. In contrast, the weaker correlation with maximum temperature suggests that daytime heating, which can aid dispersion, is a less dominant factor in overall pollution dynamics in the valley than nocturnal trapping. However, correlation does not imply causation, and ridge regression was used to disentangle effects.

4.4. Regression modeling for pollution prediction

Pollution concentrations were predicted by developing a multiple linear regression model. $PM_{2.5}$ was statistically significant (F [3,32] = 22.41, $p < 0.001$) and explained 67.8% of the variance in $PM_{2.5}$ (adjusted R^2 = 0.678). However, strong collinearity between maximum temperature and minimum temperature (Pearson's r = 0.90, $p < 0.001$) was revealed by diagnostic checks. Variance inflation factors were 7.92 for maximum temperature, 15.74 for minimum temperature, and 4.67 for precipitation (Table 6). This indicates severe multicollinearity between maximum temperature and minimum temperature, leading to unstable individual coefficients and preventing causal interpretation.

We also fitted a ridge regression (α = 0, i.e., L2 penalty) with shrinkage parameter λ selected via 10-fold cross-validation (λ_min). Coefficients shown (Table 7) are for

Table 5. Correlation coefficients between pollutants and meteorological variables

Pollutants	$PM_{2.5}$	PM_{10}	TSP	Maximum tem	Minimum tem	Precipitations
$PM_{2.5}$	1.00	0.95***	0.86***	−0.27	−0.57***	−0.60***
PM_{10}	0.95***	1.00	0.96***	−0.12	−0.45**	−0.55***
TSP	0.86***	0.96***	1.00	−0.04	−0.39*	−0.49**
Maximum tem (°C)	−0.27	−0.12	−0.04	1.00	0.91***	0.63***
Minimum tem (°C)	−0.57***	−0.45**	−0.39*	0.90***	1.00	0.83***
Precipitation (mm)	−0.60***	−0.55***	−0.49**	0.63***	0.83***	1.00

Note: *$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
Abbreviations: Tem: Temperature; TSP: Total suspended particles.

Table 6. Coefficients for the multiple regression model of $PM_{2.5}$

Predictor	Estimate	Standard error	*t*-value	*p*-value	Variance inflation factor
Intercept	−64.4380	24.6313	−2.616	0.0135 *	-
Max temperature (°C)	8.5515	1.5692	5.449	5.37×10^{-6} ***	7.92
Min temperature (°C)	−8.6240	1.5974	−5.399	6.23×10^{-6} ***	15.74
Precipitation (mm)	0.9953	0.9668	1.030	0.3110	4.67

Note: *$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 7. Ridge coefficients for $PM_{2.5}$, PM_{10}, and total suspended particles

Pollutant	Intercept	Maximum temperature	Minimum temperature	Precipitation
$PM_{2.5}$	0.241	3.843	−3.771	−1.066
PM_{10}	−44.850	8.220	−6.498	−2.008
Total suspended particles	−135.281	18.505	−13.887	−3.434

the final ridge model. Ridge regression generates biased but more stable coefficients in the presence of multicollinearity. The ridge coefficients for $PM_{2.5}$ obtained were: maximum temperature = 3.84, minimum temperature = −3.77, and precipitation = −1.07. Similar patterns were observed for PM_{10} and TSP. The negative coefficient for minimum temperature and precipitation across all pollutants aligns with the strong negative correlation reported in Table 5. The positive but non-significant precipitation coefficient in the multiple linear regression is likely due to multicollinearity with temperature. The ridge regression correctly shows a negative association (cleaning effect) for precipitation across all pollutants. These results reinforce that cooler nighttime temperatures (a proxy for inversion strength) and precipitation are the key factors in reducing $PM_{2.5}$ concentrations. The coefficient for maximum temperature remained positive, reflecting seasonal covariation with pre-monsoon dust resuspension rather than a direct causal effect. The overall pattern is consistent with seasonal dynamics as shown in Figures 1 and 2.

4.5. Air Quality Index and health implications

The seasonal AQI patterns revealed distinct drivers. In winter (December–February), the overall AQI was predominantly driven by $PM_{2.5}$ due to the accumulation of temperature inversions and stagnant atmospheric conditions. In contrast, during the pre-monsoon season (March–May), PM_{10} and TSP were the dominant contributors to the overall AQI, driven by resuspension from bare, dry surfaces and increased convective activity. Although $PM_{2.5}$ remained elevated in winter, the coarse particles pushed the AQI into the "Unhealthy" (151–200) or "Very Unhealthy" (201–300) categories, especially in the pre-monsoon season. This distinction indicates that effective AQI management requires season-specific mitigation strategies, with winter focused on fine particles and spring on coarse dust.

When considering monthly averages, $PM_{2.5}$ concentrations often fell into the "Moderate" (51–100) category of AQI, but daily peaks frequently reached "Unhealthy levels" during inversion events. In contrast, coarse particles (PM_{10} and TSP) drove the overall AQI falling into "Unhealthy" or "Very Unhealthy" categories during pre-monsoon seasons. This provides evidence that coarse particles (PM_{10} and TSP), mainly from road dust, construction, and industry, may cause a more immediate and serious AQI-dependent health risk in Kathmandu, although $PM_{2.5}$ remains the major pollutant for long-term health impacts.

However, since AQI values are calculated from monthly averages, these results may underestimate short-term extreme pollution episodes. Hence, the reported AQI categories should be interpreted as indicative of general conditions. They do not provide a precise representation of daily exposure risks.

4.6. Cluster analysis of pollution: Weather profiles

Analysis using *k*-means clustering (k = 3) grouped the 36 months into distinct profiles 9 (Table 8), explaining 68.10% of the total variance (between-cluster sum of squares/total sum of squares). The clustering was performed to support seasonal interpretation and to effectively identify the dominant air quality regimes.

(i) Cluster 1 (9 months): Cold, stagnant, and high $PM_{2.5}$ (inversion-driven winter days): Low temperature, low precipitation, high $PM_{2.5}$, stagnant, and typical winter pollution episode.

(ii) Cluster 2 (11 months): Warm, dry, and high coarse particles (pre-monsoon months with elevated PM_{10} and TSP): Due to low rain and high temperatures, higher pollution levels indicate characteristics of peak coarse-particle pollution.

(iii) Cluster 3 (16 months): Warm, wet, and clean (monsoon months): Moderate to low pollution due to high temperatures and high precipitation, especially during monsoon and post-monsoon months.

5. Implications and recommendations

5.1. Public health implications

The 4–5 months of the long winter constitute a sustained public health emergency, as $PM_{2.5}$ levels remain consistently high. Furthermore, the pre-monsoon season (March–May) poses significant health risks due to elevated levels of PM_{10} and TSP, which can exacerbate respiratory problems,

Table 8. Results of *k*-means clustering

Cluster	$PM_{2.5}$	PM_{10}	TSP	Maximum tem (°C)	Minimum tem (°C)	Precipitation (mm)	Description
1 (n = 9)	78.2	112.4	198.5	18.3	6.2	0.8	Cold, stagnant, high $PM_{2.5}$
2 (n = 11)	60.1	102.2	199.1	28.5	16.8	1.2	Warm, dry, high coarse particles
3 (n = 16)	28.4	48.9	89.3	27.1	18.5	9.4	Warm, wet, clean

Abbreviations: Tem: Temperature; TSP: Total suspended particles.

particularly among the elderly, children, and those with pre-existing health conditions. The findings necessitate integrating air quality data with public health systems and boosting healthcare plans from November to May. The study strongly recommends promoting clean technologies and improving public transportation. Future research should focus on evaluating the effectiveness of current interventions and conducting cost–benefit analyses for sustainable air quality management.

5.2. Policy and management recommendations

5.2.1. Short-term (1–2 years)

Implement seasonal action plans covering both the winter and pre-monsoon periods. For winter, focus on early warnings such as odd–even vehicle rationing, strict enforcement of emission standards, and halting large-scale constructions. Similarly, during pre-monsoon (March–May), water unpaved roads to suppress dust, cover construction sites, and focus on road cleaning to reduce resuspended dust.

5.2.2. Long-term (3–5 years)

A long-term plan may include emission source control, urban planning and greening, and regional cooperation. It is essential to encourage the adoption of cleaner technologies, including improved waste management practices, and to promote public transportation to reduce vehicular emissions, which are major contributors to air pollution. Implement urban planning measures to reduce the urban heat island effect and promote city greening to improve air quality.

5.3. Limitations and future study

This study has several limitations. First, the study relies on data from only two stations, Ratna Park and Kirtipur, for a relatively short period from 2021 to 2023, which may limit spatial and temporal generalizability. Second, AQI values were calculated using monthly averages rather than standard 24-hour concentrations, which may fail to reflect the actual severity of air quality during high-pollution episodes. Third, using monthly mean concentrations to analyze seasonal trends may obscure short-term pollution peaks and extreme events, potentially underestimating acute exposure risks and associated health impacts. Fourth, the AQI for TSP was estimated using an adapted scaling approach due to the absence of standard breakpoints, which introduces additional uncertainty and limits direct comparison with established AQI values. Finally, the study does not include other important meteorological variables, such as relative humidity, wind speed, boundary-layer height, and solar radiation, which might have significantly affected the predictive results. These limitations may affect the accuracy of AQI interpretation and health risk assessment.

Future studies should incorporate data from all Kathmandu Valley Air Quality Monitoring Network stations and extended time series, and should use machine learning models with a detailed set of meteorological and temporal predictors. This would improve forecast accuracy and is an essential field for future study. Furthermore, future studies should focus on conducting source apportionment analyses to precisely quantify contributions from different emission sectors, thereby informing targeted mitigation strategies. In addition, integrating health outcomes data would enable more robust quantitative assessments of the public health impacts of air pollution exposure.

6. Conclusion

This study's findings offer a comprehensive statistical understanding of air quality dynamics in the Kathmandu Valley. The results demonstrate severe, seasonally exacerbated pollution problems: $PM_{2.5}$ was elevated in winter (driven by temperature inversions) and in pre-monsoon, while PM_{10} and TSP peaked during the pre-monsoon period, as dust resuspended under dry, hot conditions. During both seasons, substantial health risks arise from PM_{10} and TSP, which are key components of poor AQI. Meteorological factors also contribute significantly to pollution variability, but they are not the sole drivers, underscoring the importance of stringent emission controls and season-specific mitigation strategies.

Controlling air pollution in Kathmandu requires a dual strategy: immediate, effective, and robust measures to protect public health, especially during the winter season, and long-term, sustained efforts to introduce cleaner technologies and sustainable urban planning. The results and evidence presented in this study can serve as a scientific basis for urban planners, policymakers, and public health administrators to formulate and implement effective, seasonally focused interventions to improve air quality in Kathmandu Valley.

However, interpretations of AQI and health impacts should be made cautiously, as the analysis is based on monthly-averaged data and an adapted AQI framework for TSP. Future studies using higher temporal resolution data would provide a more precise assessment of short-term exposure risks. Accordingly, the AQI-based findings should be interpreted cautiously, as they reflect generalized monthly conditions rather than short-term exposure dynamics.

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Conflict of interest

The authors declare they have no competing interests.

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Methodology: Lal Babu Sah Telee
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Availability of data

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