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Co-Occurrence and Correlation Trends of PM_{10}, $PM_{2.5}$, and O_3 in Bangalore City: Diurnal, Seasonal, and Inter-Annual Coupling and Its Implications

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Abstract

Background: Rapid urban growth has turned air pollution into a stubborn public-health problem across Indian cities, and Bangalore is no exception. What stays poorly mapped is how particulate matter (PM_{10} and $PM_{2.5}$) and ground-level ozone (O_3) rise and fall together. The coupling across the day, the seasons, and successive years matters for any evidence-based control strategy, yet few studies have quantified it for Bangalore city.

Methods: Hourly PM_{10}, $PM_{2.5}$, and O_3 records were drawn from six of the thirteen Continuous Ambient Air Quality Monitoring Stations (CAAQMS) operated by the Central Pollution Control Board (CPCB) and the Karnataka State Pollution Control Board (KSPCB) across Bangalore, spanning 25 June 2018 to 31 December 2023. Quality-controlled daily averages were sorted into diurnal, seasonal (monsoon, post-monsoon, winter, summer), and yearly windows. Descriptive statistics, Chi-square tests of independence, and Pearson lag correlations (±96 intervals at 15-minute resolution, i.e. ±96 × 15 min = ±24 h) were computed in Python and R 4.0.5.

Results: PM_{10} topped out at 77.84 μg/m^3 in 2022 and $PM_{2.5}$ at 34.36 μg/m^3; both indicates the lowest annual means during COVID-19 lockdown period and 2020. Winter carried the heaviest particulate load (PM_{10}: 88.82 μg/m^3; $PM_{2.5}$: 40.32 μg/m^3), while O_3 peaked in summer (36.09 μg/m^3). Every Chi-square test returned $p < 0.001$. Independence between PM and O_3 was rejected in each temporal segment. Lag correlations peaked near +50 fifteen-minute intervals (≈ +12.5 h; O_3–PM_{10}: $r = 0.191$; O_3–$PM_{2.5}$: $r = 0.207$), a roughly half-day delay in the ozone response to precursor emissions.

Conclusions: PM and O_3 in Bangalore are coupled statistically and through shared precursor chemistry. The coupling bears directly on forecasting, exposure assessment, and joint emission control. Real-time CAAQMS data should feed dynamic interventions, especially during winter inversions and summer photochemical episodes.

Keywords: PM_{10}; $PM_{2.5}$; O_3; Air quality; Bangalore; Chi-square test; Lag correlation; Photochemical Pollution; CAAQMS; Seasonal variation

Introduction

Bangalore grew fast, and its air paid for it. Once marked as India's Garden City and later as its Silicon Valley, the metropolis has absorbed decades of population growth, industrial expansion, and an expanding vehicle fleet, and its air quality has slipped accordingly (Guttikunda et al., 2019a). Two air pollutants dominate the local burden: particulate matter (PM_{10} and $PM_{2.5}$) and ground-level ozone (O_3). Particles below 10 and 2.5 μm in aerodynamic diameter travel deep into the airways and tied to asthma, bronchitis, and cardiovascular disease (WHO, 2021). Ozone is different in origin but no gentler. A secondary pollutant built by photochemistry, it aggravates respiratory illness and drives systemic oxidative stress (Beig et al., 2007; Balakrishnan et al., 2019). Long-term exposure to these pollutants linked to a heavy global mortality toll, with $PM_{2.5}$ alone implicated in millions of premature deaths each year (Cohen et al., 2017; Burnett et al., 2018).

The sources are mixed and private vehicles and chronic congestion push PM_{10} and $PM_{2.5}$ upward (Guttikunda et al., 2019a). A construction boom keeps resuspended dust in the air (Devi et al., 2025). Industry adds volatile organic compounds (VOCs) and nitrogen oxides (NO_x) that, under Bangalore's strong sunlight, cook into O_3 (Peshin et al., 2017). None of these pollutants acts alone, PM and O_3 occur together, the individual health effects may compound (Qu et al., 2023; Gopikrishnan et al., 2026). Delhi and Beijing offer the cautionary precedent: simultaneous PM and O_3 exposure produced a synergistic effects that raise morbidity and mortality among children, the elderly, and people with pre-existing disease (Bell et al., 2004; Pope & Dockery, 2006; Liu et al., 2019). Across India, ground-level ozone runs highest along urban corridors thick with precursor emissions (Gorai et al., 2017; Naja & Lal, 2002). The temporal and spatial behaviour of PM_{10}, $PM_{2.5}$, and O_3 in Bangalore is worth pinning down, and health, policy and environmental management (Suthar et al., 2023). This study uses a five-and-a-half-year record, from 25 June 2018 to 31 December 2023, drawn from six of the thirteen CAAQMS across the city. Chi-square tests and lag correlations are applied to trace how the three pollutants co-occur and correlate at daily, seasonal, and yearly scales. The aim is a scientific analysis of spatiotemporal air quality data for control measures in a city pulled between technological ambition and environmental strain (Guttikunda et al., 2019b; Yadav et al., 2014). Materials and Methods

Data Collection

Bangalore's regulatory network comprises thirteen CAAQMS operated by the Central Pollution Control Board (CPCB) and the Karnataka State Pollution Control Board (KSPCB). This study draws on six selected for continuous PM_{10}, $PM_{2.5}$, and O_3 coverage over the study period. The Bapuji Nagar, Hebbal, Hombegowda Nagar, and Silk Board stations are run by the KSPCB; BTM Layout and Peenya are by CPCB. The air samples covers from residential, commercial, industrial, and traffic-heavy ground, which gives reasonable coverage of the city's uneven urban fabric (Suthar et al., 2023; Devi et al., 2025). Each station measures PM_{10}, $PM_{2.5}$, and O_3 in real time. Particulate matter is captured by beta-attenuation monitors, which pull ambient air through a filter tape and read the attenuation of beta radiation as mass builds up on the tape - continuous, high-resolution, and low-latency (CPCB, 2019). Ozone is measured by UV photometric analysers that track absorption at 254 nm, and readings are both precise and immediate (CPCB, 2011). Both instrument types are calibrated on the CPCB schedule and feed a central data-acquisition system that logs hourly values (Tiwari et al., 2013).

The record runs from 25 June 2018 to 31 December 2023, Hourly readings were averaged to daily values, and the daily series was divided into three ways: into diurnal blocks (day 06:00–18:00; night 18:00–06:00), into the four India Meteorological Department seasons (monsoon June–September; post-monsoon October–November; winter December–February; summer March–May), and into calendar years (2018–2023). Quality control was straightforward. Values beyond three standard deviations were

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dropped, and short gaps were filled by linear interpolation, following CPCB protocols (CPCB, 2011; Pant et al., 2018).

Statistical Analysis

The data of particulate matter and ozone was applied for the pollutants variation and to relate. Means and standard deviations, computed across diurnal, seasonal, and yearly segments to summarise variability and trend (Suthar et al., 2023; Guttikunda et al., 2019b; Harrison & Yin, 2000).

Co-occurrence was tested with Chi-square tests of independence. The statistic is

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where O_i is the observed frequency of a co-occurrence - say, PM_{10} and O_3 both exceeding their threshold in the same interval - and E_i is the frequency expected if the two were independent. A p-value under 0.05 marks a significant association. Here every test returned $p = 0.0000$. The chance of seeing co-occurrences this strong under independence is effectively nil, which points to shared emission sources or common meteorological drivers and firmly rejects the null (Qu et al., 2023).

Temporal coupling was examined with Pearson lag correlations between O_3 and each PM fraction, swept across ±96 fifteen-minute intervals (i.e. ±96 × 15 min = ±24 h) to match the native cadence of the CAAQMS acquisition system. The coefficient is

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

with X_i and Y_i the two pollutant concentrations at interval i and $\bar{X}$, $\bar{Y}$ their means. Lags are counted in 15-minute steps, so ±96 intervals span ±24 h and the peak at +50 intervals falls at roughly +12.5 h. Reading the profile across lags shows whether one pollutant leads or trails the other, which hints at the mechanism behind the link. Ozone's lagged response to its precursors is well established; peak O_3 usually arrives several hours after the precursors are released, because the photochemistry takes time to run (Seinfeld & Pandis, 2016; Peshin et al., 2017). All computations were carried out in Python (Jupyter, using pandas, matplotlib, seaborn, scipy, and scikit-learn) and in R 4.0.5 (R Core Team, 2021), which keeps the workflow reproducible (Lal et al., 2000; Kumar et al., 2015a).

Results

Yearly Trends

Between 2018 and 2023 the annual averages moved around more than a little. PM_{10} crested in 2022 at 77.84 µg/m^3 and $PM_{2.5}$ at 34.36 µg/m^3, a high-pollution stretch that tracks intensified urban activity (Suthar et al., 2023; Devi et al., 2025). The floor came in 2020: PM_{10} at 62.53 µg/m^3 and $PM_{2.5}$ at 27.97 µg/m^3, pulled down by the emission cuts of the COVID-19 lockdown (Sharma et al., 2020; Kumar et al., 2020; Sicard et al., 2020). Ozone took a different path. It peaked in 2019 at 44.93 µg/m^3, dropped to 21.55 µg/m^3 by 2022, then edged back to 23.12 µg/m^3 in 2023. The pattern reflects human activity and weather acting together (Gopikrishnan et al., 2026; Guttikunda et al., 2019a). Figures 1 and 2 were clearly shows the inter-annual trend and the full daily timeseries.

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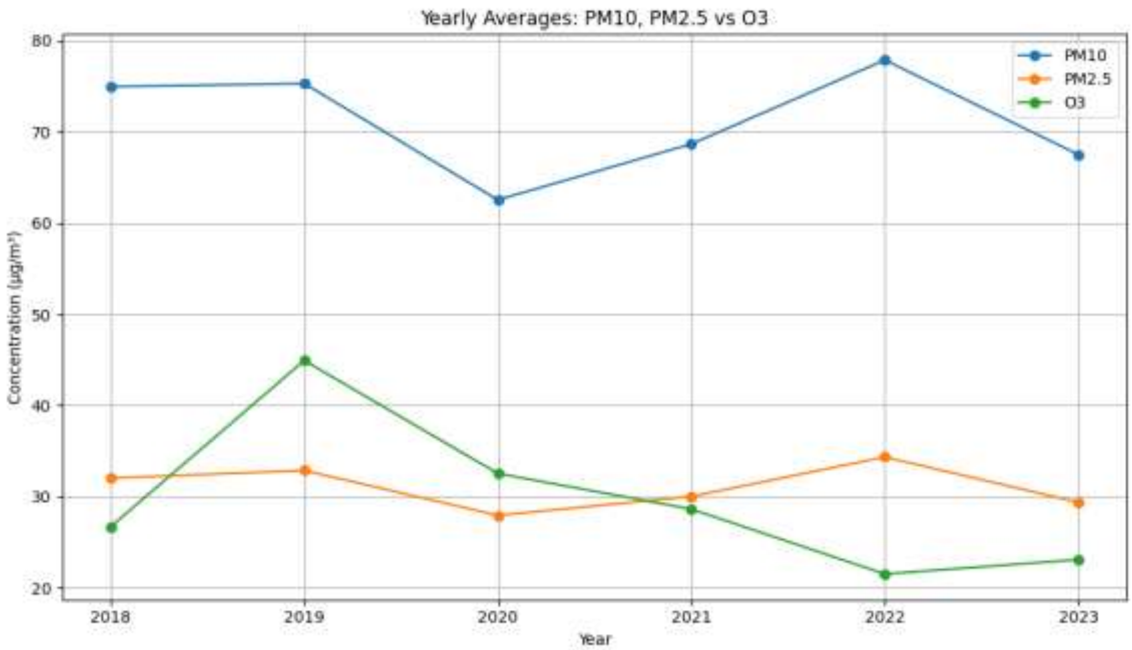

Figure 1. Yearly average concentrations (µg/m^3) of PM_{10}, $PM_{2.5}$, and O_3 across the six CAAQMS monitoring stations used in this study, Bangalore, 2018–2023.

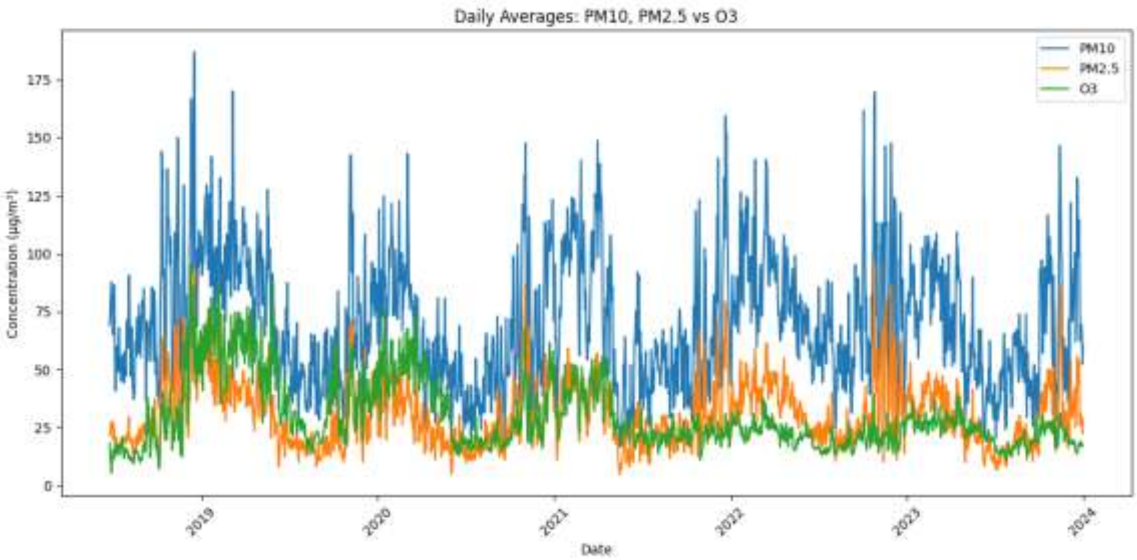

Figure 2. Daily average concentrations (µg/m^3) of PM_{10}, $PM_{2.5}$, and O_3 (June 2018 to December 2023).

Seasonal Variation

Season shapes the numbers sharply; the monsoon is cleanest level of PM_{10} 51.46, $PM_{2.5}$ 19.77, O_3 20.24 µg/m^3, because rain scavenges particles and dims the sunlight that drives photochemistry (Tiwari et al., 2013). After the rains, levels climb: PM_{10} 74.14, $PM_{2.5}$ 36.48, and O_3 26.30 µg/m^3, as clearer skies and lighter winds let pollutants pool. Summer pushes O_3 to its annual high of 36.09 µg/m^3, with PM_{10} at 77.58 and $PM_{2.5}$ at 33.63 µg/m^3 was driven by strong sun and heat (Kumar et al., 2015a; Beig et al., 2007; Naja & Lal, 2002). Winter is the particulate season; PM_{10} reaches 88.82 µg/m^3 and $PM_{2.5}$ 40.32 µg/m^3, with O_3 at 35.17, as temperature inversions cap the surface and trap the emissions (Guttikunda & Kopakka, 2014; Pant et al., 2018; Yadav et al., 2014). These swings line up with reported across urban India (Sharma et al., 2016; Lal et al., 2000). Figure 3 summarises the seasonal contrast.

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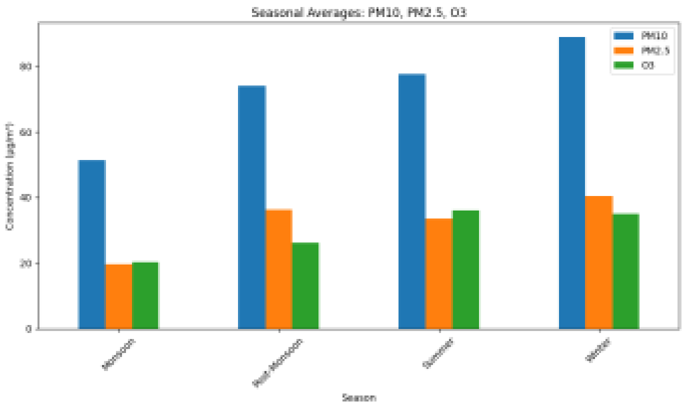

Figure 3. Seasonal variation of PM_{10}, $PM_{2.5}$, and O_3 concentrations (μg/m^3) in Bangalore.

Diurnal Patterns

The day-night split is smaller but real. By day (06:00 - 18:00) the means are PM_{10} 70.54, $PM_{2.5}$ 30.20, and O_3 33.12 μg/m^3, peak traffic and active photochemistry together (Lal et al., 2000; Peshin et al., 2017). At night (18:00–06:00) PM_{10} nudges up to 71.28 and $PM_{2.5}$ to 32.00 μg/m^3, likely from weaker dispersion under a shallow nocturnal boundary layer, while O_3 falls to 24.29 μg/m^3 as photochemistry stops and NO titration takes over (Beig et al., 2007; Kumar et al., 2015a). Bangalore's ozone cycle mirrors the other tropical Indian cities, where daytime production sets the afternoon peak (Naja & Lal, 2002; Gorai et al., 2017). Figure 4 gives the day-versus-night comparison.

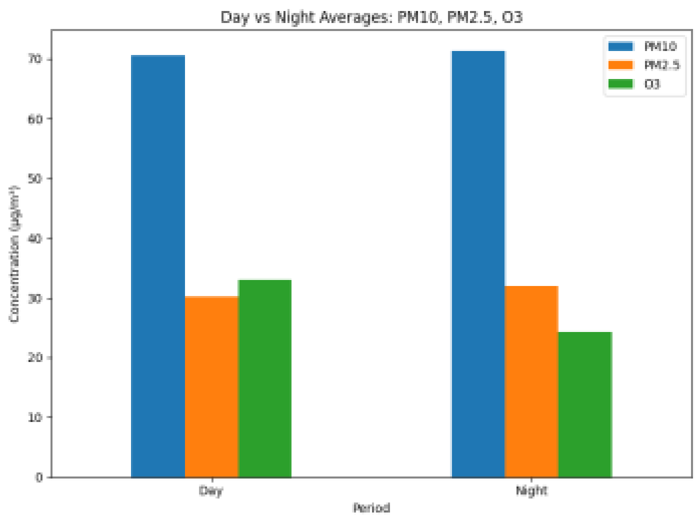

Figure 4. Comparison of Day and night mean concentrations (μg/m^3) of PM_{10}, $PM_{2.5}$, and O_3 in Bangalore. Day is 06:00–18:00 and night 18:00–06:00 local time.

Analysis of Chi-Square Test

The Chi-square tests confirmed the co-occurrence between PM and O_3 in every segment, all at $p < 0.001$. Daytime returned the largest statistics of 14,014.83 for PM_{10} - O_3 and 11,440.56 for $PM_{2.5}$ - O_3 is the fingerprint of sunlight-fuelled coupling. Summer followed, at 3,528.80 (PM_{10} - O_3) and 2,944.97 ($PM_{2.5}$ - O_3), conditions that favor pollutant synergy (Gopikrishnan et al., 2026). Even the monsoon stayed significant, if weaker: 1,221.16 for PM_{10} - O_3 and 210.14 for $PM_{2.5}$ - O_3. Across the board the p-values were negligible and observed co-occurrences depart so far from the independence expectation that chance can be ruled out, which reinforces a shared environmental or emission driver (Qu et al., 2023; Seinfeld &

Pandis, 2016). The categorical structure behind these tests appears in Figures 5 (seasonal) and 6 (diurnal).

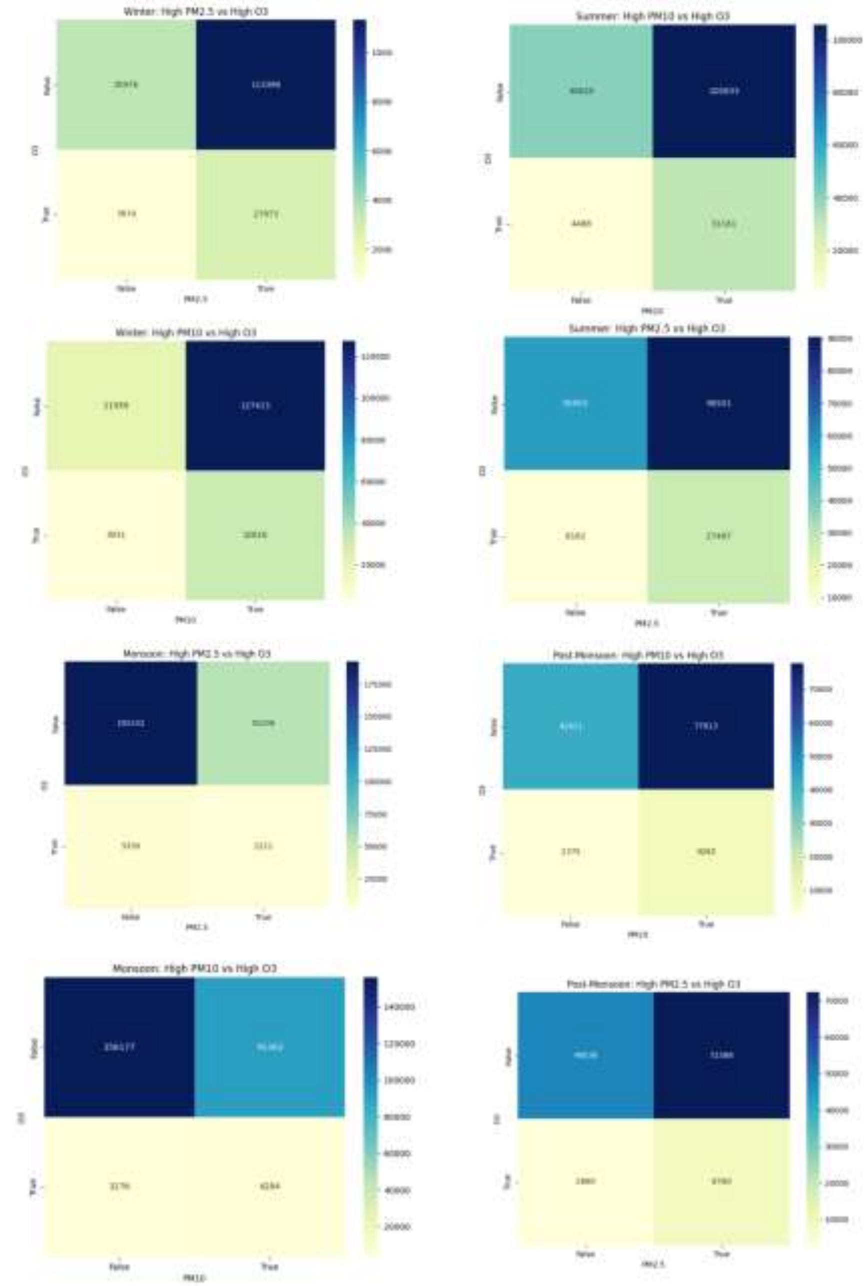

Figure 5. Categorical co-occurrence plots for high-PM / high-O_3 events across the four seasons (winter, summer, monsoon, post-monsoon) for the PM_{10}–O_3 and $PM_{2.5}$–O_3 pairs. Each panel cross-tabulates the binary "high" indicators (True/False); the imbalance in the True - True cell relative to expected frequencies drives the significant Chi-square statistics reported in the text (all $p < 0.001$).

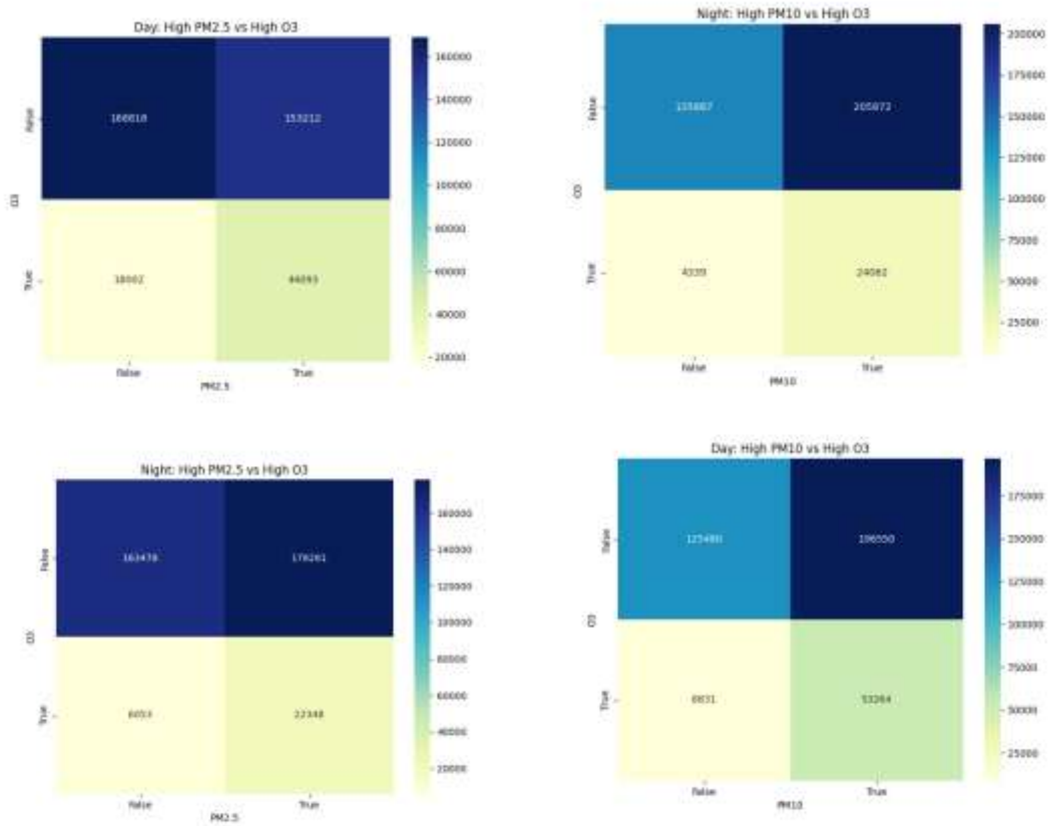

Figure 6. Categorical co-occurrence plots for high-PM / high-O_3 events under day and night conditions for the PM_{10}–O_3 and $PM_{2.5}$–O_3 pairs.

Lag Correlation Analysis

The lag profile carries the temporal story. Lags are read in 15-minute intervals over a ±96-interval (±24 h) window. At the far negative lag (−96 intervals ≈ −24 h) the correlations were 0.2147 for O_3 - PM_{10} and 0.2075 for O_3 - $PM_{2.5}$, indicate that earlier O_3 tracks later PM. At zero lag it was weak (0.1089 and 0.0861) shows the little instantaneous co-variation. On the positive side the correlation it was increased again, peaking near +50 intervals (≈ +12.5 h) at 0.1910 for O_3 - PM_{10} and 0.2073 for O_3 - $PM_{2.5}$. whereas a half-day delay in the ozone response, consistent with the time NO_x and VOC precursors need to photochemically process into O_3 (Seinfeld & Pandis, 2016; Peshin et al., 2017). A delayed O_3 peak relative to primary pollutants is a familiar feature of urban air, where production needs both sustained sunlight and enough precursors (Lal et al., 2000; Kumar et al., 2015a). Figure 7 shows the full profile.

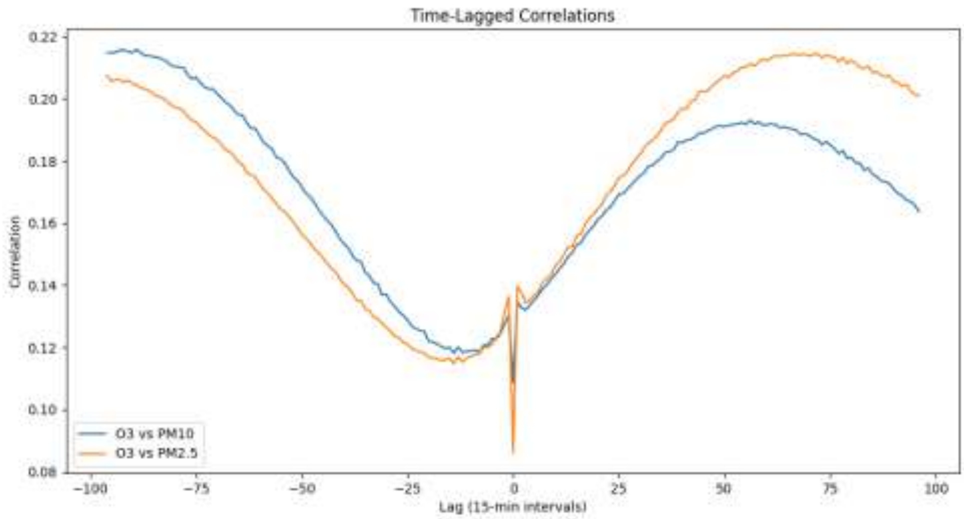

Figure 7. Lag correlation coefficients between O_3 and PM_{10} (top) / $PM_{2.5}$ (bottom) across a window of ±96 fifteen-minute intervals (i.e. ±24 h). Positive lags indicate an O_3 response following PM changes. The peak near +50 intervals (≈ +12.5 h, roughly half a day) reflects the photochemical delay in secondary O_3 formation from PM-associated NO_x and VOC precursors.

Daily Extremes

The daily extremes fit the seasonal picture, the highest PM_{10} (187.13 µg/m^3) and $PM_{2.5}$ (93.83 µg/m^3) both reached on 18 December 2018, deep in winter, and the peak O_3 (95.41 µg/m^3) on 9 December 2018. The low value was observed in the monsoon: PM_{10} at 20.60 µg/m^3 and $PM_{2.5}$ at 6.79 µg/m^3 on 4 July 2023, and O_3 at 5.53 µg/m^3 on 29 June 2018 - wet deposition and suppressed photochemistry (Harrison & Yin, 2000; Beig et al., 2007; Tiwari et al., 2013).

Discussion

The results of PM_{10}, $PM_{2.5}$, and O_3 were behaving as a coupled system rather than three separate problems. The significant co-occurrences, strongest in summer and winter, tie the pollutants to shared sources and common atmospheric processing (Suthar et al., 2023; Gopikrishnan et al., 2026). Summer's large Chi-square values fit a season built for photochemical O_3 production, with particles offering surfaces for heterogeneous reactions (Qu et al., 2023; Seinfeld & Pandis, 2016). Winter works differently. Heavy particulate loading and persistent O_3 co-occurrence there point to trapping of temperature inversions that keep pollutants interacting even as sunlight weakens (Guttikunda & Kopakka, 2014; Kumar et al., 2015b; Pant et al., 2018). Particles as reaction surfaces is old ground, reviewed at length elsewhere (Harrison & Yin, 2000; Pope & Dockery, 2006).

The lag results sharpen the point, Weak zero-lag correlations fit comfortably with the different origins of the two PM largely primary, O_3 secondary - while the stronger positive lags suggest PM-linked emissions (traffic and industrial VOCs and NO_x) act as O_3 precursors that show up after roughly half a day, the +50-interval (≈12 h) peak (Kumar et al., 2015a; Seinfeld & Pandis, 2016; Peshin et al., 2017). It sets the clock for forecasting and for timing any intervention. The photochemistry that turns precursor gases into ozone has been modelled and validated repeatedly across Indian cities, and the delayed response holds up (Naja & Lal, 2002; Gorai et al., 2017; Beig et al., 2007).

$PM_{2.5}$ values fits well above the WHO annual guideline of 5 µg/m^3, which may carries chronic respiratory and cardiovascular risk (WHO, 2021; Balakrishnan et al., 2019). Pair it with O_3 and the harm may compound, as co-exposure studies linking the mixture to higher mortality suggest (Cohen et al., 2017; Burnett et al., 2018). The exposure is not evenly shared; the residents near Silk Board's traffic or the Peenya industrial belt suggest for protection, not later (Guttikunda et al., 2019a; Liu et al., 2019; Suthar et al., 2023; Devi et al., 2025).

Policy has to work both ends the primary emissions and secondary formation. Tighter vehicle standards, more public transit, and green infrastructure would reduces the PM and O_3 precursors alike (Nowak et al., 2014; Kumar et al., 2015b; Guttikunda et al., 2019b). Real-time CAAQMS feeds can drive responsive measures, rerouting of traffic when a spike begins, and that responsiveness is where the city's resilience will come from (CPCB, 2011; Suthar et al., 2023; Gorai et al., 2017). Seasonal source-apportionment work using positive matrix factorisation has already named the main contributors, and those belong at the top of any city action plan (Sharma et al., 2016; Guttikunda et al., 2019a; Yadav et al., 2014).

Conclusion

PM_{10}, $PM_{2.5}$, and O_3 in Bangalore are not independent, and the data says so plainly. Chi-square tests reject independence in every temporal segment, and lag correlations place the ozone response about half a day behind its precursors, a coupling shaped by season and time of day. The consistently negligible p-values leave little room for a chance explanation and argue for an integrated, rather than pollutant-by-pollutant, air-quality strategy. The real-time monitoring paired with routine analytics gives policymakers a practical lever on fronts, protecting health and environment in a fast-growing city. The findings offer an evidence base for future interventions in Bangalore and a template other rapidly urbanising Indian cities could adapt (Naja & Lal, 2002; WHO, 2021; CPCB, 2009; Qu et al., 2023; Suthar et al., 2023; Devi et al., 2025; Guttikunda et al., 2019b). The next step is to fold in meteorological reanalysis, chemical transport modelling, and high-resolution exposure estimates to sharpen attribution and forecasting.

Data Availability

The raw 15-minute observations analysed are archived by the CPCB and KSPCB and are publicly retrievable through the Central Control Room for Air Quality Management portal (https://airquality.cpcb.gov.in/). Processed daily, seasonal, and lag-correlation outputs are available from the corresponding author on reasonable request.

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