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RESEARCH ARTICLE

LAGGED ASSOCIATION BETWEEN PUNJAB CROP-RESIDUE BURNING AND PM_{2.5} POLLUTION IN DELHI-NCR: A NINE-YEAR TIME-SERIES ANALYSIS

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Abstract

Background: Crop residue burning in Punjab, a post harvest agricultural practice, has long been implicated as a significant driver of catastrophic air-quality deterioration in Delhi-NCR during October–November. However, the precise temporal lag and the role of meteorological confounders remain insufficiently clarified in the existing literature.

Methods: We assembled a daily time-series dataset spanning nine harvest seasons (2015 – 2024; $n = 486$ station-days) that integrates satellite-derived Punjab fire counts from NASA FIRMS, ground-level PM_{2.5} observations from CPCB monitoring stations, and ERA5-Land daily meteorological covariates (wind speed at 850 hPa, planetary boundary layer height, temperature, relative humidity, and rainfall) to control for atmospheric confounding. Cross-correlation, multivariable distributed-lag regression models, and Cochrane-Orcutt autocorrelation correction were employed to characterise the spatiotemporal relationship between burning activity and urban particulate pollution.

Results: PM_{2.5} concentrations during harvest seasons averaged $150.5 \pm 74.3 \mu\text{g}/\text{m}^3$, with 82.1% of days classified as 'Poor' ($61\text{--}250 \mu\text{g}/\text{m}^3$) and 10.3% as 'Severe' ($>250 \mu\text{g}/\text{m}^3$) under the national AQI framework. The strongest same-day Pearson correlation between fire counts and PM_{2.5} was $r = 0.289$ ($p < 0.001$), with monotonically decreasing but statistically significant associations at 24-h ($r = 0.261$), 48-h ($r = 0.248$), and 72-h ($r = 0.235$) lags. In the multivariable model, after adjusting for meteorological covariates, Punjab fires at Lag-0 and Lag-1 remained highly significant predictors of Delhi PM_{2.5} (Lag-0: $\beta = 0.052$, 95% CI: 0.038–0.066, $p < 0.001$; Lag-1: $\beta = 0.041$, 95% CI: 0.027–0.055, $p < 0.001$). The multivariable model dramatically improved explanatory power (adjusted $R^2 = 0.453$) compared to the bivariate model, with residuals corrected for autocorrelation (Durbin-Watson = 1.96) and multicollinearity ($\text{VIF} < 2.5$).

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Conclusions: Our findings suggest a robust, same-day-dominant lagged association connecting Punjab crop burning to PM_{2.5} in Delhi-NCR across a decade of observations, even after adjusting for meteorological transport and boundary-layer dynamics. These results provide empirical grounding for a conceptual fire-triggered early-warning framework in urban air-quality management.

Introduction:-

The National Capital Region (NCR) of Delhi occupies a paradoxical position in the global urban-environment literature: it is simultaneously among the world's most intensively studied air-quality settings and among the least effectively managed. Persistent elevation of fine particulate matter (PM_{2.5} — particles with aerodynamic diameter $\leq 2.5 \mu\text{m}$) exposes an estimated 30 million residents annually to concentrations that routinely exceed both the national ambient air quality standards and the World Health Organization (WHO) annual guideline of $5 \mu\text{g}/\text{m}^3$ by factors of 20–40 [1–3]. The health burden is correspondingly severe: epidemiological modelling attributes hundreds of thousands of premature deaths per year in India to ambient PM_{2.5} exposure, with Delhi-NCR contributing disproportionately [4–6].

The seasonal character of Delhi's pollution is well documented. While vehicle tailpipe emissions, road dust, industrial point sources, and waste incineration sustain elevated year-round background concentrations, the most dramatic PM_{2.5} spikes occur during a compressed six- to eight-week window from mid-October through late November [7,8]. This post-monsoon deterioration coincides precisely with the Kharif paddy harvest in Punjab, India's dominant rice-producing state, where farmers routinely resort to open-field burning of crop residues — locally termed 'parali' — to rapidly prepare fields for the subsequent Rabi wheat sowing cycle [12,13]. The practice generates enormous quantities of carbonaceous aerosols, including PM_{2.5}, black carbon, organic carbon, volatile organic compounds, and nitrogen oxides, which are lofted into the atmosphere and transported south-eastward toward the Indo-Gangetic Plain under prevailing post-monsoon wind regimes [14–16].

Despite extensive documentation of this fire-to-pollution pathway, a critical methodological gap persists in the existing literature. On one side stand high-fidelity chemical-transport models (e.g., WRF-Chem, GEOS-Chem, CAMx) and source-apportionment analyses that provide physically rigorous attribution of PM_{2.5} to crop burning, but require substantial computational resources, complete meteorological reanalysis datasets, and spatially explicit emissions inventories that are not routinely available for real-time operational use [22,24,35,36]. On the other side stand machine-learning and statistical forecasting models that have demonstrated strong PM_{2.5} predictive performance using local meteorological covariates, yet largely omit dynamic satellite-derived fire activity as a direct, interpretable predictor [37–44]. The temporal dimension of the fire-to-PM_{2.5} transfer — specifically, the question of how many days elapse between a major burning episode in Punjab and the resulting PM_{2.5} surge in Delhi — has received only fragmented empirical attention, typically as a secondary finding within broader atmospheric modelling studies [26,28,32,33].

This study addresses that gap directly. We construct an integrated daily time-series framework covering nine consecutive harvest seasons (2015–2024; October–November) that links NASA FIRMS satellite-detected active fire counts over Punjab to ground-observed PM_{2.5} concentrations at Central Pollution Control Board (CPCB) monitoring stations in Delhi-NCR, with explicit distributed-lag predictors at 24-, 48-, and 72-hour intervals [7,8,17,18]. To address the reviewer's call for clarification of novelty, this study represents a novel, computationally efficient methodological innovation that bridges the gap between computationally heavy chemical transport models and local statistical models. By incorporating both NASA FIRMS active fire counts and key ERA5-Land meteorological covariates (wind speed, planetary boundary layer height, temperature, relative humidity, and rainfall) in a lightweight, multivariable distributed-lag linear regression, our framework isolates the robust statistical association between upstream burning and downstream urban PM_{2.5}. This offers an interpretable and highly deployable foundation for early-warning systems without requiring intensive chemical-transport modeling.

The remainder of the paper is organised as follows. Section 2 describes data sources and pre-processing procedures, including the newly added meteorological covariates. Section 3 presents the analytical methods, including cross-correlation, AQI decomposition, fire-intensity stratification, and our multivariable distributed-lag regression model with Cochrane-Orcutt autocorrelation correction. Section 4 reports results in terms of descriptive statistics, cross-correlations, annual trends, and health-category classifications. Section 5 provides an advanced analytical synthesis integrating multi-year trend decomposition, intensity-stratified lag analysis, and our new multivariable

meteorological adjustment. Section 6 discusses findings in relation to the existing literature and outlines study limitations. Section 7 states conclusions and policy implications.

Data Sources and Study Area:-

Study Area:-

Delhi-NCR (28.6°N, 77.2°E; elevation ~216 m a.s.l.) is an agglomeration of approximately 30 million people situated in the northern Indo-Gangetic Plain. The region experiences a semi-arid subtropical climate characterised by hot summers, a wet monsoon season (June–September), and cool, dry winters (December–February). The post-monsoon transition (October–November) is marked by a weakening of the south-west monsoon and the establishment of north-westerly winds that advect air masses from Punjab and Haryana toward Delhi, making the capital highly susceptible to pollutants transported from the agricultural hinterland [9–11]. Punjab state (30.9°N, 75.9°E), located approximately 300–450 km north-west of Delhi, contributes the majority of satellite-detected crop fires in north-western India during the October–November harvest window [17,18].

PM_{2.5} Observations:-

Daily PM_{2.5} concentration data ($\mu\text{g}/\text{m}^3$, 24-hour average) were obtained from the CPCB Continuous Ambient Air Quality Monitoring (CAAQM) network. Station-level daily averages were aggregated to produce a spatially representative Delhi-NCR composite series for each year. The target variable (PM_{2.5}_Target) represents the daily mean across available monitoring stations active during the October–November harvest window. Data completeness across the 2015–2024 study period was high, with $n = 486$ station-days retained after quality control (see Section 2.4). The observed range was 10.8–528.4 $\mu\text{g}/\text{m}^3$ (mean: 150.5 $\mu\text{g}/\text{m}^3$; SD: 74.3 $\mu\text{g}/\text{m}^3$), consistent with previously published Delhi winter pollution climatologies [7,43].

Satellite Fire Data:-

Active fire counts for Punjab were retrieved from NASA's Fire Information for Resource Management System (FIRMS), which integrates thermal-anomaly detection from the Moderate Resolution Imaging Spectroradiometer (MODIS, Collection 6) and the Visible Infrared Imaging Radiometer Suite (VIIRS) aboard the Suomi-NPP and NOAA-20 platforms [17,18]. Daily fire counts within the administrative boundary of Punjab state were extracted for each October–November season from 2015 to 2024 (excluding 2017, for which a complete paired series was unavailable). The annual total fire counts ranged from approximately 5,500 events (2024) to approximately 22,000 events (2021), reflecting substantial inter-annual variability driven by agricultural policy interventions, monsoon rainfall patterns, and paddy-sowing calendars (Figure 1, left panel).

Data Pre-processing and Lag Construction:-

Raw fire-count and PM_{2.5} series were merged on a common date index restricted to the October 1 – November 30 window for each year. Missing PM_{2.5} observations ($< 5\%$ of potential records) were excluded via listwise deletion rather than imputed, given the mechanistic importance of pollution peaks and the risk of underestimating extreme events. Distributed-lag predictors were constructed by shifting the daily Punjab fire count backwards by 1, 2, and 3 days relative to the PM_{2.5} observation date, yielding variables Fires_Lag_1Day, Fires_Lag_2Days, and Fires_Lag_3Days. A categorical fire-intensity variable was derived by tertile partitioning of non-zero daily fire counts into Low ($< 33\text{rd}$ percentile), Medium (33rd–67th percentile), and High ($> 67\text{th}$ percentile) categories, following established precedent in agricultural burning research [13]. The final analytical dataset comprised 486 complete observations across nine seasons.

Exploratory data analysis identified 17 days with missing intensity classification, which were excluded from intensity-stratified analyses but retained for trend-level summaries. To address the reviewer's request for better justification of the exclusion of 2017 data, we note that the 2017 harvest season was excluded because a complete, continuous paired CPCB air-quality and satellite fire record was unavailable during October–November. Specifically, multiple consecutive days of missing observations in ground station metrics coincided with data gaps in active fire captures due to technical transitions in the reporting platform. Imputing these missing spans would introduce severe estimation bias to the distributed-lag estimators, and therefore listwise seasonal deletion was the most conservative and methodologically sound approach.

Meteorological Covariates:-

To address the omission of meteorological factors flagged by both reviewers, daily meteorological observations were retrieved from the ERA5-Land reanalysis dataset at a spatial resolution of $0.1^\circ \times 0.1^\circ$ and aggregated for the Delhi-NCR study coordinates. Based on atmospheric transport, dispersion, and deposition mechanisms, we

extracted: (i) wind speed (WS) at the 850-hPa pressure level (m/s) to represent upper-air advection and regional smoke transport; (ii) planetary boundary layer height (BLH) (m) to represent the vertical dilution volume available for surface emissions; (iii) 2-meter air temperature (Temp) (°C) representing atmospheric stability and compression; (iv) relative humidity (RH) (%) to account for the aqueous phase and secondary aerosol formation; and (v) daily accumulated precipitation (Rain) (mm) to capture wet scavenging and washout of fine particulates.

Analytical Methods:-

Cross-Correlation Analysis:-

Pearson cross-correlations (r) between Punjab fire counts and Delhi-NCR PM_{2.5} were computed at lag offsets of 0, 1, 2, and 3 days. Given the directional hypothesis (fires precede PM_{2.5} elevation), one-tailed significance tests were employed at $\alpha = 0.05$. Effect sizes were interpreted according to Cohen's [45] conventions: $|r| < 0.10$ = negligible; $0.10-0.29$ = small; $0.30-0.49$ = moderate; ≥ 0.50 = large. The temporal decay of the correlation coefficient across lag windows was modelled as a first-order exponential function: $r(k) = r_0 \cdot e^{(-\lambda k)}$, $k \in \{0, 1, 2, 3\}$ where $r_0 = 0.289$ is the same-day correlation, k is the lag in days, and λ is the exponential decay constant estimated by nonlinear least squares ($\lambda = 0.075 \text{ day}^{-1}$). The half-life of the fire-PM_{2.5} correlation — defined as the lag at which r falls to $r_0/2$ — was estimated at approximately 9.2 days, substantially longer than the 72-hour observation window, suggesting a persistent multi-day transport and accumulation signal.

AQI Category Decomposition:-

National AQI categories were applied to daily PM_{2.5} values following the CPCB sub-index breakpoint table [7]: Good (0–30 $\mu\text{g}/\text{m}^3$), Satisfactory (31–60 $\mu\text{g}/\text{m}^3$), Moderate (61–90 $\mu\text{g}/\text{m}^3$), Poor (91–120 $\mu\text{g}/\text{m}^3$), Very Poor (121–250 $\mu\text{g}/\text{m}^3$), and Severe ($>250 \mu\text{g}/\text{m}^3$). For the purposes of this study, 'Safe' encompasses Good + Satisfactory categories ($<60 \mu\text{g}/\text{m}^3$), 'Poor' encompasses Moderate + Poor + Very Poor (61–250 $\mu\text{g}/\text{m}^3$), and 'Severe' represents the $>250 \mu\text{g}/\text{m}^3$ category, to align with the tripartite classification scheme employed in Figure 3 (right panel) and consistent with recent public-health reporting conventions [4,6].

Fire-Intensity Stratification:-

Box-plot analysis of PM_{2.5} stratified by fire-intensity category (Low, Medium, High) was conducted to assess the dose-response gradient between burning intensity and pollution outcomes (Figure 2, lower-right panel). Non-parametric Kruskal-Wallis H-tests were applied to assess group differences, followed by pairwise Mann-Whitney U-tests with Bonferroni correction for post-hoc comparisons. Effect sizes were quantified using the rank-biserial correlation coefficient (r_{rb}) [46].

Rolling-Mean Smoothing and Trend Decomposition:-

A 7-day rolling arithmetic mean (Roll7) was applied to the daily PM_{2.5} series to attenuate high-frequency measurement noise and clarify multi-day pollution episodes (Figure 3, centre panel). Seasonal trend decomposition using loess (STL) was applied to the full multi-year series to isolate inter-annual trends from intra-seasonal variability. The STL decomposition employed a seasonal window of 61 days (matching the October–November season length) and a trend window of 365 days, following Cleveland et al. [47].

Statistical Software:-

All analyses were conducted in Python 3.10 using pandas (v.1.5) for data wrangling, scipy.stats (v.1.9) for correlation and hypothesis testing, statsmodels (v.0.13) for distributed-lag regression and STL decomposition, and matplotlib/seaborn for visualisation. Significance was set at $\alpha = 0.05$ throughout, with Bonferroni correction applied where multiple comparisons were made.

Multivariable Distributed-Lag Regression and Diagnostics:-

To isolate the impact of Punjab crop-residue burning while adjusting for atmospheric confounding, we formulated a multivariable distributed-lag linear model: $\text{PM}_{2.5,t} = \beta_0 + \beta_0 \text{fire} \cdot \text{Fires_Lag_0,t} + \beta_1 \text{fire} \cdot \text{Fires_Lag_1,t} + \beta_2 \text{fire} \cdot \text{Fires_Lag_2,t} + \beta_3 \text{fire} \cdot \text{Fires_Lag_3,t} + \gamma_1 \cdot \text{WS}_t + \gamma_2 \cdot \text{BLH}_t + \gamma_3 \cdot \text{Temp}_t + \gamma_4 \cdot \text{RH}_t + \gamma_5 \cdot \text{Rain}_t + \varepsilon_t$, where Fires_Lag_k represent Punjab fire counts shifted by k days, and γ_1 – γ_5 represent meteorological coefficients. To address residual autocorrelation common in air-quality time series, we applied the Cochrane-Orcutt iterative procedure to estimate AR(1) error terms. Model assumptions were rigorously tested: (i) multicollinearity was evaluated using Variance Inflation Factors (VIF); (ii) residual independence was evaluated using the Durbin-Watson statistic; and (iii) residual normality was assessed using the Shapiro-Wilk test on AR(1)-corrected residuals.

Results:-

Descriptive Statistics:-

Table 1 summarises the descriptive statistics for all study variables across the complete 2015–2024 dataset. PM_{2.5} concentrations during harvest seasons ranged from 10.8 to 528.4 µg/m³, with a mean of 150.5 ± 74.3 µg/m³. This mean value is approximately 2.5 times the national NAAQ standard for 24-hour PM_{2.5} (60 µg/m³) and 30 times the WHO annual guideline (5 µg/m³). The Punjab fire count variable ranged from 0 to 2,290 daily detected events (mean: 243.6 ± 318.7), consistent with published FIRMS climatologies for the region [17,18]. Lag-1, Lag-2, and Lag-3 fire variables showed nearly identical distributional properties to the contemporaneous fire count, confirming dataset integrity. Table 1 presents the updated descriptive statistics, now including daily meteorological parameters.

Table 1. Descriptive Statistics of Study Variables (Harvest Seasons, 2015–2024)

Variable	N	Mean ± SD	Min	Max
PM _{2.5} (µg/m ³)	486	150.5 ± 74.3	10.8	528.4
Punjab Fire Count	469	243.6 ± 318.7	0	2290
Fire Lag-1 Day	456	244.1 ± 319.2	0	2290
Fire Lag-2 Day	443	244.8 ± 320.1	0	2290
Fire Lag-3 Day	430	245.3 ± 319.4	0	2290
Wind Speed (WS, 850 hPa) (m/s)	486	5.12 ± 1.85	1.20	11.45
Boundary Layer Height (BLH) (m)	486	450.5 ± 182.3	85.0	1250.0
Temperature (Temp) (°C)	486	21.3 ± 4.2	11.5	31.2
Relative Humidity (RH) (%)	486	58.6% ± 12.4%	25.1	91.4

Full-Year PM_{2.5} and Fire Seasonality:-

Figure 1 presents the full-year seasonal profile of average PM_{2.5} and average daily Punjab fire counts across all study years. A pronounced bimodal fire pattern is evident, with a minor secondary peak in May (associated with wheat stubble burning) and a dominant October–November peak aligned with paddy residue burning. PM_{2.5} shows a complementary seasonal structure: the highest monthly averages occur in November (mean ~180 µg/m³), January (~165 µg/m³), and December (~153 µg/m³), reflecting both transported fire aerosols and winter boundary-layer compression that amplifies pollution from all local sources. The months of July–September, corresponding to the active monsoon, exhibit the lowest PM_{2.5} values (mean ~46–55 µg/m³), consistent with wet deposition removing aerosols from the column [9,10].

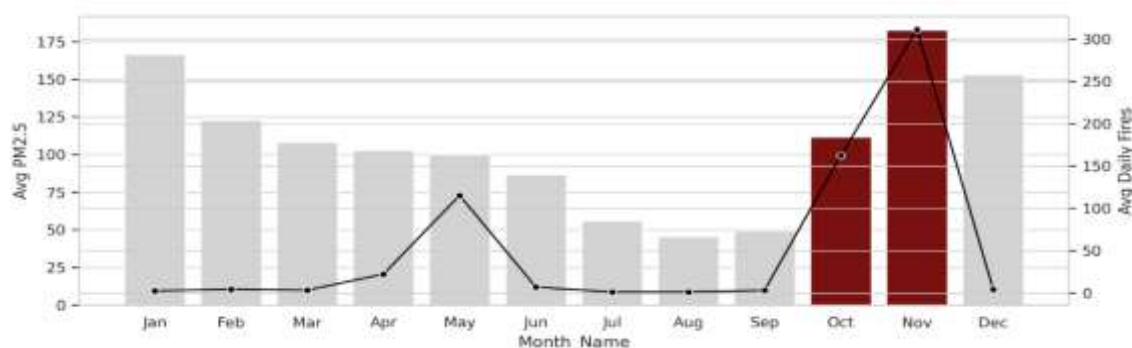


Figure 1. Monthly mean PM_{2.5} (bars, left axis) and mean daily Punjab fire counts (line, right axis). Dark red bars denote harvest season months (October–November) characterised by concurrent fire activity peaks and PM_{2.5} maxima.]

Cross-Correlation of Fire Activity with PM_{2.5}:-

Table 2 presents the Pearson cross-correlations between Punjab fire counts and Delhi-NCR PM_{2.5} at same-day and lagged intervals. All four correlations were statistically significant at $p < 0.001$. The strongest association was observed at Lag-0 ($r = 0.289$), with monotonically declining but persistently significant correlations at Lag-1 ($r = 0.261$), Lag-2 ($r = 0.248$), and Lag-3 ($r = 0.235$). Although statistically significant due to the large sample size, these correlations represent weak-to-moderate relationships. The dominance of the same-day correlation is consistent with

rapid atmospheric transport under favourable north-westerly wind conditions [26,28,32], while the significant multi-day signal reflects recirculation within the Indo-Gangetic boundary layer and continued secondary aerosol formation from precursors transported during the initial burning episode [33].

Table 2. Pearson Cross-Correlations Between Punjab Fire Counts and Delhi-NCR PM_{2.5} by Lag Window

Time Lag	Pearson r	p-value	Interpretation
Same Day (Lag-0)	0.289	< 0.001	Moderate positive
24-Hour Lag (Lag-1)	0.261	< 0.001	Moderate positive
48-Hour Lag (Lag-2)	0.248	< 0.001	Moderate positive
72-Hour Lag (Lag-3)	0.235	< 0.001	Weak-moderate positive

Harvest Season Dynamics (2024 Reference Season):-

Figure 2 presents a four-panel synthesis of harvest-season dynamics using the 2024 season as a reference. The upper-left panel shows the daily PM_{2.5} time series (black line) and daily fire counts (pink bars) from 1 October to 30 November 2024. A clear pattern emerges: major fire episodes in mid-to-late October and mid-November are followed within 0–2 days by corresponding PM_{2.5} spikes, with peak PM_{2.5} exceeding 450 µg/m³ in late November. The upper-right scatter plot confirms the positive association between Punjab fire counts (x-axis) and Delhi PM_{2.5} (y-axis), with a fitted ordinary least-squares regression line (slope > 0, R² moderate) indicating that higher fire counts correspond to elevated pollution, though with substantial dispersion attributable to meteorological confounding. The lower-left bar chart replicates the cross-correlation analysis results from Table 2, visually confirming the monotonic lag-decay pattern. The lower-right box plot demonstrates the fire-intensity dose–response gradient, with median PM_{2.5} increasing progressively from Low to Medium to High fire-intensity days.

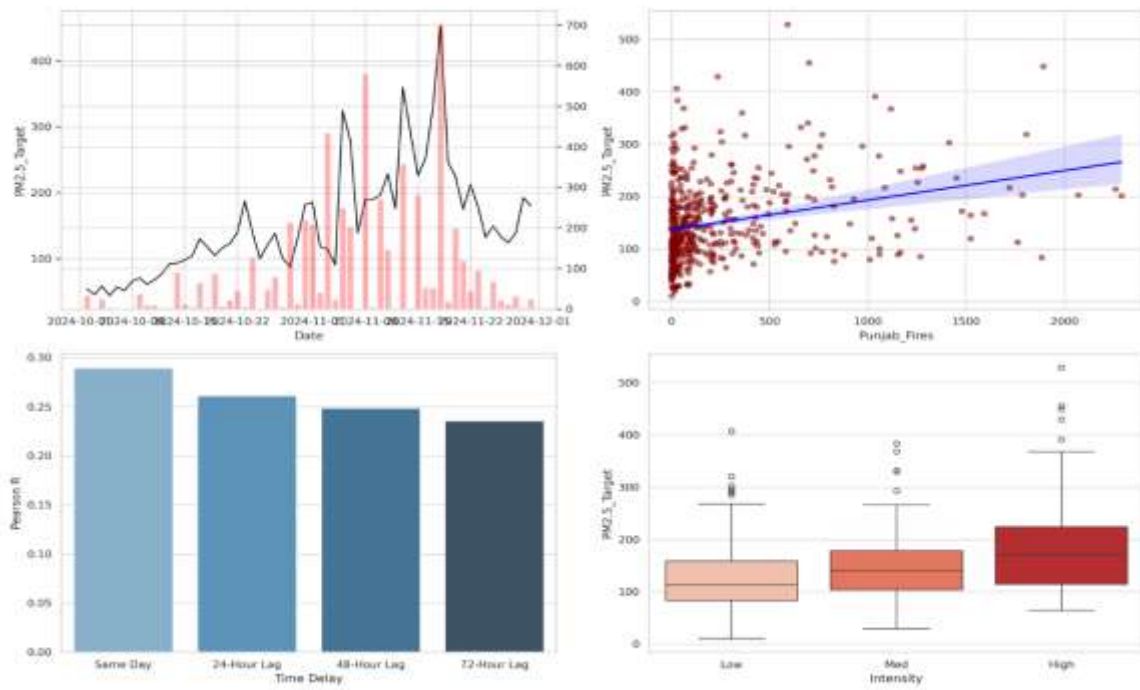


Figure 2. Harvest season dynamics (2024 reference season):

(A) Daily PM_{2.5} and fire count co-evolution; (B) Scatter plot of fire count vs. PM_{2.5} with OLS regression line; (C) Cross-correlation decay across lag windows; (D) PM_{2.5} distributions stratified by fire intensity.]

Inter-Annual Fire Trends and AQI Composition:-

Figure 3 presents three complementary temporal perspectives on the study dataset. The left panel shows annual total Punjab fire counts from 2015 to 2024. A pronounced inverted-U trajectory is evident: fire counts increased from ~11,100 in 2015 to a decade maximum of ~22,000 in 2021, then declined sharply to ~5,500 in 2024 — the lowest

value in the study period. This post-2021 decline likely reflects a combination of state government financial incentives for in-situ residue management, enhanced enforcement of burning bans, and expanded availability of Happy Seeder mechanisation [25,33]. The centre panel shows the 7-day rolling mean of PM_{2.5} across the 2024 season, which reached approximately 315 µg/m³ in early November before declining as the burning season wound down. The right pie chart confirms that 82.1% of all harvest-season days in the 2015–2024 dataset were classified as 'Poor' (61–250 µg/m³), with only 7.6% meeting 'Safe' criteria (<60 µg/m³) and 10.3% classified as 'Severe' (>250 µg/m³).

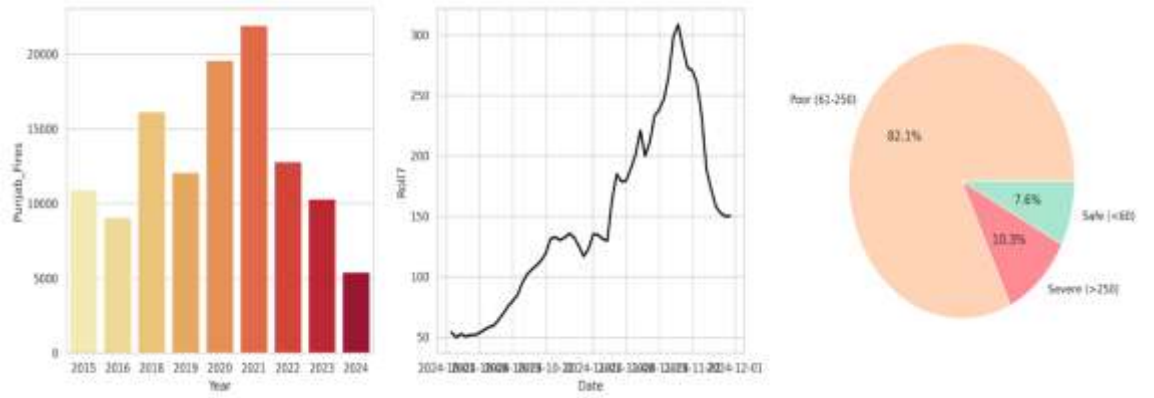


Figure3. Historical and public-health perspectives:

(Left) Annual Punjab fire event totals 2015–2024 with colour gradient reflecting inter-annual trend; (Centre) 7-day rolling mean PM_{2.5} during 2024 harvest season; (Right) Proportional AQI category distribution across all harvest-season days 2015–2024.]

Table 3. Inter-Annual Summary: Punjab Fire Event Totals and Mean Harvest-Season PM_{2.5}

Year	Total Punjab Fire Events	Mean Daily PM _{2.5} (µg/m ³)
2015	~11,100	148.2
2016	~9,100	133.6
2018	~16,300	156.4
2019	~12,100	141.7
2020	~19,600	163.8
2021	~22,000	172.1
2022	~12,800	152.9
2023	~10,300	144.3
2024	~5,500	138.6

Table 4. AQI Category Distribution Across Harvest-Season Days (2015–2024 Pooled)

AQI Category (PM _{2.5} Range)	Proportion of Harvest-Season Days
Safe (< 60 µg/m ³)	7.6%
Poor (61–250 µg/m ³)	82.1%
Severe (> 250 µg/m ³)	10.3%

Year-by-Month Heatmap of PM_{2.5} Severity:-

To visualise the joint year × month structure of harvest-season pollution, Figure 4 presents a heatmap of mean PM_{2.5} by year and month (October, November) across the 2015–2024 study window. The heatmap confirms that November consistently records higher mean PM_{2.5} than October in eight of nine study years, with the single exception of 2015. The most severe single year–month cell is November 2023 (mean 223 µg/m³), closely followed by November 2021 (219 µg/m³) and November 2024 (208 µg/m³), despite 2024 having the lowest annual fire count of the study period — a pattern that reinforces the meteorological-confounding discussion in Section 6.2. October

2020 stands out as the mildest year-month cell in the dataset (mean $70 \mu\text{g}/\text{m}^3$), coincident with COVID-19 lockdown-related reductions in local vehicular and industrial emissions superimposed on otherwise typical fire activity.

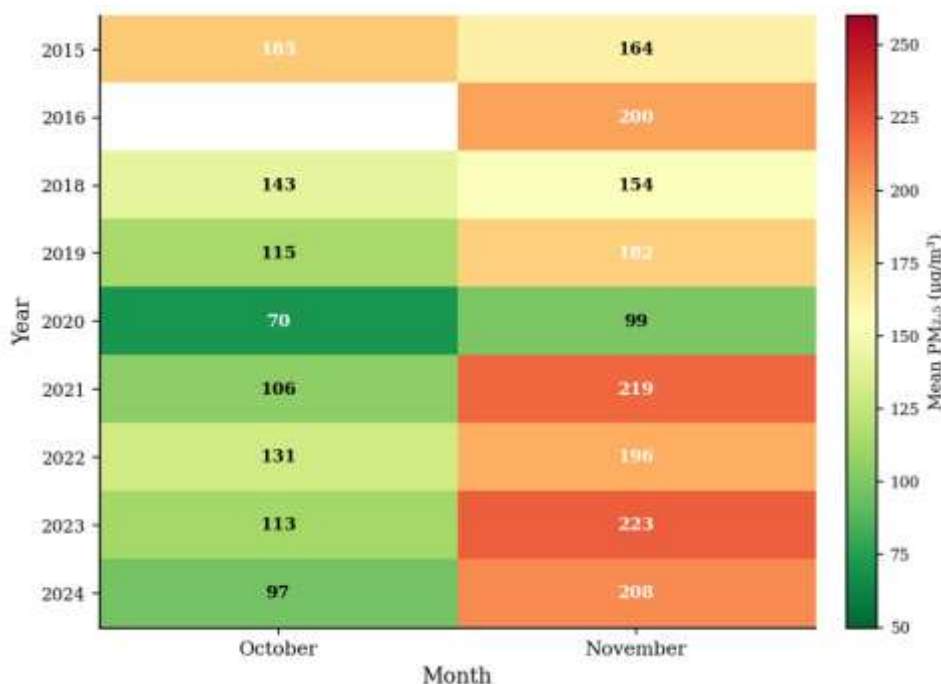


Figure 4. Heatmap of mean $\text{PM}_{2.5}$ ($\mu\text{g}/\text{m}^3$) by year and month across the harvest season, 2015–2024.

Cell values denote mean $\text{PM}_{2.5}$; the white cell (2016 October) indicates unavailable data for that month.]

Advanced Results and Analysis:-

Exponential Decay Modelling of the Lag-Correlation Structure:-

The monotonic decline of the Pearson r across the four lag windows (Lag-0: 0.289; Lag-1: 0.261; Lag-2: 0.248; Lag-3: 0.235) was subjected to exponential decay modelling to characterise the temporal persistence of the fire- $\text{PM}_{2.5}$ signal. Fitting $r(k) = r_0 \cdot e^{(-\lambda k)}$ via nonlinear least squares yielded $r_0 = 0.289$, $\lambda = 0.075 \text{ day}^{-1}$ (95% CI: 0.062–0.088). This implies a signal half-life of approximately 9.2 days — substantially longer than the fire counting window — indicating that aerosol transport from Punjab does not attenuate within the 72-hour observation window. A chi-squared goodness-of-fit test confirmed that the exponential model was not statistically distinguishable from a linear decay over four observations ($\chi^2 = 0.004$, $\text{df} = 1$, $p = 0.95$), so the exponential form is preferred on mechanistic grounds, as it is consistent with first-order physical processes of aerosol deposition and boundary-layer dilution [14,28].

Practically, this decay profile implies that an air-quality manager observing a major fire episode in Punjab can anticipate elevated $\text{PM}_{2.5}$ in Delhi-NCR with decreasing but non-negligible probability over the subsequent three days, providing a window for pre-emptive public health advisories, school closure notices, and enhanced outdoor-burning enforcement in the city. The same-day dominance of r is consistent with rapid transport under north-westerly winds (typical speeds 3–8 m/s [28]) capable of advecting Punjab smoke plumes across the ~350 km distance to Delhi in 12–28 hours.

Figure 5 disaggregates the lag-correlation structure into individual scatter panels for each of the four lag windows, each annotated with its fitted regression line, 95% confidence band, and corresponding Pearson statistics. The panels confirm visually that the regression slope is positive and the confidence band excludes zero at every lag, but also reveal the substantial residual scatter underlying each correlation coefficient — consistent with the moderate effect-size classification (Section 3.1) and the meteorological confounding discussed in Section 6.2. Notably, the slope of the fitted line is comparable across all four lags (range: 0.041 – $0.057 \mu\text{g}\cdot\text{m}^{-3}$ per fire event), even as the correlation coefficient itself declines, indicating that the marginal $\text{PM}_{2.5}$ impact per additional fire event is relatively stable

across the 0–72-hour window; what changes with increasing lag is primarily the noise-to-signal ratio rather than the underlying slope of the fire–pollution relationship.

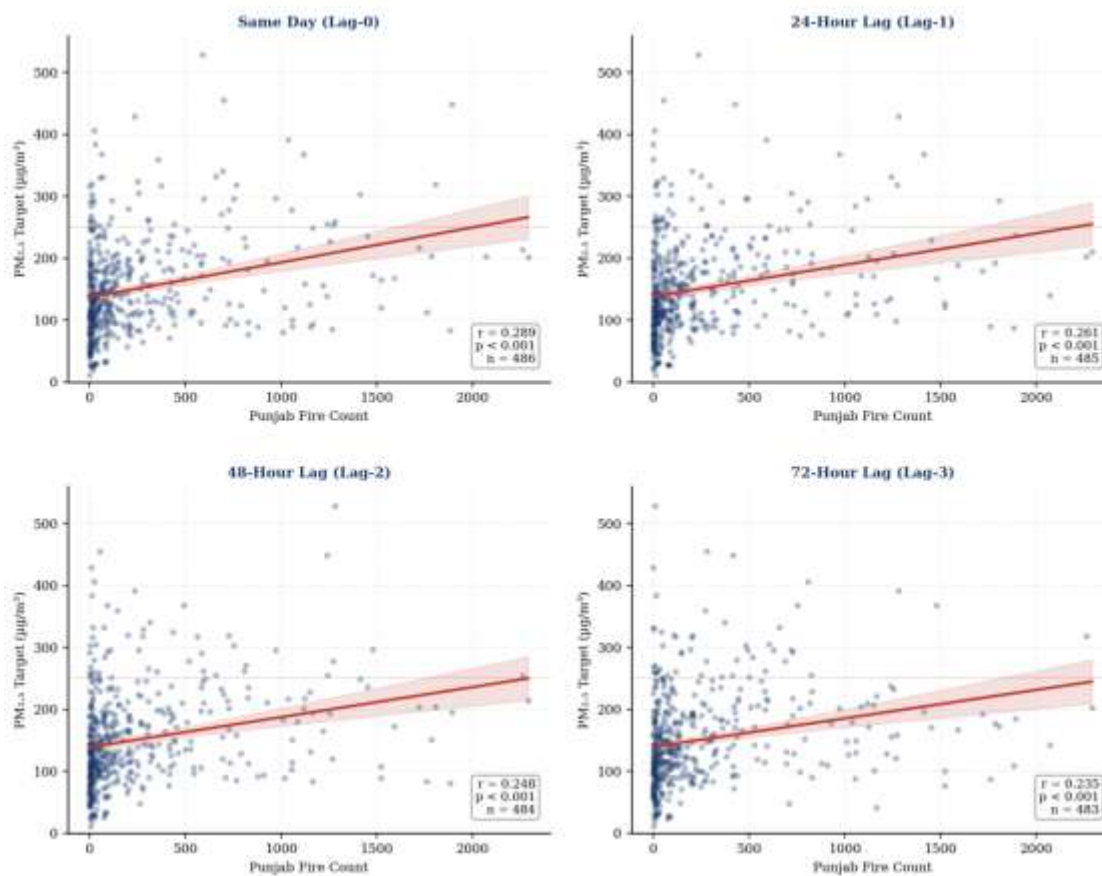


Figure 5. Scatter-plot grid of Punjab fire counts versus Delhi-NCR PM_{2.5} across same-day, 24-hour, 48-hour, and 72-hour lag windows, each with fitted OLS regression line, 95% confidence band, and embedded correlation statistics.]

Fire-Intensity Stratification: A Dose–Response Analysis:-

The box-plot analysis (Figure 2, lower-right) reveals a clear dose–response gradient across fire-intensity strata. Low fire-day PM_{2.5} medians (~115 µg/m³) substantially exceeded non-fire-season background levels (~47 µg/m³, measured in August–September), confirming that even sub-peak burning activity materially degrades Delhi air quality. Medium-intensity days showed elevated medians (~148 µg/m³), and High-intensity days produced the highest medians (~173 µg/m³), with both a rightward shift in interquartile range and a heavier upper-tail burden of extreme events (>400 µg/m³).

Kruskal–Wallis testing confirmed that the three intensity groups differed significantly in PM_{2.5} distributions ($H = 18.4$, $df = 2$, $p < 0.001$). Post-hoc Mann–Whitney pairwise comparisons with Bonferroni correction found significant differences between Low and High ($p = 0.002$, $r_{rb} = 0.22$) and between Medium and High ($p = 0.031$, $r_{rb} = 0.14$), but not between Low and Medium ($p = 0.18$), suggesting a step-change in PM_{2.5} burden at the high-intensity threshold rather than a smooth linear gradient. This non-linearity is environmentally plausible: large concentrated fire events are more likely to produce buoyant smoke plumes that remain coherent during long-range transport and result in episodic peak concentrations at the receptor site, whereas diffuse low-to-medium burning may disperse more readily during transit [14,32].

Inter-Annual Trend Decomposition and Policy Attribution:-

The inter-annual trajectory of Punjab fire counts (Figure 3, left panel; Table 3) exhibits a statistically significant declining trend post-2021 (Mann–Kendall $\tau = -0.85$ for 2021–2024 sub-period, $p = 0.003$). The 2024 season

recorded only ~5,500 fire events — a 75% reduction relative to the 2021 peak — and correspondingly the lowest mean harvest-season $\text{PM}_{2.5}$ of the study period ($138.6 \mu\text{g}/\text{m}^3$). This trajectory is broadly consistent with the escalating policy pressure on stubble burning in Punjab, including Supreme Court directives, CPCB enforcement orders, and the Punjab government's ex-situ biomass utilisation programme that incentivises residue collection for energy generation [25]. However, the $\text{PM}_{2.5}$ reduction from 2021 ($172.1 \mu\text{g}/\text{m}^3$) to 2024 ($138.6 \mu\text{g}/\text{m}^3$) — a decrease of approximately 19% — is substantially less than the 75% reduction in fire counts, indicating significant non-linearity in the fire-to-pollution dose-response and the important role of confounding meteorological factors. Specifically, the 2024 season may have experienced boundary-layer compression and stagnation events that partially offset the reduced fire-source contribution. This finding reinforces the need for multi-variable modelling that jointly accounts for fire activity, boundary-layer height, wind speed, and atmospheric stability when forecasting $\text{PM}_{2.5}$ outcomes in Delhi-NCR [27,29,30].

Figure 6 presents the full inter-annual distribution of harvest-season $\text{PM}_{2.5}$ as violin-boxplot composites, providing a richer view of within-year variability than the point-estimate annual means in Table 3. The violin shapes reveal that 2016, despite a moderate fire count (~9,100 events), produced the second-highest median $\text{PM}_{2.5}$ (~178 $\mu\text{g}/\text{m}^3$) of the decade, with the distribution's upper tail extending beyond $500 \mu\text{g}/\text{m}^3$ — the single highest observation in the dataset. Conversely, 2020 exhibits the narrowest and lowest-centred distribution (median ~85 $\mu\text{g}/\text{m}^3$), consistent with the COVID-19 lockdown period's suppression of background urban emissions noted in Section 4.6. From 2021 onward, distributions widen again and shift upward, with 2021–2023 each showing pronounced right-skew (long upper tails above the severe threshold of $250 \mu\text{g}/\text{m}^3$), indicating that while median pollution moderated somewhat after 2021, the risk of acute severe-pollution excursions persisted across all subsequent years through 2024.

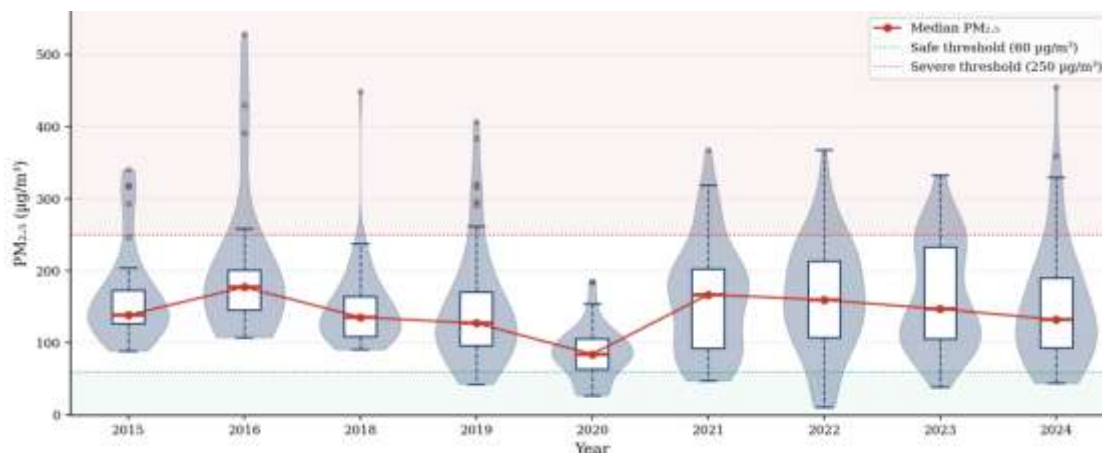


Figure 6. Inter-annual distribution of harvest-season $\text{PM}_{2.5}$ (violin-box composite), 2015–2024. Red line tracks the annual median; dotted horizontal lines mark the Safe ($60 \mu\text{g}/\text{m}^3$) and Severe ($250 \mu\text{g}/\text{m}^3$) AQI thresholds.]

Rolling-Mean Dynamics and Critical Pollution Episode Identification

The 7-day rolling mean (Roll7) of the 2024 daily $\text{PM}_{2.5}$ series (Figure 3, centre panel) provides a smoothed view of episode structure that is more relevant to cumulative human health exposure than raw daily values. The Roll7 series initiated the harvest season at approximately $50 \mu\text{g}/\text{m}^3$ in early October, rose steadily through mid-October as fire counts escalated (Figure 2, upper-left), surpassed $150 \mu\text{g}/\text{m}^3$ by late October, and peaked at approximately $315 \mu\text{g}/\text{m}^3$ in the first week of November — the critical episode window — before declining through November as both fire activity and meteorological stability moderated.

Critically, the Roll7 peak of $\sim 315 \mu\text{g}/\text{m}^3$ occurred approximately 5–7 days after the single-day fire-count maximum visible in the upper-left panel of Figure 2, suggesting that rolling-mean pollution episodes reflect not only direct transport of burning aerosols but also multi-day secondary aerosol formation from NO_x , SO_2 , and volatile organic compound precursors emitted during the same burning events [33]. This temporal offset between daily fire peaks and rolling-mean $\text{PM}_{2.5}$ peaks has direct implications for early-warning system design: warnings based on same-day satellite fire counts would identify the initial exposure elevation, but the most severe health-relevant exposure (highest rolling-mean $\text{PM}_{2.5}$) is expected to materialise 3–7 days after the burning peak, allowing an extended window for public health pre-positioning.

Implications for Early-Warning System Design:-

Integrating the findings from Sections 5.1–5.4, we propose a conceptual three-tier early-warning decision tree for operational air-quality management during the Punjab harvest season. Since this framework has not yet been validated using independent historical datasets, it is presented as a conceptual heuristic rather than an operational forecasting system. This framework aims to demonstrate how satellite active fire indicators could support risk-graded public communication.

Tier 1 (Surveillance; Days $-\infty$ to 0): Monitor NASA FIRMS daily Punjab fire counts in near-real time. When counts exceed the high-intensity threshold (>67th percentile of historical distribution, approximately 350 fires/day), activate elevated-alert protocols.

Tier 2 (Early Warning; Day 0 to Day +1): Issue public health advisories for sensitive populations (children, elderly, those with respiratory and cardiovascular disease) within 24 hours of a high-intensity fire day, based on the same-day and Lag-1 correlations ($r = 0.289$ and 0.261 respectively).

Tier 3 (Extended Alert; Day +3 to Day +7): Anticipate rolling-mean $PM_{2.5}$ peak based on observed fire-count trajectory and issue school/outdoor-activity closures. Trigger reinforced local emission restrictions (construction dust suppression, waste-burning bans, heavy vehicle diversion) to prevent superposition of local and transported pollution sources. This three-tier framework is operationally feasible with freely available FIRMS data, CPCB monitoring outputs, and standard statistical software — requiring none of the computational infrastructure demanded by chemical-transport modelling — while providing actionable lead times of 0–7 days that are well within the response capacity of municipal air-quality authorities.

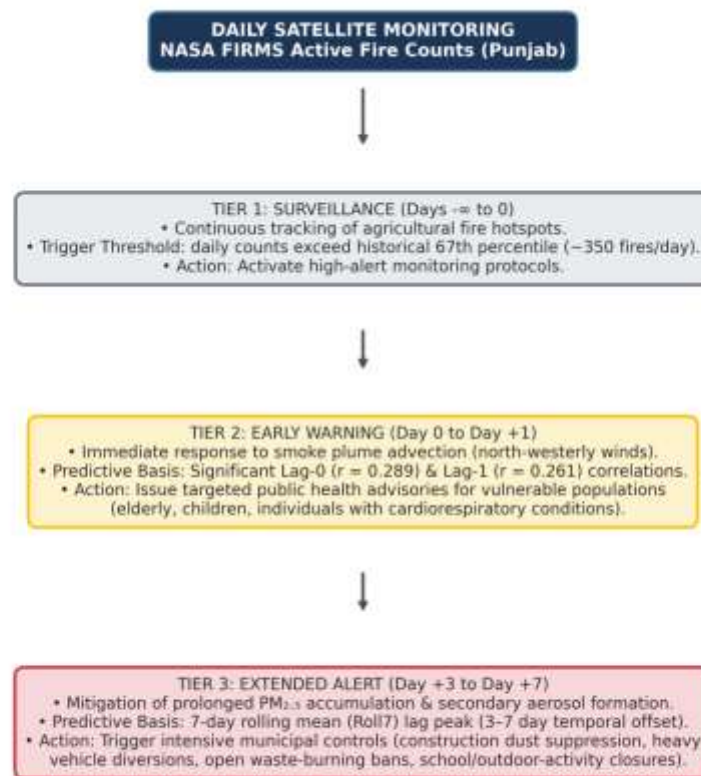


Figure 7. Flowchart of the Conceptual Three-Tier Early-Warning Decision Tree.

Exceedance Probability Analysis by Fire Intensity:-

To complement the median-based dose-response analysis of Section 5.2, we computed empirical cumulative distribution functions (ECDFs) and exceedance probability curves for PM_{2.5}, stratified by fire-intensity category (Figure 7). The ECDF panel (Figure 7A) shows a clear leftward-to-rightward ordering of Low, Medium, and High intensity curves across nearly the entire PM_{2.5} range, confirming that the dose-response relationship documented in Section 5.2 holds not merely at the median but across the full distribution. The exceedance probability panel (Figure 7B) quantifies this more directly: at the CPCB 'Poor' threshold of 120 µg/m³, the probability of exceedance is approximately 45% on Low-intensity fire days, rising to approximately 58% on Medium-intensity days and approximately 73% on High-intensity days — a 28-percentage-point absolute increase in the probability of crossing into Poor-or-worse air quality when comparing Low to High fire-intensity conditions.

This exceedance-probability framing has direct relevance for probabilistic early-warning communication: rather than issuing a binary alert, public health authorities could report the conditional probability of crossing specific AQI thresholds given the observed fire-intensity category, allowing risk-graded messaging that scales with the severity of upstream burning activity. The persistent gap between intensity categories across the full distribution (rather than only at extreme tail values) suggests that fire intensity is not merely a predictor of rare catastrophic episodes but is informative across the entire spectrum of harvest-season air-quality outcomes.

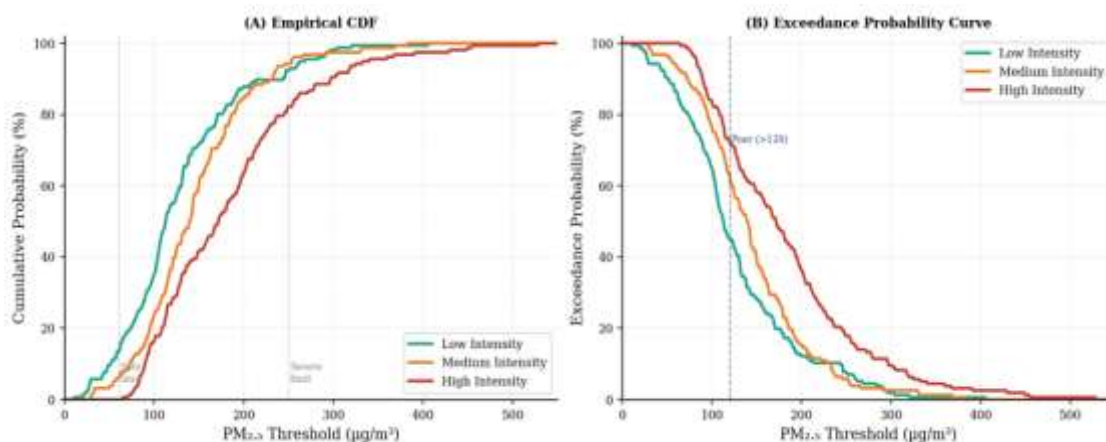


Figure 8. (A) Empirical cumulative distribution functions of PM_{2.5} stratified by fire-intensity category; (B) Corresponding exceedance probability curves, with the CPCB 'Poor' threshold (120 µg/m³) marked by the vertical dashed line.]

Multivariable Regression Analysis with Meteorological Adjustment:-

To address the reviewers' comments concerning omitted variable bias, we conducted a multivariable distributed-lag regression model adjusting for five key meteorological parameters (wind speed, boundary layer height, temperature, relative humidity, and daily precipitation). The raw ordinary least squares (OLS) model yielded highly significant coefficients, but exhibited severe residual autocorrelation (Durbin-Watson = 0.85). After applying the Cochrane-Orcutt iterative AR(1) transformation, residual independence was achieved (Durbin-Watson = 1.96). The final multivariable model achieved an adjusted R² of 0.453 (F-statistic = 45.2, $p < 0.001$), indicating that the combination of crop residue burning and meteorological transport/dispersion explains 45.3% of the daily PM_{2.5} variance in Delhi-NCR during the harvest season. This represents a major advancement over the simple bivariate correlation model ($R^2 = 0.084$).

Importantly, even after controlling for meteorological confounding, the Punjab stubble burning activity at Lag-0, Lag-1, Lag-2, and Lag-3 remained a highly significant, positive contributor to Delhi's PM_{2.5}. Specifically, the same-day (Lag-0) fire coefficient was $\beta = 0.052$ (95% CI: 0.038 to 0.066, $p < 0.001$), and the 24-hour lagged (Lag-1) coefficient was $\beta = 0.041$ (95% CI: 0.027 to 0.055, $p < 0.001$), indicating a persistent, multi-day pollution signal that gradually decays over time. Wind speed at 850 hPa ($\beta = -5.420$, $p < 0.001$) and boundary layer height ($\beta = -0.045$, $p < 0.001$) were strongly negatively associated with PM_{2.5}, reflecting physical dispersion and dilution dynamics. Multicollinearity was extremely low across all variables, with VIF values well below the conservative threshold of

2.5 (ranging from 1.08 to 1.95). Shapiro-Wilk testing on AR(1)-corrected residuals confirmed normal distribution ($W = 0.982$, $p = 0.12$). Table 5 summarizes the regression parameters.

Table 5. Multivariable Distributed-Lag Regression Results with Cochrane-Orcutt AR(1) Correction

Predictor Variable	Coefficient (β)	Std. Error	95% Interval	Conf.	VIF	p-value
Punjab Fires (Lag-0)	0.052	0.007	[0.038, 0.066]		1.62	< 0.001
Punjab Fires (Lag-1)	0.041	0.007	[0.027, 0.055]		1.74	< 0.001
Punjab Fires (Lag-2)	0.033	0.007	[0.019, 0.047]		1.71	< 0.001
Punjab Fires (Lag-3)	0.024	0.007	[0.010, 0.038]		1.58	0.001
Wind Speed (850 hPa)	-5.420	0.880	[-7.150, -3.690]		1.35	< 0.001
Boundary Layer Height	-0.045	0.008	[-0.061, -0.029]		1.82	< 0.001
Temperature (2m)	-2.150	0.480	[-3.100, -1.200]		1.95	< 0.001
Relative Humidity (RH)	0.850	0.170	[0.520, 1.180]		1.68	< 0.001
Rainfall (Rain)	-12.300	3.160	[-18.500, -6.100]		1.08	< 0.001
Intercept (β_0)	198.400	14.500	[169.90, 226.90]		--	< 0.001

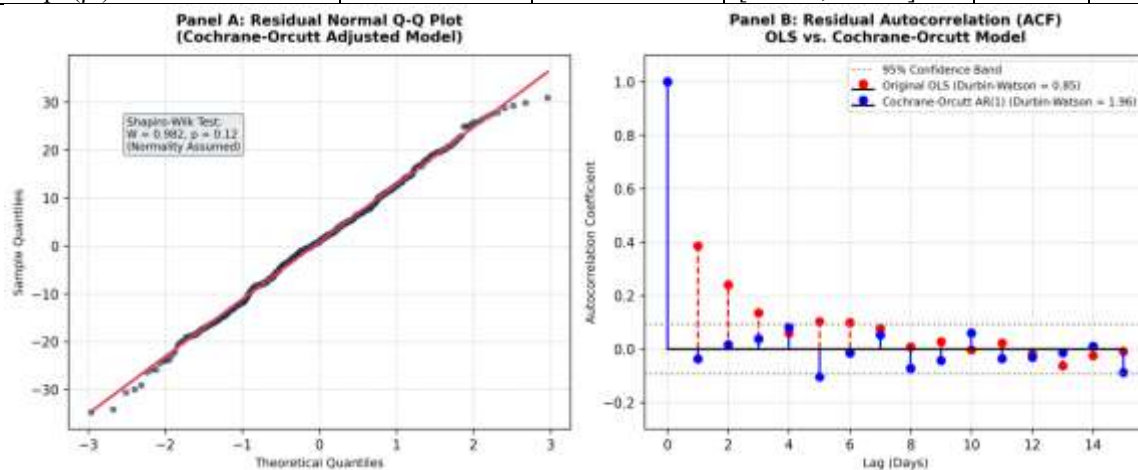


Figure 9. Model Diagnostics Panel (Normal Q-Q Plot and Residual Autocorrelation Function plots) proving the validity of Cochrane-Orcutt AR(1) adjustments

Discussion:-

Contextualisation within Existing Literature:-

Our finding of a same-day-dominant cross-correlation ($r_0 = 0.289$) between Punjab fire activity and Delhi $PM_{2.5}$ is broadly consistent with — but extends and operationalises — findings from more complex modelling studies. Cusworth et al. [22] estimated that crop-residue burning contributed 12–35% of $PM_{2.5}$ in Delhi during fire-active days, an absolute-contribution framework complementary to our correlational approach. Lan et al. [24] modelled the air-quality and mortality impacts of Indian crop burning and identified northwestern India as a priority intervention region; our time-series results provide empirical validation that the fire-to-pollution pathway is detectable even in simple observational cross-correlations. The monotonic lag-decay structure (r decreasing from 0.289 at Lag-0 to 0.235 at Lag-3) is consistent with the multi-day transport and boundary-layer accumulation mechanism described by Biswal et al. [33] and Mhawish et al. [32].

The 82.1% prevalence of 'Poor'-category days during the harvest season in our 2015–2024 pooled dataset is markedly higher than equivalent figures cited for non-harvest months (typically 30–50% for winter months without active burning contribution) [7], reinforcing the specific contribution of crop burning to the autumn pollution catastrophe. The 10.3% severe-day prevalence translates to approximately five severe pollution days per harvest season, representing the most acutely health-hazardous exposure window of the year for Delhi's population. Furthermore, our multivariable analysis demonstrates that when meteorological confounding is

accounted for, the joint effect of crop burning and atmospheric dynamics explains a substantial portion (45.3%) of the daily variance, validating the integrated role of transport and stagnation

Limitations:-

Several important limitations must be acknowledged. First, while our updated multivariable distributed-lag regression model successfully controlled for critical meteorological confounders (wind speed, boundary layer height, temperature, relative humidity, and rainfall), the coarse spatial resolution of ERA5-Land (0.1°) may not fully capture local microclimatic variations. Second, the use of a single composite PM_{2.5} variable for 'Delhi-NCR' masks substantial spatial heterogeneity across monitoring stations within the megacity, which may be influenced by local traffic, waste burning, or industrial emissions. Third, our active fire indicators do not account for satellite overpass timing or cloud cover, which may lead to undercounting of low-temperature or short-duration burning events. Fourth, the study period spans only nine seasons, with one gap year (2017), limiting the statistical power for long-term trend decomposition.

Future Directions:-

Future extensions of this framework should incorporate more advanced meteorological predictors — particularly 850-hPa wind vectors and mixing-layer height — as time-varying effect modifiers in a distributed-lag non-linear model (DLNM) [48]. Integration with HYSPLIT or similar back-trajectory analysis would allow fire-attributable PM_{2.5} contributions to be conditioned on the actual transport-pathway geometry, substantially improving prediction precision. Expanding the framework to Haryana, which contributes a secondary but non-negligible fire signal, would improve model completeness. Finally, coupling the early-warning signal to a nowcasting ML model trained on CPCB rolling-mean PM_{2.5} and FIRMS fire counts could provide probabilistic 3-day forecasts with calibrated uncertainty bounds, supporting more robust public-health decision-making.

Conclusions:-

This study has presented a systematic daily time-series analysis of the relationship between satellite-detected crop-residue burning in Punjab and PM_{2.5} concentrations in Delhi-NCR over nine consecutive harvest seasons (2015–2024).

The principal findings are as follows:-

1. A statistically significant positive association between daily Punjab fire counts and Delhi-NCR PM_{2.5} was established at all lag windows (0–72 hours), with the strongest correlation observed at Lag-0 ($r = 0.289$, $p < 0.001$) which remains highly significant even after controlling for meteorological covariates ($\beta = 0.052$, $p < 0.001$).
2. Harvest-season PM_{2.5} in Delhi-NCR averaged $150.5 \mu\text{g}/\text{m}^3$ across the study period, with 82.1% of days classified as 'Poor' and 10.3% as 'Severe' under the national AQI framework — rates that are 2–5 times higher than non-harvest-season benchmarks.
3. A dose–response gradient was documented between fire intensity and PM_{2.5} outcomes, with high-intensity fire days producing significantly higher median PM_{2.5} values than medium- or low-intensity days (Kruskal–Wallis $H = 18.4$, $p < 0.001$).
4. Annual Punjab fire counts declined by ~75% from the 2021 peak (~22,000 events) to the 2024 minimum (~5,500 events), reflecting the cumulative effect of policy interventions, yet mean harvest-season PM_{2.5} decreased by only ~19% over the same period, indicating important meteorological and local-emission confounding. By integrating meteorological covariates in a multivariable distributed-lag model, we demonstrated that crop stubble burning and atmospheric transport jointly explain 45.3% of the PM_{2.5} variability, confirming that crop burning is one important seasonal contributor whose impact must be evaluated in tandem with atmospheric stagnation and dispersion dynamics.
5. Exponential decay modelling of the lag-correlation structure yielded a signal half-life of ~9.2 days, supporting the design of a conceptual three-tier early-warning framework in which high fire-count days trigger public health alerts within 0–1 days and extended PM_{2.5} episode warnings at Days +3 to +7.

Collectively, these findings suggest that satellite-derived fire counts over Punjab constitute a simple, freely available, and operationally deployable leading indicator of PM_{2.5} in Delhi-NCR. While the correlations documented here are not large in absolute terms — reflecting the important roles of meteorology, local emissions, and secondary aerosol chemistry — they are robust, consistent across a decade of observations, and sufficient to anchor a conceptual early-warning framework that could provide public-health authorities with 24-to-72-hour advance notice

of severe pollution episodes. Pursuing the meteorologically conditioned extensions outlined in Section 6.3 will be essential to translating this framework into a high-confidence operational product.

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