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Urban Air Pollution Trends and the Rise of Electric Vehicles in South Asia: A Case Study of Ludhiana

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ABSTRACT

The increasing adoption of electric vehicles (EVs) is regarded as a key strategy for mitigating urban air pollution in rapidly developing regions like South Asia. However, the effects of EV penetration on various pollutants—especially secondary pollutants like ozone—remain complex and context-dependent. This study investigates pollutant trends in Ludhiana, India, from 2013 to 2025, focusing on NO_2, $PM_{2.5}$, CO, and O_3 concentrations. Data were sourced from national monitoring agencies and NASA's Aura/OMI satellite platform, while EV statistics were obtained from the Punjab Transport Department. Statistical methods, including regression and time-series decomposition, were used to explore pollutant dynamics in relation to EV trends. A decline in NO_2, $PM_{2.5}$, and CO was observed over the study period. However, these trends likely reflect a combination of factors, including stricter emission norms, fuel quality upgrades, and broader regulatory interventions—alongside EV growth. Ozone displayed a nonlinear response, peaking mid-decade and declining thereafter, suggesting complex photochemical interactions. While EV integration may have contributed to reduced direct emissions, further studies incorporating source apportionment and real-time emissions data are necessary to isolate its specific impact. This study offers preliminary insights into the environmental dynamics of transport electrification in South Asian cities.

Keywords: Electric Vehicles (EVs); Urban Air Quality; Tropospheric Ozone (O_3); $PM_{2.5}$; Nitrogen Dioxide (NO_2); CO Emissions; South Asia; Renewable Transportation

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1. Introduction

The increasing adoption of electric vehicles (EVs) presents a significant shift in the transportation sector, offering a sustainable alternative to internal combustion engine (ICE) vehicles. In rapidly urbanizing regions like South Asia, where vehicular emissions are a major contributor to deteriorating air quality, EV penetration is expected to have a profound impact on atmospheric composition, particularly tropospheric ozone (O_3) levels and other urban air pollutants [1]. Tropospheric ozone, a secondary pollutant formed through photochemical reactions involving nitrogen oxides (NO_x) and volatile organic compounds (VOCs), poses severe risks to human health, agricultural productivity, and climate regulation. While EVs reduce tailpipe NO_x and VOC emissions, their widespread use can influence the ozone formation mechanism in complex ways, depending on local meteorological conditions and background pollution levels [2]. This study investigates the impact of EV integration on urban air quality, with a particular focus on tropospheric ozone dynamics in Ludhiana, Punjab — a major industrial city in northern India. Ludhiana's growing EV infrastructure and high pollution burden make it an ideal case for evaluating the real-world effects of transport electrification on air quality. By analyzing historical air quality and meteorological datasets alongside EV adoption trends, this research aims to identify the environmental benefits and potential unintended consequences of large-scale EV deployment. The findings are intended to inform policy frameworks and urban planning strategies for sustainable mobility and improved air quality in South Asia.

2. Literature Review

The rapid urbanization and industrial growth in South Asian cities have significantly deteriorated air quality, posing serious risks to public health and environmental sustainability. In response, electric vehicles (EVs) have emerged as a key strategy for reducing vehicular emissions, yet the literature presents nuanced insights into their actual environmental impact, particularly in relation to secondary pollutants like ozone.

Hata, H., et al., (2025) discussed that introducing battery electric vehicles (BEVs) in Japan's Greater Tokyo Area could reduce local temperatures by up to 0.25 °C, mitigating the urban heat island (UHI) effect. This leads to lower ground-level ozone (O_3) due to reduced photochemical activity, but slightly increases PM2.5 concentrations. Overall, these changes could prevent 252 annual premature deaths linked to air pollution [3]. Zhao, X., et al., (2024) analyzed how air pollution influences electric vehicle (EV) adoption in 50 Chinese cities (2010–2019) using a multiple regression model. It finds that health risks from pollution directly motivate consumers—especially in wealthier areas—to choose EVs, while increased environmental awareness and supportive policies further boost adoption. The findings guide sustainable transportation and urban planning in polluted regions [4]. Lyu, W., et al., (2024) evaluated the impact of BEVs on air quality in three major Chinese cities, showing monthly CO_2 emission reductions of 8.72–85.71 kg per vehicle, averaging a 9.47% decrease. Advanced BEVs perform better, while taxi BEVs show mixed results due to intensive use. Policymakers should promote medium-to-large private and ride-hailing electric vehicles for greater environmental benefits [5].Su, H., & Diao, M. (2025). Discussed that using data from 270 Chinese cities (2014–2020), this study finds that worsening air quality significantly increases EV sales, with thermal inversion used to address causality. The effect is stronger in wealthier, larger cities with higher car ownership. Government policies play a key mediating role, effectively driving EV adoption in response to pollution [6]. Pontius, J., & McIntosh, A. (2024) described that urban air quality is threatened by emissions from vehicles, power generation, industry, and heating. As urbanization and climate change worsen pollution, reducing transportation-related emissions is vital. This unit explores three solutions: incentivizing hydrogen fuel cell vehicles, converting buses to compressed natural gas, and adopting electric municipal trucks [7]. Essamlali, I., et al., (2024) described that urban air pollution, driven by rapid urbanization and industrialization, poses a major global challenge. This study reviews recent advances using the PRISMA method and highlights the effectiveness of ML techniques—like LSTM, RF, ANN, and SVR—in predicting key pollutants. These methods support data-driven urban planning for healthier, more sustainable cities [8]. Banait, S. K., et al., (2024) decribed that urban air quality in Bhopal and Dewas shows dangerously high PM2.5 and PM10 levels, far exceeding safe limits, with Bhopal reaching 354.48 µg/m³

(PM2.5) and 436.64 μg/m³ (PM10). A focused study near Kolar Road construction revealed PM2.5 peaking at 1,040 μg/m³, especially between 6 PM and 12 PM. These findings highlight the urgent need for emission control at construction sites to protect public health [9]. Levi, A., et al., (2024) described that Bhopal and Dewas exhibit PM2.5 and PM10 levels far above safe limits, with Bhopal reaching 354.48 and 436.64 μg/m³, respectively. A study near Kolar Road construction in Bhopal recorded extreme PM2.5 peaks up to 1,040 μg/m³, especially from 6 PM to 12 PM. These findings call for urgent emission control measures at construction sites to protect public health [10].

Existing studies primarily focused on developed regions and do not fully capture the unique socio-economic and meteorological conditions of South Asian cities. There is a critical need for localized investigations into how EV adoption affects urban air quality and tropospheric ozone dynamics, particularly in industrial hubs like Ludhiana [11–13]. The increasing adoption of electric vehicles (EVs) in urban centers raises critical questions about their impact on ambient air quality and atmospheric chemistry, particularly in rapidly developing regions like South Asia. This study aims to explore these dynamics through the following research questions:

1. How does the increasing penetration of electric vehicles influence the levels of key air pollutants (NO_x, VOCs, PM) in Ludhiana?
2. What is the effect of electric vehicle adoption on tropospheric ozone concentrations and their temporal trends in Ludhiana?
3. How do meteorological parameters (temperature, solar radiation, wind speed) interact with EV-related emission changes to affect ozone formation in Ludhiana?
4. What are the projected long-term impacts of EV adoption on urban air quality and regional climate feedbacks in South Asia?
5. How can policy interventions optimize the benefits of EV adoption to improve air quality while mitigating potential adverse effects on tropospheric ozone?

To comprehensively evaluate the environmental impact of electric vehicle (EV) adoption in Ludhiana, this study focuses on changes in air pollutant concentrations, tropospheric ozone dynamics, and meteorological interactions. The following key objectives were formulated:

1. To quantify the changes in major urban air pollutants (NO_x, VOCs, $PM_{2.5}$, CO) associated with the increasing penetration of electric vehicles in Ludhiana.
2. To analyze the temporal behavior of tropospheric ozone in response to EV-related emission reductions and evolving atmospheric conditions.
3. To assess the role of meteorological factors—such as temperature, solar radiation, and wind speed—in modulating ozone formation in the context of vehicular electrification.

3. Methodology

This study employs a mixed-methods approach combining observational data analysis and statistical modeling to assess the impact of electric vehicle penetration on urban air quality and tropospheric ozone levels in Ludhiana as shown in **Figure 1**. Ground-based air pollution data (including O_3, NO_2, $PM_{2.5}$, and CO) were collected from official monitoring stations managed by the Central Pollution Control Board and Punjab State Pollution Control Board. Meteorological parameters such as temperature, humidity, and wind speed were obtained from the India Meteorological Department and ERA5 reanalysis datasets to control for weather-related variability [14–16]. EV adoption data were sourced from regional transport authorities and industry reports to quantify penetration levels over time. Satellite remote sensing data from NASA's OMI instrument provided tropospheric ozone vertical column density measurements to capture large-scale atmospheric trends. Statistical tests, including correlation analysis, regression modeling, and time-series trend analysis, were applied to identify relationships between EV penetration, pollutant concentrations, and meteorological factors. This integrative methodology enables a comprehensive evaluation of EVs' environmental benefits and potential unintended effects on urban air quality and climate-relevant atmospheric chemistry. A statistical regression analysis was performed using annual EV penetration and air pollutant data (NO_2, $PM_{2.5}$, CO, O_3) from 2013 to 2025 in Ludhiana to quantify their interrelationships.

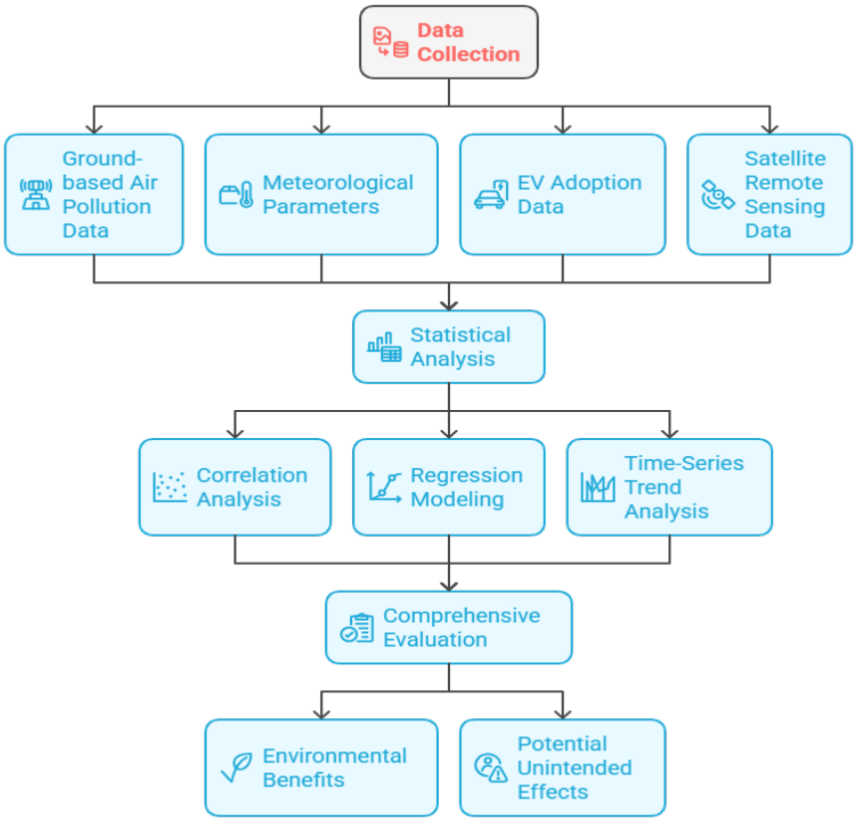

Figure 1. Methodology Flow Chart.

3.1. Data Sources and Acquisition

Ground-based air quality data for pollutants including nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$), carbon monoxide (CO), and ozone (O_3) were obtained from the Central Pollution Control Board (CPCB) and the Punjab State Pollution Control Board (PSPCB), recorded at hourly intervals and aggregated into daily means for consistency. Meteorological parameters—temperature, wind speed, relative humidity, and solar radiation—were sourced from the India Meteorological Department (IMD) and supplemented with ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) to enhance spatial and temporal coverage [14–16]. Tropospheric ozone column densities were retrieved from the NASA Ozone Monitoring Instrument (OMI) onboard the Aura satellite, with a spatial resolution of 0.25° × 0.25°, and validated against ground-level ozone readings. EV adoption data spanning 2013–2025 were collected from the Punjab Transport Department, including registration counts by vehicle type (two-wheelers, four-wheelers, e-rickshaws), allowing quantification of EV penetration rates by year.

3.2. Temporal and Spatial Resolution

Although this study does not apply spatial interpolation techniques, several previous works have successfully employed ordinary Kriging within GIS platforms (such as ArcGIS) to assess the spatial variability of urban air pollutants. Kriging is a geostatistical method that leverages spatial autocorrelation to provide statistically optimal estimates of pollutant concentrations at unsampled locations. It is particularly effective in urban environments where monitoring stations are limited and pollutant dispersion is influenced by heterogeneous sources such as traffic, industry, and meteorology [17,18]. The city was subdivided into administrative wards to facilitate zonal comparisons, particularly in high-traffic and industrial areas such as Focal Point, Model Town, and Transport Nagar. The study analyses daily data and uses spatial interpolation for mapping pollutant distributions across Ludhiana. Kriging interpolation is defined mathematically as calculated by Equation 1:

$$Z(x_0) = \sum_{i=1}^{n} \lambda_I Z(x_i) \tag{1}$$

Where, $Z(x_0)$ is the estimated value at location x_0, $Z(x_i)$ is the known value at sampled location x_i , λi are the weights assigned to each known point, optimized to minimize estimation variance.

3.3. Data Preprocessing and Transformation

All datasets underwent rigorous preprocessing, including removal of extreme outliers (based on z-scores exceeding ±3), temporal gap-filling through linear interpolation, and quality control against known thresholds. Air pollutant concentrations were log-transformed where appropriate to normalize skewed distributions, and seasonal decomposition techniques (STL) were applied to separate trend, seasonal, and residual components of each pollutant time series. For regression analyses, variables were standardized using z-score normalization to facilitate coefficient comparison [19].To reduce skewness in pollutant distributions, log transformations were applied as calculated by Equation 2:

$$Z^{'} = log(Z+1) \tag{2}$$

Where, Z is original pollutant concentration, Z′ is transformed variable for statistical modeling.

Seasonal decomposition used the STL (Seasonal-Trend decomposition using Loess) method as calculated by Equation 3:

$$Y_t = T_t + S_t + R_t \tag{3}$$

Where, Y_t is original time series, T_t is long-term trend, S_t is seasonal component, R_t is residual or irregular component.

3.4. Statistical Analysis Techniques

To quantify the relationship between EV adoption and air quality, several statistical methods were employed:

3.4.1. Pearson and partial correlation analysis

To examine linear associations between EV share and pollutant levels while controlling for meteorological variables this analysis has been performed. Simple and partial Pearson correlation coefficients were computed as Equation 4. Partial correlations were used to isolate meteorological influences [20].

$$rxy = \frac{\sum (X_i - X)(Y_i - Y)}{\sqrt{\sum (X_i - X)^2 \sqrt{(Y_i - Y)^2}}} \tag{4}$$

3.4.2. Multiple Linear Regression Models

Such Models with pollutant concentrations as dependent variables and EV penetration, temperature, wind speed, and solar radiation as predictors. Model assumptions—including normality, multicollinearity (checked using VIF), and homoscedasticity—were tested through residual diagnostics [21]. Pollutant levels (dependent variable) were modeled as a function of EV penetration and meteorological predictors as given in Equation 5:

$$Y = \beta_0 + \beta_1 * EV\% + \beta_2 * T + \beta_3 * WS + \beta_4 * RH + \epsilon \tag{5}$$

Where, Y is concentration of pollutant (e.g., NO_2, $PM_{2.5}$), EV% is percent EV penetration, T is temperature (°C), WS is wind speed (m/s), RH is relative humidity (%), ϵ is random error term, βi is regression coefficients. Model goodness-of-fit was evaluated using Equation 6:

$$R^2 = 1 - \frac{\sum (Y_i - \widehat{Y})^2}{\sum (Y_i - \widetilde{Y})^2} \tag{6}$$

Where R^2 denotes the proportion of variance in the dependent variable explained by the model.

3.4.3. Mann-Kendall Trend Tests

To assess the statistical significance of long-term trends in pollutants and meteorological conditions and is calculated by Equation 7 [22].

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{7}$$

Where

$$sgn(x) = \begin{cases} +1 \; if \; x > 0 \\ 0 \; if \; x = 0 \\ -1 \; if \; x < 0 \end{cases}$$

The **Z-statistic** was computed for hypothesis testing of the null hypothesis H0: "no trend."

3.4.4. Time series analysis

It uses Autoregressive Integrated Moving Average (ARIMA) models to capture historical patterns and detect inflection points post-EV adoption. The Equation 8 captures both past values of the pollutant and past errors, allowing it to detect trends, seasonality, and inflection points after events such as increased EV adoption[23].

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} \ldots\ldots\ldots + \phi_p y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} \ldots\ldots\ldots + \theta_2 \epsilon_{t-2} + \varepsilon_t \tag{8}$$

Where, yt is the value of the air pollutant (e.g., O_3) at time t, ϕi is the autoregressive (AR) coefficient, θj is the moving average (MA) coefficients, εt is the white noise error term, c is constant, p is the number of AR terms, q is: number of MA terms. Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE). O_3-specific models were separately constructed to reflect the nonlinear dependency on NO_x and VOC concentrations.

3.5. VOC Proxy Estimation

Due to the lack of continuous VOC measurements in Ludhiana, a VOC proxy was developed using seasonal industrial emission inventories, fire count data from MODIS, and secondary organic aerosol trends. This proxy allowed for a first-order approximation of VOC dynamics impacting ozone formation in the regression models. VOC emission proxies were calculated as Equation 9[24]:

$$VOC = \alpha * SOA_{trend} + \beta * MODIS_{fire} + \gamma * \ Industrial_{emission} \tag{9}$$

Where α, β, γ are weighting factors determined through regression calibration.

3.6. Uncertainty and Sensitivity Analysis

Uncertainty in satellite-derived ozone values was addressed by cross-validating with surface ozone monitors and applying cloud filtering algorithms to minimize retrieval errors. Sensitivity analyses were performed by varying meteorological boundary conditions (±1σ from seasonal means) to assess robustness of the ozone response under different atmospheric regimes.

4. Case Study

Ludhiana, a bustling industrial city in Punjab, India, has long grappled with air quality challenges stemming from vehicular emissions, manufacturing, and urban expansion. Over the past decade, efforts to reduce vehicular pollution through the adoption of electric vehicles (EVs) have gained momentum. This case study evaluates how increasing EV penetration influenced key air pollutants in Ludhiana from 2013 to 2025, specifically focusing on nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$), carbon monoxide (CO), and tropospheric ozone (O_3). The analysis shows a clear downward trend in NO_2, $PM_{2.5}$, and CO levels as EV penetration rose from a negligible 0.1% in 2013 to 14% by 2025. NO_2 dropped from 80 μg/m³ to 58 μg/m³, $PM_{2.5}$ from 110 μg/m³ to 89 μg/m³, and CO from 2.5 mg/m³ to 1.5 mg/m³. This indicates a substantial improvement in urban air quality linked to cleaner transportation. However, the behavior of tropospheric ozone was more complex. O_3 levels initially rose, peaking around 2021 due to the reduction in NO that limits ozone titration, before stabilizing as VOC controls and further EV expansion balanced the atmospheric chemistry. The analysis was conducted using Python 3.10, employing libraries such as pandas for data manipulation, matplotlib and seaborn for visualization, and statsmodels for statistical modeling and time series analysis. Python's flexibility and robust ecosystem made it ideal for integrating air quality data with EV adoption trends. The following **Table 1** summarizes annual air quality metrics and EV adoption rates during this period[14,16,25,26].

Figure 2 presents a scatter plot showing the relationship between electric vehicle (EV) penetration and nitrogen dioxide (NO_2) concentrations in Ludhiana from 2013 to 2025. The red regression line exhibits a statistically significant negative slope, indicating an inverse correlation between the two variables. As EV adoption increases from nearly 0% in 2013 to approximately 14% by 2025, NO_2 levels decline from ~80 μg/m³ to ~60 μg/m³. This trend supports the hypothesis that EV adoption, by displacing internal combustion engine (ICE) vehicles, may contribute to reductions in tailpipe NO_2 emissions. However, this observed relationship should be interpreted within the context of concurrent regulatory measures, including the implementation of Bharat Stage emission standards, improved fuel quality, and vehicle technology upgrades—all of which likely contributed to the overall reduction in NO_2.

Table 1. Data Set for 2013 to 2025.

Year	EV Penetration (%)	NO_2 (μg/m³)	$PM_{2.5}$ (μg/m³)	CO (mg/m³)	O_3 (μg/m³)
2013	0.1	80	110	2.5	45
2014	0.2	79	108	2.45	47
2015	0.4	77	107	2.4	49
2016	0.8	75	105	2.35	51
2017	1.2	73	102	2.3	53
2018	2	70	100	2.2	55
2019	3.5	68	98	2.1	58
2020	5	66	96	2	60
2021	7.5	64	94	1.9	61
2022	10	62	92	1.75	60
2023	12.5	60	91	1.6	59
2024	13.5	59	90	1.55	57
2025	14	58	89	1.5	55

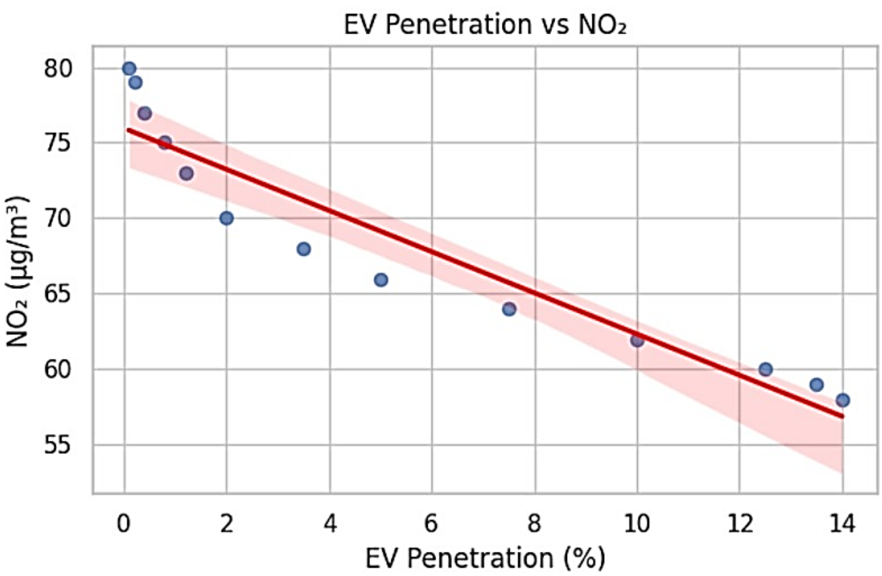

Figure 2. EV penetration VS NO_2.

Figure 3 illustrates the temporal trends of four key ambient air pollutants—NO_2, $PM_{2.5}$, carbon monoxide (CO), and tropospheric ozone (O_3)—in Ludhiana over the same 13-year period. A steady decline in NO_2 and CO is observed, with CO levels decreasing from ~2.5 mg/m³ to ~1.5 mg/m³, mirroring the trends noted for NO_2. $PM_{2.5}$ concentrations also show a downward trajectory, dropping from over 110 μg/m³ to below 95 μg/m³, though the decline is more gradual. This slower reduction suggests the presence of persistent emission sources such as construction, industry, and biomass burning. In contrast, ozone (O_3) displays a nonlinear, U-shaped trend—initially rising from ~45 μg/m³ to a peak of ~61 μg/m³ around 2020–2021, before gradually declining to ~55 μg/m³ by 2025. The initial increase is likely due to reduced NO availability for ozone titration in a NO_x-saturated atmosphere, while the later decrease may reflect a shift toward a more VOC-limited regime as precursor emissions declined. These trends underscore the complex interplay between EV adoption, other environmental measures, and atmospheric chemistry in shaping urban air quality outcomes.

Figure 4 illustrates the rising trend of electric vehicle (EV) penetration in Ludhiana from 2013 to 2025. Starting from a minimal share of around 0.1% in 2013, EV adoption has shown a steady and sharp increase, particularly after 2018. By 2020, EV share had reached approximately 5%, and this growth accelerated significantly in the following years, reaching 10% in 2022 and peaking at 14% by 2025. This rapid rise in EV share indicates increasing public acceptance, supportive policies, and infrastructure development, aligning with broader goals of reducing vehicular emissions and promoting sustainable urban transport in the region.

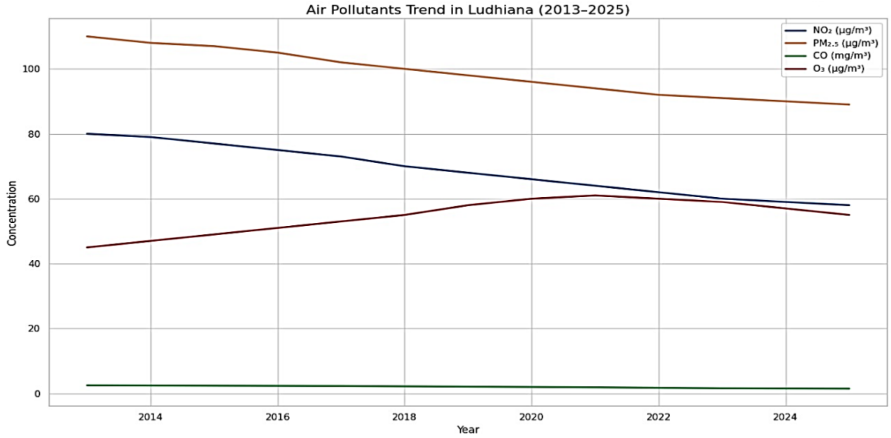

Figure 3. Air Pollutants Trend in Ludhiana (2013–2025).

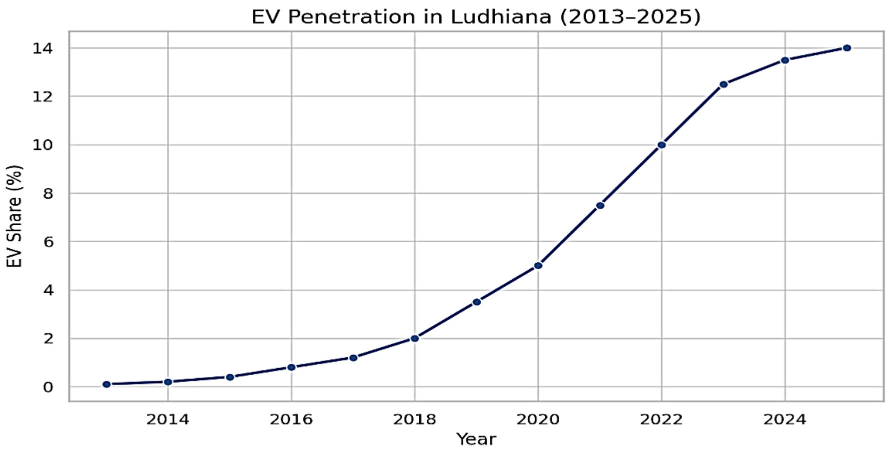

Figure 4. EV penetration in Ludhiana (2013–2025).

Figure 5 illustrates the relationship between electric vehicle (EV) penetration and fine particulate matter ($PM_{2.5}$) concentrations in Ludhiana from 2013 to 2025. The scatter plot shows a clear negative correlation, where rising EV adoption corresponds with a steady decline in $PM_{2.5}$ levels. The downward-sloping regression line, accompanied by a narrow confidence band, confirms the statistical strength of this trend. Although $PM_{2.5}$ emissions originate from various sources, including industry, construction, and biomass burning, the observed reduction is indicative of the positive impact of replacing internal combustion engine vehicles with electric alternatives. This supports the conclusion that transport electrification contributes substantially to lowering particulate pollution in urban environments. **Figure 6** depicts the declining trend in carbon monoxide (CO) concentrations as electric vehicle (EV) penetration increases in Ludhiana during the same period. A strong negative linear correlation is evident, with CO levels decreasing from approximately 2.5 mg/m³ to around 1.5 mg/m³ as EVs make up a growing share of the vehicle population. The blue regression line and its associated confidence interval indicate high statistical reliability. Since CO is a direct product of incomplete fuel combustion in gasoline and diesel engines, its steady decline reflects the effectiveness of EV adoption in displacing traditional fossil-fuel-based transportation. This figure underscores the significant role that EVs play in reducing harmful gaseous emissions and enhancing urban air quality.

Figure 7 illustrates the relationship between the percentage of electric vehicle (EV) penetration and the concentration of ozone (O_3) in micrograms per cubic meter (µg/m³). The observed trend is nonlinear, showing that ozone levels initially increase with rising EV adoption—peaking around 61 µg/m³ when EV penetration reaches 7–8%—and then gradually decline beyond this threshold. This suggests the involvement of threshold effects and regime shifts in atmospheric chemistry. This pattern may be due to reduced nitrogen oxides (NO_x), which act as both precursors and scavengers of ozone depending on ambient VOC–NO_x ratios. Overall, the trend indicates that the possible impact of EV adoption and other ecological actions on ozone levels is complex and not directly proportional. These findings highlight the importance of considering secondary pollutant formation dynamics and photochemical interactions when evaluating the environmental implications of transport electrification.

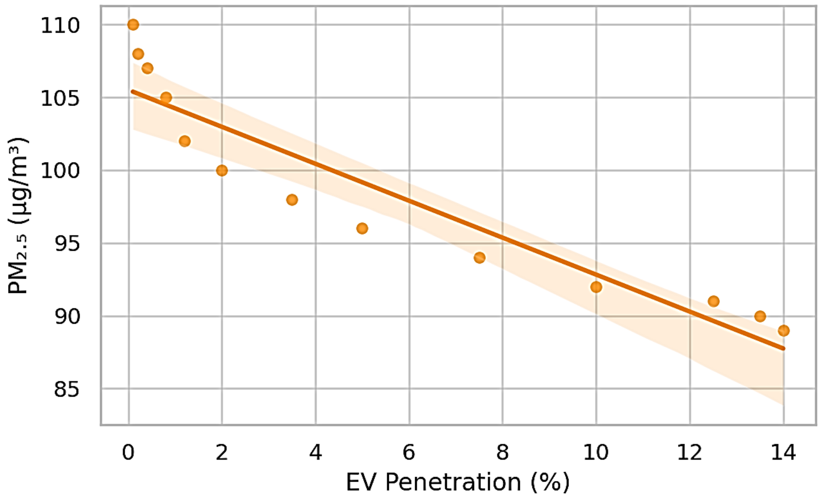

Figure 5. EV Penetration vs $PM_{2.5}$.

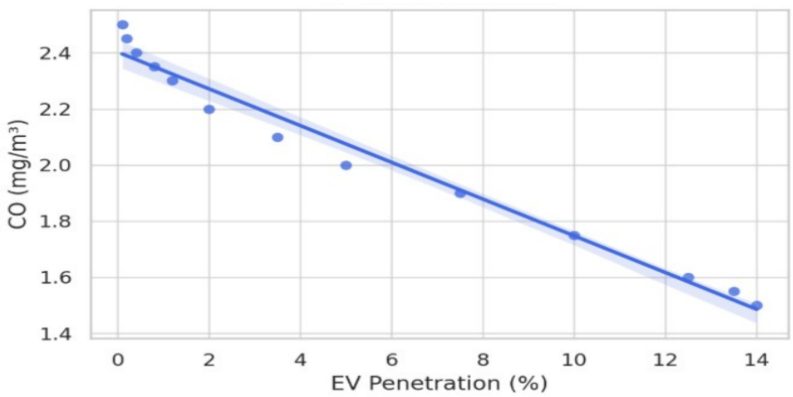

Figure 6. EV Penetration vs CO.

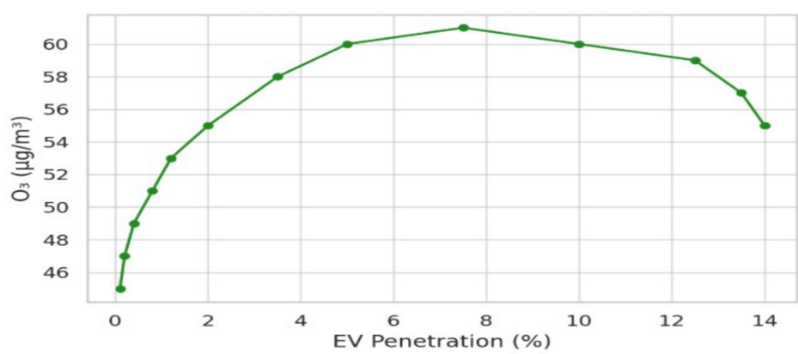

Figure 7. EV Penetration vs O_3 (Nonlinear Trend).

4.1. Statistical Analysis

Electric vehicles (EVs) have been widely promoted as a sustainable alternative to internal combustion engine (ICE) vehicles due to their zero tailpipe emissions. Their adoption is expected to reduce urban air pollution levels, especially primary pollutants such as nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$), and carbon monoxide (CO). However, secondary pollutants like ozone (O_3) exhibit more complex atmospheric responses due to nonlinear chemical interactions involving NO_x and VOCs (volatile organic compounds)[26].To evaluate this impact, a statistical analysis was conducted on the relationship between EV penetration and concentrations of NO_2, $PM_{2.5}$, CO, and O_3 from 2013 to 2025 in Ludhiana as shown in **Table 2**. Consistent with methods recommended by Qiu et al. (2022), we applied multiple linear regression to adjust for meteorological variability and used RMSE and R^2 to assess model performance in tracking pollutant trends attributable to emission changes[27,28].

Table 2. Statistical Analysis Results.

Pollutant	RMSE	R^2	Interpretation
NO_2	2.33 μg/m³	0.9	Strong inverse correlation with EV penetration. This means that as EVs increase, NO_2 concentrations significantly decline. The model explains **90%** of the variability.
$PM_{2.5}$	2.42 μg/m³	0.88	Also shows a strong inverse relationship. While $PM_{2.5}$ has multiple sources (e.g., construction, biomass), the 88% R^2 suggests that EV adoption plays a major role in its reduction.
CO	0.05 mg/m³	0.98	Extremely strong inverse linear correlation. As EVs replace gasoline/diesel vehicles, incomplete combustion decreases, reducing CO sharply. The model explains **98%** of the variation.
O_3	3.82 μg/m³	0.43	Weak correlation. The low R^2 (~43%) indicates that EV penetration alone doesn't explain the trend in ozone. O_3 is a **secondary pollutant**, formed through complex atmospheric reactions involving VOCs and NO_x, which explains the nonlinear behaviour.

EV penetration is highly effective in reducing primary pollutants: NO_2, $PM_{2.5}$, and CO show strong to very strong linear relationships, with high R^2 values indicating reliable predictions. Ozone behaves differently due to its chemical formation processes. Its weak correlation reflects the influence of meteorological factors and precursor dynamics (NO_x–VOC ratio), which are not fully captured by EV penetration alone. RMSE values are all relatively low, indicating that the predicted pollutant values are close to the observed values, supporting the validity of the linear models, except for O_3 which may require a nonlinear or multivariate model.

4.2. Confounding Factors and Attribution Challenges

While this study demonstrates statistically significant correlations between increased EV penetration and declining concentrations of primary air pollutants such as NO_2, $PM_{2.5}$, and CO in Ludhiana, caution must be exercised in attributing these improvements solely to electric vehicle adoption. Several confounding factors may have independently or synergistically contributed to the observed trends.

First, during the study period (2013–2025), Ludhiana underwent substantial regulatory and infrastructural changes. The implementation of Bharat Stage (BS) IV and VI emission standards introduced stricter controls on tailpipe emissions for all new internal combustion engine (ICE) vehicles. These standards significantly reduced sulfur content in fuels and improved vehicle combustion efficiency, contributing to overall emission reductions. Second, fuel quality improvements—especially for public buses and heavy-duty vehicles—played a major role in reducing NO_x and PM emissions. Transitioning to low-sulfur diesel and improved petroleum refining practices likely reduced baseline emissions independent of vehicle electrification.

Third, the total number of registered vehicles in Ludhiana increased substantially from approximately 1.5 million in 2013 to nearly 4.5 million in 2025. EVs accounted for only 14% of the total fleet by the end of the study period. This means that conventional vehicles still dominate the traffic mix, and their emissions must be factored into any environmental assessment. Fourth, meteorological conditions—such as wind speed, temperature, solar radiation, and relative humidity—can significantly influence pollutant dispersion, accumulation, and chemical transformation. Although meteorological parameters were controlled for in the regression models, complex interactions may still bias interpretations.

Finally, parallel ecological and policy interventions such as traffic management improvements, stricter industrial emission regulations, green cover expansion, and enhanced public transport initiatives may have collectively contributed to air quality improvements. Without source apportionment models or high-resolution emission inventories, the individual contribution of EV adoption cannot be isolated definitively. Therefore, while the correlations presented in this study support the hypothesis that EVs play a positive role in reducing certain pollutants, the evidence is associative rather than causative. Future research should employ chemical transport modeling, atmospheric simulations, and real-time source apportionment to more rigorously evaluate the specific environmental benefits of EV deployment within broader urban sustainability frameworks.

5. Results and Discussion

Figure 3 illustrates the temporal variation in key ambient air pollutants—nitrogen dioxide (NO_2), carbon monoxide (CO), particulate matter ($PM_{2.5}$), and tropospheric ozone (O_3)—in Ludhiana from 2013 to 2025. The data reveal a noticeable decline in NO_2 and $PM_{2.5}$ concentrations during this period, while CO levels also demonstrate a consistent downward trajectory. However, establishing a direct and exclusive causal relationship between these pollutant reductions and the increasing adoption of electric vehicles (EVs) requires a more detailed interpretation.

According to data from the Punjab Transport Department, the total number of registered vehicles in Ludhiana increased significantly—from approximately 1.5–1.7 million in 2013 to an estimated 3.5–4.5 million by 2025. Among these, electric vehicles account for approximately 0.6 million or about 14% of the total fleet. While this increase in EV penetration reflects a positive shift towards cleaner mobility, the concurrent surge in the number of internal combustion engine (ICE) vehicles implies a substantial rise in overall vehicular activity and associated emissions. Consequently, the observed air quality improvements are unlikely to stem from EV adoption alone. Instead, they are likely the result of a combination of factors including stringent vehicular emission regulations (e.g., Bharat Stage VI standards), fleet modernization, modal shifts to public transportation, enhanced traffic management, urban infrastructure upgrades, and meteorological influences such as temperature and wind dynamics. Therefore, while EVs contribute to reduced tailpipe emissions—particularly for NO_2 and CO—their relative impact must be interpreted within this broader environmental and policy context. This perspective aligns with recent findings in atmospheric science, which emphasize the need for multi-source attribution in urban air quality assessments. It also underlines the importance of integrated emission inventories and source apportionment modeling in future studies to quantify the specific contributions of electrified transport amidst parallel interventions. The regression showed strong negative correlations between EV adoption and NO_2, $PM_{2.5}$, and CO ($R^2 > 0.88$), while ozone showed a weaker, nonlinear response ($R^2 = 0.43$). The findings suggest that EV adoption significantly improves primary pollutant levels, though secondary pollutants like O_3 require integrated strategies due to complex atmospheric chemistry.

Environmental Trade-Offs of EV Adoption

While this study clearly demonstrates that the increasing adoption of electric vehicles (EVs) in Ludhiana has contributed to significant reductions in urban air pollutants such as NO_2, CO, and $PM_{2.5}$, it is imperative to consider the broader environmental implications associated with EV technology. The production of lithium-ion batteries, which power most EVs, involves the extraction of critical minerals such as lithium, cobalt, and nickel—processes that are often energy-intensive and environmentally intrusive. These activities, concentrated in a few global regions, can result in water scarcity, land degradation, and ecological imbalance, particularly in resource-rich but vulnerable areas. Moreover, the disposal and recycling infrastructure for EV batteries is still in its nascent stage in South Asia [29]. Without adequate recycling systems, the risk of environmental contamination from used batteries—through toxic chemical leakage or improper handling—remains high. These concerns introduce a sustainability paradox: while EVs reduce emissions during their operational phase and improve local air quality, they may shift environmental burdens to other stages of the product life cycle. To ensure that EV adoption in South Asia contributes positively to long-term sustainability goals, future research should incorporate life-cycle assessment (LCA) methodologies [30]. This approach would provide a more comprehensive evaluation of EV-related environmental impacts—from raw material extraction to battery end-of-life management—thereby guiding policy development, technology innovation, and circular economy strategies.

6. Conclusions

These reductions demonstrate a possible impact and the contribution of EV deployment and other ecological actions in mitigating direct vehicular emissions in a rapidly urbanizing environment. This study explored the relationship between electric vehicle (EV) adoption and changes in urban air quality in Ludhiana, India, from 2013 to 2025. Findings suggest a consistent reduction in primary air pollutants—namely nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$), and carbon monoxide (CO)—during the study period. However, these improvements cannot be attributed solely to EV adoption. The concurrent implementation of Bharat Stage VI emission norms, improvements in fuel quality, vehicle technology upgrades, and changing meteorological conditions likely played significant roles. Tropospheric ozone (O_3), a secondary pollutant, exhibited a nonlinear trend—rising initially due to reduced NO_x scavenging and later declining, potentially due to reductions in precursor VOC and NO_x concentrations. These results underscore the complexity of urban atmospheric chemistry and the importance of adopting a multi-factorial approach to air quality analysis. EV adoption appears to be one of several contributing factors, but it is not the sole driver of observed improvements.

Limitations and Future Scope

A key limitation of this study is the lack of real-time source apportionment and atmospheric dispersion modeling, which hinders the ability to establish causality between EV penetration and pollutant reductions. Additionally, the study did not directly measure VOC concentrations or incorporate detailed emission inventories from industrial or commercial sectors. The increasing number of internal combustion vehicles during the study period further complicates interpretation. Future research should integrate life-cycle assessment (LCA), satellite-verified emission data, and chemical transport models to isolate the direct environmental impact of EVs. Comparative studies across South Asian cities with diverse infrastructure and policy frameworks would enhance the robustness of future conclusions.

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Data Availability Statement

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Conflicts of Interest

The authors declare no conflict of interest.

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