Article

Not peer-reviewed version

Post-Pandemic Stability and Variability of Urban Air Pollutants in Mexico City: A Multi-Pollutant Temporal Analysis for Environmental Sustainability

Eva Selene Hernández-Gress *, David Conchouso González, Cristopher Antonio Muñoz-Ibañez

Posted Date: 27 February 2026

doi: 10.20944/preprints202602.1196.v1

Keywords: urban air quality; post-pandemic period; Mann–Kendall test; non-parametric trend analysis; Mexico city; ozone; particulate matter; environmental sustainability

Article

Post-Pandemic Stability and Variability of Urban Air Pollutants in Mexico City: A Multi-Pollutant Temporal Analysis for Environmental Sustainability

Eva Selene Hernández-Gress *, David Conchouso González and Cristopher Antonio Muñoz-Ibañez

Tecnologico de Monterrey, Engineering and Sciences School, Pachuca 42080, Hidalgo, Mexico
* Correspondence: evahgress@tec.mx

Abstract

Urban air quality is a key component of environmental sustainability and public health in large metropolitan areas. Following the substantial but temporary improvements in air quality observed during the COVID-19 lockdowns, it remains unclear whether structural changes in urban air pollution have persisted in the post-pandemic period. This study analyzes the temporal dynamics of major atmospheric pollutants in Mexico City between 2021 and 2024, including CO, NO_2, NO_x, O_3, PM_{10}, $PM_{2.5}$, and SO_2, using hourly data collected by the official air quality monitoring network SIMAT. Annual and monthly median concentrations were computed to reduce the influence of extreme values and short term pollution episodes. Station level monotonic trends were evaluated using the non-parametric Mann–Kendall test, complemented by Sen's slope estimator to quantify the magnitude and direction of change. Absolute and relative changes between 2021 and 2024 were also analyzed to capture incremental variations not reflected by trend significance tests, together with hourly monthly analyses to characterize diurnal and seasonal patterns. Results indicate that no statistically significant monotonic trends were detected for any pollutant across the analyzed stations ($p > 0.05$), suggesting an overall stabilization of air quality levels during the post-pandemic period. Nevertheless, moderate increases in annual median concentrations were observed at specific locations, particularly for PM_{10}, $PM_{2.5}$, NO_2, and NO_x, with relative changes ranging from approximately 5% to 35%. Persistent diurnal and seasonal patterns were identified, closely associated with traffic activity, photochemical processes, and meteorological conditions. These findings suggest that, although no robust long-term trends are evident, incremental increases and stable temporal structures remain relevant from a sustainability perspective. Continued monitoring and targeted air quality management strategies are therefore necessary to support long-term urban environmental sustainability.

Keywords: urban air quality; post-pandemic period; Mann–Kendall test; non-parametric trend analysis; Mexico city; ozone; particulate matter; environmental sustainability

---

1. Introduction

1.1. Global Relevance of Urban Air Quality

Air quality remains a central challenge for urban sustainability, particularly in large metropolitan areas experiencing sustained population growth, increasing traffic congestion, and intensified industrial activity. In megacities such as Mexico City, these dynamics exacerbate atmospheric emissions and pose significant challenges for public health and environmental governance. Monitoring and analyzing air quality is therefore a critical component not only for informing public policy but also for raising societal awareness and supporting preventive health strategies.

 doi:10.20944/preprints202602.1196.v1

From a development perspective, urban air pollution has often been discussed within the framework of the environmental Kuznets curve, whereby pollution levels initially increase during early stages of economic development and are expected to decline as income rises and cleaner technologies are adopted [1]. However, empirical evidence suggests that this transition is neither automatic nor guaranteed, particularly in rapidly growing urban regions. Assessing whether air quality trends exhibit sustained temporal improvements is thus essential for advancing cleaner and more resilient cities.

The public health implications of air pollution are well documented. Prolonged exposure to particulate matter and gaseous pollutants has been associated with systemic inflammatory responses, respiratory diseases, childhood asthma, lung cancer, and cardiovascular conditions [2]. Moreover, air pollution has been linked to premature mortality from cardio-respiratory illnesses [3], among numerous other adverse health outcomes [4].

In the Latin American context, the ESCALA multicity study highlighted alarming associations between air pollution and mortality. In Mexico City, PM_{10} concentrations were significantly associated with increased mortality from cardiopulmonary, respiratory, cardiovascular, cerebrovascular, and chronic obstructive pulmonary diseases, while ambient ozone (O_3) was also linked to all cause mortality, albeit with smaller effect sizes compared to particulate matter [5].

Consistent with this evidence, the World Health Organization [6] has emphasized that ambient air pollution causes millions of premature deaths annually and leads to substantial losses in healthy life years. Generating integrated, longitudinal, and well analyzed air quality information is therefore essential for supporting environmental education strategies, improving public health outcomes, and advancing sustainable urban development [2]. In this regard, air quality management directly contributes to the United Nations Sustainable Development Goals, particularly Goal 3 (Good Health and Well-Being) and Goal 11 (Sustainable Cities and Communities) [7].

1.2. COVID-19 Lockdowns and the Post-Pandemic Rebound

The COVID-19 pandemic introduced an unprecedented natural experiment for urban air quality. During periods of strict lockdown, numerous studies reported temporary reductions in atmospheric pollution, largely driven by declines in vehicular traffic and industrial activity. In particular, significant decreases in nitrogen dioxide (NO_2) were observed across many urban regions [8,9].

However, evidence regarding the persistence of these improvements remains inconclusive. Pollutants less directly linked to mobility, such as $PM_{2.5}$, often showed limited or delayed responses to lockdown measures [10, 8, 11). In the Mexican context, reductions in air pollutant concentrations during COVID-19 were lower than initially expected, suggesting structural sources of pollution beyond short-term mobility changes [12].

Additionally, secondary pollutants such as ozone (O_3) exhibited complex and sometimes counterintuitive behavior. While primary pollutants like SO_2 and NO_2 declined in many regions, O_3 concentrations remained stable or even increased in certain cities due to altered photochemical regimes [10,13]. Importantly, most studies agree that these air quality improvements were largely transient, with pollutant levels rebounding during the post-lockdown period [11].

1.3. Knowledge Gap and Research Motivation

Despite the growing body of literature on air quality during the COVID-19 pandemic, several limitations persist. Most existing studies are short-term, focus on a single pollutant, or concentrate exclusively on the year 2020. Comprehensive post-pandemic assessments that simultaneously examine multiple pollutants over extended periods remain scarce, particularly in Latin American megacities.

Mexico City, one of the largest metropolitan areas worldwide, represents a critical yet underexplored case in this regard. There is limited empirical evidence evaluating how air pollutant dynamics evolved during the post-pandemic period using recent data, station-level resolution, and

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2026 doi:10.20944/preprints202602.1196.v1

robust statistical approaches. Addressing this gap is essential for distinguishing between temporary disruptions and structural changes in urban air quality.

To respond to this need, the present study conducts a multi-pollutant analysis using hourly data from 2021 to 2024 obtained from the Mexico City Atmospheric Monitoring System (SIMAT), operated by the Secretariat of the Environment of Mexico City [14]. By applying robust non-parametric methods, this research examines post-pandemic air quality dynamics and compares the behavior of primary and secondary pollutants, generating evidence relevant for urban sustainability and policy design.

1.4. Objective and Contributions

The objective of this study is to analyze the post-pandemic temporal dynamics of major atmospheric pollutants in Mexico City during the period 2021–2024. The main contributions of this work are fourfold: (i) it provides a recent multi year, multi pollutant assessment of air quality in a Latin American megacity; (ii) it applies robust non-parametric trend analysis methods suitable for non normal and heteroscedastic environmental data; (iii) it compares the temporal behavior of primary and secondary pollutants at the station level; and (iv) it offers empirical evidence to support urban sustainability strategies and air quality governance in the post pandemic context.

2. Materials and Methods

2.1. Global Studies on Temporal Air Pollution Dynamics in Large Cities

A substantial body of literature has examined temporal trends, interannual variability, and seasonal patterns of air pollutants in large urban areas worldwide. These studies consistently highlight the role of traffic intensity, urban growth, meteorological conditions, and regional characteristics in shaping air quality dynamics. In Asian megacities, particulate matter and nitrogen-based pollutants have been widely analyzed using both ground-based monitoring and modeling approaches. For instance, [15] investigated $PM_{2.5}$ concentrations along heavily trafficked routes in Seoul, South Korea, employing the RLINE dispersion model and finding strong agreement with national monitoring networks. Long-term analyses in Iran and China further revealed pronounced diurnal and seasonal patterns in PM_{10} concentrations, often linked to dust events, temperature, and humidity [16,17].

Multi-city and multi-pollutant studies have expanded this perspective by incorporating broader spatial scales and more diverse analytical techniques. Research conducted in several Indian megacities demonstrated strong associations between particulate matter, gaseous pollutants, and climatic factors, identifying consistent seasonal trends using correlation analysis and non-parametric methods such as the Mann–Kendall test [18] . Similarly, large-scale assessments across hundreds or thousands of Chinese cities combined satellite observations, statistical modeling, and machine learning approaches to analyze tropospheric NO_2 columns and air pollution islands, highlighting the influence of urban form, vegetation cover, and socioeconomic drivers [19,20]. These global studies demonstrate the value of long-term, multi-year analyses for understanding air pollution dynamics and supporting policy design. However, many remain focused on specific pollutants, limited geographic regions, or single methodological perspectives, constraining their applicability to post-disruption urban contexts.

2.2. Methodological Approaches and Temporal Scales

Methodologically, air quality trend studies exhibit considerable heterogeneity in terms of spatial resolution, temporal coverage, and analytical depth. Some investigations rely on station-level monitoring data to characterize pollutant behavior over extended periods, applying time series models such as ARIMA or non-parametric trend detection techniques [16,21]. Others integrate satellite derived observations with meteorological variables and machine learning algorithms, enabling broader spatial coverage and the assessment of urban scale drivers [19,22]. Despite these advances, several limitations persist. A significant proportion of studies focus on short term periods or specific interventions, such as traffic restrictions or emission control policies, while fewer examine multi-year post-intervention dynamics. Moreover, although multi pollutant analyses are increasingly common, they are often limited to two or three contaminants, reducing their ability to capture interactions between primary and secondary pollutants across different temporal scales.

2.3. Evidence from Mexico and Latin America

In Mexico and other Latin American countries, air quality research has primarily emphasized short term analyses, often motivated by specific emission sources, festive events, or the COVID-19 lockdown period. Several studies document variations in $PM_{2.5}$, PM_{10}, and NO_2 concentrations in response to localized factors such as industrial activity, traffic intensity, or seasonal events. For example, [23] characterized particulate matter levels in Atoyac, Mexico, linking seasonal variability to sugarcane industry activity and associated health impacts. [24] analyzed short-term increases in $PM_{2.5}$ concentrations during Christmas and New Year celebrations in Querétaro using low-cost sensors, while [25] reported reductions in NO_2 and $PM_{2.5}$ associated with compliance with traffic speed limits. Recent methodological contributions have incorporated satellite observations and machine learning techniques to estimate pollutant concentrations in urban environments. [22], for instance, developed a random forest model combining Sentinel satellite data, meteorological variables, and ground-based observations to estimate NO_2 concentrations in Mexico City. However, these studies generally focus on single pollutants or limited temporal windows, with few addressing post-2021 dynamics in a comprehensive, multi-pollutant framework.

2.4. COVID-19 Studies and Transition to the Post-Pandemic Period

The COVID-19 pandemic provided a natural experiment to assess the sensitivity of urban air quality to abrupt changes in mobility and economic activity. Studies conducted in Mexico and other Latin American megacities consistently reported short term reductions in traffic-related pollutants such as NO_2, CO, and PM_{10} during lockdown periods, while secondary pollutants exhibited more heterogeneous responses [26,27]. In some cases, $PM_{2.5}$ concentrations remained stable despite mobility restrictions, underscoring the contribution of non-traffic emission sources. Importantly, existing evidence suggests that these improvements were largely temporary, with pollutant levels rebounding during the post-lockdown phase. Nevertheless, most COVID-related studies focus on the year 2020 or early 2021, leaving a critical gap in understanding how air quality has evolved during the subsequent recovery period. Comprehensive post-pandemic assessments covering multiple pollutants, extended time horizons, and station-level data in Latin American megacities remain limited.

Systematic reviews further support the notion that COVID-19 lockdowns led to widespread but temporary improvements in air quality. A recent PRISMA, based systematic review synthesizing evidence from multiple regions worldwide reported significant reductions in most ambient air pollutants, including $PM_{2.5}$, PM_{10}, NO_2, SO_2, CO, during lockdown periods, primarily attributed to reduced industrial activity and road traffic. However, the review also highlighted controversial and region-specific responses of ozone (O_3), with increases frequently observed, particularly in East Asia, largely driven by meteorological and photochemical factors. Importantly, these findings reinforce the view that air quality improvements during the pandemic were largely transitory and do not necessarily indicate long term structural changes [28]. A summary of selected studies in presented in Table A1 in the Appendix.

3. Materials and Methods

3.1. Study Area and Data Source

This study focuses on Mexico City, one of the largest metropolitan areas in Latin America and a region facing persistent air quality challenges. Hourly concentrations of major atmospheric

 doi:10.20944/preprints202602.1196.v1

pollutants—carbon monoxide (CO), nitrogen dioxide (NO_2), nitrogen oxides (NO_x), ozone (O_3), particulate matter (PM_{10} and $PM_{2.5}$), and sulfur dioxide (SO_2)—were obtained for the period from January 2021 to December 2024 from the Mexico City Atmospheric Monitoring System (SIMAT), operated by the Secretariat of the Environment of Mexico City [14].

The SIMAT network provides continuous measurements through 34 fixed monitoring stations distributed across the metropolitan area and constitutes the official reference system for air quality surveillance in the city. Of these, 21 monitoring stations met the data availability criteria and were consistently operational throughout the 2021–2024 period. The nomenclature and geographic characteristics of the monitoring stations are provided in Appendix A (Table A2).

3.2. Data Preprocessing and Quality Control

Prior to analysis, the hourly database was cleaned to ensure internal consistency and to reduce the influence of anomalous records. Specifically, the preprocessing stage included: (i) removal of duplicated timestamps; (ii) exclusion of physically implausible observations (e.g., negative concentrations); and (iii) elimination of records identified as invalid when quality flags were available. No temporal imputation was performed. This decision aimed to preserve observed variability and avoid introducing artificial smoothing or bias in subsequent median aggregation and trend detection.

3.3. Data Completeness Criteria and Station Selection

To ensure comparability across years and reduce the sensitivity of summaries to missingness, analyses were restricted to station pollutant series meeting a minimum data completeness threshold. A station was included for a given pollutant if at least 70% of hourly observations were available within the corresponding aggregation period (monthly and/or annual). Stations failing to meet this criterion were excluded for that pollutant and period. This criterion was applied consistently across the entire 2021–2024 horizon.

Because particulate matter series frequently present larger data gaps in monitoring networks, PM_{10} and $PM_{2.5}$ analyses were limited to stations satisfying the completeness threshold across the study period. Consequently, PM_{10} and $PM_{2.5}$ results are interpreted cautiously as they reflect the subset of stations with consistent temporal coverage rather than the full monitoring network.

3.4. Temporal Aggregation and Descriptive Indicators

Urban air pollutant concentrations commonly exhibit skewed distributions and episodic peaks associated with short-term events (e.g., traffic surges, meteorological stagnation). Therefore, median values were used as robust summary statistics for temporal aggregation. Three aggregation levels were computed:

1. Monthly medians (by month and year) to describe interannual seasonality and recovery patterns.
2. Hourly monthly medians (by hour of day and month) to characterize diurnal cycles and seasonal structure.
3. Annual medians (by station and year) to support trend detection and station-level comparisons.

To facilitate comparability across years, hourly monthly heatmaps were displayed using a fixed color scale based on the global concentration range observed during 2021–2024 for each pollutant. This approach prevents visual artifacts that can arise when each year is plotted with an independent scale.

3.5. Absolute and Relative Change Metrics

To complement trend testing and capture incremental variations over the study horizon, absolute and relative changes between 2021 and 2024 were computed at the station level based on annual medians:

 doi:10.20944/preprints202602.1196.v1

Absolute change:

$$\Delta_{\text{abs}} = \tilde{C}_{2024} - \tilde{C}_{2021} \quad (1)$$

Relative change (%):

$$\Delta_{\%} = \frac{\tilde{C}_{2024} - \tilde{C}_{2021}}{\tilde{C}_{2021}} \times 100 \quad (2)$$

where $\tilde{C}_y$ denotes the annual median concentration in year y. These indicators provide an interpretable measure of change even when formal trend tests are underpowered due to short time series. Absolute change is Delta_abs and relative change is Delta_pct in Tables 1 to 8.

3.6. Trend Detection Using Mann–Kendall and Sen's Slope

Long-term monotonic trends were assessed at the station level using the non-parametric Mann–Kendall test applied to annual median concentrations for each pollutant over the 2021–2024 period. The Mann–Kendall test was selected because it does not assume normality, is robust to outliers, and is widely used in environmental time series analysis [29,30].

To quantify the magnitude and direction of monotonic change, Sen's slope estimator was computed alongside the Mann–Kendall statistic. Sen's slope provides a robust estimate of the median rate of change and is commonly used in conjunction with the Mann–Kendall test for environmental applications [30,31]. Detailed formulations of both methods are available in the cited literature.

Statistical significance was evaluated at the 5% level ($\alpha = 0.05$). Given the short temporal span of the analysis (four annual observations), results were interpreted primarily in terms of: (i) statistical significance at $\alpha = 0.05$; (ii) the sign and magnitude of Sen's slope estimates; and (iii) consistency with absolute and relative change metrics, as well as with the observed seasonal and diurnal concentration patterns.

3.5. Reporting Conventions and Interpretation

Results are reported through (i) monthly median evolution plots, (ii) hourly monthly median heatmaps, and (iii) station-level tables summarizing annual medians, change metrics, and trend statistics. Because the study period is limited to four years, the trend analysis is intended to detect strong monotonic signals and to characterize post-pandemic stability versus incremental shifts, rather than to establish causal effects. Accordingly, findings are discussed in relation to urban sustainability and air quality governance implications under a post-pandemic recovery context.

4. Results

This section presents the post-pandemic temporal dynamics of major atmospheric pollutants in Mexico City during the 2021–2024 period. Results are reported separately for each pollutant to highlight differences between primary and secondary emissions, combining descriptive temporal patterns (monthly and hourly monthly medians), station-level absolute and relative changes, and non-parametric trend detection using the Mann–Kendall test and Sen's slope estimator.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2026 doi:10.20944/preprints202602.1196.v1

4.1. CO Results

Figure 1 shows the monthly evolution of median CO concentrations in Mexico City from 2021 to 2024. A consistent seasonal pattern is observed across all years, with higher concentrations during winter months (January–February and November–December) and lower levels during late spring and early summer (May–June). Interannual differences suggest a gradual rebound in CO levels after 2021, particularly evident in late 2023, while 2024 exhibits higher variability during mid-year months.

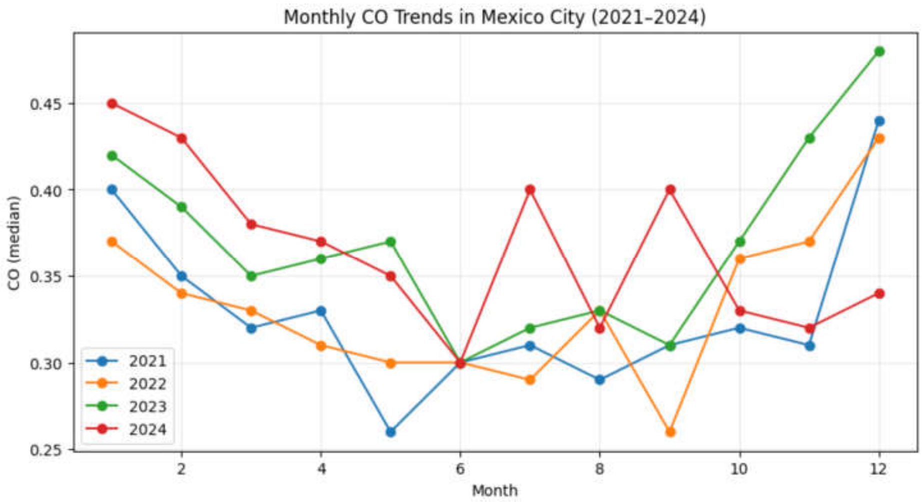

Figure 1. Montly evolution, CO.

For comparability across years, hourly monthly heatmaps were displayed using a fixed color scale based on the global concentration range observed during 2021–2024.

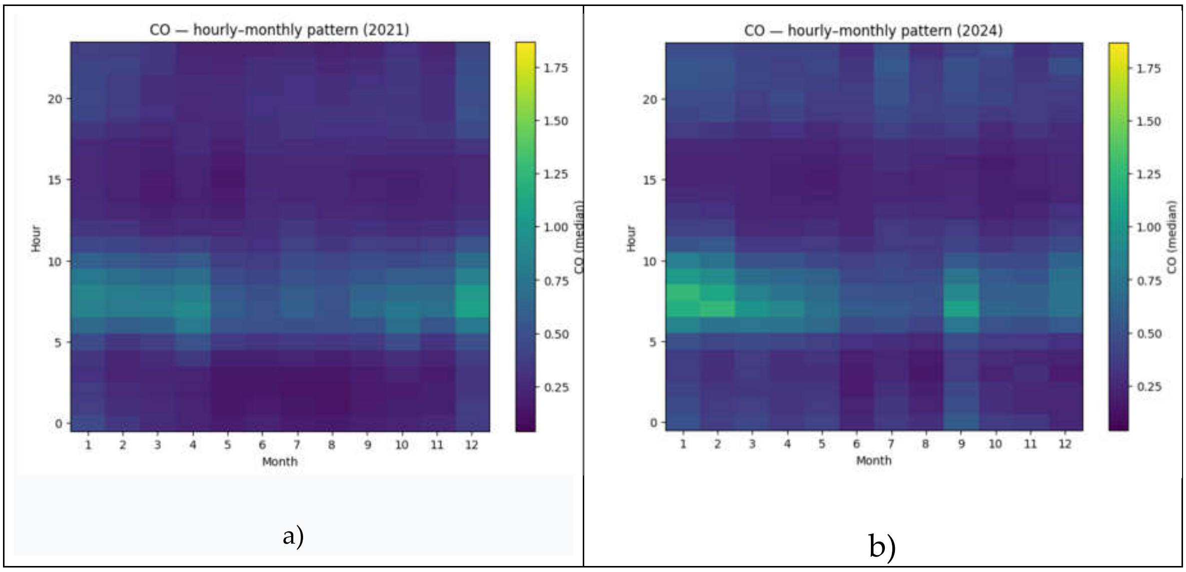

Figure 2. Hourly–monthly median CO concentration patterns, a)2021, b)2024.

Figure 2 shows the hourly monthly median CO concentration patterns for 2021 and 2024 using a common color scale. In both years, a pronounced morning peak between 7:00 and 9:00 is observed, consistent with traffic related emissions. Compared to 2021, 2024 exhibits higher peak intensities during winter months and increased variability in late summer and early autumn, suggesting a post pandemic rebound in vehicular activity.

Table 1 summarizes the absolute and relative changes in annual median CO concentrations between 2021 and 2024 at the station level. While some stations such as LPR exhibited stable concentrations over the study period, others showed substantial increases. Notably, CCA and FAC

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2026 doi:10.20944/preprints202602.1196.v1

experienced relative increases of 36% and 29% (delta-pct)respectively, despite having moderate baseline concentrations in 2021.

Table 1. Annual median CO concentrations.

Estacion	2021	2022	2023	2024	Delta_abs	Delta_pct
LPR	0.46	0.49	0.51	0.46	0.00	0.000000
SAC	0.35	0.33	0.37	0.36	0.01	2.857143
MGH	0.34	0.33	0.36	0.36	0.02	5.882353
BJU	0.31	0.32	0.35	0.34	0.03	9.677419
FAR	0.28	0.27	0.30	0.32	0.04	14.285714
MER	0.39	0.39	0.45	0.45	0.06	15.384615
UIZ	0.33	0.33	0.37	0.39	0.06	18.181818
CUA	0.25	0.27	0.31	0.31	0.06	24.000000
FAC	0.31	0.30	0.36	0.40	0.09	29.032258
CCA	0.25	0.28	0.32	0.34	0.09	36.000000

Given the skewed distribution and episodic peaks characteristic of urban CO concentrations, median values were used as robust summary statistics for hourly, monthly, and annual aggregation. Trend detection was subsequently performed using the non-parametric Mann–Kendall test applied to annual median concentrations.

Station-level Mann–Kendall tests did not detect statistically significant monotonic trends at the 5% significance level for the 2021–2024 period in Table 2. However, all stations exhibited positive Sen's slope estimates, indicating a consistent upward tendency in annual median CO concentrations. In several stations (e.g., CCA, CUA, and UIZ), p-values below 0.10 suggest a marginally increasing trend, which is consistent with the observed absolute and relative increases reported in Table 1.

Table 2. Sation-level Mann–Kendall tests, CO.

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
CCA	no trend	0.089429	1.698416	0.030000	0.2550	0.09	36.000000
CUA	no trend	0.148562	1.444630	0.020000	0.2600	0.06	24.000000
UIZ	no trend	0.148562	1.444630	0.020000	0.3200	0.06	18.181818
MER	no trend	0.245278	1.161895	0.025000	0.3825	0.06	15.384615
FAC	no trend	0.308180	1.019049	0.035000	0.2825	0.09	29.032258
FAR	no trend	0.308180	1.019049	0.016667	0.2650	0.04	14.285714
BJU	no trend	0.308180	1.019049	0.010000	0.3150	0.03	9.677419
MGH	no trend	0.470101	0.722315	0.008333	0.3375	0.02	5.882353
SAC	no trend	0.734095	0.339683	0.006667	0.3450	0.01	2.857143
LPR	no trend	1.000000	0.000000	0.010000	0.4600	0.00	0.000000

Overall, the results indicate a stable and recurring seasonal and hourly structure in CO concentration with higher concentrations during winter and morning peak hours, a general upward tendency in CO levels from 2021 to 2024, and notable spatial heterogeneity in station level changes. While formal trend detection is limited by the short temporal span, the combined evidence from descriptive statistics, spatial patterns, and Sen's slope estimates suggests a post 2021 increase in CO concentrations in Mexico City.

4.2. NO_2 Results

Figure 3 illustrates the monthly evolution of median NO_2 concentrations in Mexico City from 2021 to 2024. A pronounced seasonal pattern is observed across all years, with higher concentrations during winter months and lower levels during summer, reflecting the combined effects of traffic related emissions and enhanced photochemical activity during warmer periods. Compared to 2021, subsequent years exhibit higher NO_2 levels, particularly during winter months, indicating a gradual rebound in urban activity. Interannual variability is more pronounced for NO_2 than for CO, consistent with the stronger sensitivity of NO_2 to short-term emission changes and atmospheric conditions.

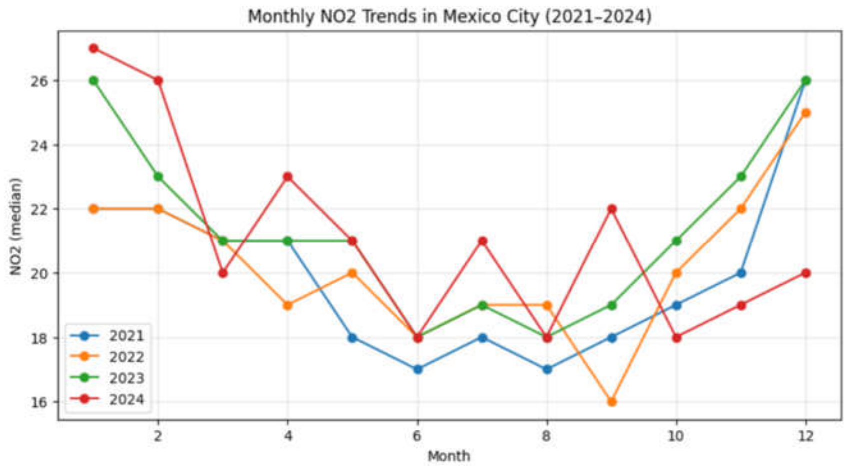

Figure 3. Monthly evolution, NO2.

Figure 4 shows the hourly monthly median NO_2 concentration patterns for 2021 and 2024 using a common color scale. In both years, pronounced morning peaks between 7:00 and 10:00 are observed across most months, followed by lower concentrations during midday hours, consistent with photochemical NO_2 depletion under high solar radiation. Compared to 2021, 2024 exhibits higher morning peak intensities and increased persistence of NO_2 concentrations, particularly during winter months, suggesting enhanced traffic related emissions and post pandemic recovery of urban activity.

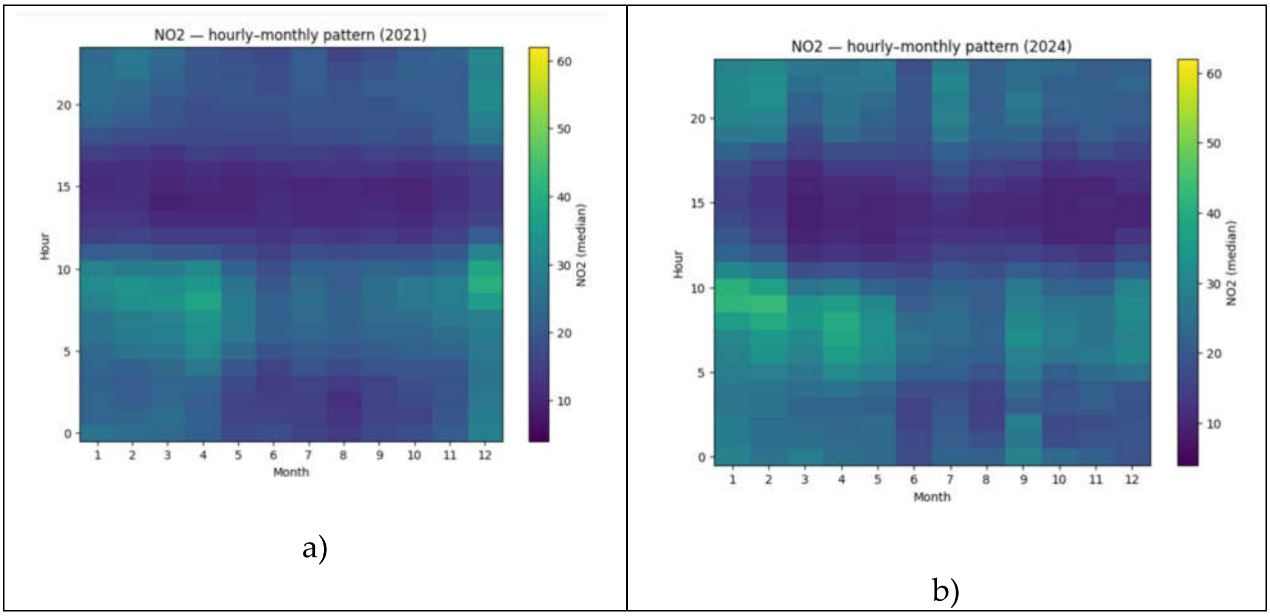

Figure 4. Hourly monthly median NO2 concentration patterns, a)2021, b)2024.

Table 3 reports the absolute and relative changes in annual median NO_2 concentrations at the station level between 2021 and 2024. While some stations (e.g., MON and SAC) exhibited stable concentrations over the study period, most locations showed moderate increases. The largest relative increases were observed at MER and FAC (≈15%), indicating a sustained rise in traffic related NO_2 emissions. The magnitude of changes is smaller than that observed for CO, but more spatially consistent, reflecting the strong linkage between NO_2 and vehicular activity

Table 3. Sation-level Mann–Kendall tests, *NO_2*.

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
MER	no trend	0.089429	1.698416	1.416667	26.875	4.0	14.814815
FAC	no trend	0.148562	1.444630	1.000000	19.000	3.0	15.000000
MGH	no trend	0.148562	1.444630	0.833333	23.250	2.0	8.333333
SAG	no trend	0.245278	1.161895	0.833333	19.750	2.0	10.000000
CCA	no trend	0.371093	0.894427	0.166667	18.750	1.0	5.555556
FAR	no trend	0.470101	0.722315	0.833333	16.750	2.0	11.111111
BJU	no trend	0.470101	0.722315	0.666667	21.000	1.0	4.761905
CUT	no trend	1.000000	0.000000	0.166667	17.250	1.0	6.250000
MON	no trend	1.000000	0.000000	0.000000	13.000	0.0	0.000000
SAC	no trend	1.000000	0.000000	0.000000	19.000	0.0	0.000000

Station-level Mann–Kendall tests applied to annual median NO_2 concentrations did not detect statistically significant monotonic trends at the 5% significance level over the 2021–2024 period, which is expected given the short length of the time series. Nevertheless, all monitoring stations exhibited positive Sen's slope estimates, indicating a consistent upward tendency in NO_2 concentrations across Mexico City. Several stations, such as CCA and FAC, showed relatively larger slopes and absolute increases, suggesting localized intensification of traffic-related emissions.

4.3. O_3 Results

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2026 doi:10.20944/preprints202602.1196.v1

Figure 5 shows the monthly evolution of median O_3 concentrations in Mexico City from 2021 to 2024. In contrast to primary pollutants, O_3 exhibits a pronounced spring maximum, with peak concentrations occurring between March and May across all years. This pattern reflects enhanced photochemical activity driven by increased solar radiation and the availability of precursor pollutants. Compared to 2021, subsequent years show progressively higher springtime O_3 levels, with 2024 displaying the highest peak values. The temporal behavior of O_3 differs markedly from that of CO and NO_2, underscoring the secondary nature of ozone formation and its nonlinear response to emission change

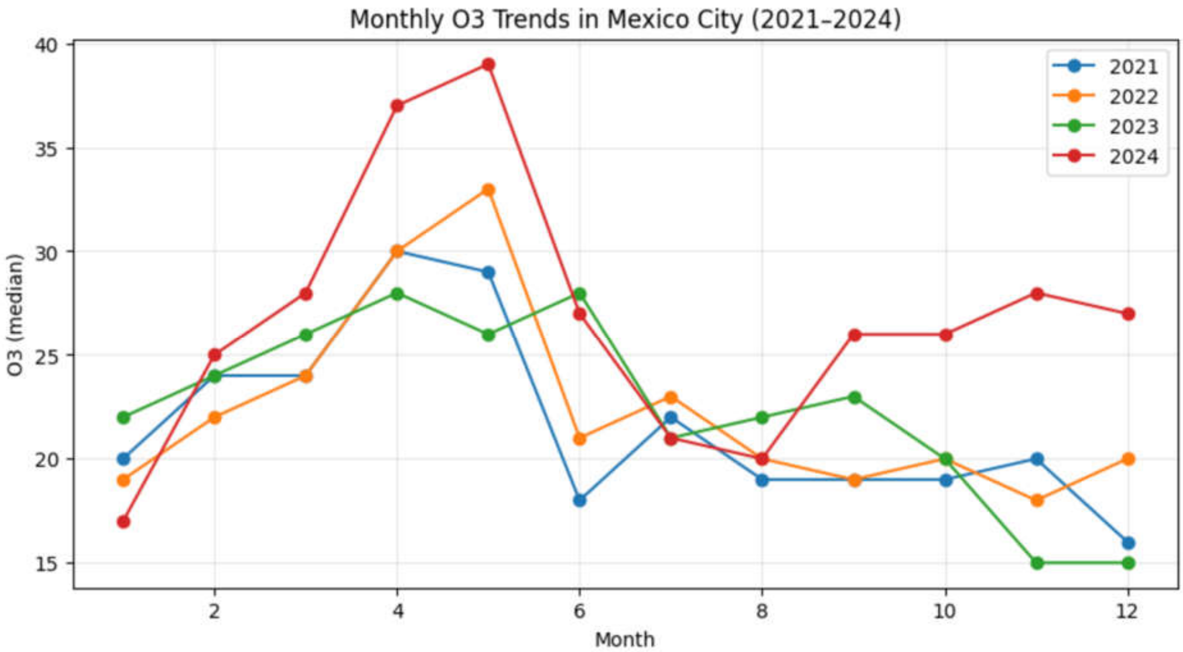

Figure 5. Monthly evolution, O3.

Figure 6 shows the hourly monthly median O_3 concentration patterns for 2021 and 2024 using a common color scale. O_3 displays a pronounced diurnal cycle, with minimum concentrations during nighttime and early morning hours and maximum levels during midday to early afternoon (approximately 12:00–16:00), consistent with photochemical formation under high solar radiation. Seasonally, the highest O_3 concentrations occur during spring months (March–May). Compared to 2021, 2024 exhibits higher and more persistent daytime O_3 levels during the spring peak period, suggesting intensified photochemical activity and increased precursor availability and/or favorable meteorological conditions.

doi:10.20944/preprints202602.1196.v1

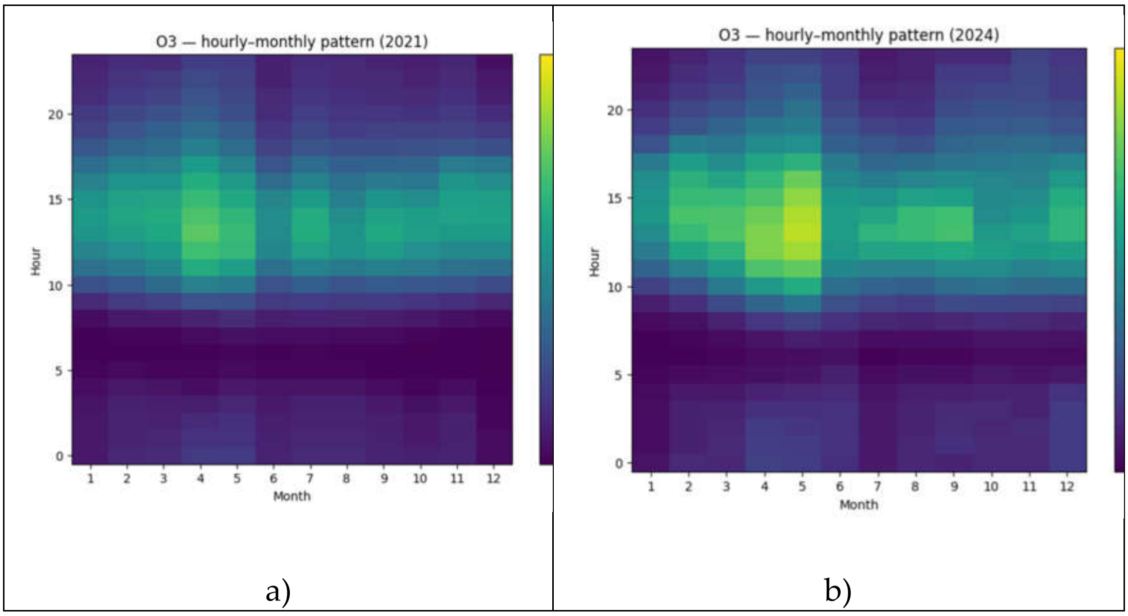

Figure 6. Hourly–monthly median NO2 concentration patterns, a)2021, b)2024.

Table 4 summarizes station-level Mann–Kendall trend statistics together with absolute and relative changes in annual median O_3 concentrations between 2021 and 2024. Although no statistically significant monotonic trends were detected at the 5% level due to the short time series, all stations exhibited positive Sen's slope estimates and substantial absolute and relative increases, particularly at CUT and SAC, where relative changes exceeded 50%

Table 4. Sation-level Mann–Kendall tests, *O3*.

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
CUT	no trend	0.089429	1.698416	2.666667	16.000	10.0	55.555556
MON	no trend	0.089429	1.698416	2.000000	25.000	6.0	24.000000
SAC	no trend	0.089429	1.698416	3.583333	21.125	11.0	50.000000
SAG	no trend	0.089429	1.698416	1.333333	18.500	5.0	29.411765
UIZ	no trend	0.089429	1.698416	1.500000	20.250	6.0	28.571429
PED	no trend	0.148562	1.444630	2.000000	23.000	9.0	36.000000
TLA	no trend	0.148562	1.444630	1.333333	17.000	5.0	27.777778
MGH	no trend	0.308180	1.019049	1.666667	19.000	4.0	19.047619
BJU	no trend	0.470101	0.722315	1.833333	19.750	8.0	36.363636
NEZ	no trend	0.470101	0.722315	2.166667	20.750	7.0	30.434783

O_3 exhibits a strong spring maximum, a pronounced daytime peak aligned with photochemical formation, and evidence of increasing levels after 2021, with 2024 showing the most intense springtime values. The temporal behavior of O_3 differs markedly from CO and NO_2, reinforcing the secondary nature of ozone formation and its nonlinear response to precursor availability and meteorological conditions.

4.4. PM_{10} Results

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2026 doi:10.20944/preprints202602.1196.v1

Figure 7 presents the monthly evolution of median PM_{10} concentrations in Mexico City for the period 2021–2024, based on stations meeting the minimum data completeness criteria. PM_{10} exhibits a clear seasonal pattern, with higher concentrations during winter and early spring and lower levels during the summer months, consistent with the combined effects of resuspension processes, atmospheric stability, and precipitation. Interannual comparisons indicate higher PM_{10} levels in 2024 across most months relative to previous years, particularly during spring and autumn. Although the analysis is limited to five stations due to data availability constraints, the observed patterns are consistent across locations, suggesting a generalized increase in PM_{10} levels after 2021.

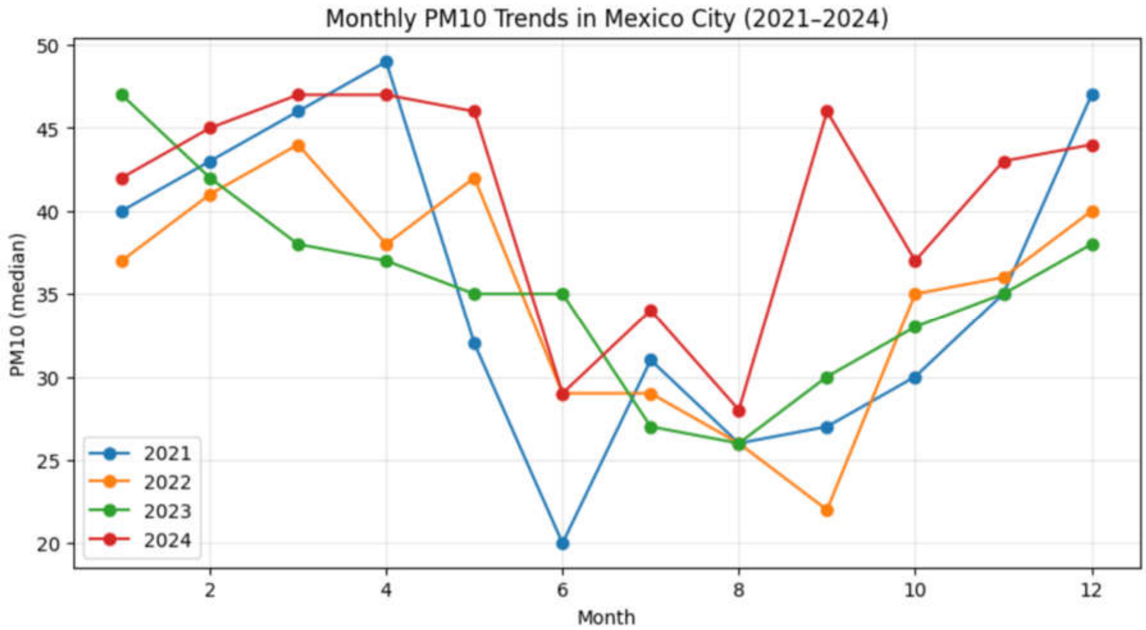

Figure 7. Monthly evolution, PM10.

The hourly monthly heatmaps of PM_{10} reveal a consistent diurnal cycle, with higher concentrations during morning hours and lower levels overnight, alongside a clear seasonal pattern characterized by higher values in the first half of the year. These patterns are consistent across the available monitoring stations and reflect the influence of local emission sources and meteorological conditions. Due to data completeness constraints, PM10 analyses were limited to five stations with sufficient temporal coverage.

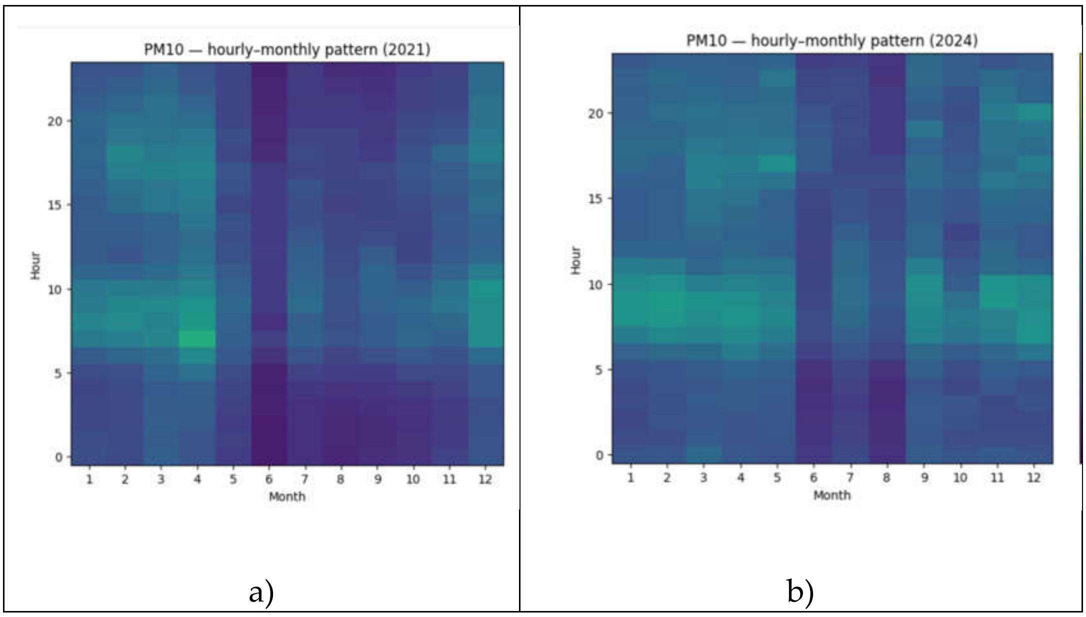

Figure 8. Hourly monthly median PM10 concentration patterns, a)2021, b)2024.

Table 5 reports the Mann–Kendall trend test and Sen's slope estimates for annual median PM10 concentrations at stations with sufficient data coverage (n = 5). No statistically significant monotonic trends were detected between 2021 and 2024 ($p > 0.05$ for all stations). While some sites, such as BJU and UIZ, exhibited moderate absolute increases over the study period, these changes were not consistent enough to yield significant trends. This result suggests that PM_{10} levels during the study period were dominated by short term variability and seasonal dynamics rather than sustained interannual changes.

Table 5. Sation-level Mann–Kendall tests, *PM_{10}.*

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
BJU	no trend	0.148562	1.444630	3.333333	27.00	8.0	26.666667
MER	no trend	0.470101	0.722315	1.166667	33.75	4.0	11.428571
CUT	no trend	1.000000	0.000000	-0.333333	39.50	1.0	2.439024
FAC	no trend	1.000000	0.000000	0.000000	33.50	3.0	8.823529
UIZ	no trend	1.000000	0.000000	1.166667	37.75	7.0	17.073171

4.5. $PM_{2.5}$ Results

The $PM_{2.5}$ analysis was limited to five monitoring stations with sufficient data availability over the 2021–2024 period. Monthly median concentrations exhibit a clear seasonal pattern, with higher levels during the spring months and lower values in mid-year, consistent with regional meteorological conditions (Figure 9).

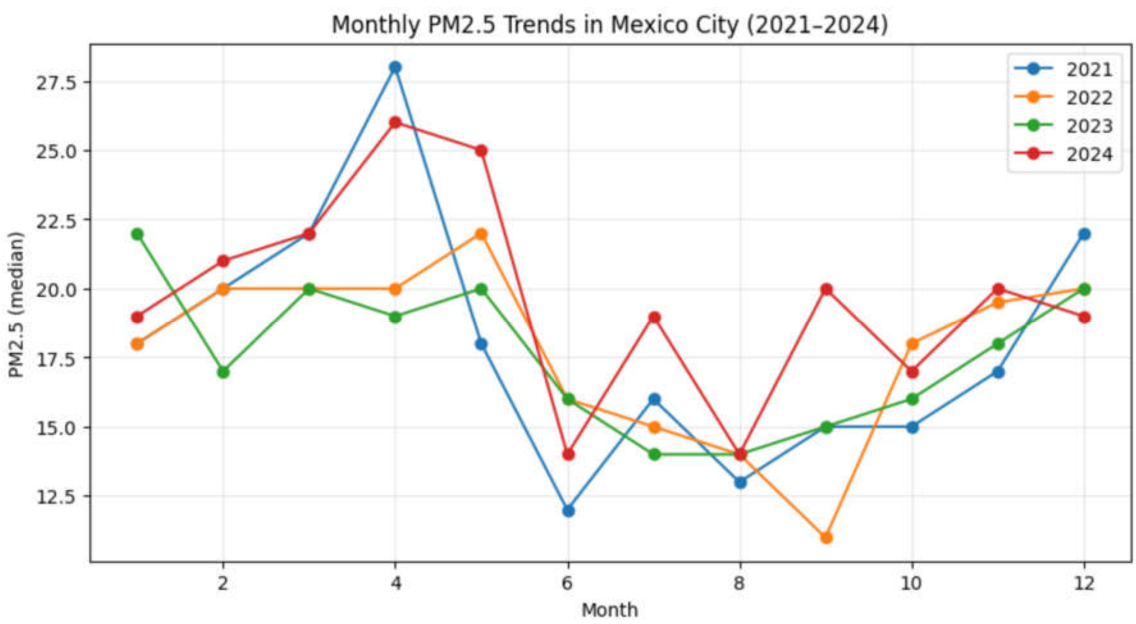

Figure 9. Monthly evolution, $PM_{2.5}$.

The results of the trend analysis for $PM_{2.5}$ indicate that no statistically significant monotonic trends were detected at any of the analyzed stations during the 2021–2024 period, according to the Mann–Kendall test ($p > 0.05$ in all cases). Nevertheless, the analysis of absolute and relative changes reveals moderate increases in annual median $PM_{2.5}$ concentrations at several stations.

doi:10.20944/preprints202602.1196.v1

In particular, stations such as BJU, CCA, FAR, and UIZ exhibited absolute increases of approximately 2 µg/m³, corresponding to relative increases of about 10–13% compared to 2021 levels, whereas MER maintained nearly constant concentrations throughout the study period. Although small, the positive Sen's slope estimates suggest a slight upward signal that is not yet sufficient to be characterized as a statistically significant trend within the analyzed time horizon.

Table 6. Sation-level Mann–Kendall tests, *PM* $_{2.5}$.

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
BJU	no trend	0.148562	1.444630	0.583333	17.125	2.0	11.764706
CCA	no trend	0.371093	0.894427	0.333333	15.500	2.0	12.500000
FAR	no trend	1.000000	0.000000	0.333333	17.000	2.0	11.111111
MER	no trend	1.000000	0.000000	0.000000	20.000	0.0	0.000000
UIZ	no trend	1.000000	0.000000	0.333333	19.000	2.0	10.000000

These results indicate that, while no robust long-term trend is observed, incremental changes in $PM_{2.5}$ are present and may reflect interannual variability and the influence of local and seasonal factors rather than a sustained structural change in air quality.

4.6. SO_2 Results

Sulfur dioxide (SO_2) concentrations remained consistently low throughout the 2021–2024 period, with very limited temporal variability across the monitoring stations. Due to the low dynamic range of the observed values, no statistically significant monotonic trends were identified using the Mann–Kendall test. The observed month fluctuations reflect discrete changes around detection-level concentrations rather than meaningful long-term variability. SO_2 exhibited stable conditions over the study period, suggesting a limited contribution of stationary combustion sources within the urban monitoring network and reinforcing the dominance of other pollutants in shaping recent air quality dynamics in Mexico City.

The trend analysis for sulfur dioxide (SO_2) indicates no statistically significant monotonic trends at any of the analyzed stations during the 2021–2024 period, according to the Mann–Kendall test (Table 7). Sen's slope estimates were close to zero, further supporting the absence of sustained long-term changes.

Table 7. Sation-level Mann–Kendall tests, *SO2.*

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
CUT	no trend	0.371093	-0.894427	-0.166667	2.25	-1.0	-50.0
FAC	no trend	0.371093	-0.894427	-0.166667	2.25	-1.0	-50.0
FAR	no trend	0.371093	0.894427	0.166667	0.75	1.0	100.0
LPR	no trend	0.371093	-0.894427	-0.166667	2.25	-1.0	-50.0
NEZ	no trend	0.371093	0.894427	0.166667	0.75	1.0	100.0
CCA	no trend	1.000000	0.000000	0.000000	1.00	0.0	0.0
MER	no trend	1.000000	0.000000	0.000000	2.00	0.0	0.0
MGH	no trend	1.000000	0.000000	0.000000	2.00	0.0	0.0

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 27 February 2026 doi:10.20944/preprints202602.1196.v1

Although some stations exhibit relatively large absolute and relative changes between 2021 and 2024, these variations are driven by the very low concentration levels and the limited dynamic range of SO_2 measurements, often fluctuating around detection level values. Consequently, percentage changes should be interpreted with caution, as they do not reflect meaningful environmental shifts. Overall, SO_2 concentrations remained low and stable throughout the study period, suggesting a limited influence of stationary combustion sources within the urban monitoring network and reinforcing the secondary role of SO_2 in recent air quality dynamics in Mexico City.

4.7. NO_x Results

Nitrogen oxides (NO_x) exhibited a clear seasonal pattern, with higher median concentrations during winter months and lower values in mid-year, consistent with traffic related emission dynamics. However, the Mann–Kendall test did not identify statistically significant monotonic trends at any monitoring station during the 2021–2024 period.

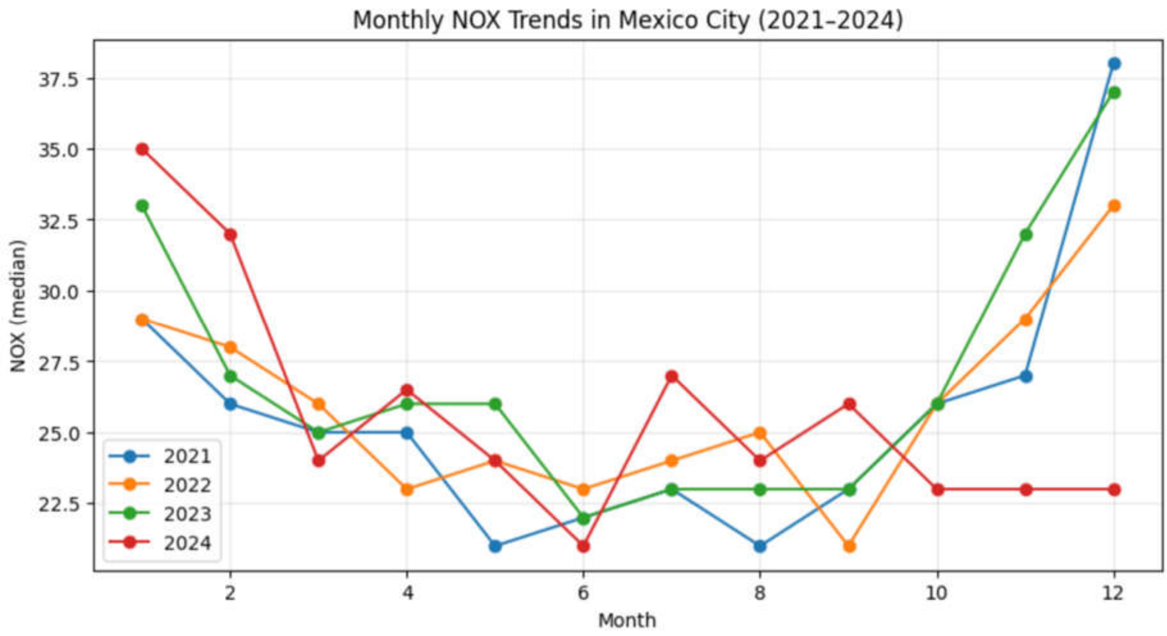

Figure 10. Monthly evolution, Nox.

Sen's slope estimates were generally small and heterogeneous across stations, indicating the absence of a sustained long-term increase or decrease. The observed absolute and relative changes between 2021 and 2024 reflect interannual variability rather than structural shifts in NO_x emissions. The stability of NO_x concentrations reinforces the findings obtained for NO_2 and supports the interpretation that primary traffic related emissions remained relatively stable in Mexico City during the post-pandemic period.

Table 8. Sation-level Mann–Kendall tests, *SO_2.*

Station	trend	p	z	sen_slope	intercept	Delta_abs	Delta_pct
MGH	no trend	0.245278	1.161895	0.416667	30.875	1.0	3.225806
MER	no trend	0.308180	1.019049	1.416667	37.375	4.0	10.810811
SAG	no trend	0.308180	1.019049	0.833333	24.250	2.0	8.333333
CCA	no trend	0.371093	0.894427	0.333333	21.500	2.0	10.000000
FAC	no trend	0.470101	0.722315	0.666667	26.000	1.0	3.703704

CUT	no trend	0.734095	-0.339683	-0.666667	22.500	-1.0	-4.761905
MON	no trend	1.000000	0.000000	0.000000	15.000	0.0	0.000000
SAC	no trend	1.000000	0.000000	-0.166667	22.750	-1.0	-4.347826

Table 9 presents a summary of post pandemic pollutant behavior, trend signal refers to the qualitative indication of temporal change inferred from the combined evidence of Sen's slope direction and magnitude, absolute and relative changes between 2021 and 2024, and the consistency of seasonal and diurnal patterns, even in the absence of statistically significant monotonic trends at $\alpha = 0.05$.

Table 9. Summary of temporal patterns and post-pandemic changes (2021–2024).

Pollutant	Peak hours	Peak months	Seasonal pattern	Δ 2021–2024	Stations with largest increase	Trend signal*
CO	07:00–09:00	Jan–Feb, Nov–Dec	Winter maximum	↑ Moderate (up to +36%)	CCA, FAC, CUA	Weak positive
NO_2	07:00–10:00	Dec–Feb	Winter maximum	↑ Moderate (~10–15%)	MER, FAC	Weak positive
O_3	12:00–16:00	Mar–May	Spring maximum	↑ Strong (up to +55%)	CUT, SAC	Positive (non-linear)
PM_{10}	06:00–10:00	Jan–Apr	Winter–spring	↑ Mild–moderate	BJU, UIZ	No clear trend
$PM_{2.5}$	Morning	Feb–Apr	Late winter–spring	↑ Mild (~10–13%)	BJU, CCA	No clear trend
SO_2	—	—	Stable	≈ No change	—	No trend
NO_x	Morning	Dec–Feb	Winter	≈ Stable	MER, CCA	No trend

*Trend signal is a qualitative synthesis and does not imply statistical significance.

5. Discussion

This study provides a comprehensive multi-pollutant assessment of air quality dynamics in Mexico City during the 2021–2024 post-pandemic period. Across all analyzed pollutants (CO, NO_2, NO_x, O_3, PM_{10}, $PM_{2.5}$, and SO_2), the Mann–Kendall test did not identify statistically significant monotonic trends at the station level. This result indicates an overall stabilization of air pollutant concentrations rather than pronounced long-term improvements or deteriorations following the COVID-19 mobility disruptions. The absence of significant monotonic trends should not be interpreted as an absence of change. Instead, the observed behavior suggests that air quality in Mexico City has entered a post-pandemic steady state, characterized by interannual variability and seasonal dynamics rather than structural shifts in emissions.

Primary pollutants directly linked to combustion processes, such as CO, NO_2, and NO_x, exhibited consistent seasonal patterns dominated by traffic activity, with higher concentrations during winter months and lower levels during mid-year. Despite moderate absolute and relative increases at some stations, the absence of statistically significant monotonic trends suggests that post-pandemic mobility recovery did not translate into sustained structural emission changes.

 doi:10.20944/preprints202602.1196.v1

In contrast to primary pollutants, ozone (O_3) exhibited greater variability and more pronounced seasonal dynamics, with elevated concentrations during spring and early summer months. This behavior reflects the complex photochemical formation of O_3, which depends not only on precursor availability but also on meteorological conditions such as solar radiation and temperature. Although no statistically significant monotonic trends were detected, the persistence of high O_3 levels during photochemically active periods highlights the nonlinear response of secondary pollutants to stable precursor emissions. This finding underscores the challenge of controlling ozone pollution through traffic emission reductions alone and emphasizes the importance of integrated precursor management strategies.

For PM_{10} and $PM_{2.5}$, the analysis was limited to stations with sufficient data coverage. Results indicate moderate increases in annual median concentrations at several stations, particularly for $PM_{2.5}$, with relative changes on the order of 10–15% between 2021 and 2024. However, these increases were not statistically significant according to the Mann–Kendall test, and Sen's slope estimates remained small. This suggests that particulate matter concentrations are influenced primarily by interannual variability, local conditions, and seasonal factors, rather than by sustained emission growth. The limited spatial coverage for $PM_{2.5}$ and PM_{10} highlights persistent challenges in long term particulate monitoring and suggests that caution is warranted when extrapolating city wide conclusions for these pollutants.

SO_2 concentrations remained consistently low throughout the study period, with minimal variability and a very limited dynamic range. The absence of statistically significant trends, combined with near-zero Sen's slope estimates, indicates that stationary combustion sources currently play a minor role in shaping urban air quality dynamics in Mexico City. Observed relative changes in SO_2 should be interpreted cautiously, as they are largely driven by fluctuations around detection-level concentrations rather than meaningful environmental changes.

6. Conclusions

This study provides a recent (2021–2024) multi-pollutant assessment of post-pandemic air quality dynamics in Mexico City using robust non-parametric methods. The combined evidence from absolute and relative changes, Sen's slope estimates, and temporal patterns indicates that several pollutants exhibited moderate to strong increases during the study period, particularly CO, NO_2, and O_3, as summarized in Table 9.

Primary pollutants (CO, NO_2, and NO_x) displayed stable and recurring seasonal patterns dominated by traffic related emissions, consistent with previous findings in large metropolitan areas [15,32] In contrast, the secondary pollutant ozone (O_3) exhibited pronounced springtime maxima and a clear post-2021 increase, reflecting its nonlinear photochemical formation and sensitivity to meteorological conditions.

Although no statistically significant monotonic trends were detected due to the short temporal horizon, the presence of consistent upward signals across multiple pollutants suggests that current air quality management strategies have been insufficient to achieve sustained improvements. While Mexico City has avoided severe post-pandemic deterioration, the absence of clear long-term reductions indicates a need to strengthen integrated mitigation approaches.

In line with [4] effective urban air quality strategies should combine city renaturalization, the promotion of sustainable mobility, and data-driven management tools, including real time monitoring and advanced spatial interpolation techniques, supported by environmental education initiatives from early stages.

6.1. Limitations and Future Research

This study is subject to several limitations. First, the relatively short temporal horizon (four years) limits the statistical power of trend detection methods. Second, data availability constraints, particularly for particulate matter, reduced spatial coverage in some analyses. Finally, meteorological

 doi:10.20944/preprints202602.1196.v1

variables were not explicitly modeled and should be incorporated in future work to disentangle emission-driven changes from atmospheric effects.

Future research should extend the temporal scope, integrate meteorological normalization, and explore nonlinear interactions among pollutants to better inform long term air quality management strategies.

Author Contributions: Conceptualization, E.S.H.-G.; methodology, E.S.H.-G.; software,E.S.H.-G.; validation, D.C.G., (C.A.M.-I.); formal analysis, E.S.H.-G.; investigation, E.S.H.-G.; data curation, E.S.H.-G.; writing—original draft preparation, E.S.H.-G.; writing—review and editing methodology, D.C.G., (C.A.M.-I.); visualization, E.S.H.-G.; supervision, D.C.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Secretaría de Educación, Ciencia, Tecnología e Innovacion (SECTEI) of Mexico City through the Innovation Project *"Mapping and quantification of CH_4, CO, CO_2, NOx, and SO2 in soi and air in Mexico City as a mitigation strategy for reducing climate change effects SECTEI/083/2024."*.

Data Availability Statement: The data can be requested from the corresponding author when necessary, the datasets and the scripts used to perform the statistical and spatial analyses are in supplementary material.

Acknowledgments: The Mexico City Atmospheric Monitoring Directorate (SIMAT), administered by the Secretariat of the Environment of Mexico City (SEDEMA) under the General Directorate of Air Quality, is gratefully acknowledged for providing the data used in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix

Table A1. Summary of selected studies on temporal air pollution analysis.

Author(s)	City / Region	Period	Pollutants	Data Source	Methods	Main Focus
Lee & Batterman [15]	Seoul, South Korea	2023–2024	$PM_{2.5}$	Ground monitoring, traffic routes	RLINE dispersion model	Traffic-related $PM_{2.5}$ exposure
Kumar et al. [33]	7 cities, India	2018–2021	BC, PM_{10}, $PM_{2.5}$, NOx, CO, SO_2	Monitoring stations	Correlation analysis	Black carbon relationships
Sherrif et al. [34]	Chennai & Bengaluru, India	2019–2023	NO_2	Satellite data	Statistical modeling	Spatio-temporal NO_2 patterns
Hamidi et al. [16]	Ahvaz, Iran	2008–2019	PM_{10}	Monitoring stations	Descriptive & temporal analysis	Dust events and PM_{10}
Gulia et al. [18]	4 megacities, India	2018–2022	PM_{10}, $PM_{2.5}$, NOx, SO_2, O_3	Monitoring stations	Pearson correlation, Mann–Kendall	Seasonal variability
Chang et al. [19]	346 cities, China	2019–2023	Tropospheric NO_2	Satellite data	Random forest, SHAP	Urban drivers of NO_2

 doi:10.20944/preprints202602.1196.v1

Xiong et al. [17]	Chengdu, China	2015–2021	PM_{10}, $PM_{2.5}$, O_3, NO_2	Monitoring stations	Socio-environmental analysis	Urban growth effects
Singh et al. [35]	Handwar City, India	2023–2024	$PM_{2.5}$, PM_{10}, NO_2, SO_2	Monitoring stations	PCA, clustering, AQI	Critical pollution zones
Wen et al. [32]	SE China	2015–2060	$PM_{2.5}$, PM_{10}	Monitoring & scenarios	Forecasting, BAU scenarios	Electric vehicle adoption
Nasar-u-Minallah et al. [21]	Lahore, Pakistan	2014–2024	NOx, O_3, SO_2, PM_{10}, CO	Monitoring stations	ARIMA models	Long-term forecasting
Niu et al. [20]	>2000 cities, China	2000–2020	$PM_{2.5}$, PM_{10}	Monitoring & urban data	Durbin model	Air pollution island
Hernández-Sánchez et al. [23]	Atoyac, Mexico	–	PM_{10}, $PM_{2.5}$	Monitoring stations	Seasonal analysis	Industry and health
Monzón-Herrera et al. [22]	Mexico City	2024	NO_2	Satellite & ground data	Random forest	NO_2 estimation
Rodríguez-Trejo et al. [25]	Querétaro, Mexico	2023	$PM_{2.5}$	Low-cost sensors	Descriptive analysis	Holiday pollution
Texcaloc-Sangrador et al. (2024)	Mexico	2014–2018	NO_2, $PM_{2.5}$	Traffic & monitoring data	Regression analysis	Speed limits
Nieto-Garzón & Lozano [25]	Mexico City, São Paulo, Bogotá	2019–2021	NO_2, O_3, CO, PM_{10}	Monitoring data	Comparative analysis	COVID mobility effects
Méndez-Astudillo & Caetano [26]	Mexico City, Monterrey, Guadalajara	2020	PM_{10}, $PM_{2.5}$	Monitoring stations	Chow test, Mann–Whitney	Lockdown impacts
Martínez-Morales et al. [27]	Monterrey, Mexico	2020–2021	$PM_{2.5}$ metals	Monitoring stations	Chemical analysis	Pandemic composition

Table A1. Nomenclature associated with air quality monitoring stations.

Key	Name	Municipality	State	Latitude	Longitude
AJU	Ajusco	Tlalpan	CDMX	19.1542	-99.1626
AJM	Ajusco Medio	Tlalpan	CDMX	19.2721	-99.2077

 doi:10.20944/preprints202602.1196.v1

ATI	Atizapán	Atizapán de Zaragoza	Estado de México	19.5769	-99.2541
BJU	Benito Juarez	Benito Juárez	CDMX	19.3716	-99.1590
CAM	Camarones	Azcapotzalco	CDMX	19.4684	-99.1697
CHO	Chalco	Chalco	Estado de México	9.487227	-99.1142
CUA	Cuajimalpa	Cuajimalpa de Morelos	CDMX	19.365	-99.2917
CUT	Cuautitlán	Cuautitlán Izcalli	Estado de México	19.6467	99.2102
FAC	FES Acatlán	Naucalpan de Juárez	Estado de México	19.4824	-99.2435
GAM	Gustavo A. Madero	Gustavo A. Madero	CDMX	19.4827	-99.0946
HGM	Hospital General de México	Cuauhtémoc	CDMX	19.41161	-99.1522
INN	Investigaciones Nucleares	Ocoyoacac	Estado de México	19.2919	-99.3805
IZT	Iztacalco	Iztacalco	CDMX	19.3844	-99.1176
MGH	Miguel Hidalgo	Miguel Hidalgo	CDMX	19.4246	-99.1195
MPA	Milpa Alta	Milpa Alta	CDMX	19.2007	99.0113
PED	Pedregal	Álvaro Obregón	CDMX	19.3251	-99.2041
SAG	San Agustín	Ecatepec de Morelos	Estado de México	19.5329	-99.0303
TLA	Tlalnepantla	Tlalnepantla de Baz	Estado de México	19.5290	-99.2045
TLI	Tultitlán	Tultitlán	Estado de México	19.6025	-99.1771
UIZ	UAM Iztapalapa	Iztapalapa	CDMX	19.3607	-99.0738
VIF	Villa de las Flores	Coacalco de Berriozábal	Estado de México	19.6582	-99.0965

References

1. Dogan, A.; Pata, U.K. The role of ICT, R&D spending and renewable energy consumption on environmental quality: Testing the LCC hypothesis for G7 countries. *J. Clean. Prod.* 2022, *380*, 135038.
2. Tavares, M.S.; Rodrigues, C.T.; de Menezes, S.L.S.; Moreno, A.M. Health at risk: Air pollution and urban vulnerability. *Green Health* 2025, *1*, 21.
3. Jindal, S.K.; Aggarwal, A.N.; Jindal, A. Household air pollution in India and respiratory diseases. *Curr. Opin. Pulm. Med.* 2020, *26*, 128–134.
4. Arriazu-Ramos, A.; Santamaría, J.M.; Monge-Barrio, A.; Bes-Rastrollo, M.; Gutierrez Gabriel, S.; Benito Frias, N.; Sánchez-Ostiz, A. Health impacts of urban environmental parameters: A review of air pollution, heat, noise, green spaces and mobility. *Sustainability* 2025, *17*, 4336.

5. Romieu, I.; Gouveia, N.; A Cifuentes, L.; de Leon, A.P.; Junger, W.; Vera, J.; Strappa, V.; Hurtado-Díaz, M.; Miranda-Soberanis, V.; Rojas-Bracho, L.; et al. Multicity study of air pollution and mortality in Latin America (the ESCALA study). *Res. Rep. Health Eff. Inst.* **2012**, *171*, 5–86
6. World Health Organization. WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide. Available online: https://www.who.int/publications/i/item/9789240034228 (accessed on 29 January 2025).
7. United Nations. Transforming Our World: The 2030 Agenda for Sustainable Development. Available online: https://sdgs.un.org/2030agenda (accessed on 29 January 2025).
8. Shi, Z.; Song, C.; Liu, B.; Lu, G.; Xu, J.; Van Vu, T.; Harrison, R.M. Abrupt changes in surface air quality attributable to COVID-19 lockdowns. *Sci. Adv.* 2021,
9. Tyagi, P.; Braun, D.; Sabath, B.; Henneman, L.; Dominici, F. Short-term change in air pollution following the COVID-19 emergency. *medRxiv* 2020, 2020.08.04.20168237.
10. Adam, M.G.; Tran, P.T.; Balasubramanian, R. Air quality changes in cities during the COVID-19 lockdown: A critical review. *Atmos. Res.* 2021, *264*, 105823.
11. Yadav, S.; Dhankhar, R.; Chhikara, S.K. Significant changes in urban air quality during COVID-19 lockdown in Rohtak City. *Asian J. Chem.* 2022, *34*, 3189–3196.
12. Retana-Olvera, J.L.; Ruiz-Serrano, M. Movilidad urbana y calidad del aire en la zona metropolitana de Toluca a inicios del COVID-19. CienciAmérica. **2021**, 10, 81–98. https://doi.org/10.33210/ca.v10i2.377.
13. Zhang, Z.; Arshad, A.; Zhang, C.; Hussain, S.; Li, W. Temporary reduction in global air pollution during COVID-19 confinement. *Remote Sens.* 2020, *12*, 2420.
14. Secretariat of the Environment of Mexico City (SEDEMA). Mexico City Atmospheric Monitoring System (SIMAT). Available online: https://www.aire.cdmx.gob.mx (accessed on 29 January 2025).
15. Lee, S.J.; Batterman, S. Estimation of vehicle PM2.5 emissions with high spatio-temporal resolution and its application to air dispersion modeling in Seoul, South Korea. *Environ. Pollut.* 2025, 127479.
16. Hamidi, M.; Ghobadi, T.; Shao, Y.; Fallah, B.; Rostami, M.; Mao, R. Investigation of the role of southwestern Asia dust events on urban air pollution: A case study of Ahvaz. *Sci. Rep.* 2025, *15*, 21981.
17. Xiong, X.; Qiu, J.; Zhao, R.; Du, P.; Zhao, L. Spatiotemporal heterogeneities of air pollution in Chengdu. *Front. Environ. Sci.* 2025, *13*, 1540671.
18. Gulia, S.; Kumar, K.; Kumar, P.; Yadav, A.; Rajni. Navigating urban air pollution: Trends and climate links in Indian megacities. *Environ. Qual. Manag.* 2025, *35*, e70210.
19. Cheng, F.; Sun, Q.; Zhang, J.; Liu, J.; Lü, W.; Shen, F.; Yang, H. Nitrogen dioxide pollution in 346 Chinese cities: Spatiotemporal variations and natural drivers frommulti-source remote sensing data. *PLoS ONE* 2025, *20*, e0334535.
20. Niu, L.; Zhang, Z.; Liang, Y.; van Vliet, J. Spatiotemporal patterns of the urban air pollution island effect. *Environ. Int.* 2024, *184*, 108455.
21. Nasar-u-Minallah, M.; Jabbar, M.; Zia, S.; Perveen, N. Assessing environmental challenges in Lahore. *Environ. Monit. Assess.* 2024, *196*, 865.
22. Monzón Herrera, Y.R.; Polanco Gaytán, M.; Aquino Santos, R.T.; Babu Saheer, L.; Mendoza-Cano, O.; Macedo-Barragán, R.J. Estimating surface NO_2 in Mexico City using Sentinel-5P and machine learning. *Atmosphere* 2025, *17*, 37.
23. Hernandez-Sánchez, U.A.; Meléndez-Armenta, R.Á.; González-Moreno, H.R.; López-Méndez, M.C.; Rico-Barragán, A.A. Impacts of sugarcane industry on air quality and public health in Atoyac, México. *Urban Clim.* 2025, *64*, 102700.
24. Rodríguez-Trejo, A.; Böhnel, H.N.; Ibarra-Ortega, H.E.; Salcedo, D.; González-Guzmán, R.; Castañeda-Miranda, A.G.; Chaparro, M.A. Air quality monitoring with low-cost sensors in Querétaro. *Atmosphere* 2024, *15*, 879.
25. Texcalac-Sangrador, J.L.; Pérez-Ferrer, C.; Quintero, C.; Galbarro, F.J.P.; Yamada, G.; Gouveia, N.; Barrientos-Gutierrez, T. Speed limits and their effect on air pollution in Mexico City. *Sci. Total Environ.* 2024, *924*, 171506.
26. Nieto-Garzón, O.; Lozano, A. Different local air-pollution responses to COVID-19 lockdown measures. *Air Qual. Atmos. Health* 2025, 1–16.

doi:10.20944/preprints202602.1196.v1

27. Méndez-Astudillo, J.; Caetano, E. The effect of abrupt changes to sources of PM10 and PM2.5 concentrations in Mexico. *Atmosphere* 2023, *14*, 596.
28. SeyedAlinaghi, S.; Karimi, A.; Pashaei, A.; Kianzad, S.; Soleymanzadeh, M.; Mojdeganlou, H.; Afsahi, A.M. The effects of the COVID-19 pandemic on air pollution: A systematic review. *Coronaviruses* 2025, *6*, E030724231565.
29. Thenmozhi, M.; Kottiswaran, S.V. Analysis of rainfall trend using Mann–Kendall test and Sen's slope estimator. *Int. J. Agric. Sci. Res.* 2016, *6*, 131–138.
30. Venegas, Q.; Thomasson, M.; García, P. Trend analysis using Mann–Kendall and Sen's slope estimator. *Am. J. Environ. Sci.* 2020, *15*, 180–187
31. Sen, P.K. Estimates of the regression coefficient based on Kendall's tau. *J. Am. Stat. Assoc.* 1968, *63*, 1379–1389.
32. Wen, Z.N.; Miao, Q.Y.; Chen, J.R.; Wu, S.P.; He, L.X.; Jiang, B.Q.; Huang, Z. Heavy metal emissions from on-road vehicles in southeastern China. *Environ. Sci. Pollut. Res.* 2025, *32*, 298–313.
33. Kumar, V.; Devara, P.C.; Soni, V.K. Spatiotemporal variations in black carbon aerosol concentration in India. *MAUSAM* 2026, *77*, 219–234.
34. Sheriff, R.; Meer, M.S.; Tariq, A. Remote sensing-based assessment of vegetation and LST effects on NO_2 concentrations. *Eng. Rep.* 2026, *8*, e70436.
35. Singh, J.; Kumar, P.; Kale, A.; Yadav, A.K.; Maurya, P.K.; Kumar, D.; Ahamad, F. Spatio-temporal analysis of air quality in Haridwar City. *Environ. Monit. Assess.* 2025, *197*, 889.