Open Journal of Air Pollution, 2026, 15(3), 154-176
https://www.scirp.org/journal/ojap
ISSN Online: 2169-2661
ISSN Print: 2169-2653

Analysis of Spatio-Temporal Distribution of Air Quality Index in Nairobi City County: Observations from Sentinel-5P TROPOMI

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How to cite this paper: Nyanchoka, M.V., Ndunda, E., Kitur, E., Muindi, K. and Judith, E. (2026) Analysis of Spatio-Temporal Distribution of Air Quality Index in Nairobi City County: Observations from Sentinel-5P TROPOMI. *Open Journal of Air Pollution*, **15**, 154-176.
https://doi.org/10.4236/ojap.2026.153009

Received: July 13, 2026
Accepted: September 21, 2026
Published: September 24, 2026

Abstract

The high rate of urbanisation is one of the key causes of poor air quality, particularly in low- and middle-income countries where the monitoring systems remain inadequate amidst weak policy implementation. Nairobi City County, the largest city in East and Central Africa, is witnessing a continuously growing population, thus an increase in vehicle and motorbike volume, and industrialisation, which together lead to a high level of criteria air pollutants in its varied land use areas. This study examined the spatio-temporal Air Quality Index (AQI) across four land use patterns in Nairobi, including commercial, residential, industrial, and green park, using data from six administrative sub-counties: Starehe, Westlands, Kibra, Ruaraka, Makadara, and Embakasi East for the period 2020 to 2024. Carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), and sulphur dioxide (SO_2) gas concentrations were acquired from the Sentinel-5 Precursor (Sentinel-5P) satellite, and processed using Google Earth Engine (GEE), while the fine particulate matter ($PM_{2.5}$) concentrations were obtained using ground-based low-cost sensors deployed in collaboration with AirQo. One-way Analysis of Variance (ANOVA) was used to test the differences in pollutant concentrations across the four spatial land use zones, with repeated measures ANOVA applied to assess the temporal variation across the morning, afternoon, and evening measurement periods. The one-way ANOVA results revealed that the pollutant levels across the four land use patterns differed significantly ($F = 5.41$, $p = 0.0001$). On the other hand, the post-hoc Tukey HSD test found that the pairwise differences between industrial and commercial areas ($p = 0.005$) and between commercial and green park areas ($p = 0.023$) were significant. The repeated measures ANOVA of temporal analysis showed that there was a significant difference in the concentrations between the times of the day ($F = 4.57$, $p = 0.0192$), with a significant variation between evening and afternoon ($p = 0.011$) and a not statistically significant variation between morning and afternoon ($p = 0.052$). The weighted AQI calculations derived from the study data verified that commercial areas had the highest overall AQI of 115.452 among the four land use areas, which aligns with their heavy vehicular traffic and high density of business activities. These findings support the claim that the structure of land use and time of day significantly influence pollutant levels in Nairobi. Specific policy interventions on traffic management, emissions, and strategic urban greening should be recommended to reduce exposure to pollution in all land use areas.

Keywords

Spatial Variation, Temporal Variation, Air Pollutants, Land Use Patterns, Air Quality Index, Sentinel-5P TROPOMI

1. Introduction

Air pollution is one of the most critical environmental and public health problems of the 21st century, with its effects being disproportionately experienced in the rapidly urbanising cities of low- and middle-income countries. Sub-Saharan Africa is especially vulnerable because it is the world's fastest urbanizing region with rapid population growth. Projections show continued population growth and urbanisation alongside increasing sources of emissions. Air pollution in Africa is directly linked to about 1.1 million premature deaths, yet the continent remains among the most under-monitored regions in the world, with only 19 out of 54 countries possessing adequate public air quality data [1]. Nairobi, Kenya, has continuously been listed as one of the three most polluted cities in sub-Saharan Africa alongside Lagos and Addis Ababa, making it a pressing issue that requires research evidence.

In cities, the spatial and temporal distribution of air pollutants depends on complex interactions between emission sources, land use patterns, weather conditions, and human activities. Land use patterns determine the quality and concentrations of pollutant emissions, while commercial zones most likely release high concentrations of $PM_{2.5}$, NO_2, and CO due to the fact that road transportation and industrial processes emit elevated amounts of SO_2 and NO_2 [2]. Residential areas are exposed to biomass burning, cooking, and waste burning, while green zones, which are typically associated with cleaner air, are not exempt from the dynamics of urban pollution, especially in cases of low atmospheric dispersion or high ozone formation [3]. Understanding the manner in which these disparities in land use are transformed into quantifiable changes in the concentration of pollutants is needed in the formulation of specific mitigation strategies.

The temporal factor of air quality in the city is equally critical. Diurnal changes in pollutant concentrations reveal the contribution of traffic patterns, the atmospheric boundary layer, and photochemical processes. Studies have consistently indicated that the maximum concentration of NO_2 and CO is recorded during the rush hours in the morning and evening when vehicular traffic is high, while the highest levels of ozone are observed in the afternoon hours when the precursor gases undergo photochemical reactions due to the influence of solar radiation [4]. These temporal changes are also modulated by meteorological conditions such as wind speed, temperature, humidity, and precipitation, since they regulate the spread, accumulation, and elimination of pollutants in the urban atmosphere [5]. Temporal changes in pollutants are influenced by seasonal variations since bimodal rainfall and specific dry seasons create different atmospheric conditions.

Earlier studies of air quality in Nairobi established that PM concentrations are consistently higher than the World Health Organization recommendations [6] [7]. A three-year follow-up study using a beta attenuation monitor at a central location in Nairobi reported a daily mean $PM_{2.5}$ concentration of 19.2 μg/m^3, with the lowest concentrations at 03:00 and the highest at 20:00 [8]. Further, recent research proved that fossil fuel burning, primarily traffic-related, is a major source of particulate pollution in Nairobi, accounting for approximately 85% of the total black carbon measured throughout the year [9]. These studies have either relied on satellite observations of gaseous pollutants or localized ground-based $PM_{2.5}$ monitoring, limiting their ability to simultaneously characterize the spatial distribution of atmospheric gases and near-surface particulate exposure across contrasting urban land-use categories. By integrating Sentinel-5P TROPOMI observations with AirQo ground measurements, this study provides a more comprehensive assessment of AQI variability and strengthens evidence for land-use-specific pollution management in Nairobi.

The Sentinel-5P TROPOMI sensor has transformed the ability of large-scale atmospheric surveillance with satellite-based measurements, which offer daily global coverage and a spatial resolution of about 7.2 by 3.6 kilometres and allow the detection of trace gases such as NO_2, SO_2, CO, and O_3 in diverse urban environments [10] [11]. Studies utilising Sentinel-5P data over urban centres in Africa have profiled the spatial distribution of pollutants, including spatio-temporal variations of NO_2 and land surface temperature in Nairobi [12] and the pollutant dynamics in Egyptian and Nigerian urban centres [13] [14]. However, there is limited literature on the systematic integration of Sentinel-5P satellite data and ground-level $PM_{2.5}$ measurements to analyse the distributions of AQI across land use categories in Nairobi, which represents a gap that this study aims to address.

The Sentinel-5 Precursor Satellite

In this research, the atmospheric gases data were obtained from the Sentinel-5 Precursor (Sentinel-5P) satellite, which is part of the Copernicus Earth Observation Programme under the management of the European Space Agency (ESA). The Sentinel-5P satellite was launched in October 2017 with the main aim of ensuring that air quality and atmospheric composition are monitored at a global level.

The satellite also houses the TROPOspheric Monitoring Instrument (TROPOMI), which records the interaction between sunlight and the Earth's atmosphere in different spectral bands, allowing the detection of various trace gases affecting air quality [11].

Sentinel-5P offers near-daily global coverage at a spatial resolution of about 7 by 3.5 kilometres, which is sufficiently high to detect intra-urban pollution variations across regions such as Nairobi. The data is free and can be accessed via platforms like Google Earth Engine (GEE), which allows for large-scale atmospheric analysis without the need for complicated computing infrastructure [15]. The main pollutants that TROPOMI measures include nitrogen dioxide (NO_2), which is mainly produced by traffic and industrial combustion; carbon monoxide (CO), produced by incomplete fuel combustion; sulphur dioxide (SO_2), emitted by industrial processes and the burning of fossil fuels; and the secondary pollutant ozone (O_3), formed during photochemical reactions between NO_2 and volatile organic compounds in the presence of sunlight. The various pollutants are stored as individual datasets that denote the cumulative column density of the gas in the vertical atmospheric column at a given location [8].

These datasets were filtered within GEE to cover the period from January 2020 to June 2024 and limited to the administrative jurisdiction of Nairobi County. Sentinel-5P was chosen as the main source of atmospheric data due to its consistency, high resolution, and globally validated data. This will complement ground-based monitoring networks, which remain spatially limited in the context of Nairobi [12]. Its daily revisit ability contributes to the establishment of consistent monthly and yearly averages of concentration that are necessary in the detection of trends and spatio-temporal analysis. Research demonstrates the potential of Sentinel-5P TROPOMI data for spatio-temporal monitoring of atmospheric pollutants across diverse land use types, supporting the suitability of this satellite platform for urban air quality research in data-scarce environments [16].

The present study therefore had the following objectives:

1) Characterize the spatial distribution of major atmospheric pollutants and AQI across commercial, residential, industrial, and green park land-use categories in Nairobi City;

2) Evaluate temporal variations in pollutant concentrations across different times of the day;

3) Demonstrate the value of integrating Sentinel-5P TROPOMI observations with ground-based AirQo $PM_{2.5}$ measurements for comprehensive urban air quality assessment. Based on these objectives, the null hypothesis was that there is no significant spatial or temporal difference in the concentrations of criteria air pollutants across the study area.

The findings offer empirical data to support evidence-based environmental governance and urban planning in one of the most rapidly developing urban centres in sub-Saharan Africa.

2. Methodology

2.1. Study Area

Nairobi City County is the capital of Kenya and the largest city in East and Central Africa. The city is geographically located between 1˚9' S and 1˚28' S latitude and 37˚10' E longitude, with a total area of 684 km^2 at an elevation of about 1690 metres above mean sea level. Nairobi has a bimodal rainfall pattern, with long rains from March through May and short rains from October to December. The highest temperatures are usually recorded between the months of December and March, while the coolest period occurs between the months of June and August. The 2019 national census showed Nairobi had a population of 4,397,073 people [17], though estimates published later show that the population had grown to approximately 5.2 million by 2022, with a projected increase to about 6 million by 2030 [18]. Nairobi City County is administratively divided into 17 sub-counties and 85 wards. In this study, six sub-counties were purposively chosen on the basis of their representation of various land use patterns: Starehe, Westlands, Kibra, Ruaraka, Makadara, and Embakasi East. These sub-counties were further divided into four land use categories (commercial, residential, industrial, and green park areas). This classification enabled a systematic comparison of the levels of pollutants between zones with radically different emission patterns and human activity patterns. Figure 1 demonstrates the geographical coverage of the study area, including the sites of ground-based data collection stations in the six sub-counties.

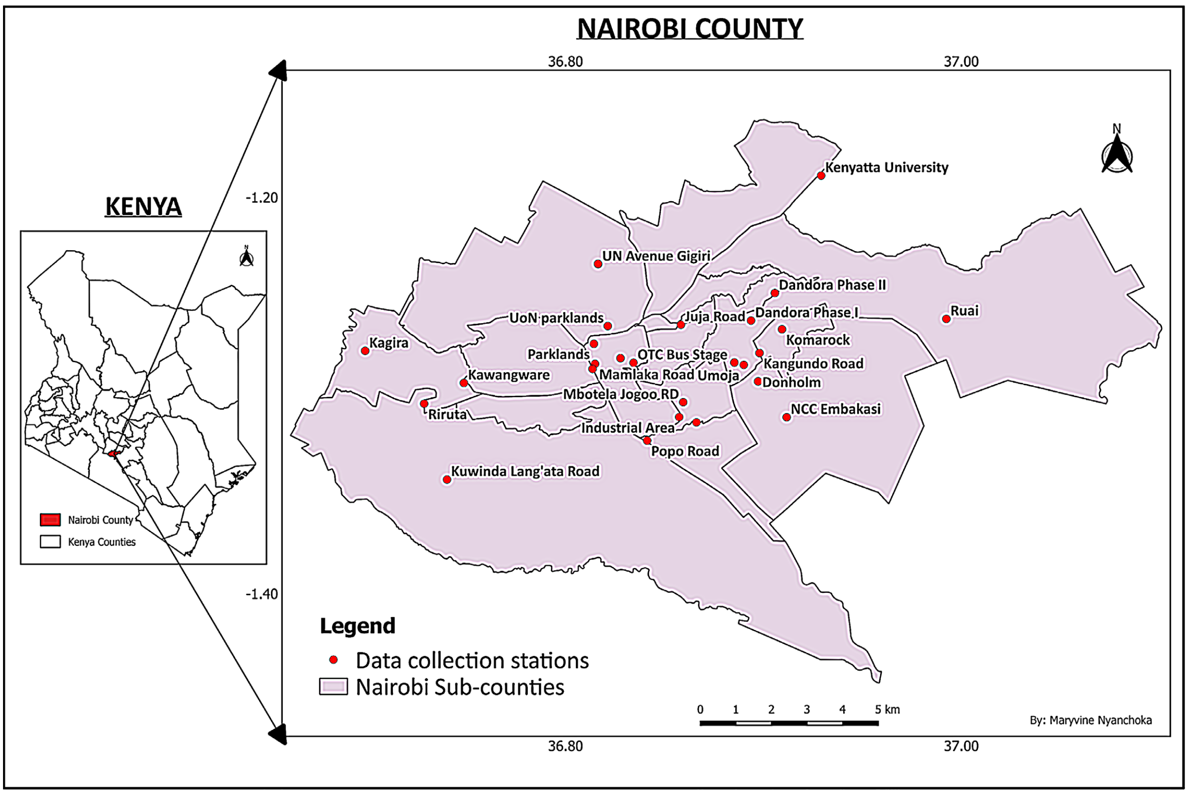


Figure 1. Study area of Nairobi City County.

2.2. Meteorological Data

The Kenya Meteorological Department provided the meteorological data, which included precipitation, relative humidity, temperature, and atmospheric pressure for the period January 2020 to June 2024 [19]. These data were applied to contextualize the observed trends in pollutant concentration by accounting for the effects of the prevailing atmospheric conditions on the dispersion, accumulation, and photochemical transformation of pollutants within the study area.

2.3. Sentinel-5P Data Acquisition and Processing

Google Earth Engine (GEE) was used to perform all pre-processing and analysis of atmospheric data. The Sentinel-5P level-3 products of CO, NO_2, O_3, and SO_2 were imported from the Copernicus archive in GEE. All pollutant datasets were spatially filtered to include Nairobi County using a shapefile of the administrative boundaries of the county and temporally to include the study period from January 2020 to June 2024. Monthly composite images were then produced using the mean reducer to minimize daily variability caused by cloud interference and orbital noise so that average concentrations for each month during the study period would be representative. The dataset was then mosaicked, a process used to select pixels with the highest quality flags, and the values of the gas column number density of those pixels were extracted and stored in tabular form along with their geographic coordinates. The processed data were exported to CSV files and raster GeoTIFF images, which were then sampled within the Nairobi study area to provide monthly concentration values in mol per square meter per pollutant. This processing approach aligns with existing literature on the methodology of assessing urban air quality using Sentinel-5P data [12] [16].

The extracted pollutant data were subsequently overlaid with land-use polygons in a QGIS environment, enabling each pixel to be assigned to one of the four land-use categories (commercial, residential, industrial, or green park). Monthly pollutant concentrations were then aggregated within each land-use class for subsequent statistical analysis and AQI computation. Because Sentinel-5P products are provided as total atmospheric column number densities (mol m^{-2}), whereas AQI thresholds are defined using near-surface pollutant concentrations (ppm or ppb), an intermediate conversion was required. Column densities were converted to approximate surface concentrations by assuming a uniform atmospheric boundary layer height of approximately 1113 m and applying the appropriate unit scaling to obtain indicative near-surface concentrations. This simplified approach facilitated comparison with AQI breakpoints across the different land-use categories while maintaining consistency among the gaseous pollutants. However, it does not explicitly account for vertical atmospheric mixing, meteorological variability, or local emission dynamics [20].

2.4. Particulate Matter Data

The $PM_{2.5}$ data were obtained through low-cost sensors that were deployed across the Nairobi City County in partnership with AirQo, an air quality monitoring network operating across 14 African nations. AirQo sensors utilise light scattering technology to quantify concentrations and simultaneously measure ambient meteorological conditions, such as humidity and atmospheric pressure, and transmit the data to a cloud-based network in near real-time [21]. The data collection for $PM_{2.5}$ spanned the period between 2023 and 2024 and was carried out in collaboration with the Nairobi County data management system. The sensors were deployed at locations in the six study sub-counties that were representative of each land use category.

2.5. Air Quality Index Calculation

The linear interpolation equation commonly used in the U.S. EPA AQI framework was applied using the pollutant-specific concentration breakpoints adopted from the WHO air-quality guideline framework. The formula used was:

$$\text{AQI} = \left[\left(I_{hi} - I_{low}\right) / \left(BP_{hi} - BP_{low}\right)\right] \times \left(C_p - BP_{low}\right) + I_{low}$$

where C_p is the rounded concentration of pollutant p, BP_{hi} and BP_{low} are the concentration breakpoints bracketing C_p, and I_{hi} and I_{low} are the AQI values corresponding to those breakpoints. For the gaseous pollutants (CO, NO_2, SO_2, and O_3), the AQI calculations were based on the approximate surface concentrations derived from the Sentinel-5P column density products as described in Section 2.3. Accordingly, the resulting AQI values are intended to provide a standardized basis for comparing relative air quality conditions across land-use categories and should not be interpreted as regulatory compliance values.

WHO AQI breakpoints were employed since they are grounded on health-based exposure limits derived from moderate or high certainty epidemiological evidence and offer a consistent and internationally comparable basis for categorising air quality into levels such as Good (0 to 50), Moderate (51 to 100), Unhealthy for Sensitive Groups (101 to 150), Unhealthy (151 to 200), Very Unhealthy (201 to 300), and Hazardous (301 to 500) [22] [23]. The resulting AQI values should be interpreted as indicative measures of relative spatial variation rather than as direct assessments of compliance with ambient air quality standards.

Weighted Air Quality Index

Following the calculation of pollutant-specific AQI values for CO, NO_2, SO_2, O_3, and $PM_{2.5}$, an overall AQI was computed for each land-use category using a weighted aggregation approach. Monthly AQI values for each pollutant were first calculated and subsequently averaged within each land-use category. The weighted AQI was then derived as:

$$\text{WAQI} = \sum_{i=1}^{n} w_i \, \text{AQI}_i$$

where AQI_i is the AQI of pollutant i and w_i is its assigned weighting factor. The resulting weighted AQI provided a single composite indicator representing the overall air quality condition for each land-use category during the study period.

To obtain a composite weighted AQI for each land-use category, pollutant-specific AQI values were combined using normalized pollutant weights. The weights were set to $PM_{2.5}$ (0.35), O_3 (0.30), NO_2 (0.15), CO (0.10), and SO_2 (0.10), summing to 1.00. The weighting scheme was informed by the relative health significance of the pollutants described in WHO (2021). The weighted AQI was calculated as: $\text{WAQI} = \sum \left(w_i \times \text{AQI}_i \right)$, where w_i represents the normalized weight assigned to pollutant i and AQI_i represents its corresponding pollutant-specific AQI. The resulting value represents a composite indicator of air-quality conditions across the land-use categories.

2.6. Statistical Analysis

Sentinel-5P and AirQo datasets represent different atmospheric quantities and differ in both measurement principles and temporal coverage. Sentinel-5P provided monthly observations of gaseous pollutants (CO, NO_2, SO_2, and O_3) for the period January 2020 to June 2024, while the AirQo monitoring network provided ground-based $PM_{2.5}$ measurements for the period 2023-2024. Consequently, analyses for the period 2020-2022 were based solely on the Sentinel-5P gaseous pollutant observations. During the overlapping period (2023-2024), the Sentinel-5P gaseous pollutant data and AirQo $PM_{2.5}$ measurements were integrated to provide a more comprehensive assessment of urban air quality across the study area. This integration capitalized on the complementary strengths of satellite-derived spatial coverage and ground-based particulate matter monitoring, while recognizing that the two datasets represent different atmospheric quantities. The integration was interpreted as complementary evidence of urban air quality patterns rather than as direct equivalence between satellite-derived column densities and ground-level $PM_{2.5}$ measurements.

Because Sentinel-5P has a fixed daytime overpass, it does not provide direct observations of pollutant concentrations during the morning, midday, and evening periods. To facilitate the temporal assessment, an extrapolation algorithm was applied to the available satellite observations to estimate pollutant concentrations for the three defined periods. The resulting values were therefore treated as estimated temporal profiles rather than direct measurements. This approach enables assessment of potential diurnal variation but does not provide the same temporal resolution as continuous ground-based monitoring.

In order to test the null hypothesis that there's no significant difference between the concentration of criteria air pollutants in space and time in Nairobi City County, two complementary statistical methods were used. One-way Analysis of Variance (ANOVA) was employed to identify whether statistically significant differences existed in mean pollutant concentrations across the four land use areas (residential, industrial, commercial, and green park). This test is suitable when comparing means across more than two independent groups with a continuous outcome variable [2]. In situations where the one-way ANOVA test gave a significant value, the Tukey Honest Significant Difference (HSD) post-hoc test was used to identify which specific pairs of land use areas varied significantly in their concentration of pollutants.

ANOVA was conducted separately for each pollutant. For the spatial analysis, the analytical units comprised the four land-use categories represented across the six selected sub-counties, resulting in 24 observations (4 land-use categories × 6 sub-counties). For the temporal analysis, three measurement periods (morning, midday, and evening) were considered across the five pollutants, resulting in 15 observations (3 time periods × 5 pollutants). Sentinel-5P gaseous pollutant observations were aggregated monthly, with 12 monthly observations per year during the study period, while $PM_{2.5}$ observations covered the 2023-2024 period. Pollutant values were standardized before pooling to account for differences in measurement scales. A two-factor ANOVA was later conducted to assess differences in pollutant concentrations across the four land-use categories and among the five pollutants.

This method considers within-subject correlation in repeated measurements over time from the same sampling locations, and thus it is suitable for identifying temporal variation of pollutant levels at various times of the day [4]. Tukey HSD post-hoc tests were again applied to identify specific temporal pairs whose differences were statistically significant. All the statistical analyses were performed at the level of significance of 0.05.

3. Results and Discussion

3.1. Spatial Variation of Air Quality Index across Land Use Areas

The one-way ANOVA findings confirmed a significant difference in the pollutant concentrations across the four land use areas in Nairobi City County, as summarised in Table 1. The F-value of 5.41 and p-value of 0.0001 suggest that land use classification is a significant explanatory variable for the pollutant concentration differences within the study area. This finding is consistent with a growing body of literature on sub-Saharan African cities demonstrating that urban land use strongly influences air quality, with industrial and commercial areas posing significantly greater risks of pollution than residential and vegetated zones [24].

Table 1. ANOVA summary for spatial variation of pollutant concentrations.

Source	Df	Sum Sq	Mean Sq	F-value	Pr (>F)
Area Land Use	3	25.78	8.593	5.41	0.0001***
Pollutant	4	15.23	3.807	2.15	0.0325*
Residuals	16	25.56	1.597		

*p < 0.05; ***p < 0.001.

The ANOVA result of high spatial variation aligns with international studies on the heterogeneity of urban pollution. The diurnal and spatial variation in gaseous pollutant concentrations across cities in China was highly structured by differences in land use, population density, and emission source profiles [4]. Similarly, a study conducted in Nairobi on the spatio-temporal distributions of NO_2 using Sentinel-5P data found that areas with higher population densities and intensive urban activities had significantly higher concentrations of NO_2 than less populated areas [12]. This study builds on this evidence by showing that the spatial organisation of pollutant concentrations is consistently applicable to a wider range of pollutants when areas are categorised by land use type.

3.2. Post-Hoc Analysis of Spatial Differences

The Tukey HSD post-hoc test identified the specific pairs of land use areas with statistically significant differences in concentrations, as indicated in **Table 2**. Among the six pairwise comparisons, significant differences were found between industrial and commercial areas ($p = 0.005$) and between commercial and green park areas ($p = 0.023$). The comparison between residential and industrial areas produced a statistically insignificant outcome ($p = 0.058$), while the other comparisons were not statistically significant.

Table 2. Tukey HSD post-hoc results for spatial variation (The asterisks indicate statistical significance and show how extreme a p-value is: more asterisks indicate higher significance).

Comparison	Difference	Lower CI	Upper CI	p adj
Residential vs Industrial	0.021	−0.001	0.043	0.058†
Residential vs Commercial	−0.012	−0.035	0.011	0.338
Residential vs Green Park	0.015	−0.008	0.038	0.185
Industrial vs Commercial	−0.033	−0.055	−0.011	0.005**
Industrial vs. Green Park	−0.006	−0.028	0.017	0.451
Commercial vs. Green Park	0.027	0.004	0.051	0.023*

*$p < 0.05$; **$p < 0.01$; †Marginally significant ($p < 0.06$).

This significant difference between industrial and commercial areas indicates the divergent emission patterns of the two land use types. The emissions from manufacturing processes and heavy machinery that generate high levels of SO_2, NO_2, and $PM_{2.5}$ are the main characteristics of industrial zones in Nairobi, which are mostly concentrated in areas such as Makadara. Conversely, commercial zones, such as the central business district within Starehe and the commercial corridors of Westlands, produce high levels of $PM_{2.5}$, NO_2, and CO due to heavy vehicular traffic, emissions from generators in businesses, and constant human activity throughout the day. Similar studies in other urban African settings have discovered that ANOVA established a significant spatial variation of CO and PM_{10} across land use zones, with industrial and commercial activities posing the most dangerous polluters in sub-Saharan settings [24].

The difference between commercial and green park spaces underscores the pollution-buffering capacity of vegetated spaces, even in an urban grid that is highly affected by the emissions of surrounding sources. Green parklands in Nairobi, including some portions of the Karura Forest and the Uhuru Park environs within the study sub-counties, consistently recorded lower concentrations of most of the pollutants compared to commercial areas. Nevertheless, this buffering effect is partial and dependent on the direction and strength of winds, proximity to surrounding roads, and the photochemical production of secondary pollutants like ozone. A study of 2615 monitoring stations in Europe and the United States revealed that the impact of urban green space on air pollution reduction was small and highly inconsistent, especially at the street level, where dense vegetation can inhibit airflow and trap pollutants [3].

The finding of residential and industrial regions ($p = 0.058$) suggests that there is a proximity between the pollution levels found in industrial areas and those experienced in residential areas. This aligns with the spatial organisation of Nairobi, where informal and semi-formal residential settlements are often found near or even within the industrial corridors. Population density is positively correlated with NO_2 concentration in Nairobi constituencies, with regions of dense informal settlements exhibiting pollution levels comparable to those in formally designated industrial areas [12]. Household energy sources such as biomass, as well as the burning of garbage, are potential contributing factors to the noted marginal significance, as they contribute to both indoor and ambient air pollution [25]. These results indicate that there is a need to develop integrated land use planning that will establish efficient buffer zones between residential areas and high-emission industrial sources.

3.3. Temporal Variation of the Air Quality Index

The repeated-measures ANOVA indicated a statistically significant difference among the estimated pollutant concentrations for the morning, midday, and evening periods ($F = 4.57$, $p = 0.0192$), as shown in **Table 3**. Because Sentinel-5P provides a fixed daytime overpass, these temporal values were estimated using the extrapolation algorithm described in Section 2.6 and should therefore be interpreted as indicative temporal patterns rather than direct observations of diurnal variability. The estimated temporal profiles are broadly consistent with bimodal patterns of traffic-related pollution reported in previous urban air-quality studies, where morning and evening traffic peaks are associated with elevated pollutant concentrations [4] [25]. However, because the Sentinel-5P observations were extrapolated to represent the three periods, this pattern should be interpreted as indicative rather than as a directly observed diurnal cycle [4] [26].

The finding aligns with studies that have investigated the diurnal pollution patterns in similar developing-country cities. An urban-scale mobile monitoring

Table 3. ANOVA summary for temporal variation in pollutant concentrations.

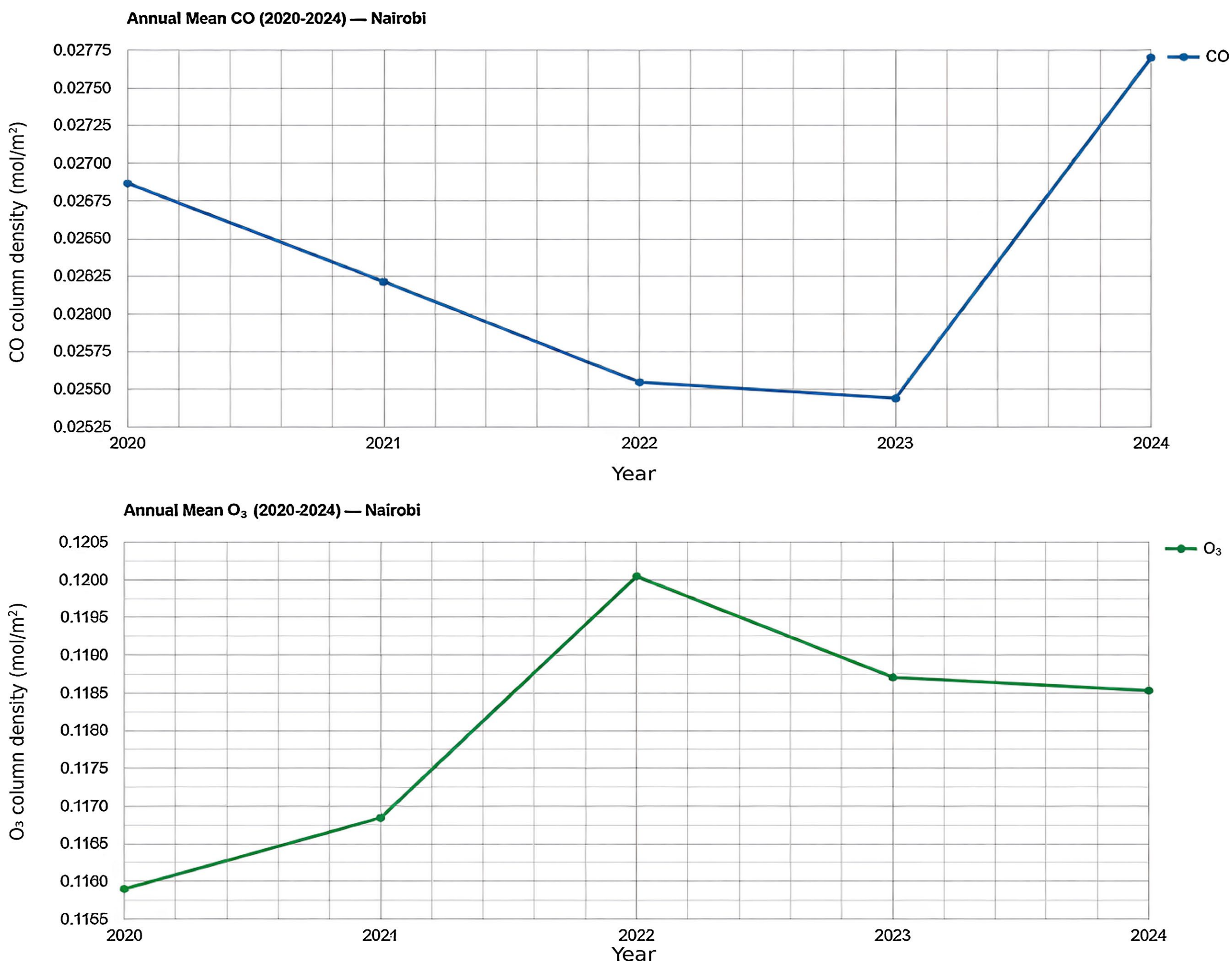
Source	Df	Sum Sq	Mean Sq	F-value	Pr (>F)
Time of Day	2	25.34	12.67	4.57	0.0192*
Residuals	12	33.56	2.80		

*$p < 0.05$.

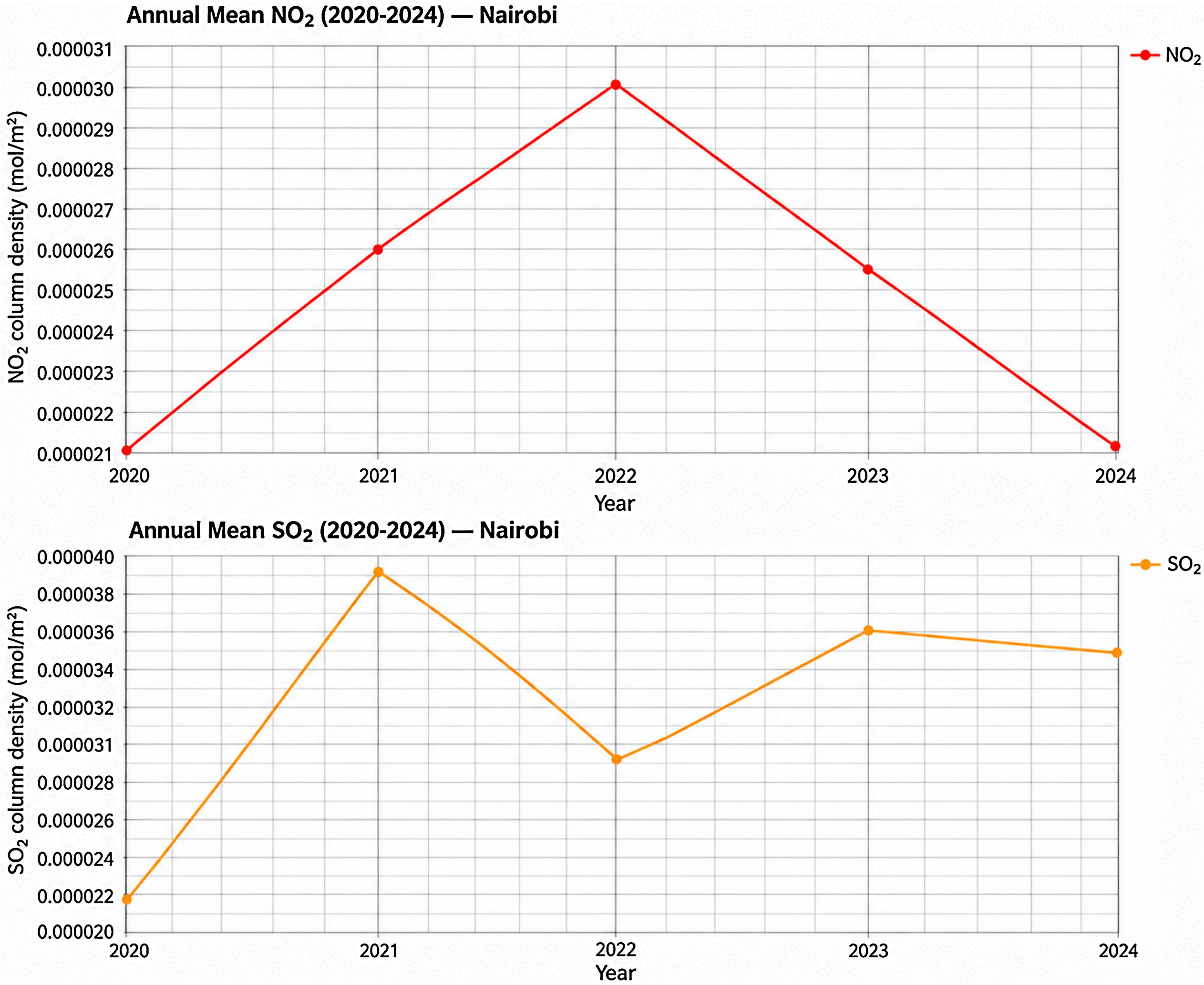
study in Shaoxing, China, revealed that the concentration of CO, NO_2, and SO_2 was significantly higher during morning and evening rush hours in all four seasons due to the concentration of vehicular traffic during commuting times [27]. Equally, a study conducted in Jakarta demonstrated that $PM_{2.5}$ levels were highest at 07:00 in urban centres due to rush hour traffic, and again in the evening due to thermal inversion effects, which inhibit vertical atmospheric mixing during nocturnal cooling [28].

Figure 2(a) and **Figure 2(b)** illustrate the annual trends in the mean concentrations of CO, O_3, SO_2, and NO_2 across Nairobi between 2020 and 2024, revealing distinct temporal patterns for each pollutant. CO exhibited a gradual decline from 2020 to 2023 before increasing sharply in 2024, resulting in the highest annual mean concentration during the study period. This suggests a recent increase in combustion-related emissions, potentially associated with growing vehicular traffic, industrial activities, or other anthropogenic sources.

In contrast, O_3 and NO_2 displayed similar temporal behaviour, with concentrations increasing steadily from 2020 to a peak in 2022, followed by a gradual decline



(a)



(b)

Figure 2. (a) Annual mean concentrations of carbon monoxide (CO) and ozone (O_3) in Nairobi City County from 2020 to 2024; (b) Annual mean concentrations of nitrogen dioxide (NO_2) and sulphur dioxide (SO_2) in Nairobi City County from 2020 to 2024.

through 2024. The concurrent rise in both pollutants up to 2022 may reflect increasing urban emissions and favourable atmospheric conditions for photochemical processes, while the subsequent decline suggests changes in emission intensity or atmospheric conditions influencing pollutant formation and dispersion.

SO_2 exhibited the greatest year-to-year variability among the pollutants. Concentrations increased markedly from 2020 to 2021, declined in 2022, and then increased again in 2023 before showing a slight reduction in 2024. Unlike CO, O_3, and NO_2, the irregular temporal pattern of SO_2 indicates that its concentrations were likely influenced by episodic industrial activities and localized combustion sources rather than sustained long-term trends. Overall, the observed annual variations demonstrate that gaseous pollutant concentrations in Nairobi have evolved differently over time, reflecting the combined influence of changing emission sources and meteorological conditions.

3.4. Post-Hoc Analysis of Temporal Differences

The Tukey HSD post-hoc analysis of the temporal variation identified the time period pairs that were significantly different, as presented in **Table 4**. The afternoon vs. evening comparison yielded a statistically significant difference ($p = 0.011$), indicating that the concentrations of pollutants during the evening hours were meaningfully higher than those recorded in the afternoon. The morning-to-afternoon comparison was not statistically significant ($p = 0.052$), although the observed decrease is consistent with the expected influence of daytime atmospheric mixing. The difference in the morning and evening comparison was insignificant ($p = 0.351$).

Table 4. Tukey HSD post-hoc results for temporal variation.

Comparison	Difference	Lower CI	Upper CI	p adj
Morning vs Afternoon	0.02	−0.001	0.043	0.052†
Morning vs Evening	−0.01	−0.033	0.013	0.351
Afternoon vs Evening	−0.03	−0.053	−0.007	0.011*

*$p < 0.05$; †$p < 0.10$ (marginal).

The concentration is high in the evening relative to the afternoon due to several factors. First, during the evening rush hour, the return of commuter traffic increases vehicular emissions of CO, NO_2, and $PM_{2.5}$, which reflects the morning peak and creates the bimodal diurnal pattern characteristic of traffic-dominated urban pollution [4]. In Nairobi, this effect is amplified by the notorious traffic jams, which extend into the evening hours and keep vehicles moving at low speeds, a factor that is linked to about a 50% increase in CO and hydrocarbon emissions relative to free-flowing traffic [29]. In addition, the atmospheric boundary layer decreases as the evening temperature falls, reducing the vertical volume available for pollutant dilution and increasing the concentration of pollutants at the surface [5].

The slight decrease in concentrations between the morning and afternoon indicates the contribution of solar heating in enhancing atmospheric mixing during the day. As the day deepens in the morning and early afternoon hours, pollutants are diluted in a greater atmospheric volume due to convective heating, temporarily reducing the surface concentrations. Such a trend has been noted and reported in various urban environments. Research conducted in Tehran recorded $PM_{2.5}$ peaks in the early morning and lower in the afternoon because of the intense boundary layer [30]. This midday decline in surface pollutant concentrations is probably accelerated by daytime convective mixing in Nairobi, where afternoon temperatures are very high during the dry season, a process that reverses in the evenings as temperatures fall and stability increases.

The absence of a significant variation between morning and evening concentrations ($p = 0.351$) shows that both timeframes are characterized by relatively high levels of pollution, which is consistent with the bimodal nature of the traffic pattern. The implication of this result is that Nairobi commuters are exposed to a high level of pollution during the morning and evening commutes. In an investigation of the in-vehicle $PM_{2.5}$ and PM_{10} concentrations in urban environments during the commute period, the research found that the morning rush hour concentrations were comparable to or slightly higher than those in the evening, depending on the traffic volume and weather conditions [31]. These rush-hour peak traffic levels within the Nairobi setting, where a large percentage of the population relies on matatus and other modes of shared transportation, constitute a major source of daily pollution exposure that requires targeted traffic management measures.

3.5. Seasonal and Meteorological Influences on Pollutant Variability

The spatial and temporal patterns of pollutant concentrations identified in this study are mediated by meteorological conditions, including wind speed and direction, temperature, humidity, and precipitation. The concentration of most pollutants has a negative relationship with wind speed, with fast winds enhancing horizontal dispersal and dilution of emissions away from their sources, while calm weather conditions lead to pollutant accumulation, particularly in highly populated commercial and industrial zones [5]. This high-accumulation density and regular traffic congestion in commercial zones of Nairobi create street canyon effects that trap the pollutants at ground level by limiting the horizontal movement of wind, which can disperse the emissions [29].

Nairobi experiences seasonal weather conditions that offer great modulation of the ground levels of pollutants, which superimpose the daily patterns identified in this study. The low precipitation and low wind speed in the dry seasons from June to August and December to February result in high concentrations of pollutants in all land use zones. Recent research found that the highest concentrations of $PM_{2.5}$ in Nairobi were observed in August during the long dry season, and the lowest concentrations were observed in April during the wet season, a pattern consistent with the role of rainfall in washing pollutants from the atmosphere [8]. Conversely, high temperatures during the dry season favour photochemical ozone formation, especially in open spaces such as green parks where the concentration of the precursors from the surrounding vehicular emissions accumulates without the shading and absorption effects of building canopies.

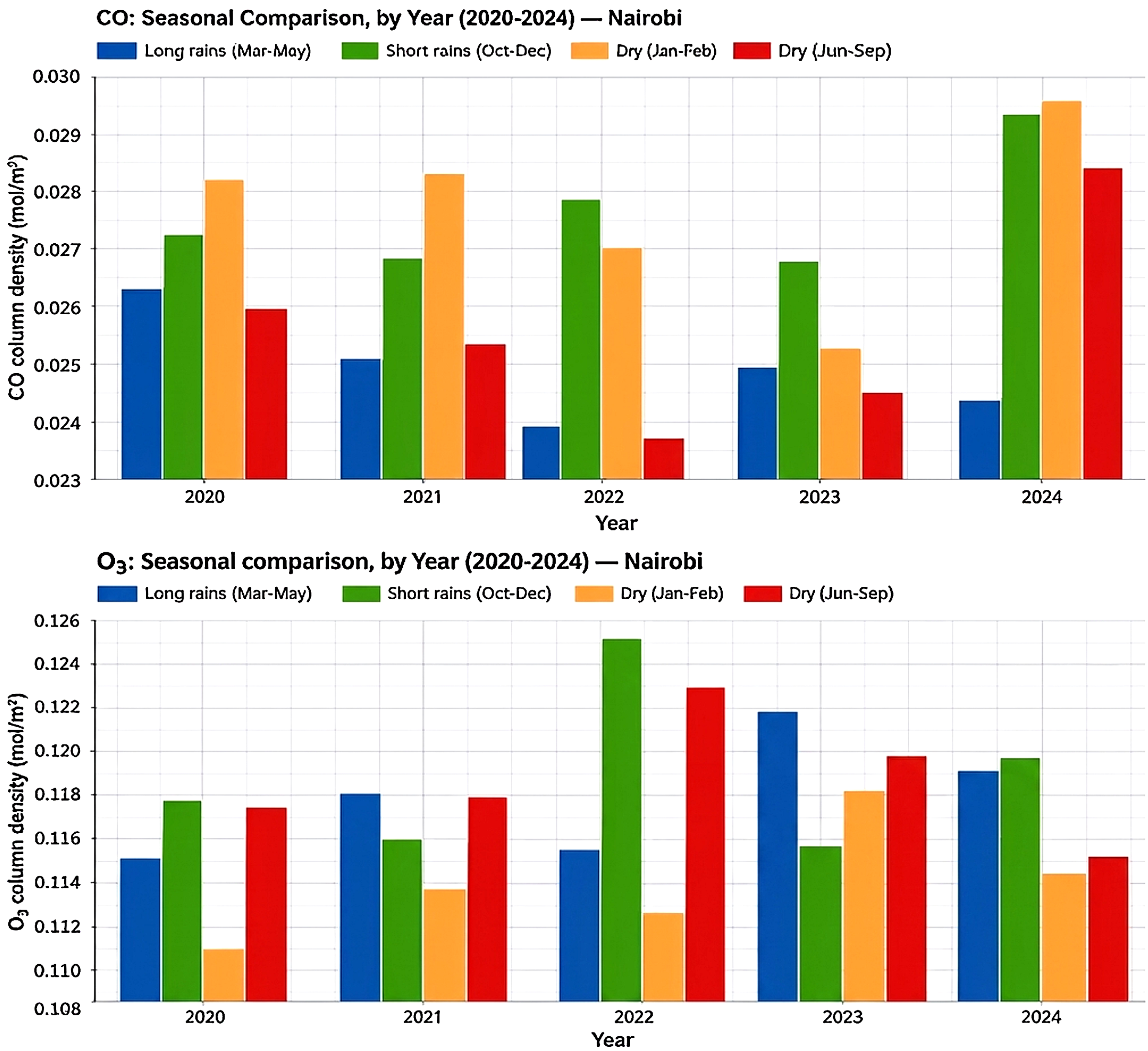
Figure 3(a) shows the seasonal variation in CO and O_3 concentrations in Nairobi. CO concentrations were generally higher during the January-February dry season and the short rains (October-December), with noticeably elevated concentrations across all seasons in 2024. O_3 displayed comparatively higher concentrations during the short rains and the June-September period in several years, consistent with seasonal differences in atmospheric conditions that favor ozone formation.

Figure 3(b) shows the seasonal variation in NO_2 and SO_2 concentrations in

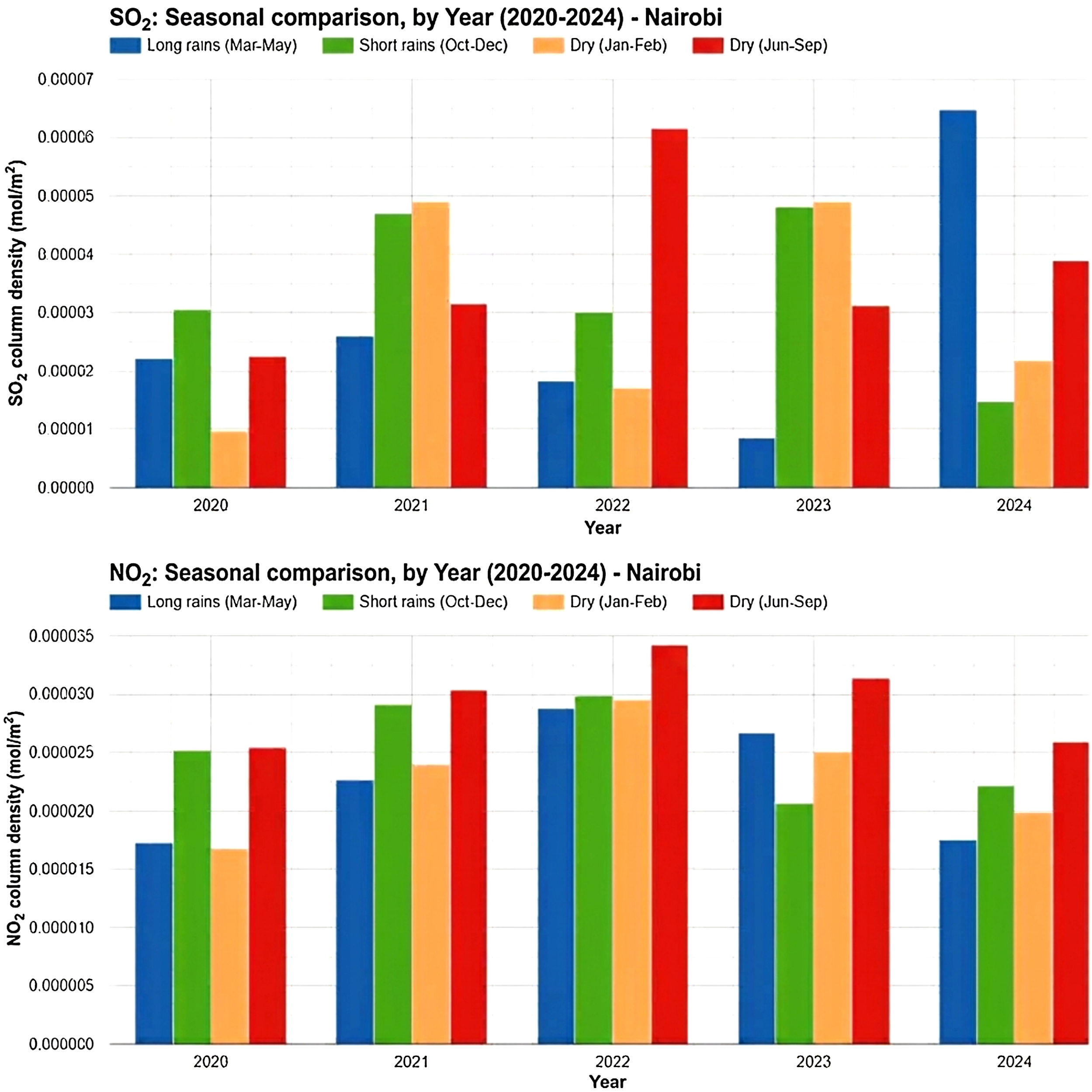
Nairobi. NO_2 exhibited a more consistent seasonal pattern, reaching its highest concentrations around 2022 and frequently peaking during the June-September dry season, reflecting the persistence of urban emission sources. In contrast, SO_2 showed considerable interannual variability, with seasonal peaks shifting across the study period rather than following a consistent seasonal trend, suggesting the influence of localized emission events.

Overall, these observations indicate that seasonal meteorological conditions influence pollutant behaviour in Nairobi, although the magnitude and timing of seasonal changes vary according to the emission characteristics and atmospheric processes governing each pollutant.

Relative humidity has a more complex effect on pollutant dynamics—high humidity promotes the hygroscopic growth of particulate matter and enhances



(a)



(b)

Figure 3. (a) Seasonal variation in mean concentrations of CO and O_3 across the long rains (March-May), short rains (October-December), dry season (January-February), and dry season (June-September) in Nairobi City County between 2020 and 2024; (b) Seasonal variation in mean concentrations of SO_2 and NO_2 across the long rains (March-May), short rains (October-December), dry season (January-February), and dry season (June-September) in Nairobi City County between 2020 and 2024.

the scattering of light, while facilitating the aqueous-phase conversion of SO_2 to sulphate aerosols. The bi-modal rainfall pattern in Nairobi generates wet and dry atmospheric regimes that impose seasonal overlays on the land use differences assessed in this study. These interrelations between meteorological conditions and sources of emissions highlight the significance of integrating weather variables into long-term air quality monitoring and modelling systems to accurately differentiate between the contributions of human activity and atmospheric variability.

4. Recommendations

4.1. Traffic Management and Emission Reduction in Commercial Areas

The weighted AQI calculations indicate that commercial areas had the highest overall AQI of all four land use zones, and that there were statistically significant pollutant concentration differences between commercial and green park areas. There is therefore an urgent need to implement traffic management interventions in commercial areas of Nairobi. The National Ministry of Transport and the Nairobi City County Government should focus on adopting low-emission zones in the central business district and other key commercial corridors, limiting access for high-emission vehicles during peak times. The promotion of vehicle electrification in commercial transport fleets, including public service vehicles, represents a high-impact long-term measure. Recent research indicates that electrification of vehicles can lead to the reduction of NO_2 concentrations by up to 75% in commercial zones, while replacement with soft mobility infrastructure, including cycling and walking, can reduce concentrations of ultrafine particles by up to 43% in Paris [32].

4.2. Industrial Emission Controls and Buffer Zones

The wide disparity between industrial and commercial areas, coupled with the small difference between residential and industrial areas, highlights the necessity for stricter emission regulations in the industrial areas of Nairobi. The National Environment Management Authority should set higher standards for stack emissions from manufacturing plants and implement frequent environmental audits. The spatial planning policies must develop and enforce sufficient buffer space between industrial operations and the surrounding residential neighbourhoods, which in Nairobi are typically very close to industrial operations due to unplanned urbanisation. These buffer zones should include the strategic planting of vegetation that demonstrates the ability to absorb pollutants, but not designs that can restrict ventilation and unintentionally build up pollutants at street level [3].

4.3. Public Education and Exposure Reduction

The estimated temporal profiles, which indicate higher concentrations during the morning and evening periods, suggest potential periods of elevated exposure for commuters and outdoor workers in Nairobi. Public health campaigns should be conducted to disseminate clear guidelines on protective behaviours during peak pollution and should also include guidance on how to avoid prolonged outdoor activities during rush hours, particularly in vulnerable groups such as children, the elderly, and people with respiratory or cardiovascular conditions. In commercial and industrial localities, employers ought to consider implementing flexible working hours to distribute the traffic demand evenly throughout the day, which would result in a less pronounced concentration of emissions that leads to the observed evening and morning pollution spikes.

4.4. Expanded Monitoring and Research Infrastructure

The findings of this study reveal the value and the limitations of the current monitoring system in Nairobi. The combination of Sentinel-5P satellites and ground-based AirQo sensors provided a complementary multi-platform dataset, but the spatial coverage of $PM_{2.5}$ and other pollutants monitoring at the sub-county level remains limited. Nairobi City County should invest in building its ground-based monitoring network, with priority given to the placement of sensors in underserved residential and informal settlements where the risk of the most severe pollution impact is highest. The creation of a long-term and comprehensive air quality database, with the partnership between the Kenya Meteorological Department, universities, and international partners, would be the foundation of evidence-based policy evaluation and the development of an emissions inventory.

A limitation of the temporal analysis is that Sentinel-5P provides a single daytime observation and cannot directly resolve the full diurnal cycle of atmospheric pollutants. The morning, midday, and evening concentrations presented in this study were therefore estimated using an extrapolation algorithm rather than being directly observed at each period. Consequently, the derived diurnal patterns, including the apparent bimodal behaviour of NO_2 and CO, should be interpreted cautiously and as indicative temporal patterns rather than direct measurements of morning and evening concentrations. Continuous ground-based observations or geostationary satellite measurements would provide a more robust basis for characterizing diurnal pollutant variability in future studies.

5. Conclusions

The present study focused on the spatio-temporal distribution of the Air Quality Index across four land use patterns in Nairobi City County using data from six sub-counties in the period 2020 to 2024. The integration of Sentinel-5P TROPOMI satellite data of atmospheric gases with ground-based AirQo sensor measurements of $PM_{2.5}$ provided a powerful multi-source dataset to describe the dynamics of pollutants at the intra-urban scale. One-way ANOVA revealed that the spatial difference of pollutants across the four land use areas was statistically significant ($F = 5.41$, $p = 0.0001$), while post-hoc Tukey HSD analysis showed that significant pairwise differences existed between industrial and commercial areas ($p = 0.005$) and between commercial and green park areas ($p = 0.023$). Weighted AQI calculations derived from the study dataset confirm that commercial areas recorded the highest overall AQI of 115.452 among the four land use zones, driven by the concentration of vehicular traffic and business activities, while green park areas recorded the lowest weighted AQI of 113.970, consistent with the partial pollution buffering role of urban vegetation as supported by the significant post-hoc difference identified between these two zones. The small difference between residential and industrial regions ($p = 0.058$) implies that the communities residing in areas that are close to industrial regions are exposed to the same amount of pollution as those found in the officially designated industrial regions.

The repeated measures ANOVA showed that there was a statistically significant temporal variation in the concentration of pollutants in the morning, afternoon, and evening ($F = 4.57$, $p = 0.0192$). Post-hoc analysis showed that afternoon concentrations were substantially lower than evening concentrations ($p = 0.011$), reflecting the role of boundary layer deepening during the daytime by solar heating and the resulting temporary dilution of the surface values, followed by nocturnal boundary layer compression and the high traffic congestion that leads to the rise of evening concentrations. The insignificant difference between the morning and afternoon reduction ($p = 0.052$) also supports the trend of bimodal diurnal pollution in accordance with traffic-based emission dynamics in urban Nairobi. These findings directly impact the policy of the national government and the City County of Nairobi. The spatial variability of AQI across land use areas requires zone-oriented methods for pollution control instead of city-wide strategies, with particular urgency in commercial and industrial areas. The temporal dynamics of pollution exposure, which are concentrated in the morning and evening hours, provide a basis for targeted health advisories and traffic demand control. Taken together, these findings contribute to the evidence base of integrated air quality governance in Nairobi and illustrate the importance of integrating satellite-based atmospheric measurements with ground-based monitoring to assess air quality in urban sub-Saharan African settings with limited data.

Author Contributions

Conceptualization: Maryvine Vena Nyanchoka and Dr. Ezekiel Ndunda; Methodology: Maryvine Vena Nyanchoka; Software: Esther Judith; Validation: Dr. Esther Kitur and Dr. Kanyiva Muindi; Formal analysis: Dr. Ezekiel Ndunda; Investigation: Maryvine Vena Nyanchoka and Dr. Ezekiel Ndunda; Data curation: Maryvine Vena Nyanchoka and Esther Judith; Writing: Maryvine Vena Nyanchoka; Writing—review and editing: Dr. Kanyiva Muindi, Dr. Esther Kitur and Dr. Ezekiel Ndunda; Visualization: Esther Judith and Dr. Kanyiva Muindi; Supervision: Dr. Esther Kitur and Dr. Ezekiel Ndunda; Project administration: Maryvine Vena Nyanchoka; Funding acquisition: Maryvine Vena Nyanchoka.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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