

Evaluating the Concentration of Air Pollutants in Different Land-Use Patterns in Nairobi

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Abstract

Air pollution has been identified as one of the major environmental risk factors affecting health. The increase in population has also led to a transformation of the city's land-use patterns, which may influence spatial variations in air quality. This study evaluates the concentration of key air pollutants (CO, NO₂, SO₂, O₃, and PM_{2.5}) across four dominant land-use classes: residential, commercial, industrial, and green spaces. Satellite-derived data for gaseous pollutants were obtained from the Sentinel-5 Precursor satellite. These datasets were accessed through Google Earth Engine for the period 2020-2024. The PM_{2.5} data were obtained from ground monitoring stations using low-cost sensors for 2023-2024. Pollutant observations were spatially assigned to land-use classes using GIS overlay techniques. Air Quality Index (AQI) values were computed for each pollutant and aggregated using a weighted approach. A one-sample t-test was conducted to assess whether the mean of each pollutant in Nairobi is significantly different from established guideline values at a 5% significance level. Results indicate that air quality in the different land-use classes is moderate, with commercial areas being slightly elevated, having a weighted AQI of 91.50. Residential, industrial, and green park areas are also in the moderate category, with the weighted AQI ranging from 89.40 to 88.35. In commercial areas, the slightly elevated AQI can be attributed to heavy traffic and business activities, therefore emitting elevated concentrations of pollutants like PM_{2.5}, NO₂, and CO. The fitting effect of the model was not significant above the acceptable limits for CO, NO₂, and SO₂, while PM_{2.5} and O₃ are significantly above the acceptable limits, indicating serious air quality concerns in the different land-use patterns. Therefore, there is a need to develop stricter pollution control strategies to reduce AQI levels. Institutions need to invest in gaseous monitoring sensors to monitor real-time pollutant concen-

trations for specified areas, and further research on pollutant concentration levels in green spaces around the city.

Keywords

Air Quality, Air Pollution, Air Quality Index, Land Use Patterns, Concentration, Nairobi

1. Introduction

Environmental risk factors, particularly air pollution, remain a major global concern due to their significant impacts on environmental quality, human health, and economic productivity. Urban areas are especially vulnerable, as increasing population density, transportation demand, and industrial activities contribute to elevated pollutant emissions and human exposure. Studies have shown that both anthropogenic and natural processes drive air pollution in cities, with traffic-related emissions, including exhaust and non-exhaust sources, being among the dominant contributors [1] [2]. Pollutants such as particulate matter (PM_{2.5} and PM₁₀), nitrogen dioxide (NO₂), sulphur dioxide (SO₂), carbon monoxide (CO), and ozone (O₃) are strongly associated with cardiovascular and respiratory diseases [3]. Population density, land utilization, economic activity, and urban function are progressively integrated dimensions affecting PM_{2.5} concentrations across 285 prefecture-level cities in China, with spatial analysis revealing that compact urban development impacts environmental quality through the mutual superposition of urban functions, with population density and economic development serving as key drivers that increase pollution levels throughout cities [4].

Rapid urbanization in cities such as Nairobi has intensified these challenges, particularly in low- and middle-income countries (LMICs), where air quality monitoring infrastructure and regulatory enforcement are often limited. The World Health Organization has established global air quality guidelines that define threshold levels for these pollutants, emphasizing that even low concentrations can pose significant health risks [5]. Globally, air pollution is the leading environmental risk factor for mortality, contributing to approximately 7.9 million deaths in 2023, with the greatest burden occurring in LMICs [6]. In Kenya, air pollution is estimated to be the eighth leading cause of premature death, accounting for approximately 19,000 fatalities annually [7]. Despite these impacts, air quality management remains constrained by limited monitoring coverage and policy implementation gaps in African countries. According to the United Nations Environment Programme, Kenya has made progress in developing air quality policies, but challenges persist in enforcement, data availability, and integration of monitoring systems [8]. In urban environments, land-use patterns play a critical role in shaping spatial variations in air pollution. Areas characterized by dense commercial activities, industrial operations, and high traffic volumes typically exhibit higher pol-

lutant concentrations compared to residential or vegetated areas.

In Nairobi, previous studies have identified commercial zones, industrial areas, and major transport corridors as key air pollution hotspots, with significant contributions from vehicular emissions and black carbon [3] [7]. However, despite these insights, there remains limited integration of spatially explicit land-use data with both satellite-derived atmospheric observations and ground-based air quality measurements in the local context. Accurate estimation of pollutant concentrations across different land-use types is essential for understanding exposure patterns and informing targeted interventions. Satellite observations, such as those from Sentinel-5P, provide spatial coverage of atmospheric pollutants, but they represent column densities that require careful interpretation when assessing ground-level conditions. Conversely, while low-cost sensor networks have been deployed across Nairobi to provide localized measurements of particulate matter, their coverage remains spatially limited [9]. These limitations highlight the need for integrated approaches that combine multiple data sources to improve the reliability of urban air quality assessments, particularly in rapidly growing cities. This study, therefore, aims to evaluate the concentration and spatial distribution of key air pollutants (CO, NO₂, SO₂, O₃, and PM_{2.5}) across major land-use types within Nairobi. Specifically, the study integrates Sentinel-5P satellite data and ground-based PM_{2.5} observations, applies Air Quality Index (AQI) analysis, and examines differences across residential, commercial, industrial, and green space areas. By linking pollutant concentrations with land-use patterns, the study provides policy-relevant insights that can support improved air quality management and urban planning in data-limited environments.

2. Methodology

2.1. Study Area

Nairobi City is the largest city in East and Central Africa and is the capital of Kenya. Geographically, it is located at 1°9'S, 1°28'S and 36°4'E, 37°1'E and covers 684 km² as shown in **Figure 1**. The city experiences a double-peaked rainfall pattern, with long rains occurring between March and May, which have recently led to flooding in the city, and short rains between October and December. Temperature patterns are characterized by warmer conditions from December to March and cooler conditions from June to August. According to the 2019 national population census conducted by the Kenya National Bureau of Statistics, Nairobi has a population of 4,397,073 [10]. The city is a major economic hub, contributing the largest share to Kenya's Gross Domestic Product, and is characterized by rapid urbanization, increasing population density, and expanding infrastructure. These dynamics make Nairobi a suitable case study for assessing the relationship between land-use patterns and air quality in a rapidly growing urban environment.

2.2. Land-Use Identification

Administratively, Nairobi is divided into 17 sub-counties and 85 wards. Land-use

classification in this study was based on a combination of planning frameworks and geospatial datasets, including the Nairobi Integrated Urban Development Master Plan (NIUPLAN, 2023), the County Integrated Development Plan (CIDP), and OpenStreetMap (OSM) land-use layers. The study focused on selected sub-counties: Starehe, Westlands, Kibra, Ruaraka, Makadara, and Embakasi East, representing diverse land-use characteristics. These areas were purposely selected to capture variation in different land use classes.

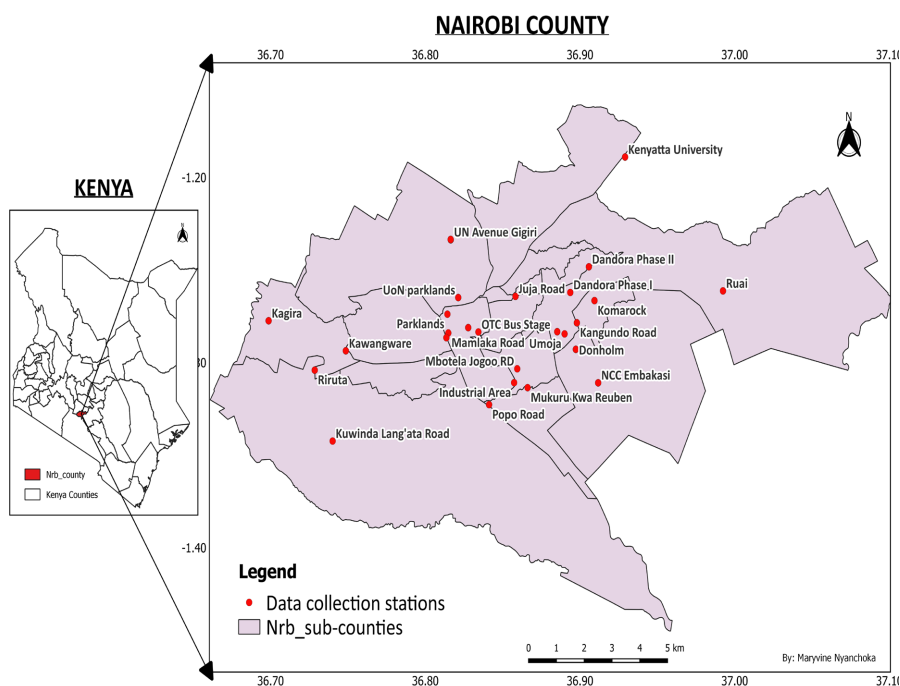


Figure 1. Study area of Nairobi City County.

Land-use categories were defined based on dominant activities and land cover characteristics as follows:

- Residential areas: include low-density residential areas (e.g., Westlands), medium-density (e.g., Embakasi East), and high-density residential areas (e.g., Kibra).
- Commercial areas: including the central business district and emerging commercial hubs (e.g., Starehe and Westlands).
- Industrial areas: characterized by manufacturing and industrial activities (e.g., Baba Dogo in Ruaraka and Viwandani in Makadara).
- Green spaces: comprising urban forests and recreational parks (e.g., Karura Forest and City Park).

Spatial boundaries for each land-use class were digitized and harmonized in QGIS software to ensure consistency across datasets. As illustrated in **Figure 2**, these land-use polygons were later used to assign both satellite-derived pollutant data and ground-based PM_{2.5} observations to their respective land-use categories through spatial overlay analysis.

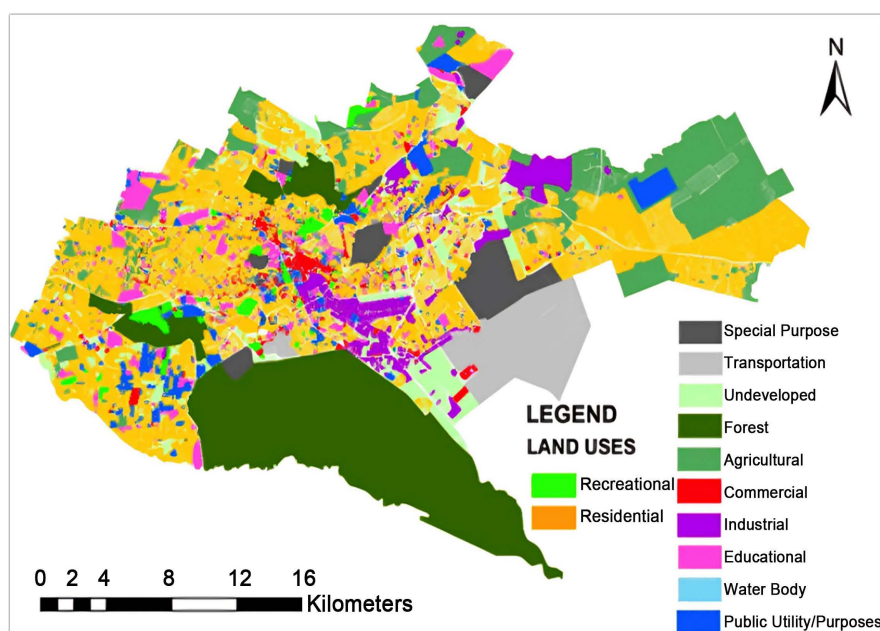


Figure 2. Nairobi City land use map.

2.3. Data Sets and Processing

The overall methodology workflow is summarized in **Figure 3**.

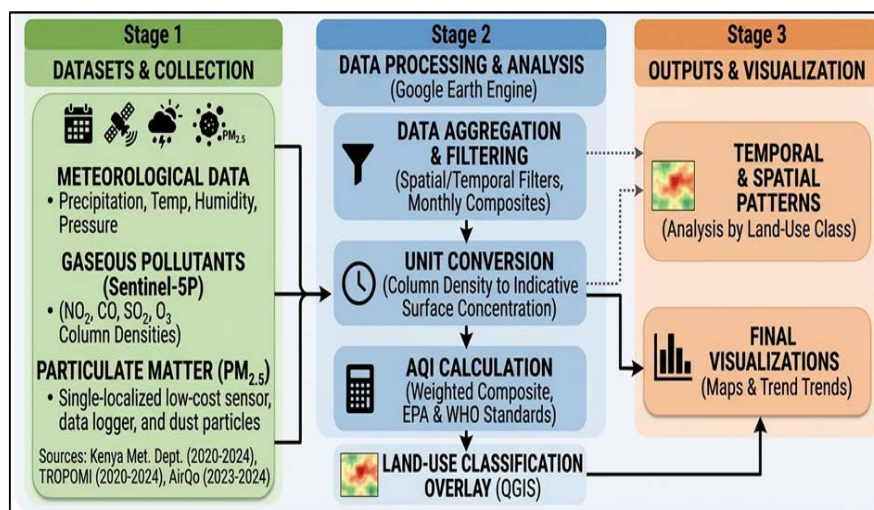


Figure 3. Methodology workflow for air quality analysis.

2.3.1. Meteorological Data

Meteorological data that consisted of precipitation, humidity, temperature, and pressure were sourced from the Kenya Meteorological Department for the period covering January 2020 to June 2024 [11]. These variables were used to provide a contextual understanding of atmospheric conditions that may influence pollutant dispersion, transformation, and seasonal variability. Data pre-processing involved temporal aggregation to monthly averages to ensure consistency with the pollutant datasets. Although meteorological variables were not directly included in the

statistical tests, they were used to support the interpretation of observed air quality patterns.

2.3.2. Sentinel-5 Precursor

The data used for the atmospheric gases were obtained from the Sentinel-5 Precursor (Sentinel-5P) satellite, which is part of the Copernicus Earth Observation Program. Sentinel-5P provides information on atmospheric pollution and can be used to determine air quality and emission hotspots [12]. The satellite carries the Tropospheric Monitoring Instrument (TROPOMI), which provides measurements of key atmospheric trace gases, including nitrogen dioxide (NO₂), carbon monoxide (CO), sulphur dioxide (SO₂), and ozone (O₃) [13]. The TROPOMI instrument provides observations at a spatial resolution of approximately 5.5 km² × 3.5 km², enabling the detection of spatial variability in air pollution at the urban scale. Each pollutant is provided as a separate dataset representing column number density (mol/m²), which reflects the total amount of gas within a vertical column of the atmosphere. NO₂ is primarily associated with traffic and industrial emissions, CO with incomplete combustion processes, SO₂ with industrial activities and fossil fuel use, and O₃ as a secondary pollutant formed through photochemical reactions. The datasets were accessed and processed using Google Earth Engine, where they were filtered to the spatial extent of Nairobi County and the temporal range 2020-2024. Monthly composites were generated from daily observations to reduce noise and ensure temporal consistency. However, as the data represent column densities rather than direct ground-level concentrations, they were interpreted with caution when used in Air Quality Index (AQI) calculations, and the results are considered indicative rather than direct measures of compliance.

2.3.3. Processing Sentinel-5P Satellite Imagery in Google Earth Engine

All pre-processing and analysis of satellite-derived pollutant data were conducted using Google Earth Engine (GEE). This platform enabled efficient handling of large-scale geospatial datasets and ensured consistency in temporal and spatial analyses.

The processing workflow consisted of the following steps:

1) Dataset Selection:

Level-3 Sentinel-5P products for CO, NO₂, SO₂, and O₃ were accessed from the Copernicus data archive within GEE. These datasets are pre-processed and gridded, making them suitable for regional-scale analysis.

2) Spatiotemporal Filtering:

Each dataset was filtered to the spatial extent of Nairobi County using administrative boundary shapefiles and constrained to the study period (2020 to 2024). This ensured consistency across all pollutant datasets. To reduce the influence of missing data and short-term variability, daily observations were aggregated into monthly composites using a mean reducer. This approach minimized noise and provided stable representations of pollutant concentrations over time. At the spa-

tial level, each Sentinel-5P pixel contributed to monthly observations (“pixel-months”). Across the study period, this resulted in approximately 575 pixel-month observations per pollutant per year for the entire study area.

3) Data Extraction and Sampling:

Quality-filtered pixels were selected using available data quality flags, and the corresponding gas_column_number_density values (mol/m^2) were extracted. The datasets were then mosaicked to create continuous spatial coverage over the study area. Pixel-level values, along with geographic coordinates, were exported as CSV tables and raster GeoTIFFs for further analysis. These pollutant data were subsequently overlaid with land-use polygons in a QGIS environment, and each pixel was assigned to a corresponding land-use class. This enabled aggregation of pollutant concentrations by residential, commercial, industrial, and green space categories.

4) Conversion of Gaseous Pollutant Data

Sentinel-5P datasets provide pollutant concentrations as column number densities (mol/m^2), whereas Air Quality Index (AQI) thresholds are defined using ground-level concentrations (ppb or ppm). To enable approximate comparison, column densities were converted to indicative surface concentrations by assuming a uniform boundary layer height of approximately 1113 m and applying appropriate unit scaling. This simplified conversion does not explicitly account for vertical atmospheric mixing, meteorological variability, or local emission dynamics [14]. In cases where the conversion introduced high uncertainty, results were interpreted as relative spatial patterns across land-use classes rather than absolute concentration values.

2.3.4. Particulate Matter Data

$\text{PM}_{2.5}$ data were obtained from a network of 13 low-cost AirQo sensors deployed across Nairobi between 2023 and 2024. AirQo is a low-cost air quality monitoring system designed and deployed across African cities, including Nairobi, to provide hyperlocal $\text{PM}_{2.5}$ measurements using calibrated optical sensors [15]. The monitoring network used in this study was designed to capture spatial variability across major land-use types, with at least two stations located within each category (residential, commercial, industrial, and green spaces). The sensors use light-scattering technology to estimate $\text{PM}_{2.5}$ concentrations and transmit data to a cloud-based platform, where calibration and quality assurance/quality control procedures are applied. These calibration processes improve the reliability of low-cost sensor measurements for urban air quality assessment [16]. Data completeness was evaluated at the monthly level. Months with fewer than 50% valid observations were excluded, while missing values within acceptable months were interpolated to maintain temporal continuity. Each monitoring station was spatially linked to land-use polygons, ensuring consistency with the classification applied to satellite-derived pollutant data. This enabled direct comparison between $\text{PM}_{2.5}$ and gaseous pollutants across the defined land-use classes.

2.4. Calculating Air Quality Index

The Air Quality Index (AQI) was computed to translate raw pollutant concentrations into standardized air quality categories that are easily interpretable in relation to human health risks. AQI values for each pollutant (CO, NO₂, SO₂, O₃, and PM_{2.5}) were calculated using the standard linear interpolation method:

$$AQI = [(I_{hi} - I_{low}) / (B_{Phi} - B_{Plow})] (C_p - B_{Plow}) + I_{low}$$

- AQI: The air quality index of the pollutant
- C_p: The rounded concentration of pollutant p
- B_{Phi}: The breakpoint is greater than or equal to C_p
- B_{Plow}: The breakpoint is less than or equal to C_p
- I_{hi}: The AQI corresponding to B_{Phi}
- I_{low}: The AQI corresponding to B_{Plow}

Pollutant concentrations derived from Sentinel-5P satellite data and PM_{2.5} sensor observations were independently converted into AQI values using pollutant-specific breakpoint tables.

2.4.1. AQI Breakpoints and Standards

AQI computation followed the pollutant-specific breakpoint structure defined by the United States Environmental Protection Agency, as in **Table 4**. These breakpoints provide standardized concentration-to-health-risk conversions widely used in global air quality assessment studies.

AQI values were then classified into standard categories:

- 0 - 50—Good
- 51 - 100—Moderate
- 101 - 150—Unhealthy for Sensitive Groups
- 151 - 200—Unhealthy
- 201 - 300—Very Unhealthy
- 300+ Hazardous

This classification provides a uniform framework for interpreting air quality conditions across land-use classes and supports comparability with global air quality studies, but not necessarily with local conditions. While AQI computation followed EPA standards, the interpretation of health risk levels was guided by the World Health Organization Air Quality Guidelines of 2025. WHO thresholds were used to contextualize observed AQI values in terms of potential health impacts, particularly for vulnerable populations. This dual-framework approach ensures computational consistency (EPA) while maintaining global health relevance (WHO).

2.4.2. Pollutant Weighting in Composite AQI

To reflect differences in health impacts, a weighted AQI approach was applied. The weights are normalized to sum to 1.0 as follows: PM_{2.5} (0.35), O₃ (0.30), NO₂ (0.15), CO (0.10), and SO₂ (0.10), based on their relative health impacts as reported in WHO [5]. A sensitivity analysis using equal weighting (0.20) confirmed that the relative ranking of land-use classes remained unchanged, indicating the

robustness of results to weighting assumptions.

2.5. Visualization

Spatial and temporal visualization techniques were used to explore patterns and communicate air quality variations across Nairobi. Time-series plots were generated for each pollutant (CO, NO₂, SO₂, and O₃) to illustrate temporal variability between 2020 and 2024. PM_{2.5} data were available for 2023-2024; therefore, combined AQI comparisons involving PM_{2.5} are limited to the overlapping period. These plots were based on monthly aggregated values derived from Sentinel-5P satellite observations and PM_{2.5} sensor measurements. Spatial distribution maps were also produced to show the geographical variation of pollutant concentrations across Nairobi County. These maps were generated using raster outputs derived from Sentinel-5P data. The 2024 annual composite was used as the representative spatial snapshot to ensure comparability across all pollutants and to minimize inter-annual variability. Pollutant concentration surfaces were visualized in a GIS environment and overlaid with OpenStreetMap data to enable spatial interpretation of air quality differences.

3. Results and Discussion

3.1. Temporal Variation of Air Pollutants (2020-2024)

Figure 4 illustrates the monthly variation of key pollutants across Nairobi in 2024. A temporal pattern is observed, with pollutant concentrations exhibiting moderate fluctuations rather than extreme variability, suggesting relatively stable emission sources throughout the year. One notable trend is the periodic increase in most pollutants, apart from SO₂, concentrations during the dry months, which can be attributed to reduced atmospheric dispersion and increased accumulation of pollutants. Conversely, slight reductions are observed during wetter months, likely due to wet deposition processes.

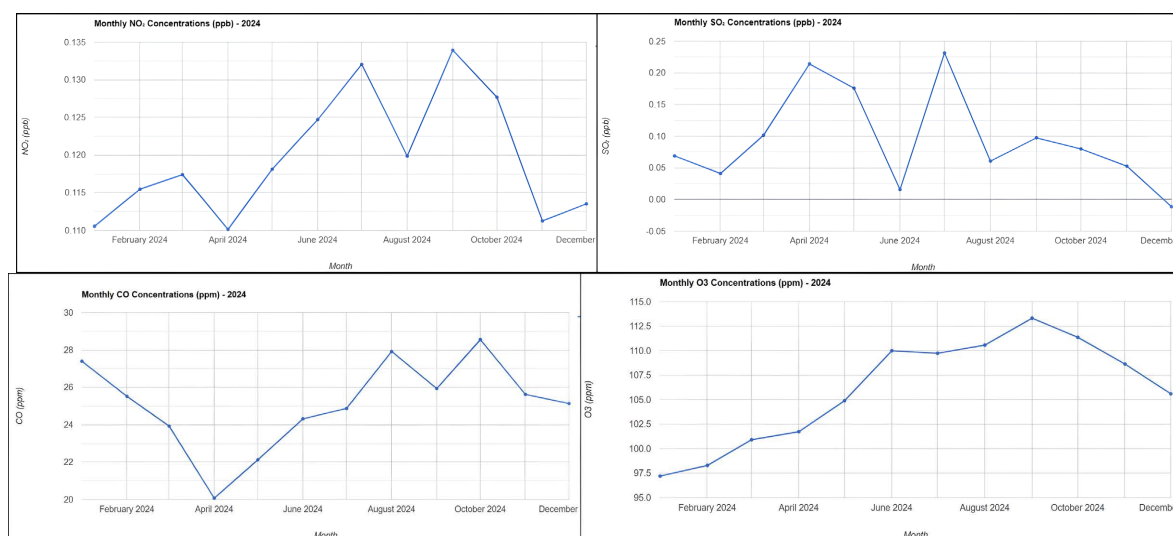


Figure 4. Nairobi pollutant time series chart (2024).

Over the five-year period (Figure 5), pollutant concentrations show no significant long-term decline, indicating that air pollution remains a persistent issue in Nairobi. For example, NO_2 concentrations exhibit minor inter-annual variability but remain within a narrow range across 2020-2024. This suggests that emission sources such as vehicular traffic and urban activities have remained relatively constant and are increasing over time. Similarly, O_3 concentrations remain consistently elevated across all years, reinforcing the dominance of secondary pollutant formation processes in the urban atmosphere.

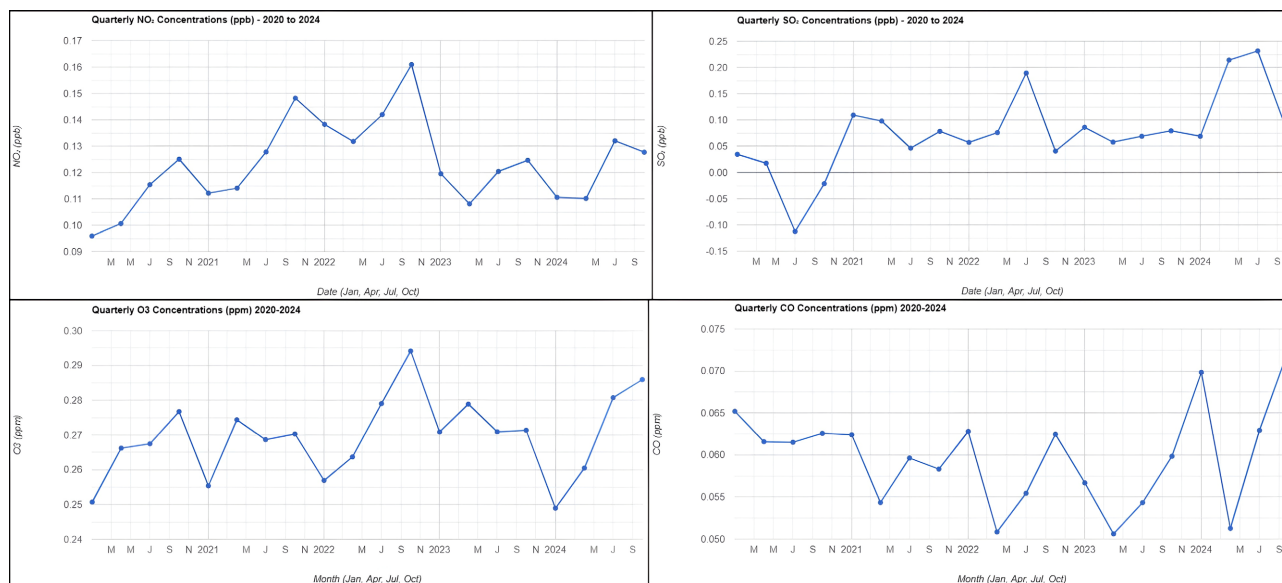


Figure 5. Nairobi annual pollutant time series chart (2020-2024).

3.2. Spatial Distribution of Pollutants

Figure 6 presents the spatial distribution of pollutants across Nairobi for 2024. The spatial patterns reveal associations between pollutant concentrations and land-use/land-cover characteristics. For instance, NO_2 concentrations are observed to peak in areas characterized by high traffic density and intense urban activity, e.g., CBD, Westlands, and Eastleigh. Concentrations decrease progressively with distance from these high-emission zones towards the city outskirts, indicating a strong link between vehicular emissions and NO_2 distribution. Similarly, $\text{PM}_{2.5}$ concentrations are highest in densely populated, industrial (*i.e.*, Viwandani) and commercial areas, reflecting the combined influence of traffic emissions, commercial activities, and possibly waste burning. In contrast, green spaces exhibit relatively lower pollutant concentrations, although not uniformly. Elevated pollutant levels are still observed in green areas located near major roads or urban centers such as Uhuru Park and Nairobi City Park, highlighting the influence of surrounding land use rather than vegetation alone.

3.3. Pollutant Concentration across Land-Use Classes

Assessing individual-level exposure to air pollutants is essential for understanding

health risks, as exposure varies based on personal mobility patterns and time spent in different microenvironments [17]. The average differences in pollutant concentrations across land-use classes are observed in **Table 1** below.

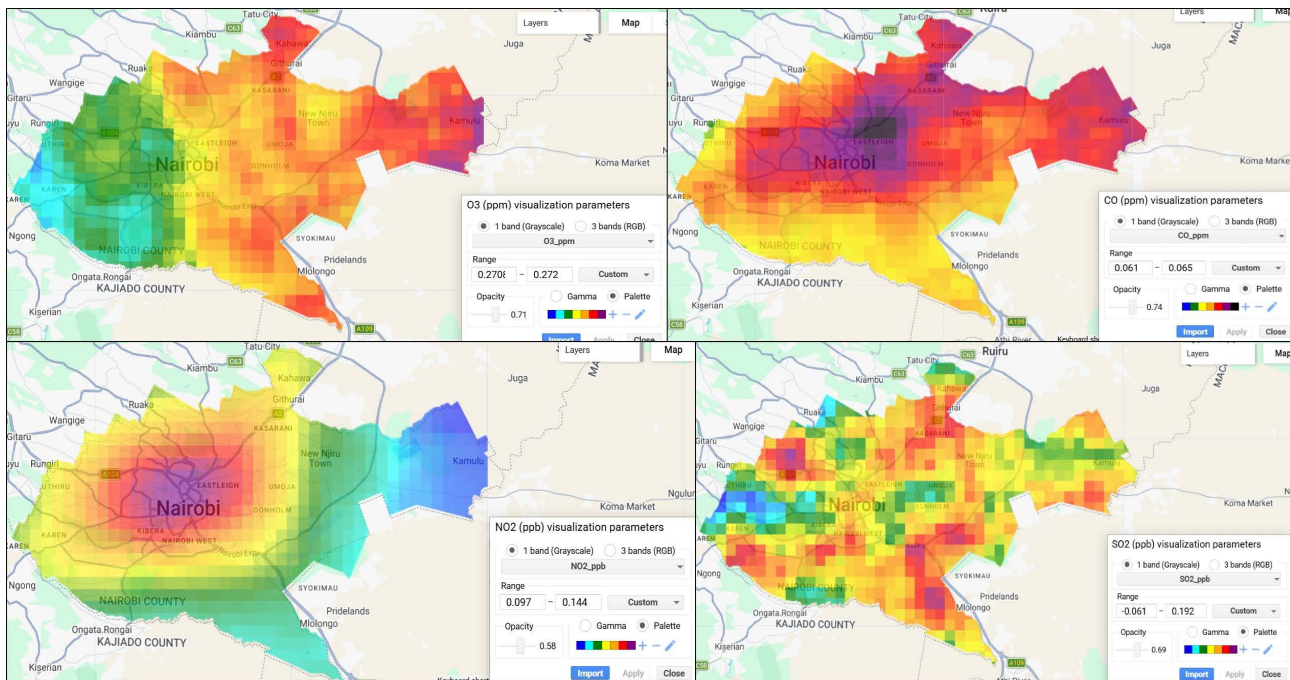


Figure 6. Nairobi pollutant distribution map (2024).

Table 1. Average concentration of pollutants in Residential/Commercial/Commercial/Green Park areas.

Land use	SO ₂ (ppb)	NO ₂ (ppb)	CO (ppm)	O ₃ (ppm)	PM _{2.5} (µg/m ³)
Residential	0.075908	0.129325	0.063686	0.1271367	16.69433
Commercial	0.091703	0.135547	0.06387	0.1271356	20.72156
Industrial	0.089841	0.12557	0.063622	0.1271579	18.05085
Green Spaces	0.072202	0.12757	0.063431	0.1271249	16.92333

Table 2. US EPA AirNow Guidelines using pollutant concentration.

Level of Concern	CO (ppm)	NO ₂ (ppb)	SO ₂ (ppb)	O ₃ (ppm) 8-hr	PM _{2.5} (ug/m ³)
Good ☐	0.0 - 4.4	0 - 53	0 - 35	0.000 - 0.054	0.0 - 9.0
Moderate ☐	4.5 - 9.4	54 - 100	36 - 75	0.055 - 0.070	9.1 - 35.4
Unhealthy for Sensitive Groups ☐	9.5 - 12.4	101 - 360	76 - 185	0.071 - 0.085	35.5 - 55.4
Unhealthy ●	12.5 - 15.4	361 - 649	186 - 304	0.086 - 0.105	55.5 - 125.4
Very Unhealthy ☐	15.5 - 30.4	650 - 1249	305 - 604	0.106 - 0.200	125.5 - 225.4
Hazardous ☐	30.5+	1250+	605+	—	225.5 and above

Table 1 reveals important insights into urban air pollution dynamics. The most notable variation is observed in PM_{2.5} concentrations, as Moderate according to the US EPA guidelines in **Table 2** above, with commercial areas recording the

highest levels ($20.72 \mu\text{g}/\text{m}^3$), followed by industrial areas ($18.05 \mu\text{g}/\text{m}^3$). This pattern reflects the combined impact of traffic congestion, economic activities, and localized emissions. In contrast, gaseous pollutants such as NO_2 and CO show minimal variation across land-use classes, suggesting that concentrations are more spatially distributed across the city, influenced by atmospheric mixing and broader emission patterns rather than strictly local sources. Additionally, the use of Sentinel-5P column measurements captures broader atmospheric conditions, which may reduce sensitivity to fine-scale spatial differences.

3.4. Air Quality Index (AQI) by Pollutant

The AQI values derived for individual pollutants (Table 3) with reference to the US EPA guidelines indicated in Table 2 and Table 4 show that:

- $\text{PM}_{2.5}$ falls within the “Moderate” category ($\text{AQI} \approx 61 - 70$), indicating a level of pollution that may pose risks to sensitive populations.
- O_3 falls within the “Very Unhealthy” category ($\text{AQI} \approx 223$), making it the most critical pollutant across all land-use classes.
- CO , NO_2 , and SO_2 fall within the “Good” category ($\text{AQI} \approx 0 - 1$), suggesting that their concentrations are relatively low and contribute minimally to the overall AQI.

The consistently high ozone levels across all land-use types highlight the importance of secondary pollutant formation, where ozone is produced through photochemical reactions involving precursor gases such as NO_2 under sunlight. This explains its relatively uniform distribution compared to more localized pollutants such as $\text{PM}_{2.5}$. It is important to note that these AQI values are indicative, as they are derived from satellite-based column measurements converted to approximate surface concentrations. Therefore, they should be interpreted as relative measures of pollution levels rather than exact compliance with regulatory standards. Overall, the results indicate that $\text{PM}_{2.5}$ and O_3 are the primary drivers of air quality concerns in Nairobi, while other pollutants contribute mainly to background concentration levels.

Table 3. Air quality index values of different land uses in Nairobi City County.

Pollutant	Residential AQI	Industrial AQI	Commercial AQI	Green Park AQI
CO	1	1	1	1
NO_2	0	0	0	0
$\text{PM}_{2.5}$	61	64	70	61
O_3	223	223	223	223
SO_2	0	0	0	0

Table 4. US EPA AirNow guidelines using AQI level.

Level of Concern	Good □	Moderate □	Unhealthy for Sensitive Groups □	Unhealthy ●	Very Unhealthy □	Hazardous □
AQI Range	0 - 50	51 - 100	101 - 150	151 - 200	201 - 300	301+

3.5. Weighted AQI across Land-Use Classes

To generate a model of the Air Quality Index (AQI) for Nairobi City, we integrated the AQI values for each pollutant across different areas of the city (residential, industrial, commercial, and green park). This model allowed us to estimate the overall air quality across Nairobi. For each pollutant, the corresponding concentration data from residential, industrial, commercial, and green park areas were used. The AQI values are calculated for each area. To generate a model that reflects the overall AQI of Nairobi, we can apply a weighted average for each area, based on the relative influence of each pollutant. Typically, the major contributors to air pollution in Nairobi are Particulate Matter (PM_{2.5}) and Ozone (O₃), and we therefore assigned higher weights to these pollutants. The following weights were assigned to each pollutant: PM_{2.5} (Major contributor)—0.35, O₃ (Major contributor)—0.30, NO₂—0.15, CO—0.10, and SO₂—0.10. The weighted AQI for each area was calculated using the formula:

$$AQI_{\text{Weighted}} = \sum (AQI_i \times \text{Weight}_i) \quad (1)$$

where:

- AQI_i is the AQI value for each pollutant,
- Weight_i is the weight assigned to each pollutant.

The weighted AQI for different areas in Nairobi City County is shown in **Table 5**.

Table 5. Weighted air quality index for selected areas in Nairobi City County.

Area	Weighted AQI
Residential	88.35
Industrial	89.40
Commercial	91.50
Green Park	88.35

The weighted AQI values for the four areas of Nairobi, as shown in **Table 5** (Residential, Industrial, Commercial, and Green Park), with Commercial having the highest weighted AQI of 91.50, indicate moderate air quality. The weighted AQI values across Nairobi's land use patterns consistently fall within the "Moderate" category, signaling moderate air quality concerns that demand policy intervention. While the general population may not experience significant health effects at these moderate levels, sensitive individuals, including children, the elderly, and people with pre-existing respiratory or cardiovascular conditions, face elevated risks of adverse health outcomes. The primary concerns are the elevated levels of pollutants like PM_{2.5} and ozone (O₃), which are known to exacerbate respiratory conditions such as asthma and bronchitis. Industrial areas are typically more affected by emissions from factories and heavy machinery, which release pollutants such as NO₂, SO₂, and PM_{2.5}. Green park and residential areas, although exhibiting slightly better weighted AQI values (88.35) than industrial zones, are

not immune to the effects of urban air pollution, particularly ozone formation during hot days or after prolonged periods of vehicular emissions. Commercial areas recorded the highest weighted AQI (91.50) due to heavy traffic and concentrated business activities that generate elevated concentrations of PM_{2.5}, NO₂, and CO. The public health relevance of EPA AQI activity recommendations under present day environmental conditions requires critical assessment, as the analysis revealed that the number needed to treat (NNT) to prevent serious disease events remained very high for the general population (greater than 18 million), patients with atherosclerotic cardiovascular disease (approximately 1.6 to 5 million), and adults with lung disease (approximately 66,000 to 202,000) during most days when PM_{2.5} was elevated (AQI 101 to 200) [18].

3.6. Land-Use Specific Analysis

3.6.1. Air Quality Index in Residential Areas

The residential areas of Nairobi exhibit a weighted AQI of 88.35, categorizing them as “Moderate” with PM_{2.5} concentrations averaging 16.69 µg/m³ (Table 5). This classification indicates that while the general population may not face immediate health risks, vulnerable groups, including children, the elderly, and individuals with pre-existing respiratory or cardiovascular conditions, are at risk of health effects. The elevated PM_{2.5} levels (61 AQI) and particularly high O₃ concentrations (223 AQI) are primary contributors to this concerning air quality status. While lower than in commercial and industrial areas, these levels still exceed recommended health thresholds, indicating persistent exposure risks. Gaseous pollutants such as NO₂ and CO show relatively uniform concentrations across residential zones, suggesting that emissions are not limited to specific hotspots but are instead distributed across the urban environment.

In Northern China, PM_{2.5} and NO₂ decreased by about 35% and 65%, respectively, during the COVID-19 lockdown, but the secondary pollutant ozone increased by 1.5 - 2 times, which may be attributed to open burning and poor waste management practices [19]. Illegal dumping and burning of waste contribute to 25% of PM_{2.5} concentrations [20]. The Dandora dumpsite, for instance, receives about 2000 tonnes of waste daily, leading to methane emissions and spontaneous combustion fires. Figure 6 shows elevated pollutant concentrations in residential areas, particularly in locations near major roads and high-density settlements such as Kibra, Embakasi and parts of Eastlands.

In informal settlements, reliance on solid fuels for cooking leads to PM_{2.5} concentrations as high as 214 µg/m³ within homes [6], which is approximately 43 times above the World Health Organization’s recommended exposure limits. Research examining kitchen human activities found that using a gas stove had the greatest impact on indoor air quality, with average increases of 13% in smoke, 24.4% in CO, 9.8% in PM₁₀, and 5.34% in PM_{2.5} compared to other kitchen activities [21]. This study also found that without windows and with insufficient ventilation, using only a range hood cannot effectively reduce PM levels [21]. In South Asia, a study identified that suspended particulate matter and SO₂ were found to

be significantly higher in residential areas than the 24h national standards; NO₂ and CO were in the normal range [22]. A study using calibrated low-cost sensors determined that PM concentration in Nairobi exceeded WHO standards, particularly in urban areas and near roadsides [3].

3.6.2. Air Quality Index in Industrial Areas

In Nairobi's industrial areas, the Air Quality Index (AQI) reflects a mix of air quality levels, with pollutants like PM_{2.5} being moderate at an AQI of 64 and O₃ at 223. These areas of Nairobi exhibit a weighted AQI of 89.40, categorizing them also as "Moderate." Several factors contribute to the observed air quality levels. Industrial emissions in factories and manufacturing plants emit pollutants such as PM_{2.5}, NO₂, and SO₂. Pollution hotspots for SO₂, as shown in **Figure 5**, are concentrated in the Industrial Area, Baba Dogo, and along Mombasa Road, etc., reflecting emissions from manufacturing and fuel combustion. In line with this study, industrial pollution emissions have been identified as the main source of urban pollutants, with urban air quality tending to be worse around sunrise compared to sunset. PM_{2.5}-dominated pollution days in China account for 38.46%. Urbanization and economic development significantly influence air pollution through multiple pathways [23].

3.6.3. Air Quality Index in Commercial Areas

The AQI values for commercial areas are as follows: Carbon Monoxide (CO) is 1; Nitrogen Dioxide (NO₂) is 0; Particulate Matter (PM_{2.5}) is 70; Ozone (O₃) is 223; Sulphur Dioxide (SO₂) is 0. These values indicate that while most pollutants fall within the "Good - Moderate" AQI range (0 - 100), Ozone levels are significantly higher, placing them in the "Very Unhealthy" category (201 - 300). This suggests that Ozone concentration in commercial areas is a major concern, potentially leading to serious health effects for the general population. Traffic congestion contributes to greenhouse gas emissions in cities such as Nairobi, which experiences heavy traffic congestion during peak hours [24]. Previous studies have found that PM_{2.5} and other related traffic pollutants have negative effects on health [25]. Commercial areas in Nairobi recorded the highest AQI, at 91.50 among all land use patterns studied, placing them firmly in the "Moderate" category. Road congestion is directly associated with increased air pollutant concentrations, with vehicles operating at reduced speeds experiencing approximately a 50% increase in CO and hydrocarbon emissions [26].

The combination of stationary traffic and high building density creates street canyon effects that trap pollutants at the pedestrian level, reducing natural ventilation and exacerbating exposure risks. In a study conducted in Paris in 2021, road traffic contributed about 50% of nitrogen oxides (NO₂) emissions and 20% of PM_{2.5} emissions in commercial areas [27]. This study of five ambitious mobility scenarios demonstrated that replacing particular utility vehicles with soft mobility reduced ultrafine particle concentrations by up to 43%, while electrification of vehicles led to the highest reductions for NO₂ at up to 75% [27]. The concentration

of business activities, including restaurants, retail establishments, and service industries, adds to the emission burden through continuous energy consumption and auxiliary transportation needs. These findings underscore the urgent need for traffic management interventions specifically tailored to commercial zones, as shown by the spatial pollutant distribution in **Figure 7**.

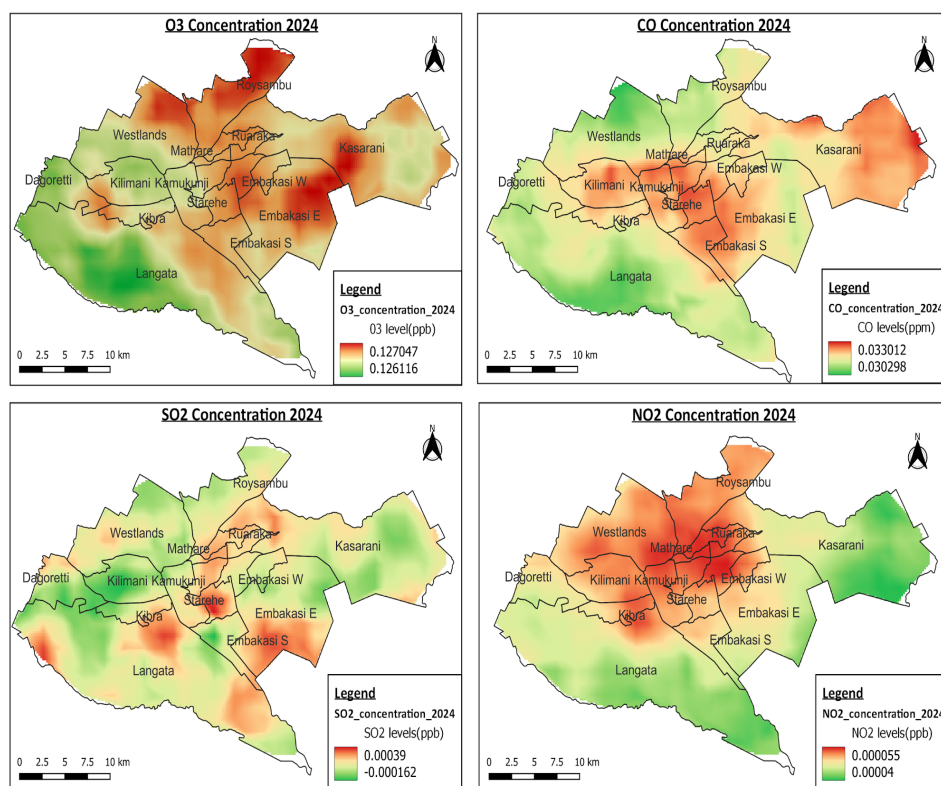


Figure 7. Pollutant concentration.

3.6.4. Air Quality Index in Green Park Areas

In Nairobi's green park areas, the Air Quality Index (AQI) for pollutants of focus reflects a mix of air quality levels, with some pollutants reaching concerning concentrations. The individual AQI values for green park areas are: Carbon Monoxide (CO) is 1; Nitrogen Dioxide (NO₂) is 0; Particulate Matter (PM_{2.5}) is 61; Ozone (O₃) is 223; and Sulphur Dioxide (SO₂) is 0. These values indicate that while most pollutants fall within the "Good-Moderate" AQI range (0 - 50), ozone levels are significantly higher, placing them in the "Very Unhealthy" category (201 - 300). This suggests that ozone concentrations in green park areas are a major concern, potentially leading to serious health effects for the general population.

The weighted AQI for green park areas (**Table 5**), calculated by combining all pollutants with assigned weights, was 88.35, placing green park areas in the "Moderate" category. The relatively elevated pollutant levels observed in some green spaces may be influenced by their proximity to major road networks or urban activity zones, rather than the land cover itself. This highlights the importance of spatial context when interpreting land-use-based air quality patterns. Dense tree

canopies can reduce ventilation in street canyons, potentially exacerbating roadside air pollution concentrations depending on vegetation structure and prevailing weather conditions [28].

A reassessment of the role of urban green space in air pollution control using data from 2615 monitoring stations across Europe and the United States between 2010 and 2019 revealed that the effect size of total green space on air pollution was weak and highly variable, particularly at the street scale (15 to 60 m radius), where vegetation can restrict ventilation. When averaged across spatial scales, a one standard deviation increase in green space resulted in only a 0.8% decline in air pollution [29]. Cities with higher population density in warmer, drier climates had higher PM levels, since land surface temperature and wind pressure were positively correlated with PM₁₀ deposition [28]. There is a need for more research to be conducted on air pollutants in green spaces located near cities.

3.7. Statistics on the Concentration of Air Pollutants in Nairobi City

To test the null hypothesis, “The concentration of criteria air pollutants in Nairobi City is not significantly above the acceptable limit,” we performed a statistical hypothesis test using the AQI data from residential, industrial, commercial, and green park areas of Nairobi. The conclusion, therefore, is that rejecting the null hypothesis for PM_{2.5} and O₃ means these pollutants are categorized as moderate rather than unhealthy in Nairobi, indicating moderate air quality concerns. Failing to reject the null hypothesis for CO₂, NO₂, and SO₂ means their concentrations are not above the acceptable limits.

Table 6. Average concentration of air pollutants in Nairobi City.

Pollutant	Mean Concentration	Acceptable Limit	t-statistic	p-value
CO	0.04	9.0	−3.76	0.005**
NO ₂	5.97e−5	53	−7.85	0.18
PM _{2.5}	16.40	10	5.23	0.000***
O ₃	0.12	0.070	6.48	0.000***
SO ₂	3.62e−5	35	−8.11	0.22

*p < 0.05, **p < 0.01, ***p < 0.001.

The statistical analysis employed one-sample t-tests to evaluate whether pollutant concentrations in Nairobi significantly exceed internationally accepted limits established by the WHO and EPA, as illustrated in **Table 6**. Results revealed critical disparities across pollutants, with PM_{2.5}, CO, and O₃ demonstrating statistically significant exceedances ($p < 0.05$), while NO₂ and SO₂ concentrations remained within acceptable thresholds. PM_{2.5} concentrations (mean: 16.40 µg/m³) significantly exceeded the WHO annual guideline of 10 µg/m³ ($p = 0.000$), indicating severe air quality concerns across all land use patterns. The United States Environmental Protection Agency recently updated AQI breakpoints for PM_{2.5},

lowering the “Good” category threshold from 12.0 to 9.0 $\mu\text{g}/\text{m}^3$ to reflect the revised level of the primary annual $\text{PM}_{2.5}$ standard and recent health science. Under these revised standards, Nairobi’s $\text{PM}_{2.5}$ levels would fall within the “Moderate” category, signaling potential health risks for sensitive populations. Ozone concentrations (0.12 ppb) substantially exceeded the WHO 8-hour guideline of 0.070 ppm ($p = 0.00001$), representing the most critical pollutant concern.

3.8. Discussions

Land use and land cover change are essential factors that affect air quality through alterations in emission sources, vegetation cover, natural processes, and urban design. Incorporating land use and land cover changes in AQI assessment offers a realistic approach to address the complexity arising from combined air pollutants’ effects, surpassing conventional AQI calculation methods [30]. Land use patterns significantly influence pollutant concentrations and subsequent health impacts. A 45% to 55% increase in urbanization has been shown to raise surface temperatures and consequently evening O_3 levels by up to 8%, while replacing 6 to 10% of urban land and 30% to 40% of natural vegetation areas with agriculture reduces O_3 by up to 10% but increases NH_3 emissions by up to 90% [31]. Furthermore, tracking of air pollution across 13,189 urban areas worldwide revealed that over 50% of urban areas showed positive correlations for all pollutant pairs, emphasizing the complex interplay between urbanization and air quality degradation [32]. These findings underscore that urban planning interventions must adopt integrated approaches that simultaneously address multiple pollutants rather than focusing on single pollutant mitigation strategies, as the spatial distribution of emissions, population density, and land use configurations creates compound effects that influence overall air quality across different urban zones.

Fixed monitoring stations alone may inadequately capture the spatial complexity of urban air pollution, as intraurban air pollutant concentrations often exhibit large spatial variabilities that can lead to exposure miscalculations [33]. Mobile air pollution monitoring can resolve fine-scale spatial variability in air pollutant concentrations, allowing communities to map air quality down to the scale of tens of meters, thereby supplementing our understanding of air quality issues in environmental justice regions [33]. The integration of satellite remote sensing with ground-based measurements addresses these limitations, as satellite-derived data provide comprehensive spatial coverage while ground stations offer high temporal resolution and localized validation [34]. This multi-platform approach is therefore ideal for capturing both the broad spatial patterns and localized pollution hotspots characteristic of complex urban environments.

4. Recommendations

Based on the findings of this study, several targeted interventions are recommended to mitigate air pollution exposure and improve public health outcomes across Nairobi’s diverse land use patterns. These recommendations address both

immediate protective measures for vulnerable populations and long-term policy strategies for sustainable air quality management. Based on the findings, targeted interventions should prioritize reducing PM_{2.5} and O₃ emissions in commercial and high-density urban areas, where pollutant concentrations were consistently higher. Strategies may include traffic emission control, improved urban planning to reduce congestion, and expansion of green infrastructure. Given the observed pollutant patterns, future work should focus on integrating higher-resolution ground monitoring with satellite observations to improve exposure assessment, particularly in urban green spaces where unexpected patterns were observed.

4.1. Public Health Protection Measures

Sensitive populations, including children, the elderly, and individuals with pre-existing respiratory or cardiovascular conditions, should limit prolonged outdoor activities during periods of elevated pollution, particularly on high ozone days and during peak traffic hours. This is especially critical in commercial areas where rush hour traffic significantly exacerbates air pollution levels. Workers and residents in industrial zones should take additional precautions by reducing outdoor exposure, with employers encouraged to implement indoor work rotations during high pollution episodes. While the presence of trees and vegetation in green park areas helps mitigate some pollution effects, outdoor exposure should remain cautious during peak hours when ozone formation is highest following prolonged vehicular emissions.

4.2. Policy and Regulatory Interventions

Stricter emissions controls are needed in industrial areas to reduce NO₂, SO₂, and PM_{2.5} concentrations from factories and heavy machinery. Commercial areas require more stringent traffic management and pollution control measures, including the promotion of vehicle electrification, implementation of low-emission zones, and expansion of public transportation infrastructure to reduce dependence on private vehicles. Urban planning interventions such as enhanced transportation infrastructure and expanded urban parks can partially mitigate these impacts, supporting findings similar to those observed in this study. Strategic urban greening initiatives should consider vegetation type, placement, and local meteorological conditions to maximize air purification benefits while avoiding street-level ventilation restrictions that can trap pollutants.

Finally, establishing a comprehensive air quality monitoring network that integrates satellite-based observations with ground-level sensors will enable real-time pollution tracking, early warning systems for high pollution days, and evidence-based evaluation of mitigation strategy effectiveness. However, vegetation cover can mitigate high temperatures through shading and evapotranspiration while reducing certain air pollutants by absorbing harmful gases. Nairobi County should, therefore, continue to increase tree cover strategically, considering vegetation type, placement, and local meteorological conditions to maximize air purification

benefits while minimizing potential street-level ventilation restrictions. Encouraging the use of air purifiers and clean energy sources in both residential and commercial buildings can further reduce indoor pollution exposure. Additionally, enhancing waste management practices and eliminating open burning can help decrease particulate matter levels across all land use zones. The need for investors to invest in ground-based measurements for gases to collect real-time data on the specific gases and for specific areas.

5. Conclusion

This study evaluated the concentration of air pollutants across different land use patterns in Nairobi City County and developed a weighted Air Quality Index model to assess overall air quality. The weighted AQI values for all land use areas consistently fall within the “Moderate” category, indicating that air quality is a concern across all zones in Nairobi. Our findings further revealed that PM_{2.5} and O₃ concentrations significantly exceeded internationally accepted WHO and EPA limits ($p < 0.05$), while CO, NO₂, and SO₂ remained within acceptable thresholds. Land use patterns influence pollutant concentrations, with commercial areas recording the highest weighted AQI, while green park areas had elevated ozone levels during hot days following prolonged vehicular emissions. This highlights the importance of integrated urban planning approaches, combining green infrastructure with emission control strategies. Further research is needed to better understand the interaction between vegetation, urban form, and air pollution in rapidly growing cities.

Conflicts of Interest

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

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