# Seasonal Variability between Major Air Pollutants and Physical Landscapes in the Greater Nairobi Metropolitan Region

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**Abstract**

Satellite data is crucial in regions lacking ground monitoring stations and is helpful in identifying areas likely to have high concentrations of pollutants harmful to human health. As these cities expand and grow, the quality of life and conditions will also be changing. The study seeks to determine the correlation between land surface temperature (LST), elevation, enhanced vegetation index (EVI), rainfall, particulate matter ($PM_{2.5}$), nitrogen dioxide ($NO_2$) and ozone ($O_3$) both day and night during the months of October-December in 2019 and 2024, January-February, June-August in the year 2020 and 2025. The results indicate a varied strength in relationship between variables in each season, both day and night. During the day the highest negative correlation is obtained between elevation and carbon monoxide, while during the night the highest negative correlation is obtained between elevation and LST in all periods analysed. In all seasons and both day and night-time, all counties have a mean $PM_{2.5}$ higher than the recommended WHO annual guidelines. Results from this study indicate the spatial and temporal variations of aerosols over different conditions and are crucial for the development of mitigation strategies that will result in improved quality of life.

## 1.0 Introduction

Human activities have shown to be the main cause of global warming, principally through greenhouse gas emissions (GHG), though natural variability has played some part (Hansen et al. 2020; Gupta and Aithal 2024). Unsustainable land use and land use change, energy use, patterns of production and consumptions are some of the factors that are driving an increase in global greenhouse gas emissions (GHG) across regions (IPCC 2023). Anthropogenic and natural emissions result in aerosols, solid and liquid particles, suspended in the air and these aerosols can change the atmospheric circulation patterns, radiation mechanisms, modify cloud lifetimes and properties and affect the air temperature (Wei et al. 2020). In urban areas, the morphology and physical layout of cities significantly affects the natural air movement thus the dispersal of heat and aerosols. This can be seen in low-density areas, brought about by urban sprawl, which are characterised by longer commutes with excessive motor vehicle dependence, resulting to higher emissions and concentrations of air pollutants (Liu 2019). Conversely, compact development and densification results in lower land consumption and reduces emissions from transportation (OECD et. al. 2025). Transformation of vegetated areas to impervious surfaces results in higher temperatures in urban areas compared to suburban areas, leading to the urban heat island effect, bringing about a higher the energy demand to cool buildings, hence increased air pollutants.

The relationship between air temperature and air pollution is complex and multifaceted. Extreme temperatures in urban areas increase pollutant concentrations by promoting chemical reactions, resulting to the formation of secondary pollutants such as ground-level ozone (Kalisa et al. 2018) and also impacting vertical dispersal of pollutants (Sheriff et al. 2025). Projections indicate that the intensity and impact of heatwaves will worsen, increasing health risks for vulnerable populations due to deteriorating air quality, and can result to economic losses (Wang et al. 2026). Each year, over 2.3 million people die from in-door air pollution and over 4 million people die from outdoor pollutants, with a broad range of respiratory, neurological and cardio-vascular diseases from exposure to poor air quality (Rentschler and Leonova 2023). The burden of the effects of extreme heat and cardio-vascular diseases in low-to-middle income countries can be linked to urbanization and industrialization (Apte et al. 2020; Sliwa et al. 2024; Meltus and Karanja 2024) and exacerbated by the demographic and socio-economic characteristics of the populace (Kunda et al. 2024).

The most common pollutants that have an effect on air quality and human health are $PM_{2.5}$, nitrogen dioxide ($NO_2$), ozone ($O_3$), sulphur dioxide ($SO_2$) and carbon monoxide (CO) (WHO 2021). Carbon monoxide is emitted from burning biomas, incomplete combustion of fossil fuels, industrial processes and contributes to the formation of smog or ground-level ozone when exposed to other pollutants and sunlight (Froidevaux et al. 2025). $PM_{2.5}$ is emitted from anthropogenic sources such as exhaust of motor vehicles, industrial processes and waste burning while natural sources include sea salt and soil dust (Roostaei et al. 2024). Ambient fine particulate matter $\leq 2.5\ \mu g/m^3$ ($PM_{2.5}$) is linked to increased risk of cardiovascular and respiratory diseases and increased mortality (McGuinn et al. 2016). Nitrogen dioxide mainly comes from the transportation sector and some of the environmental effects of $NO_2$ is the development of ground-level ozone (smog) and nitric acid which is toxic. $NO_2$ exposure irritates the airways in the respiratory system and has been linked to increased cases of lung cancer (Ang'u et al. 2022;Ji et al. 2022). Nitrogen dioxide ($NO_2$) and $PM_{2.5}$ are normally studied together as they tend to have co-exposures and have a profound effect on human health and mortality.

Africa contributes less than 4% of the total GHG emissions, yet it is disproportionately impacted by the effects of climate change (OECD et. al. 2025). Exposure to $PM_{2.5}$ has increased by 3% since 2010 in Sub-Sahara Africa (SSA) (Keel et al. 2020) due to rapid urbanization, industrialization, burning of solid waste and agricultural residue (Gualtieri et al. 2024). With Africa's urban population estimated to reach 1.4 billion by the year 2050, where

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two out of three Africans will be living in cities (OECD et. al. 2025), remotely sensed data will be integral in mitigation and adaptation policies due to the sparse number of ground-based monitoring stations (Agbo et al. 2021; Kassandros et al. 2026).

### 1.1 Satellites for Monitoring Air Pollution and LST

Land surface temperature is one of the most important biophysical factors that shape the urban environment by providing the surface energy balance, controlling the air temperature in the lower urban boundary layer, affecting the internal thermal environment of buildings (Kim et al, 2025). It changes rapidly spatially and in time due to the strong heterogeneous land surface characteristics and different thermal properties. Compared to water, land warms at a faster rate during the day because water absorbs and releases heat at a slower rate (thermal inertia) (Hansen et al. 2020). At night, urban areas consisting of concrete and asphalt cool off slowly due to their thermal properties leading to heat stress. Night-time temperature is linked closely to heat-related illnesses where the body does not cool down adequately after exposure from daytime heat, leading to accumulative strain on the body (Kim et al, 2025).

With global warming, temperatures do not rise everywhere at the same rate and at every time (Hansen et al. 2020) and obtaining values over expansive areas using ground measurements is not possible due to the complexity of surface temperatures over land (Li et al. 2013). Satellite data is therefore crucial in regions lacking ground monitoring stations and is helpful in identifying areas likely to have high concentrations of pollutants harmful to human health (Apte et al. 2020). Since the first satellite, Sputnik 1, launched in 1957 (NASA 2007), advancements have been made on earth observation (EO) systems in collecting data over land and seas. The ability of satellites to collect data is not restricted to daytime but also emissions and processes that occur at night. Geostationary Operational Environmental Satellite-R (GEOS-R) series, MOderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Site (VIIRS), Sentinel-3 are some of the EO satellites that provide frequent day and night-time land surface temperatures and aerosol optical depth (AOD) data. Ecosystem Spaceborne Thermal Radiometer Experiment on the International Space Station ((ECOSTRESS), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Landsat 8/9 provide users with day and night-time land surface temperature and are freely accessible from Google Earth Engine (GEE).

Air pollution and heat jointly are a greater health risk to urban populations that either factors alone (Kalisa and Sudmant 2025). Spatial regression models have been critical in analysing the effects of urban form on air pollution and air temperature. Using spatial econometric regression method Liu (2019) determined that an increase in urban density resulted in reduced haze pollution. Yuan et al. (2018) determined that haze pollution, caused largely by $PM_{2.5}$, was affected by urban form with population size affecting air quality. On the variability of concentration of pollutants with altitude and geographical factors, Broqueza et al. (2024) used Ordinary Least Squares (OLS) and Generalized Linear Regression (GLR) to determine the correlation between elevation, LST, carbon monoxide (CO), nitrogen dioxide ($NO_2$) and sulphur dioxide ($SO_2$) in Metro Manila Airsheds. Fuladlu and Altan (2021) analysed the relationship between LST, elevation, $PM_{2.5}$, $SO_2$, $NO_2$ and air pollution monitoring system stations in Tehran province Iran. Linear regression analysis between LST and spectral indices representing surface features such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Wetness Index (NDWI) are crucial in understanding the influence of terrain i.e. elevation, slope on LST (Roy and Bari 2022; Eshetie 2024; Rogalski 2025). Urban Thermal Field Variance Index (UTFVI), which is calculated from LST (Kikon et al. 2023), can give an indication of urban thermal comfort levels (UTCL), urban heat island (UHI) phenomenon and ecological evaluation index (EEI).

This objective of this study, therefore, is to determine the variability of major air pollutants (MAJ), elevation, LST, enhanced vegetation Index (EVI) and rainfall in different seasons of the year. The study will assess the differences in relationship between these variables both day and night time. Findings of this research will offer a better understanding on the temporal variability and levels of exposure within the different counties.

### 1.2 Study Area

Nairobi metropolitan region is surrounded by three administrative units, namely Kiambu County to the north, Machakos County to the east and Kajiado County to the South. Agglomeration of the four units would result in the formation of the Greater Nairobi Metropolitan Region (GNMR). Through the economic, social and political influence of Nairobi City, the neighbouring counties have grown to become the economic hubs of the region through the development of financial and technological centres and economic hubs of the regions (Tubei and Gaas 2023).

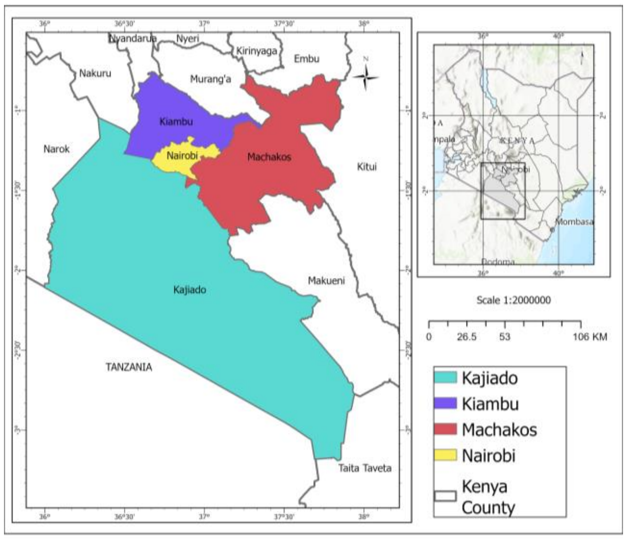


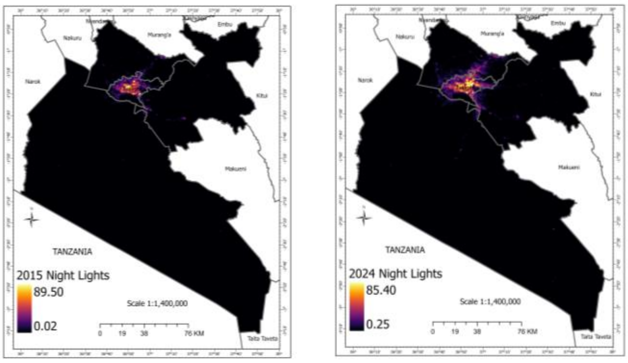

Figure 1: Location context of GNMR

The GNMR was conceptualized in 2008 through the Nairobi Metropolitan Development Plan whose goals were amongst development of infrastructure, utilities, create economic hubs, ensure inclusivity and enhance the quality of life (Mundia 2017; Tubei and Gaas 2023). The area and estimated population from the 2019 population census (RoK 2019) of the four counties is as shown in table 1. The challenges the region has experienced arising from rapid urban expansion such as lack of social amenities, poor infrastructural facilities, air pollution, and degradation of the environment emphasises the importance analysing the level of exposure of its inhabitants.

| County | Area | Pop 2020 | Pop 2025 |
|---|---|---|---|
| Nairobi | 695 $Km^2$ | 4,515,607 | 4,906,355 |
| Kiambu | 2,543 $Km^2$ | 2,500,790 | 2,754,139 |
| Machakos | 6,208 $Km^2$ | 1,441,719 | 1,518,450 |
| Kajiado | 21,901 $Km^2$ | 1,178,759 | 1,327,929 |

Table 1: County area and population in GNMR

Nightlight datasets of 2015 and 2024 of the GNMR shows changes in urban expansion occurring mainly towards Kiambu County (Figure 2). Urban expansion within the GNMR towards the suburbs therefore informed the choice of the study area.




a) b)

Figure 2: Night lights over GNMR in a) 2015 and b) 2024

## 2. Methodology

The research sought to determine the correlation between topographical and geographical characteristics over the Greater Nairobi Metropolitan Region. The variables included the land surface temperature, elevation, enhanced vegetation index (EVI), rainfall, ozone ($O_3$), CO, $NO_2$ and $PM_{2.5}$. Data was processed for the years 2019, 2020, 2024 and 2025 in three different seasons in each year as shown in table 2.

| Month | Year |
|---|---|
| October, November, December (OND) | 2019, 2024 |
| January, February, March (JFM) | 2020,2025 |
| June, July, August (JJA) | 2020,2025 |

Table 2: Months and years of data analysis

Kenya has two rainy seasons: short rains in the months of October, November and December (OND), and long rains in the months of March, April, May (MAM). The months of January and February are usually dry and hot, with higher temperatures observed in the months of February. The months of June, July and August are periods where temperatures are low and is also a dry period with little to no rainfall. Three periods, OND, JFM and JJA, were analysed to determine the interaction between all factors. The long rainy season in the months of April and May were not included in the analysis due to persistence of cloud cover.

### 2.1 Satellite Datasets

Six satellite instruments were used in the study. The Earth Observing System (EOS) Terra (EOS AM) and Aqua (EOS PM) satellites have the MOderate Resolution Imaging Spectroradiometer (MODIS) instrument, where LST and Enhanced Vegetation Index (EVI) datasets were derived. Terra (EOS AM) was launched on 18th December 1999 and crosses the Equator at approximately 10:30am and 10:30 pm daily, with a north to south orbit. Aqua (EOS PM) was launched on 4th May 2002 and it crosses the equator at approximately 1:30pm and 1:30am daily and has a south to north orbit (NASA 2024). MODIS LST products are available at a spatial resolution of 1Km. The Copernicus Sentinel-5 Precursor (Sentinel-5P) carries the TROPOspheric Monitoring Instrument (TROPOMI) measures the Aerosol Optical Depth (AOD) to obtain global observations on trace gases such as formaldehyde, sulphur dioxide, nitrogen dioxide, carbon monoxide, methane, ozone and aerosols as they all affect our health and climate (ESA 2017). Aerosol Optical Depth (AOD) is the measurement of various aerosols or is the measurement of the degree which aerosols prevent transmission of light from the grounds’ surface to the top of the atmosphere.” (Wei et al. 2020). Sentinel-5P products are available at 1Km spatial resolution. The NASA Goddard Earth Observing System (GEOS) Composition Forecasting (CF) system delivers global near real-time estimates and forecasts of compositions of the atmosphere such as fine particulate matter ($PM_{2.5}$), carbon monoxide (CO), ozone ($O_3$) sulphur dioxide ($SO_2$) and nitrogen dioxide ($NO_2$) at a spatial resolution of 5Km. It enables researchers apprehend the causes and impacts of air pollution, by tracking concentrations of gases and particles based on their size and composition (Keller et al. 2021). The Climate Hazards group InfraRed Precipitation with Station (CHIRPS) is a gridded, high resolution precipitation dataset, which combines geostationary thermal-infrared satellite-based estimates (CHIRP3), observations from global, regional and national in situ meteorological networks and from high-resolution climatology (CHPclim2) (Alaso and NCAR 2015). Resolution of CHIRPS datasets is $0.05^0$, approximately 5Km. Shuttle Radar Topography Mission (SRTM) consists of a radar system where the C-band radar data is used to develop near-global topographic maps of the earth referred to as Digital Elevation Model (DEM) has a spatial resolution of 30 meters.

### 2.2 Data Processing

$PM_{2.5}$ ($\mu g/m^3$), $O_3$, ($mol/m^2$) CO ($mol/m^2$), $NO_2$ ($mol/m^2$) were processed from an interactive tool embedded in Google Earth Engine (GEE) https://ee-mostafaayek1.projects.earthengine.app/view/global-air-quality-explorer (Ayek et al., 2025).

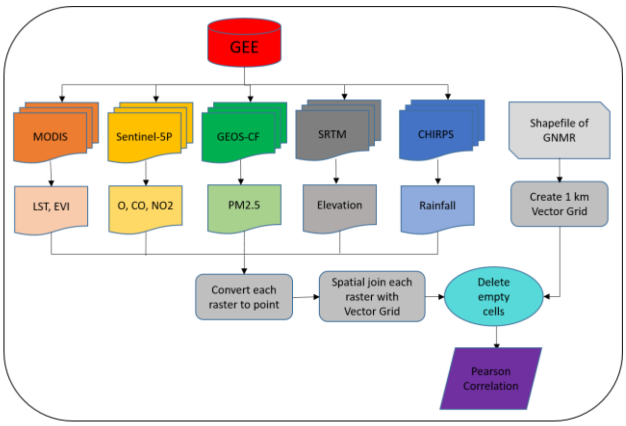



Figure 3: Summary of data analysis process

$PM_{2.5}$ datasets were downloaded for the period 10-11am and 2200-2300hours as these periods correspond to the time which MODIS TerraPM crosses the equator. $SO_2$ and methane (CH4) were not downloaded for inclusion in the analysis as their concentrations over the study area was quite minimal. The elevation (meters), rainfall (mm), EVI (unitless), LST ($^0$C) datasets were downloaded from GEE and resampled to 1Km pixel when exporting the datasets. All raster files were converted to point features and using a 1Km polygon grid over the study area, a spatial join was done for all datasets in ArcGIS Pro. The database was cleaned in MS Excel where empty grid cells, which were located at the edge of the polygon grid, were deleted. The cleaned databases were imported in Google Colab where Pearson correlation analysis was carried out. Correlation values ($r^2$) of above +/- 0.5 were considered significant and are highlighted in the results for each period studied. Values ranging from 0 to ±0.3 were considered to have a very weak correlation, ±0.3 to ±0.5 were considered to have a weak correlation, ±0.5 to ±0.7 were considered to have a moderate correlation while values above ±0.7 were considered to have a strong correlation.

## 3. Results and Discussions

### 3.1 Day-time Correlation Analysis

There were variations in the Pearson correlation for day data analysed in the years 2019, 2020, 2024 and 2025 (Figure 4) indicating that seasonal variations affect the strength of the relationship across the study area. The results and discussion highlights moderate to strong correlation values to determine the overall trends and possible variations in observations.

CO and LST have strong positive correlations during the OND period in 2019 and 2020 of 0.84 and 0.79 respectively and moderate to strong positive correlation of 0.62 and 0.77 during the JFM season in 2020 and 2025 respectively. CO has a strong negative correlation of more than -0.8 with elevation in all seasons except for JJA in 2020 where it has a moderate negative correlation of -0.5. CO also has a moderate negative correlation with rainfall and EVI in the OND periods and in the JJA period of 2025. The variation indicates that CO is positively impacted by temperature than with other variables. CO negative correlation with elevation, rainfall and EVI is during the cold and wet seasons. An analysis by Broqueza et al. (2024) determined there was a negative correlation between DEM and LST, CO, $NO_2$.

$PM_{2.5}$ and $NO_2$ have moderate positive correlations of 0.68 and 0.64 in the year 2019 and 2024 respectively during the OND season; positive correlation values of 0.69 and 0.76 in 2020 and 2025 respectively during the JFM season; positive correlation values of 0.53 in 2020 and 2025 during the JJA season. During the JJA period, $PM_{2.5}$ has positive correlations with rainfall, elevation and EVI, with rainfall having a stronger correlation of 0.82 and 0.79 in 2020 and 2025 respectively compared to the other three variables. $PM_{2.5}$ has a moderate negative correlation with LST of -0.54 and -0.57 in 2020 and 2025 respectively in the JJA period. This shows that $PM_{2.5}$ and $NO_2$ have a moderate positive correlation in all seasons in all years analysed and that increased rainfall does not result in the reduction of the concentration of the pollutant. Rainfall, elevation and EVI tend to have a positive effect on $PM_{2.5}$ during the cold season and this is seen in the negative correlation it has with LST. Ji et al. (2022) analysis of $NO_2$ and $PM_{2.5}$ in China determined a positive correlation between the two pollutants. Zhan et al. (2023) analysis of $PM_{2.5}$ determined a negative correlation with LST and positive correlation with relative humidity during the winter and autumn season. An increase in $PM_{2.5}$ in the atmosphere can reduce the LST due to scattering and absorption, with a cooling effect in the atmosphere due to the high particulate matter. Increased LST results in lower wind speeds and air pressure, thus dispersal of air pollutants becomes difficult (Yang et al. 2017).

EVI had positive moderate correlations with rainfall and elevation during the period of JJA and OND. However during the JFM period EVI had a weak correlation of 0.38 in 2020 compared to a moderate correlation of 0.51 in 2025 with elevation. The positive relationship with elevation and rainfall indicates that the amount of vegetation within the area increases with increased rainfall and altitude. In all periods, LST has a moderate to strong negative relationship with elevation, EVI and rainfall, except in the JFM period where LST has a weak negative correlation with rainfall. This weak relationship would be expected as the amount of rainfall received is lower than in other seasons. $O_3$ has a moderate negative correlation with elevation of -0.54 and -0.52 in 2020 and 2025 respectively in the JFM period. This negative relationship is stronger in the warmer season compared to the colder and wetter seasons.

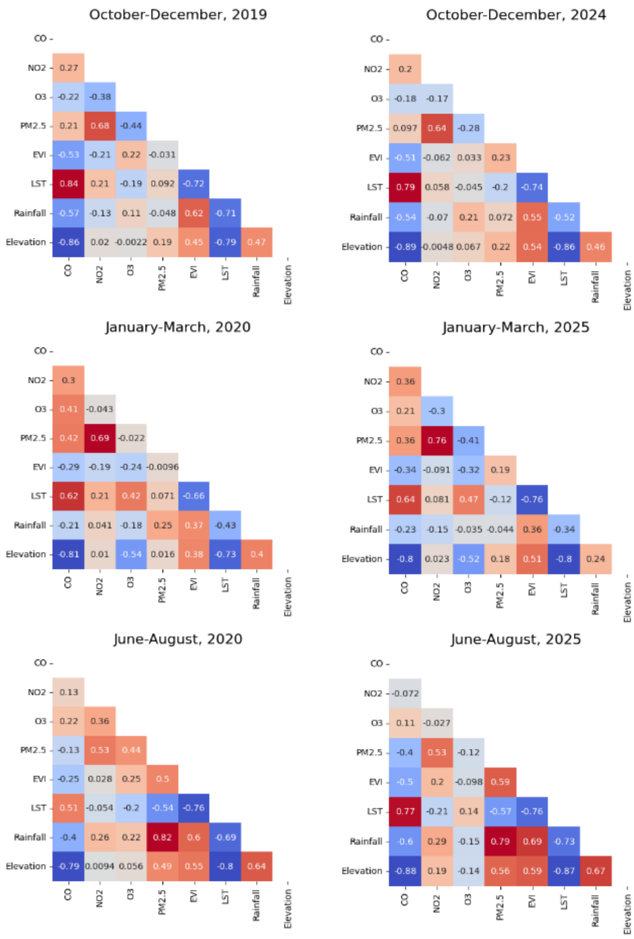



Figure 2: Linear regression of day-time LST and other variables

Factors such as vegetation and topography also have an influence on the concentration of pollutants. These results were also determined by Fuladlu and Altan (2021) where they noted a negative correlation between altitude and LST, CO and $O_3$, while LST had a positive correlation with CO and $O_3$. Pollutants can be trapped and ozone formed in areas such as in valleys surrounded by mountains. Ozone levels peak during summer due to temperature and sunlight intensity when photochemical reactions are more active (Donzelli and Morales 2024). In remote regions, ozone and its precursors can be brought about by long distance travels.

Table 3 gives a summary of the variables having the highest negative and positive correlation values, during the day-time from the years 2019 to 2025. Nyaga et al. (2025) using low cost sensors over Nairobi observed higher $PM_{2.5}$ concentrations during the dry seasons of January-February, June-September seasons, and lower concentrations during the rainy periods March-April, October-December.

| **Correlation** | **2019 & 2024** | **2020 & 2025** | |
|---|---|---|---|
| | **OND** | **JFM** | **JJA** |
| Positive | CO & LST | $PM_{2.5}$ & $NO_2$ | $PM_{2.5}$ & Rainfall |
| Negative | CO & Elevation | CO & Elevation | LST & Elevation |

Table 3: Highest correlations during the day-time

### 3.2 Night-time Correlation Analysis

Pearson correlation for night-time satellite data for the years 2019, 2020, 2024 and 2025 also showed a variation of correlation between the years (Figure 5). Data values of elevation, rainfall and EVI used in the day-time correlation analysis were used in the analysis for the correlation with night-time $PM_{2.5}$ and LST.

$PM_{2.5}$ has a moderate positive correlation with elevation in the JJA period and in the OND period of the year 2019, while with EVI, the positive correlation is only in the JJA period of 2025. $PM_{2.5}$ has a strong positive correlation with rainfall of 0.79 and 0.8 in the JJA period in the year 2020 and 2025 respectively. In the JJA period, $PM_{2.5}$ has a moderate negative correlation with LST of -0.57 and -0.61 in the year 2020 and 2025 respectively. At night the $PM_{2.5}$ still maintains a positive correlation with elevation, rainfall and EVI in the cold and wet seasons as during the day time. However in the JFM season the correlation is weak. $PM_{2.5}$ has a negative correlation with LST in the same season of JJA as during the day. This indicates that for both day and night times periods, cold and wet season's results in higher concentrations of $PM_{2.5}$ than during warmer and drier seasons. Similar results of a positive correlation between elevation and $PM_{2.5}$ during the night were also obtained by Choomanee et al. (2020) in their study in Bangkok, Thailand where they determined to compare differences in concentrations with organic carbon and elemental carbon.

LST has a strong negative correlation with elevation in all periods analysed. Except for the JFM periods, LST has moderate negative correlation with rainfall in the OND and JJA periods. LST has a moderate negative correlation with EVI in OND period, and also during the JFM and JJA periods of the year 2025. Comparing these results with day-time results, LST still maintains a negative correlation with elevation within all seasons analysed. With EVI, the negative correlation at night is only during the OND period compared to all seasons in the day-time analysis. With rainfall, a negative correlation during the day is in all seasons compare to only the cold and wets seasons of OND and JJA at night. LST often has an inverse relationship with vegetation, rainfall and elevation as seen in both day and night-time analysis. The effect is that high temperatures leads to increased evapotranspiration, leading to dry soils, resulting in lower moisture in the atmosphere and consequently reduced rainfall (Rogalski 2025).

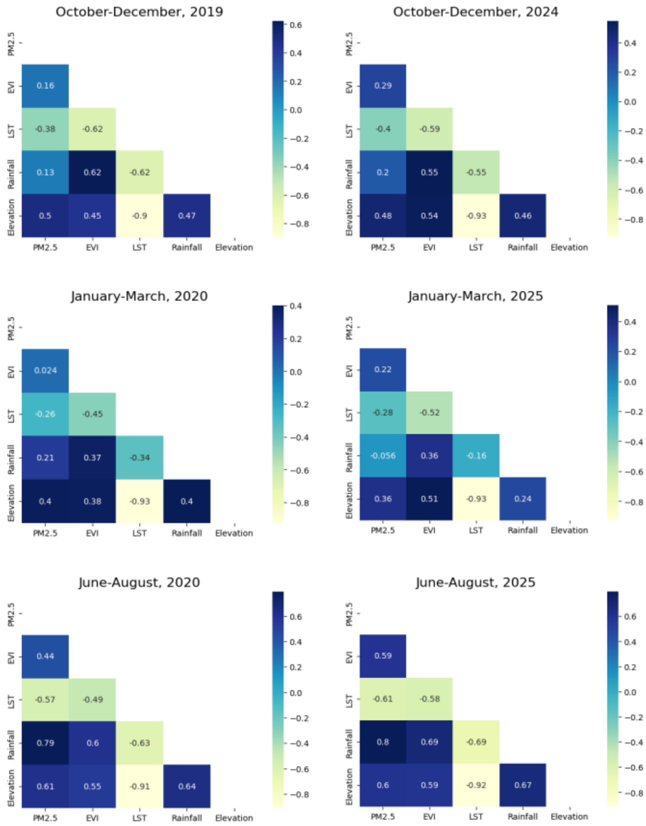



Figure 5: Linear regression of night-time LST and other variables

Table 4 summarizes the variables that have the highest correlations for the night time datasets for the analysed periods 2019 to 2025. The highest positive correlation in the period 2024 OND and 2025 JFM were between elevation and $PM_{2.5}$ .

| **Correlation** | **2019 & 2024** | **2020 & 2025** | |
|---|---|---|---|
| | **OND** | **JFM** | **JJA** |
| Positive | Elevation & $PM_{2.5}$ | Elevation & $PM_{2.5}$ | Rainfall & $PM_{2.5}$ |
| Negative | Elevation & LST | Elevation & LST | Elevation & LST |

Table 4: Night-time correlation

It has been determined that atmospheric pressure, humidity and temperature affect the concentration of air pollutants and the formation of secondary pollutants in the atmosphere (Nguyen et al. 2022). Thus elevation having the highest negative correlation values with LST and CO in both day and night-time analysis (table 3 & 4) indicates that its critical importance as a geographical element in the dispersal of pollutants.

### 3.3 Mean of maximum correlation values per County

Mean values per county for only the variables that had the highest correlation values for both day and night-time (table 3 & 4) were determined for the years 2024 and 2025 for the OND, JFM and JJA seasons (table 5 and 6). The mean elevation for each county was determined as Kajiado at 1288m, Machakos at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1353 m, Nairobi at 1652m and Kiambu at 1885m above mean sea level.

| Time | Item | Kajiado | Kiambu | Machakos | Nairobi |
|---|---|---|---|---|---|
| OND 2024 | CO | 2.8E-02 | 2.6E-02 | 2.7E-02 | 2.7E-02 |
| | $PM_{2.5}$ | 6.10 | 8.16 | 6.17 | 8.68 |
| | LST | 31.27 | 24.64 | 29.55 | 27.77 |
| JFM 2025 | $PM_{2.5}$ | 6.83 | 8.42 | 6.55 | 9.12 |
| | $NO_2$ | 9.1-06 | 1.1E-05 | 7.0E-06 | 2.5E-05 |
| | CO | 2.8E-02 | 2.6E-02 | 2.8E-02 | 2.8E-02 |
| JJA 2025 | Rain | 0.16 | 1.05 | 0.22 | 0.63 |
| | $PM_{2.5}$ | 4.77 | 12.25 | 4.56 | 9.89 |
| | LST | 27.60 | 21.12 | 26.38 | 23.89 |

Table 5: Day-time mean values per county

Intensity of pollution depends on distribution of emission sources and transportation mechanism. Nairobi city and Kiambu County have higher $NO_2$ and $PM_{2.5}$ values in all periods analysed. Rising urban expansion and increased human activities can be attributed to pollutants with night-lights indicating urban expansion within the last 9 years (Figure 2). Kiambu County has the highest $PM_{2.5}$ values amongst the four counties during the cold season of JJA which could be caused by increased warming activities as the area has lower temperatures, higher vegetation cover and elevation. Kajiado County has high CO values due to biomass burning as the area’s land cover is mainly open grassland with pastoralism as one of the economic activities. The county also boarders Tanzania, where biomass burning is rampant, and Nyaga et al. (2025) determined that during the JJAS season, through advection, pollutants could reach Nairobi due to the southerly air masses.

| Time | Item | Kajiado | Kiambu | Machakos | Nairobi |
|---|---|---|---|---|---|
| OND 2024 | $PM_{2.5}$ | 8.62 | 15.89 | 8.24 | 18.09 |
| | LST | 19.24 | 13.24 | 17.88 | 15.53 |
| JFM 2025 | $PM_{2.5}$ | 8.59 | 14.03 | 8.16 | 16.61 |
| | LST | 20.36 | 14.18 | 19.05 | 16.69 |
| JJA 2025 | $PM_{2.5}$ | 6.52 | 28.15 | 5.97 | 22.79 |
| | LST | 17.34 | 11.26 | 16.62 | 14.13 |

Table 6: Night-time mean values per county

Mean $PM_{2.5}$ values in all counties especially at night exceed the annual WHO recommended air quality guidelines (AQG) of 5ug/m$^3$ (WHO 2021). Inhabitants living in regions outside Nairobi City County, which is densely populated, and commuting to various parts within the metropolitan region, are still exposed to pollutants, especially $PM_{2.5}$ both day and night. Night-time chemistry differs from day-time and this affects the concentration of pollutants in the atmosphere. $O_3$ and $PM_{2.5}$ and associated precursors are produced by night-time nitrogen radical chemistry, then feedback into the day-time atmospheric chemistry. $PM_{2.5}$ peaks in the morning from 7:00 to 10:00 local solar time and at night between 21:00 and 23:00 local solar time indicating that air quality does not improve with reduced night movement in comparison to day-time (Manning et al. 2018).

### 3.4 Conclusion

The study comprehensively assesses the seasonal variability of various pollutants within four counties and how they correlate with geographical elements, leveraging the source data from satellite imagery. It demonstrates and emphasises the dynamics of air quality and its various patterns. The study demonstrates that meteorological factors have an impact on the variation of concentration of pollutants and that regional convection currents Statistical analysis has increasingly become pertinent in understanding variability/relationship geographical features have with other substances. The relationship between the variables LST, elevation, rainfall, EVI, $PM_{2.5}$, CO, $O_3$ and $NO_2$ has been determined using linear methods of analysis such as Pearson Correlation. Application of alternative methods of analysing non-linear relationships may bring-out the relationship between variables that had a weak correlation. The results show that the relationship between variables varies with seasons, and times of the year as well as time of the day. The correlation values indicate that elevation plays a crucial role in the concentration of pollutants both during the day and at night and with season. This is important as residents seek to move further away from the city to live in the suburbs and commute to the urban areas to undertake various economic activities. The various emissions from these activities does have an effect both day and night and this is within the urban and areas considered sub-urban. These results are crucial to local authorities to enable them understand the pollutant residents are exposed to and take measures that in tum will reduce effects on health and improve the quality of life of residents. The results emphasise that cooperation between local and regional authorities and governments is critical since pollution does not remain within its geographical source but is transported to varied regions. Thus planners, policy makers and those in the environmental design field can further develop mitigative and adaptive measures for various areas.

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