ASSESSING THE COMBINED IMPACT OF URBAN GROWTH AND AIR POLLUTION ON VEGETATION AND LAND SURFACE TEMPERATURE IN BANGLADESH

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ABSTRACT

Concern over air pollution is growing globally, especially in rapidly developing nations like South Asia. Sustainable urban development in rapidly growing regions requires monitoring key air pollutants and understanding their effects on surface temperature, vegetation health, and urban expansion. This study aims to examine the impact of key air pollutants (NO_2, SO_2, CO, O_3) on vegetation health and land surface temperature (LST) and investigate the relationship between urbanization and air pollution in the highly urbanized Dhaka City of Bangladesh for the year 2022 to 2024. The satellite-based remote sensing data are used to assess the spatiotemporal relationships between air pollutants, vegetation health, land surface temperature, and urban growth across the study area. Concentration data for air pollutants are extracted from Sentinel-5P TROPOMI using Google Earth Engine (GEE). Vegetation indices like NDVI, EVI and surface temperature are extracted from Landsat 8 and 9. A grid-based statistical approach will be applied by dividing the study area into 1 km² cells to assess local-level variability. Furthermore, built-up area growth is calculated by extracting sentinel 2, 10 m resolution dynamic land cover dataset, enabling the analysis of its correlation with air pollutant mean column density levels to better understand the environmental impacts of rapid urbanization. The analysis reveals NO_2 have the most positive and strongest relationship with land surface temperature and the weakest and negative ones with vegetation. The case of SO_2 is that there are weak and unstable connections with temperature and vegetation, which in turn, indicate the place where the local industry and vehicles might be emitting the sulfur. CO shows limited vegetation influenced but in winter moderate association with LST. O_3 is the case of temperature-driven atmospheric mixing as it is negatively associated to surface temperature but at the same time has a weakly positive correlation with vegetation. Regressions of urban growth show there is no effect on SO_2 and CO, a slow decline in the case of NO_2, and a slight increase in the case of O_3, indicating that the spread area lessens the effect of primary pollutants while at the same time affecting ozone formation. By identifying spatial and seasonal pollution patterns and their ecological implications, this study provides essential guidance for policymakers, planners, and environmental engineers, supporting evidence-based strategies to reduce pollution and strengthen environmental resilience in rapidly growing cities.

Keywords: *Air Pollutants, Vegetation, Land Surface Temperature, Urban Growth, Remote sensing*

1. INTRODUCTION

The swift growth of urban areas, which is the result of the increasing number of people living in and around the cities and the cities swallowing more land, has led to more energy consumption, industrial activities and polluting vehicles that all together are the reasons for the air quality decline. Along with that, urban expansion has a major effect on the land utilization and land cover resulting in the alteration of the local climate conditions (Wang et al., 2022). As city grows concentration of major pollutants such as CO, SO_2, NO_2 and O_3 increase. Such air pollutants were significantly higher in urban areas with lower vegetation values and higher LST, particularly near major roads and industrial regions (Rahman et al., 2024; Waheed et al., 2025).

The South Asian region is known to be one of the most polluted places globally, and the air quality continues to deteriorate because of industrialization, large population, and quick urban growth. Additionally, the increase of NO_2, SO_2, CO, and O_3 levels on the Indian Subcontinent has been strongly associated with land-use changes, transportation emissions, biomass burning, and the overall urbanization in the region (Goldberg et al., 2021; Jion et al., 2023). For example, Due to population growth and rural-urban migration, Delhi, one of the most polluted megacities in the world, has experienced tremendous expansion. During the period from 2000 to 2020, the city's inherent capacity to manage air pollution diminish mainly due to the expansion of the built-up area by about 38% and the water bodies cover reduction of 21% (Rani & Kumar, 2025). Urbanization is a global phenomenon that has turned rural areas into urban ones and is still increasing the extent of environmental stress by main factors such as land surface temperature and vegetation health, which are indicators of these changes. In the less developed countries' case, population increase and socio-economic demand lead to LULC changes quickly. Although remote sensing and GIS are the primary tools used to track these changes, as many as 97% of cities fall short of meeting air quality criteria, thus making the need for practical urban management methods all the more pressing (Wang et al., 2022). Bangladesh is also experiencing a similar situation where rapid urban development, increasing population density, and the upward trend in industrial activities are shifting LULC, thereby raising the level of pollutants and making it difficult to manage quality of air (Rahman et al., 2024).

Although numerous studies have examined the relationships between air pollutants, vegetation, and land surface temperature, the existing literature shows several important gaps that justify the present research. Prior works have generally explored pairwise relationship, such as vegetation-NO_2 interaction (Rahaman et al., 2023; Wang et al., 2025). Other studies have evaluated general air quality dynamics without integrating land -cover variables or urban growth (Girotti et al., 2025; Pavel et al., 2021; Wang et al., 2025). However, no studies combine air pollutants, vegetation indices, surface temperature, and urban expansion within a single analytical framework. Such an Approach helps to identify where land cover change and warming intensify pollution, highlight critical hotspots, and clarify which environmental drivers matter most. By showing how improving vegetation cover and reducing urban heat can lower pollutant kevels and health risks, this integrated perspective become important for effective air quality management and sustainable urban planning in Dhaka.

This paper aims to evaluate the spatiotemporal relationship between major air pollutants, vegetation health and land surface temperature and to analysis the impact of urban growth on the concentration of key air pollutants in Dhaka city. It provides an integrating understanding of how these environmental components interact across space and time.

2. MATERIALS AND METHODS

2.1 Study Area

Dhaka, the capital city of Bangladesh, is located at 23°46′51.193″ N and 90°16′45.2532″ E coordinates (Figure 1) has taken as the study area. The city covers an area of around 304.16 km^2 and has more than 16 million inhabitants, making it one of the most densely populated megacities in the world. The vertical and horizontal urban expansion has significantly altered the city's land cover, affecting the urban microclimates(Ahmed et al., 2013).

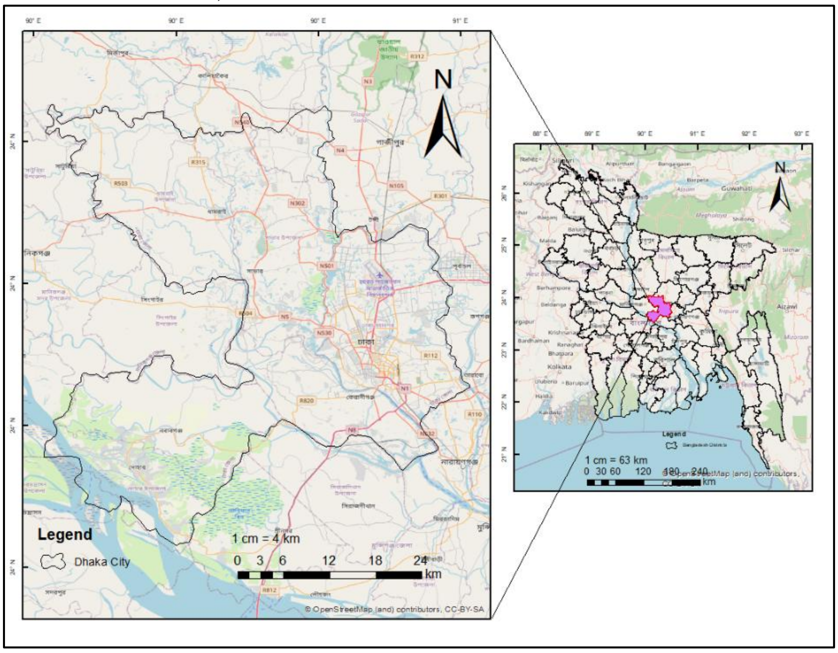

Figure 1: The location of the study area on the maps of Dhaka City

2.2 Data Collection

Google Earth Engine (GEE) had been used for analysis because it is the finest powerful cloud-based geospatial platform that enables large-scale environmental monitoring. Standard preprocessing included cloud masking, atmospheric corrections, spatial resampling to common grids where required, and seasonal compositing for analysis. Table 1, summarizes variables, sources, units, and resolutions used in this study.

Table 1: Metadata retrieved from satellite of data

Variable	Source	Units	Resolution
NO_2 Concentration	Sentinel-5P	mol/m^2	1113.2 m
SO_2 Concentration	Sentinel-5P	mol/m^2	1113.2 m
CO Concentration	Sentinel-5P	mol/m^2	1113.2 m
O_3 Concentration	Sentinel-5P	mol/m^2	1113.2 m
NDVI	Landsat 8	No units	30m
EVI	Landsat 8	No units	30m
LST	Landsat 9	Degree Celsius	30m

2.3 Methodology

The research utilized satellite imagery from the years 2022 through 2024, with an emphasis on the principal atmospheric trace gases that the TROPOMI sensor detected. All the satellite products were acquired and processed in Google Earth Engine in order to guarantee uniform procedures, premium data, and reliable accuracy throughout. To uncover linear connections, Pearson's correlation was used to analyse surface temperature, vegetation indices, and air pollutants, while the seasonal and temporal variations were studied to reveal trends over time. This integrated statistical and satellite-based methodology offers a complete picture of the environmental dynamics that impact the health of vegetation.

2.3.1 Calculation of Normalized Difference Vegetation Index (NDVI)

NDVI quantifies green vegetation by contrasting near-infrared (NIR) and red reflectance (Huang et al., 2021). It is computed per pixel as**:**

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

2.3.2 Calculation of Enhanced Vegetation Index (EVI)

By lessening the impact of canopy background signals and atmospheric impacts on the vegetation signal, especially in areas with high biomass density, EVI is an enhanced vegetation index intended to improve vegetation monitoring(Jarchow et al., 2018). The formula of EVI is expressed:

$$EVI = 2.5 * \frac{(NIR-RED)}{(NIR+C1*RED-C2*BLUE+L)} \quad (2)$$

Where, C1 = 6, C2= 7.5, L=1

2.3.3 Calculation of Land Surface Temperature

Land Surface Temperature (LST) was derived from Landsat 9 thermal bands using a multi-step approach implemented in Google Earth Engine (GEE). The process involved five main steps (Sobrino et al., 2004).

Step 1: Conversion of DN to Radiance: Digital Numbers (DN) were converted to top-of-atmosphere (TOA) radiance using the radiometric rescaling factors provided in the metadata.

$$L\lambda = ML * Q_{cal} + AL - O_i \quad (3)$$

Step 2: Radiance to Brightness Temperature (BT): TOA radiance was then transformed into Brightness Temperature (BT) in Kelvin using the thermal constants $K1$ and $K2$.

$$BT = \frac{K2}{\ln\left(\frac{K1}{L\lambda}+1\right)} - 273.15 \quad (4)$$

Step 3: Proportion of Vegetation (PV): The proportion of vegetation was estimated from NDVI values, normalized between their minimum and maximum ranges.

$$PV = \left(\frac{NDVI-NDVI_{min}}{NDVI_{max}-NDVI_{min}}\right) \quad (5)$$

Step 4: Land Surface Emissivity (LSE): LSE was calculated based on PV using an empirical relationship

$$\in = 0.004 * PV + 0.9864 \quad (6)$$

Step 5: Final LST Calculation: The final LST was obtained by correcting BT with the emissivity value.

$$LST = \frac{BT}{1+\left(\frac{\lambda*BT}{p}\right)ln\,(\in)} \quad (7)$$

2.3.4 Grid Based Analysis:

The selection of 1 km^2 grid size for Dhaka city is primarily justified by the spatial resolution of the data provided by the Sentinel-5P TROPOMI satellite, which is approximately one square kilometer. By dividing the Dhaka city into 1451 grids of this size respectively, it effectively aligns the extracted air pollutants concentration data with corresponding vegetation indices and LST for statistical analysis. This resolution is considered ideal for monitoring polluting emission sources at the city level in large urban areas like Dhaka. Spatial smoothing at this scale reveals broad geographical patterns across a city, it is unsuitable for analyzing local micro-climate. Correlation strength is influenced by grid size. Larger grid cells can increase correlation strength particularly between impervious surfaces, LST and air pollutants but at the cost of increased uncertainty in detecting fine-scale cooling effect of vegetation. By averaging diverse vegetation, LST and air pollutants within each cell, a 1 km^2 grid creates uncertainty that may mask local variability. Additionally, this geographical aggregation may lessen sensitivity to localized pollution sources and small-scale vegetation effects.

2.3.5 Limitations and Uncertainty of Satellite-Derived Data:

Although satellite remote sensing provides valuable information on air pollution and environmental variability at broader spatial scales, several limitations introduce uncertainty in satellite-derived pollutant such as Sentinel-5P are sensitive to cloud cover, observations and spatial gaps. In this study, temporal averaging was applied to reduce data gaps. However, this approach may obscure short-term pollution variability. Uncertainty in pollutant retrieval further arises from assumptions embedded in radiative transfer models, atmospheric correlation procedures, and aerosol interference. These factors can introduce systematic biases in satellite-based NO_2 estimates, especially over regions with high aerosol loading, complex surface reflectance, or heterogeneous terrain. While satellite data enable large-scale analysis and multi-sensor integration, discrepancies with ground-based measurements remain inevitable. Future studies may reduce these uncertainties by integrating in situ observations, data fusion approaches, and machine-learning-based correction methods.

3. RESULTS AND DISCUSSION

3.1 Nitrogen dioxide (NO_2)

The trends in NO_2 concentrations over Dhaka reveal distinct seasonal patterns both summer and winter (Figure 2). In summer, NO_2 showed fluctuations, with a peak in 2023 (1.372×10^{-4} mol/m^2) and a trough in 2022 (1.180×10^{-4} mol/m^2). Despite this year-to-year variation, the overall change from 2022 to 2024 indicates a slight increase (from 1.180×10^{-4} mol/m^2 to 1.232×10^{-4} mol/m^2), representing a rise of ~4.4%. The Standard Deviation (SD) of summer NO_2 ranged from 0.216 (2024) to 0.357 $\times10^{-4}$ mol/m^2 (2023), and the Coefficient of Variation (CV) from 17.53% (2024) to 26.02% (2023), indicating moderate relative variability across summers. Conversely, winter NO_2 concentrations declined over the study period. From 2022 to 2023 there was a pronounced decrease, followed by a slight reduction in 2024, with values changing from 2.274 (2022) to 1.807 (2023) and 1.773×10^{-4} mol/m^2 (2024). Overall, winter NO_2 decreased by ~22.0% between 2022 and 2024. The SD during winters ranged from 0.540 (2024) to 0.867 $\times10^{-4}$ mol/m^2 (2022), while CV ranged from 30.46% (2024) to 38.13% (2022), reflecting higher relative variability in winter than in summer. These findings highlight clear seasonal contrasts and short-term trends in Dhaka's NO_2, underscoring the need for continued monitoring and targeted mitigation during the winter period.

3.2 Sulfur dioxide (SO_2)

The trends in SO_2 concentrations over Dhaka show clear seasonal contrasts (Figure 2). In summer, SO_2 increased steadily from 2022 (1.196×10^{-4} mol/m^2) to 2023 (1.563×10^{-4} mol/m^2) and reached a peak in 2024 (1.940×10^{-4} mol/m^2). Overall, summer SO_2 rose by ~62.2% between 2022 and 2024. The Standard Deviation (SD) during summers ranged from 0.524 (2022) to 0.692 $\times10^{-4}$ mol/m^2 (2024), and the Coefficient of Variation (CV) from 34.81%–43.83%, indicating moderate relative variability across seasons. In winter, SO_2 concentrations declined over the study period, dropping from 2.007 (2022) to 1.252 (2023) and 0.994 $\times10^{-4}$ mol/m^2 (2024). This represents an overall ~50.5% decrease from 2022 to 2024. Winter SD values ranged from 0.503 (2024) to 0.691×10^{-4} mol/m^2 (2023), while CV spanned 33.83%–55.17%, reflecting higher relative variability in winter than in summer. These results underscore pronounced seasonal dynamics and short-term temporal changes in SO_2 over Dhaka, with elevated summer levels and declining winter concentrations.

3.3 Carbon Monoxide (CO)

The CO trends over Dhaka exhibit slight year-to-year variance along with seasonal variations (Figure 2). During the summer, CO fell from 0.0473 mol/m² in 2022 to a trough in 2023 (0.0448 mol/m²), then rose to a peak in 2024 (0.0496 mol/m²), resulting in an approximate 4.8% increase from 2022 and 2024. With a CV of 1.03% to 1.17%, the summer SD varied from 4.86×10^{-2} mol/m² (2022) to 5.22×10^{-1} mol/m² (2023), suggesting minimal relative fluctuation. During the winter, CO increased by around 2.2% overall, from 0.0484 mol/m² in 2022 to 0.0481 mol/m² in 2023 to 0.0495 mol/m² in 2024. Winter SD ranged from 9.34×10^{-3} mol/m² (2022) to 1.27×10^{-3} mol/m² (2023) and 5.22×10^{-1} mol/m² (2024); corresponding CV values were 1.93%, 2.65%, and 1.06%, respectively, a little more variable in 2023 but typically low. With summer reaching a peak in 2024 and winter exhibiting slight interannual variations, these findings indicate slight rising trends in CO in both seasons.

3.4 Ozone (O_3)

There were slight but distinct seasonal variations in the O_3 trends over Dhaka (Figure 2). O_3 declined from 0.1315 mol/m² in 2022 to a trough of 0.1290 mol/m² in 2023, then increased to a peak of 0.1341 mol/m² in 2024, resulting in an overall increase of almost 2.0% between 2022 and 2024. The summer SD and CV showed very little relative variability, ranging from 1.08×10^{-2} mol/m² (2023) to 1.31×10^{-1} mol/m² (2024) and ~0.08%-0.10%, respectively. During the winter, O_3 rose from 0.1118 mol/m² in 2022 to a peak of 0.1200 mol/m² in 2023, then slightly decreased to 0.1177 mol/m² in 2024. The total increase between 2022 and 2024 was around 5.2%. Winter SD ranged from 1.18×10^{-2} mol/m² (2024) to 2.49×10^{-2} mol/m² (2023), with CV ranging from ~0.10% to 0.21%, indicating low-to-moderate relative variability and a somewhat more variable winter in 2023. With summer peaking in 2024 and winter peaking in 2023, these findings indicate modest rising trends in O_3 throughout both seasons.

3.5 Vegetation Indices (NDVI, EVI)

From 2022 to 2024 (Figure 3(a) and 3(b)), there were discernible seasonal differences in Dhaka's Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). During the summer, NDVI readings increased from 0.379 in 2022 to a peak of 0.411 in 2023 before declining to 0.383 in 2024, indicating a little rise of about 1.1% during the research period. EVI increased from 0.355 in 2022 to 0.404 in 2023 before marginally declining to 0.342 in 2024, following a similar pattern. The summer NDVI and EVI had Standard Deviations (SD) of 0.179 to 0.196 and 0.186 to 0.187, respectively, with moderate variability (43 to 55%) indicated by the Coefficient of Variation (CV) values. In contrast to summer, both indices showed bigger magnitudes but more stability in the winter. While EVI grew from 0.245 to 0.340 during the same period, NDVI increased significantly from 0.267 in 2022 to 0.398 in 2023 and remained at this level through 2024. Compared to summer, the winter SD values (0.142 to 0.232) and CV (56-59%) indicate somewhat higher variability. Overall, vegetation greenness in Dhaka improved after 2022, particularly during the winter months, likely reflecting favourable climatic conditions and seasonal vegetation growth patterns. These results highlight the strong seasonality and temporal dynamics of vegetation cover, which are essential for assessing urban ecosystem health and land surface processes.

3.6 Land surface temperature (LST)

Seasonal variations were evident in the LST patterns over Dhaka (Figure 3(a) and 3(b)). LST varied during the summer, peaking around 37.20°C in 2023 and falling to 26.40°C in 2022. Overall, from 2022 (26.40°C) to 2024 (27.85°C), summer LST increased by about 5.5%. Summer variability showed a higher interannual spread during the very warm 2023 summer, with SD = 1.44 to 3.91°C and CV = 5.45 to 10.51% (highest in 2023). Wintertime LST rose from 22.00°C in 2022 to 26.84°C in 2023 before falling to 22.47°C in 2024, resulting in a net rise of about 2.2% (2022 to 2024). With CV = 5.01 to 6.35%, winter variability was significantly smaller (SD = 1.25 to 1.40°C). These findings emphasize the seasonal patterns of urban surface heating throughout Dhaka, with a notable summer warming spike in 2023 accompanied by more mild winter changes.

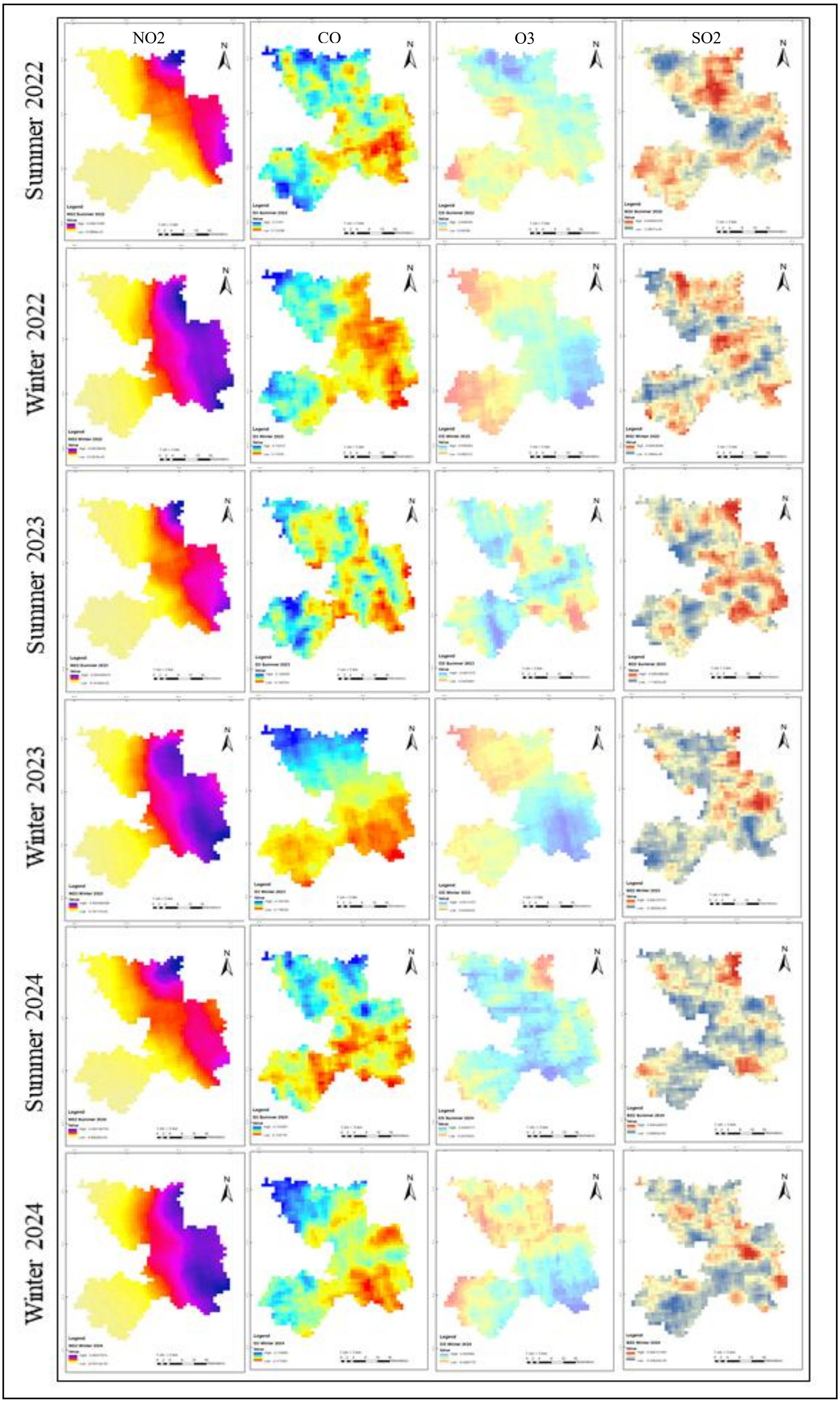

Figure 2: Concentration maps of Air pollutants in Dhaka for 2022 to 2024

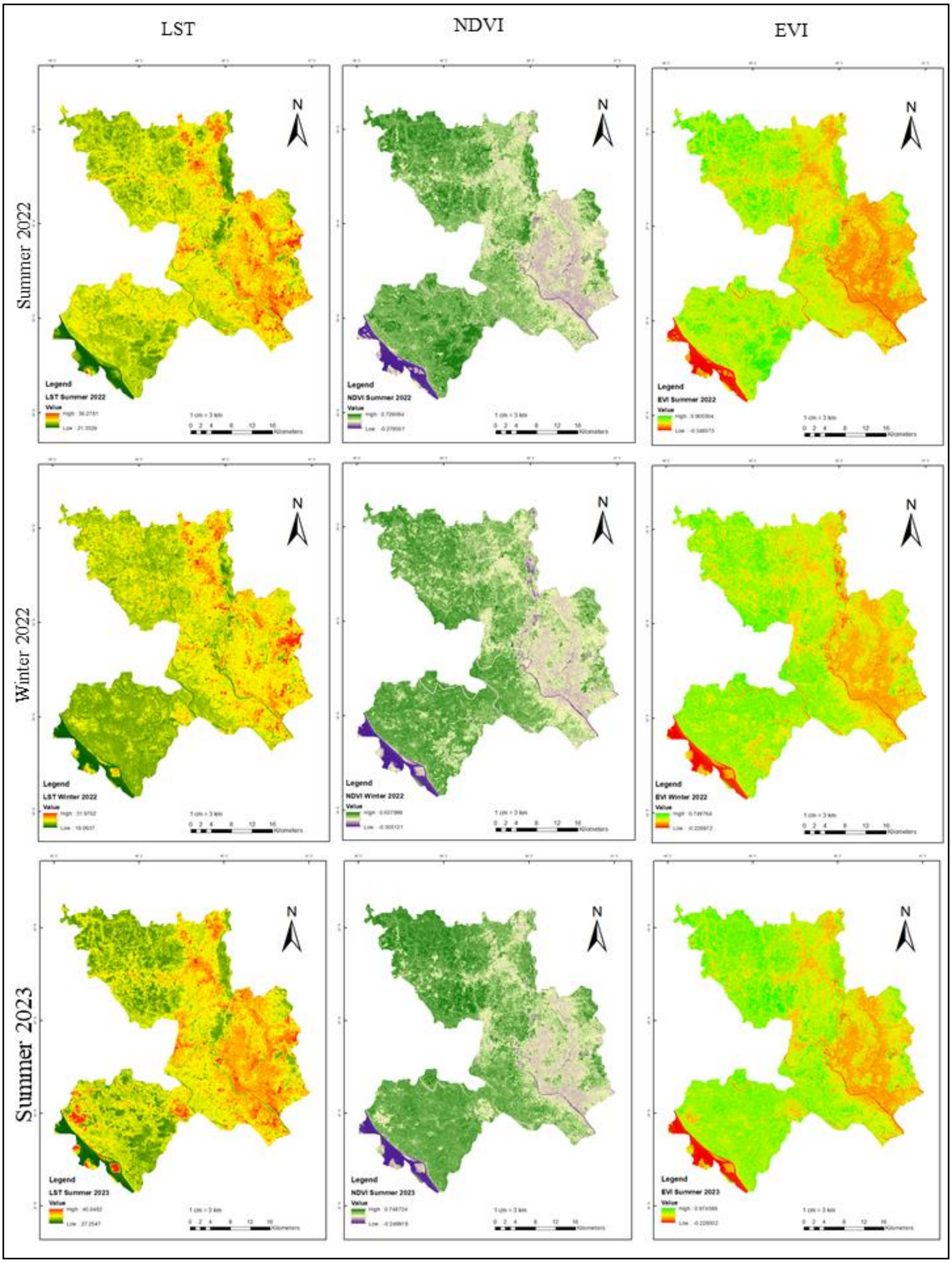

Figure 3(a): Spatial distribution of LST, NDVI, and EVI across Dhaka City for summer 2022, winter 2022, and summer 2023, showing seasonal variability

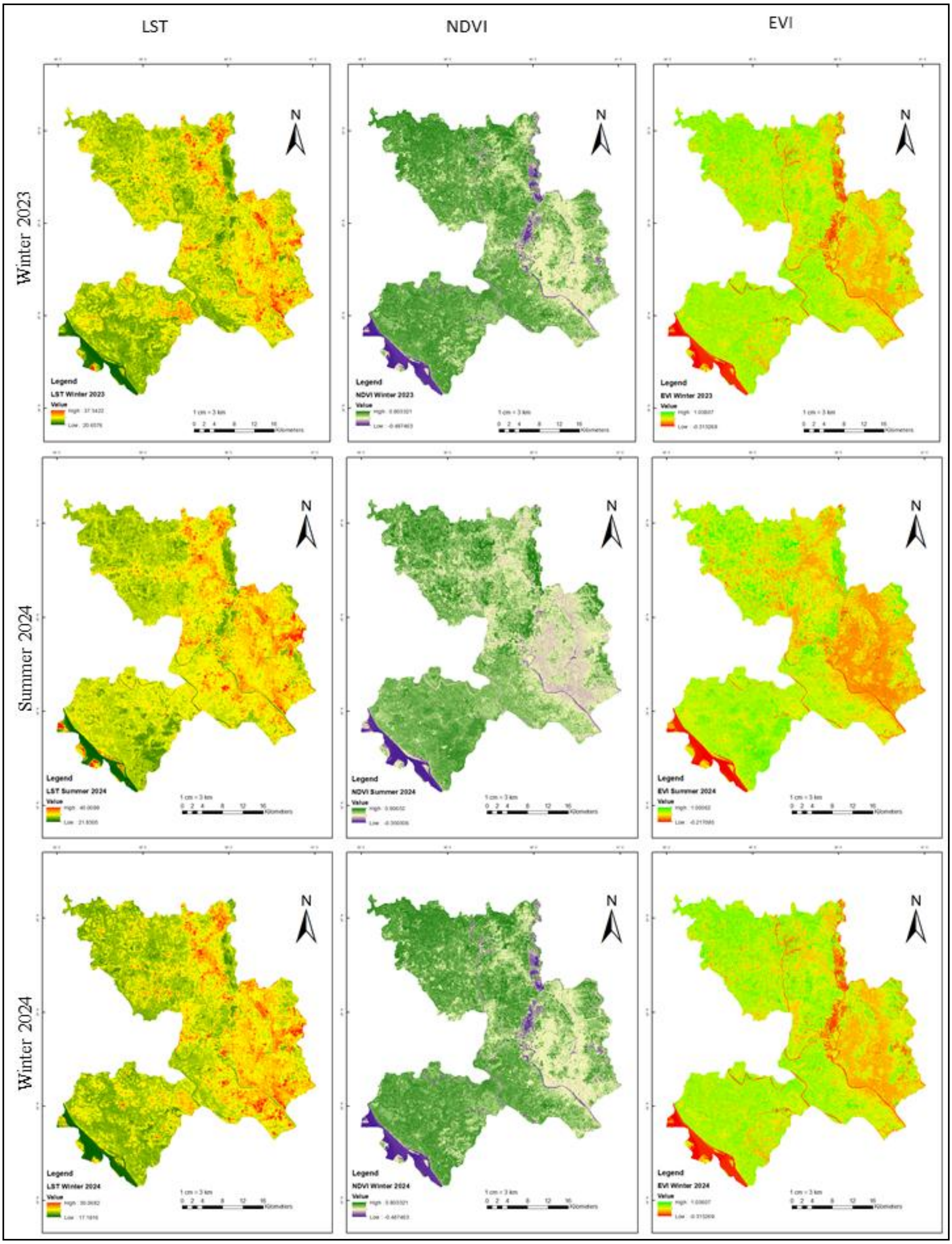

Figure 3(b): Inter-annual variation of LST, NDVI, and EVI for Dhaka City for winter 2023, summer 2024, and winter 2024

3.7 Correlation between Vegetation Indices, LST, and Air Pollutants

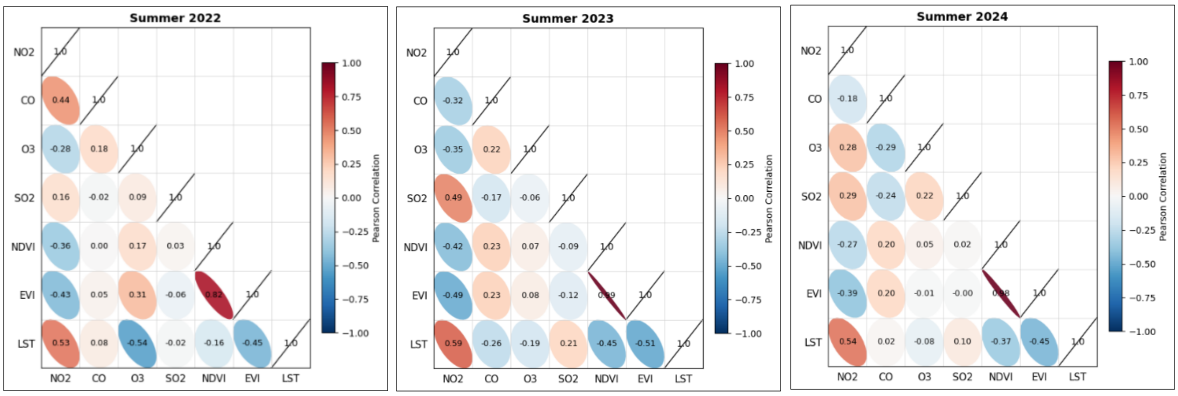

Figure 4(a): Pearson Correlation Correlogram of pollutants with Vegetation indices and LST for the summer season from 2022 to 2024

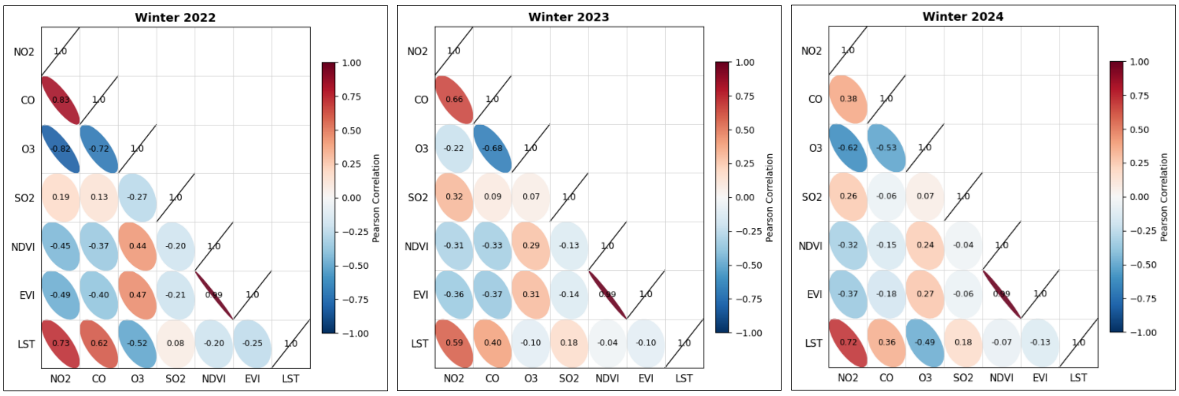

Figure 4(b): Correlogram of Pearson correlation between air pollutants, vegetation indices, and land surface temperature during winter (2022–2024)

NO_2 concentration over Dhaka show clear seasonal contrast linked to emission sources, urban morphology and surface temperature (Figure 4(a) and 4(b)). During summer, positive correlation with LST and negative correlation with NDVI and EVI indicate temperature-driven accumulation in densely built-up, traffic-dominated areas with limited vegetation. In winter stronger NO_2 and LST associations and weaker vegetation influence reflect reduced dispersion and minimal vegetation uptake. Overall, NO_2 variability is primarily controlled by vehicular emissions, with vegetation playing a secondary mitigating role. SO_2 exhibits weak and inconsistent relationships with vegetation and LST across seasons, suggesting dominance of localized industrial sources rather than land cover effects, while winter stability enhances accumulation. CO shows limited vegetation influence but moderate winter association with LST, indicating combustion related emissions and reduced dispersion in dense urban areas. O_3 variability is mainly governed by seasonal photochemical processes, with higher summer temperatures enhancing formation (Figure 4(a) and 4(b)). These findings highlight the importance of traffic emission control, industrial regulation, urban greening and heat-mitigation strategies for effective air quality management in Dhaka.

3.8 Impact of Urban Growth and Air Pollution

The study utilized TROPOMI data from 2022 to 2024 to assess how the increase in urban area (km^2) relates to the column number density of specific gases. In Regression analysis, the R^2 (coefficient of determination) indicates the proportion of variance in the dependent variable (air pollutant) that is predictable from the independent variable (urban growth) (Figure 5). The very low R^2 values for SO_2 and CO in the TROPOMI based analysis indicate the urban growth along explain almost none of the

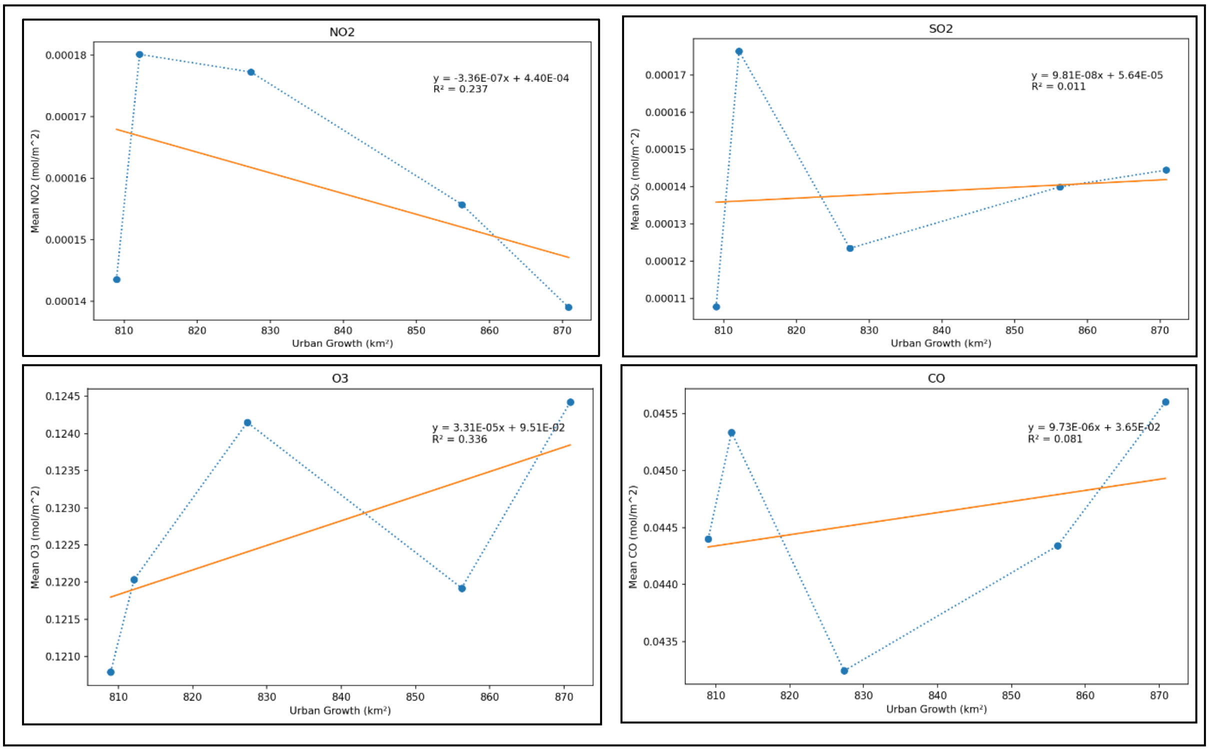

Figure 5: Variation of mean air pollutants with urban growth in Dhaka (2022–2024)

variability while the negative relationship observed for NO_2 suggests a gradual decline concentration with urban expansion, likely reflecting the spatial dispersion of emissions and reduced localized pollution intensity. On the other hand, O_3 shows moderate trend (R^2 = 0.34) indicating O_3 levels generally rise with urbanization. Several limitations have been found related to low R^2 value such as spatial variability and intermingling for TROPOMI maps revealed that areas of high and low column density were often overlapping across the city. This variability makes it challenging to provide a definitive interpretation of regional gas levels based solely on land use. The findings were determined independently, without considering environmental variables. The sources indicated that key environmental factors such as temperature, wind, humidity, and altitude were not included in the regression despite their significant impact on air pollutant levels.

4. CONCLUSIONS

From a policy and urban planning perspectives, this finding of Dhaka city provides several actionable insights. The strong association between NO_2, LST and reduced vegetation highlights the urgent need to prioritize traffic emission control in densely build-up and road dominated areas. NO_2 and CO concentrations can be considerably decreased by taking steps like tightening can emission regulations, encouraging public and non-motorized transportation and enhancing traffic flow management. The significance of preserving current green areas and growing urban greening projects such as roadside plants, urban parks and green buffers along important transportation routes, is highlighting by seasonal mitigating impact of vegetation.

Stricter industrial zoning, the relocation of high emission activities away from residential areas, and more stringent enforcement of emission regulations are all necessary because the weak but spatially localized behaviour of SO_2 indicated that its concentration is primarily driven by industrial facilities. Furthermore, the combined influence of high surface temperatures and urban expansion on pollutant accumulation highlights the necessity of integrating heat mitigation strategies such as cool roofs, reflective materials, and increased canopy cover into urban development plans. Incorporating air quality indicators into land-use planning and climate adaptation frameworks can support more resilient, healthier, and sustainable urban growth in Dhaka, offering valuable guidance for planners and policymakers in rapidly urbanizing megacities.

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Declaration of Use of AI

The authors declare that AI tools were used in a limited matter during the preparation of this manuscript. AI-based language models were utilized solely for language refinement, clarity improvement and structuring of selected of the manuscript. The AI tools were not used for data analysis, methodology development or result generation. All scientific interpretations, analyses and conclusions remain the sole responsibility of the authors.

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