Ecological Questions 36 (2025) 4: 83–97 http://dx.doi.org/10.12775/EQ.2025.038

Assessing the Impact of Urbanization on Air Pollution and Land Surface Temperature Using Remote Sensing Data in Google Earth Engine: A Case Study of Tehran Province (2018–2022)

Behnam Asghari Beirami[2], Seyed Omid Reza Shobairi[1,*], Gulahmadov Nekruz[1], Parvizi Hotam[1], Nasrulloev Farhod[1]

[1] Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, China
[2] Imam Hossein University, Tehran, Iran
*Corresponding author e-mail: omidshobeyri214@gmail.com

Received: 5 May 2025 / Accepted: 31 October 2025

Abstract. This study examines the environmental impacts of urbanisation trends in Tehran Province, Iran, from 2018 to 2022, utilising Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) data as a proxy for human activities. Its effects on air pollution (nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3) from Sentinel-5P and land surface temperature (LST) from Moderate Resolution Imaging Spectroradiometer (MODIS)) were analysed in Google Earth Engine (GEE). VIIRS DNB showed a sharp upward trend, indicating rapid urbanization. NO_2 pollution increased significantly across the region, while CO and O_3 exhibited weak decreasing and increasing trends, respectively. Daytime and nighttime LST rose by approximately 1°C overall, reflecting the urban heat island (UHI) effect despite fluctuations. Correlation analysis (r) revealed strong links between DNB and NO_2/CO (r=0.59–0.72) (a key contribution underscoring urbanisation's direct emission drivers), moderate with nighttime LST (r up to 0.38), and weak with O_3, underscoring urbanisation's role in driving pollution and heat. These findings emphasise the need for intensified emission controls, green infrastructure, and sustainable urban planning in rapidly growing cities like Tehran.

Keywords: Urbanization, Air pollution, Correlation analysis, Land surface temperature (LST), MODIS, VIIRS DNB, Sentinel 5P.

1. Introduction

Urbanization is a growing trend in most countries around the world, characterized by the rapid migration of people from rural areas to urban areas. This trend has gradually led to the physical expansion of the city, which is accompanied by challenges such as air pollution and rising LST (Liang & Gong, 2020; Bonafoni & Keeratikasikorn, 2018).

Tehran, Iran's capital and a major Middle Eastern metropolis, faces rapid urbanization, driving increased vehicle traffic, greenhouse gas emissions, and land cover changes that degrade air quality and elevate LST through intensified UHI effects. Concurrently, other Iranian regions, such as Golestan, confront distinct ecological threats like wildfires, which exacerbate regional air pollution via smoke emissions (Asadi Oskouei et al., 2024). These varied challenges underscore the need for integrated, nationwide environmental monitoring to address urbanization's multifaceted impacts.

Various studies have shown that in urban areas, due to increased human activities, high levels of atmospheric pollutants such as nitrogen dioxide (NO2), carbon monoxide (CO), and ozone (O3) are always observed, which have a very severe impact on the health of citizens (Manisalidis et al, 2020). On the other hand, the growth of the city is mainly accompanied by the destruction of natural vegetation and its replacement with impervious surfaces, which causes heat retention and intensification of the UHI effect (Zhang et al., 2022).

Remote sensing technology can be considered a powerful approach to monitor a wide range of environmental changes. Datasets collected by satellites such as Sentinel-5P (Ialongo et al., 2020) and Moderate Resolution Imaging Spectroradiometer (MODIS) (Colombi et al., 2007; Shobairi et.al., 2024) can be considered as a valuable tool to monitor air pollution and climate parameters with high speed and accuracy over a wide geographical area. On the other hand, nighttime data (obtained from remote sensing sensors such as Visible Infrared Imaging Radiometer Suite (VIIRS) (Li et al., 2014) and the old Defense Meteorological Satellite Program (DMSP) Operational Lines can System (OLS)) can be considered as a valuable proxy for urbanization (Zhang et al., 2011). These data show the intensity of artificial light emission, which is well correlated with urban population density and economic activity.

The main objectives of this study are to quantify the extent of urbanization in Tehran Province between 2018 and 2022 using VIIRS DNB data as a proxy for human activity, and urban growth, to analyze the spatial and temporal variations of key air pollutants (NO_2, CO, and O_3) derived from Sentinel-5P satellite data, and to assess the changes in LST using MODIS observations. The study aims to evaluate the correlations between urbanization, air pollution, and LST to determine which environmental parameters are most affected by urban growth. Finally, it seeks to provide insights and recommendations for sustainable urban planning and environmental management in Tehran, emphasizing strategies to mitigate air pollution and the UHI effect in rapidly developing metropolitan areas.

2. Materials and Methods

2.1. Study Area

Tehran, the capital of Iran, was selected as the study area due to its rapid urbanization and increasing environmental challenges. Tehran Province is one of the largest provinces in Iran with an area of approximately 17,000 km^2 and a population of over 14 million. It has a semi-arid climate with hot summers and cold winters, and its air pollution levels have been a persistent issue due to high traffic congestion, industrial activities, and geographical and topographic conditions. In this study, the boundary of Tehran Province was extracted from a shapefile and loaded into Google Earth Engine (GEE) to define the extent of the province (Fig. 1). A binary mask was generated to preserve pixels within Tehran Province for analysis.

A

B

C

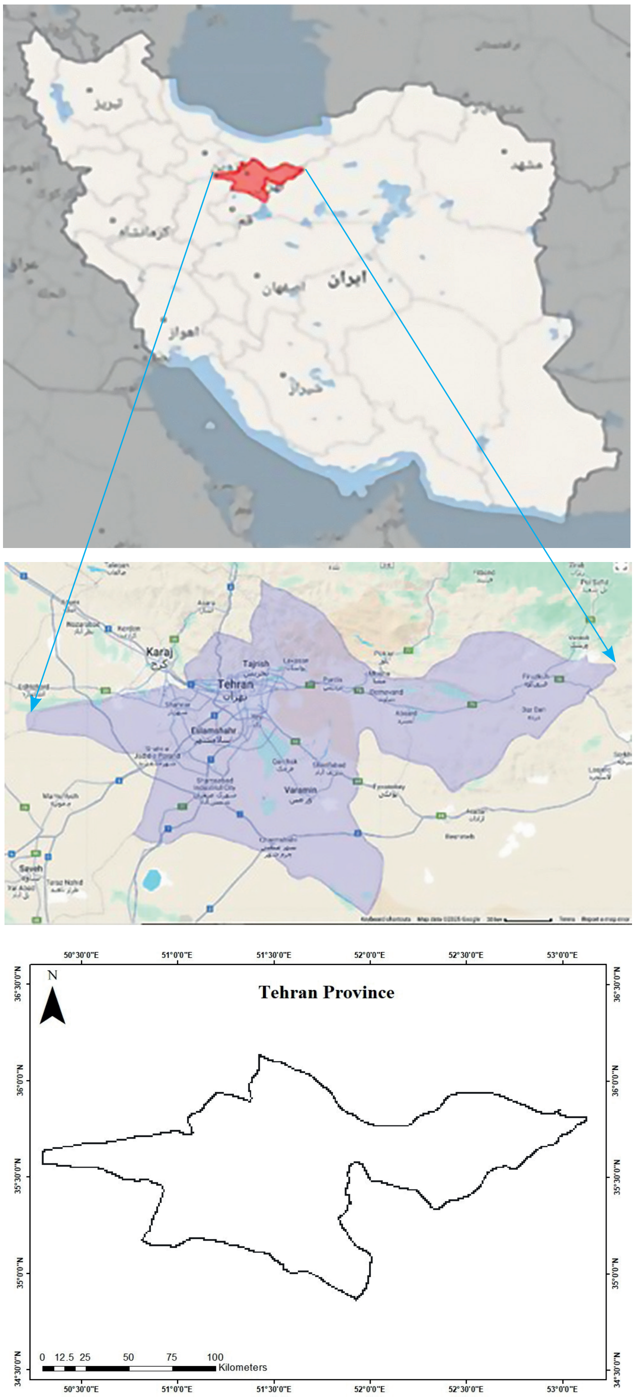

Figure 1. Location of the study area: A – in Iran ; B – Tehran Province ; C –boundary of the study area

2.2. Datasets

In this section, first, the used products, including DNB, Air pollutants, and LST datasets, are introduced. Afterward, the methodology of the study is explained.

The study utilized multiple satellite datasets as follows:

- **VIIRS DNB products**

The VIIRS-DNB aboard the Suomi National Polar-orbiting Partnership (Suomi NPP) satellite captures global nighttime light emissions, facilitating studies of urbanization and human activity patterns. The NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG dataset in GEE provides monthly average radiance composites, corrected for stray light artifacts, ensuring enhanced data quality. These composites are available as the monthly product in GEE. Cloud cover was determined using the VIIRS Cloud Mask product (VCM), and data near the edges of the swath were excluded to maintain consistency. The dataset spans from 2014 onwards, offering extensive temporal coverage for analyzing trends in nighttime lights. However, users should note that certain regions may lack good quality data for specific months due to factors like persistent cloud cover or solar illumination, especially in tropical areas or polar regions during their respective summer months.

- **Sentinel 5p air pollutants products**

Sentinel-5P, equipped with the TROPOspheric Monitoring Instrument (TROPOMI), offers high-resolution atmospheric data, crucial for monitoring air pollutants such as nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3). In GEE, these datasets are accessible for detailed analysis. For instance, the NO_2 product provides near real-time measurements of atmospheric NO_2 concentrations, aiding in air quality assessments. Similarly, the CO product delivers near real-time imagery of CO concentrations, essential for understanding pollution sources and atmospheric chemistry.

- **MODIS LST products**

The MODIS/Terra LST and Emissivity daily global 1km (MOD11A1) dataset provides daily per-pixel LST (both in day and night format) and emissivity measurements at a 1-kilometer spatial resolution. In GEE, this dataset is accessible under the identifier MODIS/006/MOD11A1, enabling users to analyze daily LST patterns and their temporal dynamics.

2.3. Methodology

This study utilizes the Google Earth Engine (GEE) platform to analyze urbanization and environmental changes in Tehran from 2018 to 2022, focusing on DNB data, atmospheric pollutants (NO_2, CO, O_3), and LST.

2.3.1. Data Processing

- **DNB Processing:**
  1. Data Selection: The VIIRS Nighttime Day/Night Band Composites Version 1 dataset (NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG) was selected for its monthly average radiance values.
  2. Filtering: The dataset was filtered to include only data over Tehran's geographical boundaries and within the 2018–2022 timeframe.
  3. Band Selection: The 'avg_rad' band, representing average radiance, was extracted for analysis.
  4. Computation of Annual Mean DNB: Annual mean radiance values were calculated to observe urbanization trends over time.
  5. Application of Tehran Mask: A spatial mask corresponding to Tehran's administrative boundaries was applied to isolate the area of interest.
  6. Extraction of Mean DNB: The mean DNB values within whole Tehran province were computed for subsequent correlation analyses.
- **Atmospheric Pollutants Processing:**
  1. Data Selection: The Sentinel-5P datasets for NO_2 (COPERNICUS/S5P/NRTI/L3_NO2), CO (COPERNICUS/S5P/OFFL/L3_CO), and O_3 (COPERNICUS/S5P/NRTI/L3_O3) were utilized.
  2. Filtering: Each dataset was filtered to encompass the province's area in the study period (2018–2022).
  3. Band Selection: The relevant pollutant bands ('NO_2_column_number_density' for NO_2, 'CO_column_number_density' for CO, and 'O_3_column_number_density' for O_3) were selected.
  4. Computation of Annual Mean Concentrations: Annual mean concentrations for each pollutant were calculated to assess long-term trends.
  5. Application of province mask: The province spatial mask was applied to retain values solely within the study area.
  6. Extraction of Mean Pollutant Concentrations: Mean concentrations for each pollutant within whole province were extracted for further analysis.
- **LST Processing:**
  1. Data Selection: The MODIS/Terra LST and Emissivity Daily Global 1km dataset (MODIS/061/MOD11A1) was chosen for its daily LST measurements.
  2. Filtering: The dataset was filtered to include data over province and within the 2018–2022 period.
  3. Band Selection: The 'LST_Day_1km' and 'LST_Night_1km' bands were selected for daytime and nighttime temperatures, respectively.

4. Conversion to Degrees Celsius: Raw LST values, originally in Kelvin, were converted to degrees Celsius by °C = (DN × 0.02) - 273.15.
5. Computation of Annual Mean LSTs: Annual mean LSTs for both day and night were computed to assess temperature trends.
6. Application of province mask: The province spatial mask was applied to focus analyses within the province's boundaries.
7. Extraction of Mean LSTs: Mean LST values for Tehran were extracted for subsequent correlation analyses.

2.3.2. Analysis Method

To analyze the spatiotemporal variations of urbanization and environmental parameters, three primary analyses were conducted:

Spatial Distribution Analysis: The spatial distribution of each variable (DNB, NO_2, CO, O_3, LST) was examined using annual mean values over Tehran. This analysis helped visualize the intensity and spatial patterns of urbanization, air pollutants, and LST over time.

Temporal Trend Analysis: To assess the long-term trend of each variable, a linear regression model was applied to the annual mean values over the study period (2018–2022). The slope of the fitted trend line was used as an indicator of the rate of change for each variable. A positive slope indicated an increasing trend, while a negative slope represented a decreasing trend. In this study, R^2 (the coefficient of determination) is used to measure how well a fitted line explains the variability of the dependent variable. R^2 ranges from 0 to 1, where: $R^2 = 1$: The model perfectly explains all variability, and $R^2 = 0$: The model explains none of the variability. It is calculated as follows (Chicco et al., 2021):

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{1}$$

where:

***SS*res** (Residual Sum of Squares): $\sum (y_i - \hat{y}_i)^2$, the sum of squared differences between actual values (y_i) and predicted values ($\hat{y}_i$).

***SS*tot** (Total Sum of Squares): $\sum (y_i - \bar{y}_i)^2$, the sum of squared differences between actual values (y_i) and the mean of the dependent variable ($\bar{y}_i$).

Correlation Analysis: The Pearson correlation coefficient (r) was computed to quantify the relationship between variables. The correlation coefficient is given by Cui et al. (2020):

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{2}$$

where x_i and y_i are the individual sample points, and $\bar{x}$ and $\bar{y}$ are the sample means. This coefficient provided insights into how variable influences each other.

3. Experimental Results

This section presents the experimental results, focusing on the spatial distributions (highlighting regional patterns of parameters within the study area) and temporal trends of DNB, air pollutants (NO_2, CO, and O_3), and LST from 2018 to 2022. The findings include statistical correlation analysis between these variables to assess the impact of urbanization on air pollution and LST variations in Tehran Province.

3.1. Annual Trend Analysis

DNB

Analysis of VIIRS DNB data over Tehran Province (2018–2022) reveals a steady upward temporal trend in mean radiance values (strong positive R^2), indicating intensified urban expansion and human activities aligned with rising population density and economic growth; spatially, high-intensity light emissions concentrated in central Tehran (with the largest increases in commercial/residential cores) showed gradual outward spread to suburbs, reflecting sprawl and infrastructural development (Fig. 2). This positions DNB as a robust proxy for urbanization's environmental impacts.

Air Pollutants (NO_2, CO, O_3)

The spatial analysis of Sentinel-5P data from 2018 to 2022 consistently reveals that NO_2 and CO concentrations are highest in the central urban areas of Tehran Province. For NO_2, the distribution maps (Fig. 3) show a persistent pattern of elevated levels forming distinct hot spots in densely populated regions, strongly indicative of high traffic emissions and industrial activities. Similarly, CO maps (Fig. 4) consistently depict the highest concentrations within the city's core, reflecting stable emission sources from traffic and residential heating. In contrast, O_3 spatial variations (Fig. 5) across the province are more complex, with some areas consistently showing higher concentrations, but without the clear central urban hot spot pattern observed for NO_2 and CO. This difference highlights the varying nature of emission sources and atmospheric chemistry governing each pollutant's distribution.

Regarding temporal trends from 2018 to 2022, the analysis reveals distinct patterns for each pollutant. NO_2 levels exhibited a significant upward trend ($R^2 = 0.61$), as shown by the scatter plot and fitted line in Figure 3, indicating a notable increase likely driven by urban expansion and growing

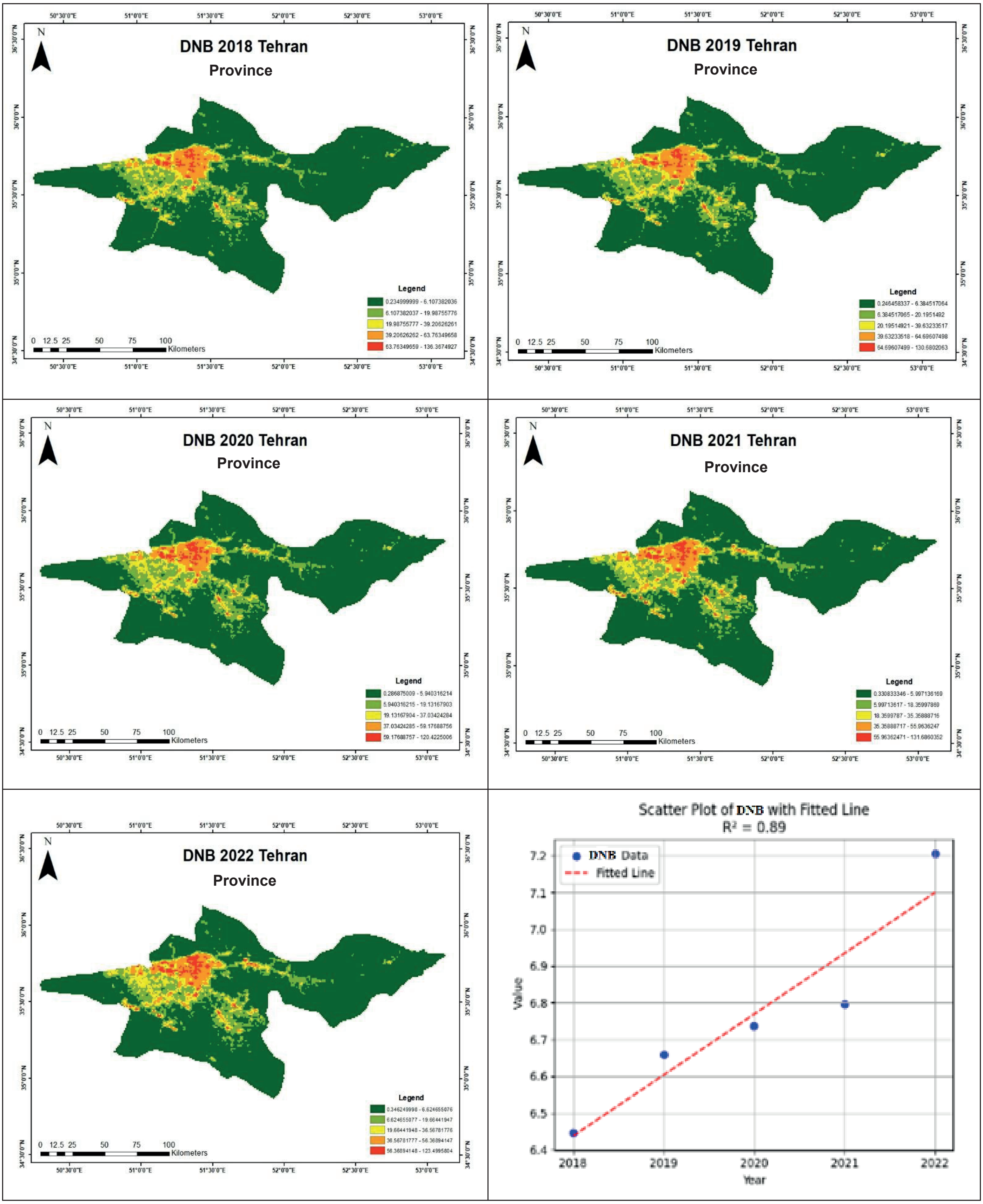

Figure 2. Source: VIIRS DNB, NASA, 2018–2022. Spatial distribution and annual trend of DNB value (nanoWatts/sr/cm^2) in Tehran Province

vehicular/industrial emissions. CO showed a relatively stable trend with a weak downward shift (R^2 = 0.13) (Fig. 4), suggesting a minor decrease over time despite consistent emission sources, possibly influenced by slight changes in traffic volume or economic activity. Conversely, O_3 displayed a very weak and statistically non-significant increasing trend (R^2 = 0.05) (Fig. 5), with year-to-year fluctuations more likely influenced by meteorological conditions and seasonal variations rather than a strong underlying change in emissions. These differing trends underscore the need for pollutant-specific mitigation strategies.

To summarize the findings, it should be noted that:

The annual averages from Sentinel-5P showed that NO_2 increased significantly (R^2=0.61), which is related to greenhouse gas emissions from vehicles and industries and is concentrated in central urban areas (Fig. 3). CO showed a stable trend with minor fluctuations and a weak downward shift (R^2=0.13), while O_3 had a weak increasing trend (R^2=0.05), which was influenced by photochemical reactions (Figs 4 and 5).

LST

LST exhibited a rising trend, particularly in urbanized regions (Figs 6 and 7). The increase in LST can be linked to UHI effects caused by increased built-up areas and reduced vegetation cover. The most significant temperature increases were recorded in densely populated districts, further supporting the role of urbanization in altering surface temperature patterns.

The analysis of MODIS daytime LST data over Tehran from 2018 to 2022 shows a gradual warming trend, with higher temperatures observed in southern and central urban areas compared to the northern regions, which are more vegetated and elevated. The spatial maps indicate a persistent UHI effect, where densely built-up areas exhibit higher LST values. The scatter plot with a fitted trend line reveals a weak R^2, suggesting a slight increase in LST over time, likely driven by urbanization, reduced vegetation cover, and increased anthropogenic heat emissions. However, the relatively weak trend indicates that other environmental and climatic factors also contribute to LST variations in the region.

The MODIS nighttime LST analysis over Tehran from 2018 to 2022 shows a general warming trend, though a weak R^2. The spatial distribution of LST indicates that urban areas, especially in the southern and central regions, retain more heat at night compared to the northern, more vegetated areas. This pattern suggests the presence of a UHI effect, because built-up areas release stored heat more slowly than natural ones. However, the low R^2 suggests that other factors like weather conditions, wind patterns, and surface material properties influence nighttime LST variations.

To summarize the findings, it should be noted that:

MODIS LST analysis (2018–2022) revealed gradual warming in both daytime and nighttime values (~1°C increase overall; weak R^2≈0.14 to moderate R^2≈0.29), with higher temperatures in southern/central urban areas versus cooler northern vegetated zones, underscoring UHI effects from impervious surfaces and reduced evapotranspiration (Figs 6–7). Nighttime LST showed stronger heat retention (slower cooling) than daytime, amplifying UHI intensity after dusk, though both exhibited similar spatial gradients tied to urban density.

3.2. Correlation Analysis

Pearson correlation coefficients (r, 2018–2022) were computed across variables to quantify relationships (Fig. 8), grouped thematically below. Ranges reflect year-to-year variations, with interpretations emphasizing key drivers like emissions, photochemistry, and UHI effects. Overall trends highlight urbanization's (DNB) dominant role in primary pollutants and nighttime LST, with exceptions for secondary pollutants like O_3.

Pollutant-Pollutant Interactions: NO_2 and CO exhibited consistently strong positive correlations (r = 0.77–0.82), attributable to shared anthropogenic sources such as vehicle exhausts and industrial combustion prevalent in Tehran's urban core; this stability underscores their co-emission from traffic and energy use. In contrast, NO_2-O_3 links were weak and variable (r = 0 in 2019 to 0.22 in 2021), reflecting NO_2's role as an O_3 precursor in sunlight-driven reactions, modulated by local meteorology (e.g., wind dispersion) and diurnal cycles that disrupt linear associations. CO-O_3 showed dynamic shifts: weak positive in 2018 (r=0.1, minimal overlap), moderate negative in 2019–2020 (r≈-0.30 to -0.44, possibly from CO scavenging O_3 precursors amid emission peaks), and moderate positive in 2021–2022 (r≈0.56–0.57, aligned with enhanced photochemistry from rising industrial/traffic activity and warmer conditions).

Pollutant-LST Interactions: NO_2 correlated lowly with LST_day (r=0.02–0.17) but moderately with LST_night (r=0.28–0.42), suggesting pollution hotspots exacerbate nighttime UHI by trapping heat in impervious urban surfaces, though daytime solar forcing dilutes the signal; additional factors like vegetation cover likely mediate daytime weakness. CO displayed stronger positive ties to both LST_day and LST_night (peaking at r=0.81 for nighttime in 2020), linking traffic-derived CO to warmer urban microclimates where emissions accumulate under low ventilation. O_3-LST evolved from negative (early years, r<0; higher heat promoting precursor dilution via convection) to positive (later, r>0.2; elevated temperatures accelerating photochemical O_3 production), illustrating temperature's dual role in O_3 dynamics amid changing emission patterns.

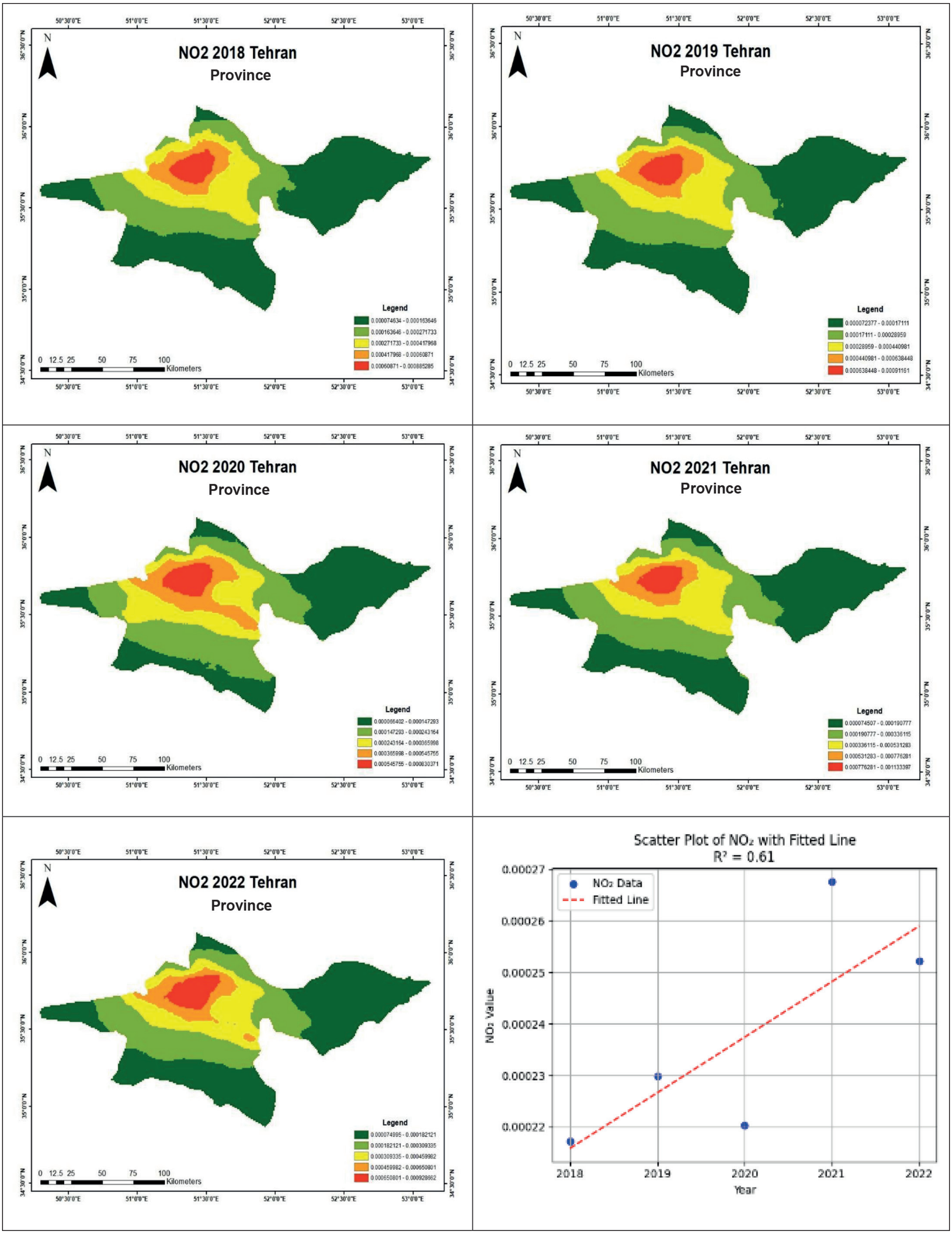

Figure 3. Source: NO_2, ESA sentinel, 2018–2022. Spatial distribution and annual trend of NO_2 values (mol/m^2) in Tehran Province

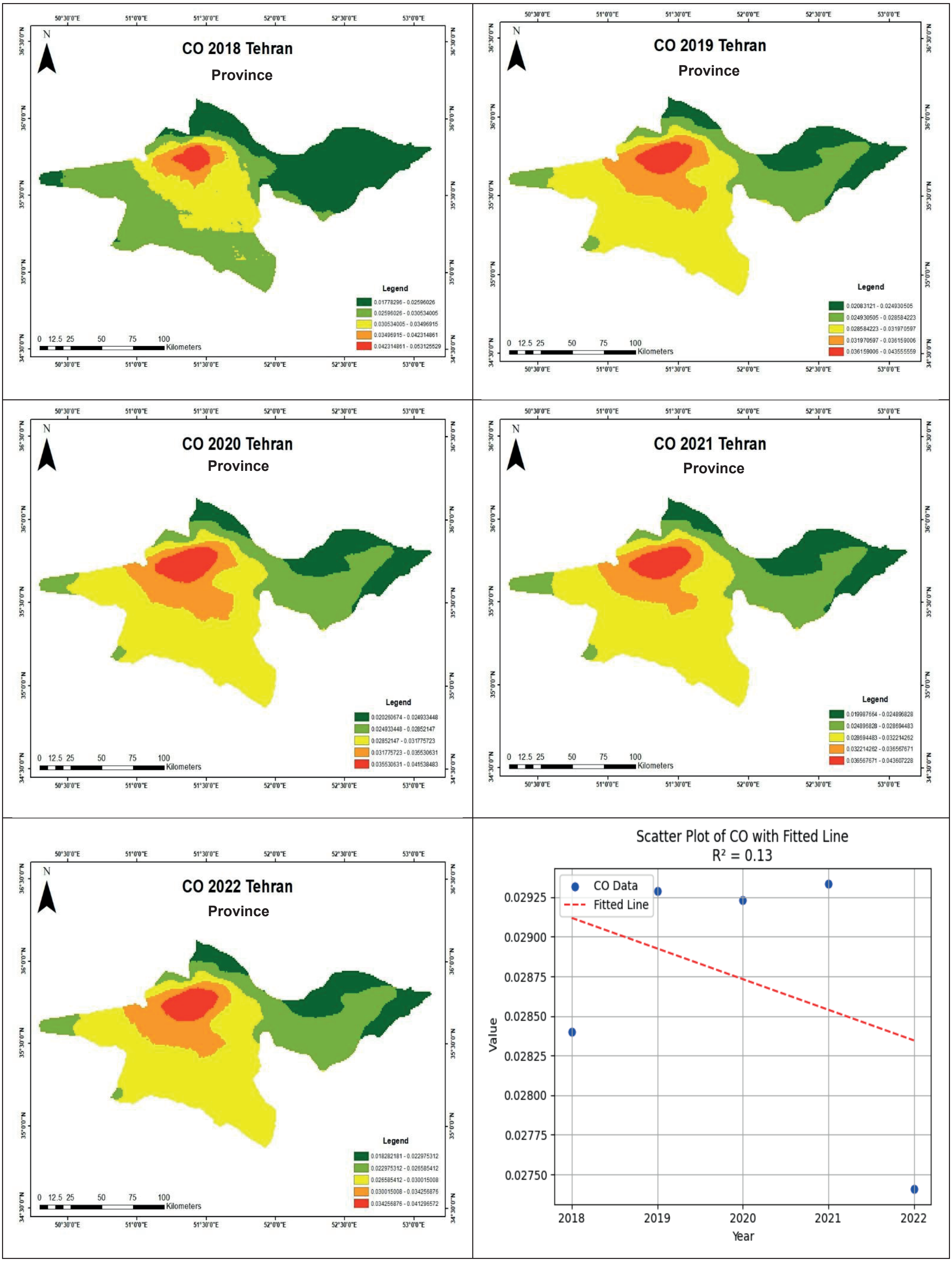

Figure 4. Source: CO, ESA sentinel, 2018–2022. Spatial distribution and annual trend of CO values (mol/m^2) in Tehran Province

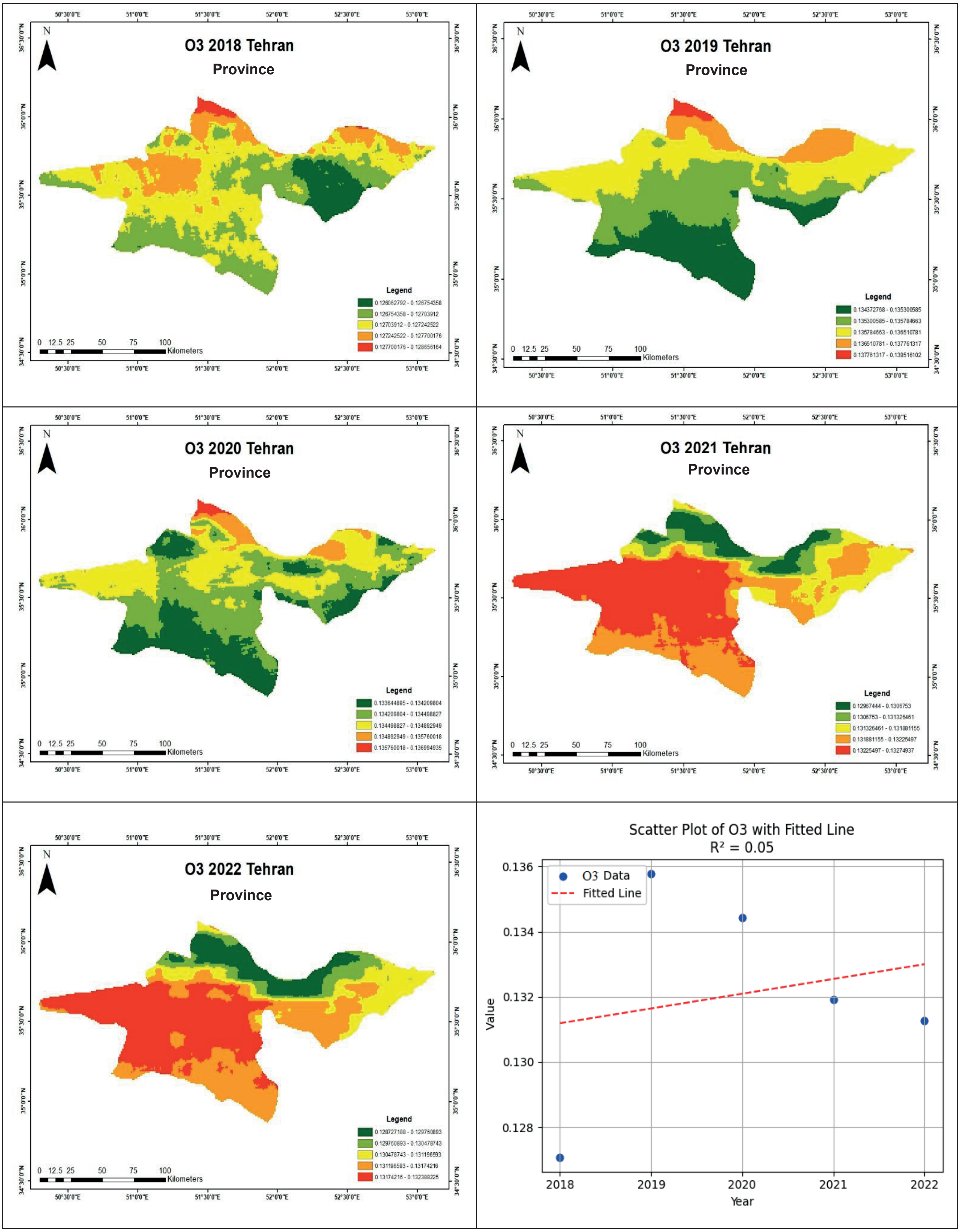

Figure 5. Source: O_3, ESA sentinel, 2018–2022. Spatial distribution and annual trend of O_3 values (mol/m^2) in Tehran Province

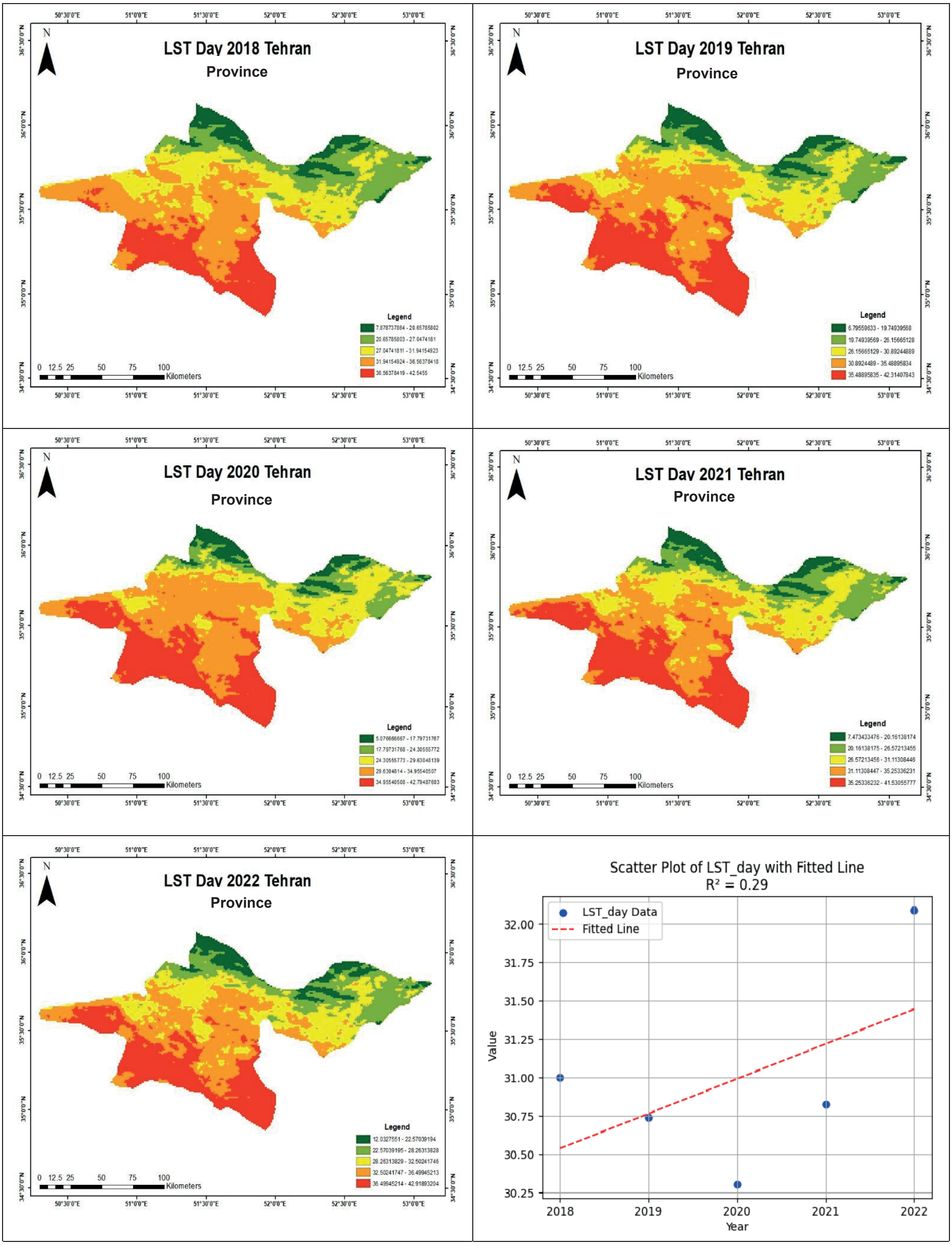

Figure 6. Source: LST_day, NASA, 2018–2022. Spatial distribution and annual trend of LST_day values (°C) in Tehran Province

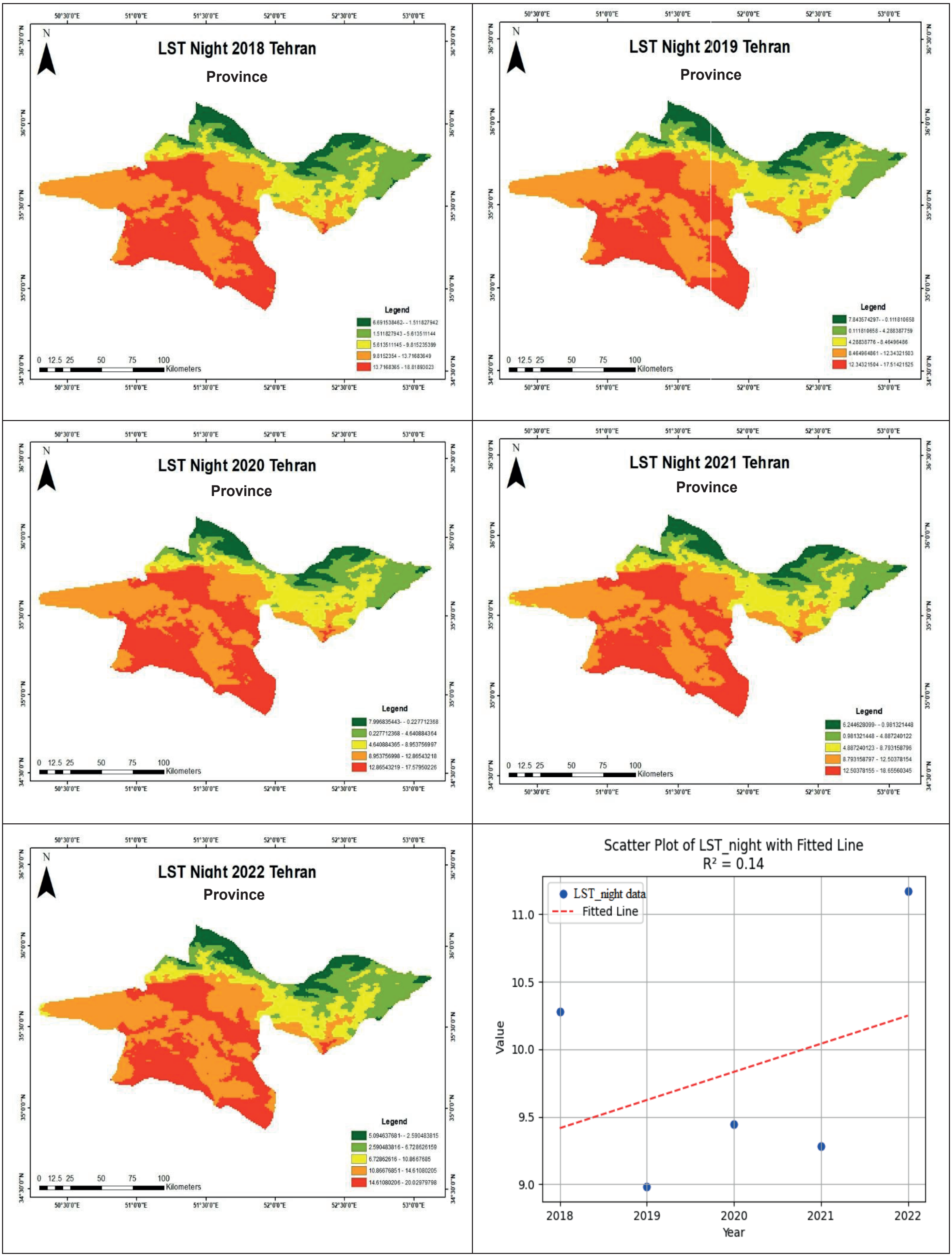

Figure 7. Source: LST_night, NASA, 2018–2022. Spatial distribution and annual trend of LST_night values (°C) in Tehran Province

[94]

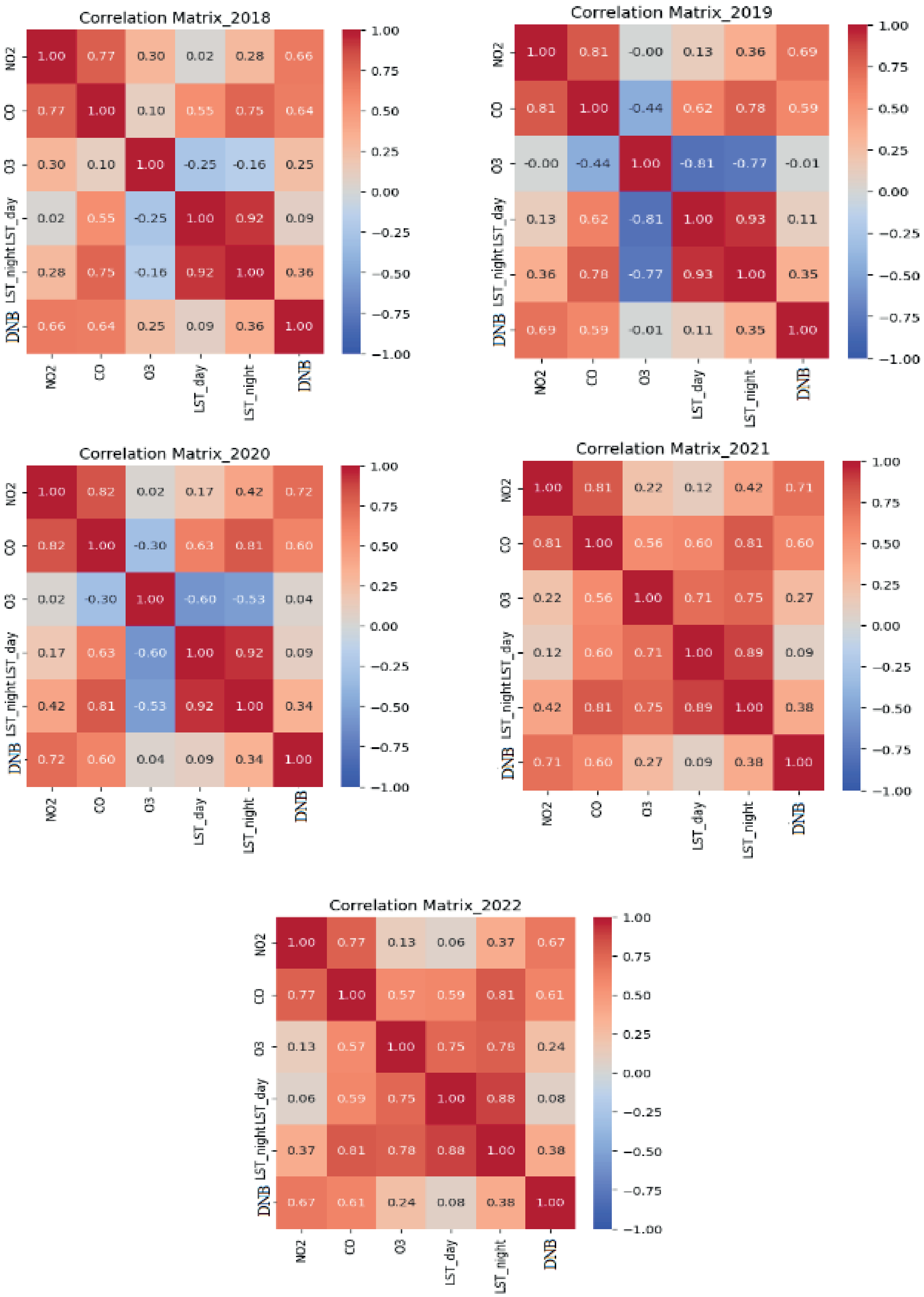

Figure 8. Correlation matrices for different years

Pollutant-DNB Relationships: As a urbanization proxy, DNB showed moderate-to-strong positive correlations with NO_2 (r=0.66–0.72) and CO (r=0.59–0.64), directly tying light intensity (reflecting population/economic density) to emission-intensive activities like commuting and manufacturing; spatial congruence in central Tehran reinforces this. However, DNB-O_3 was weak and inconsistent (r=-0.01 in 2019 to 0.27 in 2021), indicating O_3's limited direct response to urban sprawl, dominated instead by volatile organic compounds, NO_2 photolysis, and weather variability.

LST-DNB Linkages: DNB weakly correlated with LST_day (r≈0.1 in 2018, influenced by transient solar/atmospheric inputs), but moderately with LST_night (r up to 0.38 in 2021), evidencing UHI intensification in high-DNB zones where anthropogenic heat and reduced evapotranspiration sustain nocturnal warming.

These thematic patterns (strong for direct-emission proxies (NO_2/CO-DNB) and moderate for UHI (nighttime LST-DNB)) affirm urbanization's cascading environmental effects, while O_3's exceptions highlight needs for integrated modeling. All analyses used province-wide annual means.

To summarize the findings, it should be noted that:

Pearson correlations (2018–2022) between DNB, pollutants, and LST showed: strong positive links between DNB and NO_2/CO, reflecting urbanization-driven emissions; moderate correlation between DNB and nighttime LST, indicating UHI heat retention; and weak/negative ties between DNB and O_3, due to complex photochemical drivers. NO_2 and CO correlated strongly, while NO_2-LST links were low-to-moderate (stronger at night). O_3-LST shifted from negative to positive over time. These patterns confirm urbanization's direct influence on NO_2/CO and nighttime heat.

Based on the findings, in Tehran, urbanization (as measured by DNB) is closely linked to increased pollutant levels and elevated temperatures. Strong correlations between DNB and both NO_2 and CO indicate that denser urban activities, such as traffic and industrial operations, drive higher emissions. Additionally, urban areas show a moderate relationship between DNB and LST night, reflecting the UHI effect where built-up areas retain more heat. These findings are important for policymakers because they highlight the direct environmental impacts of urban expansion, emphasizing the need for targeted strategies to manage urban growth, reduce emissions, and mitigate heat retention in cities.

4. Discussion

This study investigates the environmental impacts of rapid urbanization in Tehran, Iran's capital, from 2018 to 2022, focusing on air pollution (NO_2, CO, and O_3) and LST using remote sensing data from VIIRS, Sentinel-5P, and MODIS. Tehran Province spans ~17,000 km² (~730 km² for Tehran city) with a population exceeding 14 million (as of 2022 estimates), characterized by rapid urbanization, high vehicular density (>4 million vehicles), and industrial hubs contributing to persistent air quality challenges. Our findings reveal critical insights into the relationships between urbanization, air pollution, and LST, aligning with and extending prior research on urban environmental dynamics.

Correlation analyses indicate that urbanization, as proxied by VIIRS Day/Night Band (DNB) data, has a strong influence on air pollution and LST. A primary contribution of this study is the robust DNB-NO_2/CO correlations (r=0.59–0.72), quantifying urbanization's causal role in primary pollutant surges via traffic/industry, offering novel remote-sensing evidence for Tehran's policy targeting. The moderate to strong correlation between DNB and NO_2 (ranging from 0.66 in 2018 to 0.72 in 2020) underscores urbanization as a key driver of NO_2 pollution, consistent with findings by Fuladlu and Altan (2021), who reported similar positive correlations between urbanization and NO_2 in Tehran using Sentinel-3 SLSTR and Sentinel-5P data (Fuladlu & Altan, 2021). These results highlight the urgent need for sustainable urban planning and pollution control measures to mitigate the adverse environmental effects of rapid urban growth in Tehran. Similarly, the correlation between DNB and CO (0.59–0.64 across 2018–2022) indicates that vehicular and industrial emissions, tied to urban activity, are primary pollution sources, corroborating studies in other metropolitan areas like China, India, where studies such as Siddiqui et al. (2022) and Zheng et al. (2019) linked NO_2 and CO increases to urban expansion and traffic congestion. The correlation between CO and DNB follows a similar trend, suggesting that vehicular and industrial emissions remain primary sources of air pollution in Tehran. These findings reinforce the argument that cities with high levels of economic activity and industrialization tend to experience significant increases in NO_2 and CO emissions.

In contrast, O_3 exhibited weak or negative correlations with other pollutants, notably NO_2 (-0.0002 in 2019) and CO (-0.44 in 2019), reflecting complex photochemical reactions rather than direct emission-driven trends. This behavior aligns with Hu et al. (2021), who noted that O_3 formation in Chinese cities is influenced by photochemical interactions and meteorological factors, complicating its relationship with urbanization. These findings highlight the need for further research into O_3's drivers in Tehran, including seasonal and meteorological influences.

The correlation between DNB and nighttime LST (up to 0.38 in 2021) confirms the urban UHI effect, with urbanized areas retaining more heat at night due to impervious surfaces.

This is consistent with Moazzam et al. (2022), who found elevated LST in urbanized regions of Jeju Island, Republic of Korea, driven by reduced vegetation and increased built-up areas (Moazzam et al., 2022). Previous studies in other cities, such as Nairobi (Kenya), have shown similar patterns (Mwangi, 2024). Generally, higher nighttime LSTs are associated with urbanized areas due to the retention of heat in built-up environments. Our findings further indicate that the relationship between LST and NO_2 is stronger at night (0.42 in 2020) than during the day, which is consistent with previous research suggesting that pollution can increase heat retention in urban areas (Parida et al, 2021). However, the relatively low correlation between daytime LST and NO_2 suggests that factors beyond air pollution, such as land cover changes and atmospheric conditions, also play a significant role in influencing temperature variations.

Our findings also resonate with broader research on urbanization's environmental impacts. Liang et al. (2020) analyzed 626 Chinese cities, finding that urban form significantly affects air quality, similar to our observed links between DNB and NO_2/CO (Liang & Gong, 2020). Additionally, Stratoulias et al. (2024) emphasized the role of satellite remote sensing, like Sentinel-5P, in monitoring air pollution for sustainable development, aligning with our use of these data to support urban planning (Stratoulias et al., 2024). These global parallels underscore the universal challenge of managing urbanization's environmental costs.

The findings of this study have important implications for urban planning and air quality management in Tehran. The strong association between DNB and air pollution underscores the need for policies that promote cleaner transportation options, such as expanded public transit and stricter vehicle emissions regulations. Furthermore, the observed correlation between nighttime LST and DNB suggests that increasing green spaces and implementing heat mitigation strategies could help reduce the UHI effect. Given the complex behavior of O_3, further research is needed to explore the role of meteorological factors and potential mitigation strategies. The correlation results confirm known urbanization impacts on air quality and LST. NO_2 and CO are strongly linked, while O_3 exhibits complex behavior. The findings provide insights for urban planning and pollution mitigation in Tehran.

The strong DNB-NO_2/CO correlations directly support emission control measures, such as stricter vehicle standards and low-emission zones in high-DNB urban cores to curb traffic/industrial sources. Moderate DNB-LST_night links inform sustainable urban design by advocating cool roofs, permeable pavements, and zoning reforms to minimize impervious surfaces. For UHI mitigation, findings endorse green infrastructure development (like urban forests and rooftop gardens) to enhance evapotranspiration and reduce ~1°C LST rises, fostering resilient planning in Tehran. O_3 weak bonds require integrated policies that address photochemistry through Volatile Organic Compounds (VOC) control and meteorological monitoring, aligning with the global Sustainable Development Goals (SDGs) for healthier cities.

In summary, this study's findings align with global research on urbanization's environmental impacts, confirming that NO_2 and CO are strongly linked to urban activity, while O_3 exhibits complex dynamics. By integrating remote sensing with correlation analyses, we provide actionable insights for mitigating air pollution and UHI effects in Tehran, contributing to sustainable urban development strategies worldwide.

5. Conclusion

Urbanization in Tehran Province, proxied by rising VIIRS DNB from 2018–2022, drove significant NO_2 increases and ~1°C rises in daytime/nighttime LST via UHI effects (most pronounced at night due to heat retention in urban surfaces) with CO showing minor fluctuations and O_3 exhibiting minimal correlation due to photochemical complexities. Strong DNB-NO_2/CO correlations and moderate DNB-nighttime LST links highlight traffic/industrial emissions as key drivers, while weak DNB-O_3 ties underscore indirect influences. These insights, derived from integrated Sentinel-5P and MODIS data in GEE, align with global urban studies on rapid-growth cities and emphasize policy actions: Implement low-emission zones in central Tehran, expand the Bus Rapid Transit (BRT) network to reduce reliance on >4 million private vehicles, and establish urban forests in southern districts to mitigate ~1°C LST increases, aligning with Iran's Clean Air Act. Offer subsidies for electric vehicles to address socio-economic barriers, targeting a 10% NO_2 reduction by 2030. Satellite-based monitoring offers a scalable model for assessing environmental costs, with future research needed on seasonal/meteorological/socio-economic factors to refine equitable strategies and foster resilient urban environments.

References

Bonafoni, S., & Keeratikasikorn, C., 2018, Land surface temperature and urban density: Multiyear modeling and relationship analysis using MODIS and Landsat data. Remote Sens. 10(9), 1471.

Chicco, D., Warrens, M.J., & Jurman, G., 2021, The coefficient of determination R-squared is more informative than

SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. PeerJ Comput. Sci. 7, e623.

Colombi, A., De Michele, C., Pepe, M., Rampini, A., & De Michele, C.D., 2007, Estimation of daily mean air temperature from MODIS LST in Alpine areas. EARSeL eProc., 6(1): 38–46.

Cui, W., Sun, Z., Ma, H., & Wu, S., 2020, The correlation analysis of atmospheric model accuracy based on the Pearson correlation criterion, [in:] IOP Conf. Ser.: Mater. Sci. Eng. 780(3), 032045.

Fuladlu, K., & Altan, H., 2021, Examining land surface temperature and relations with the major air pollutants: A remote sensing research in case of Tehran. Urban Clim. 39, 100958. https://doi.org/10.1016/j.uclim.2021.100958

Hu, C., Kang, P., Jaffe, D.A., Li, C., Zhang, X., Wu, K., & Zhou, M., 2021, Understanding the impact of meteorology on ozone in 334 cities of China. Atmos. Environ. 248, 118221. https://doi.org/10.1016/j.atmosenv.2021.118221

Ialongo, I., Virta, H., Eskes, H., Hovila, J., & Douros, J., 2020, Comparison of TROPOMI/Sentinel-5 Precursor NO_2 observations with ground-based measurements in Helsinki. Atmos. Meas. Tech. 13(1): 205–218.

Li, H., Sun, D., Yu, Y., Wang, H., Liu, Y., Liu, Q., Du, Y., Wang, H., & Cao, B., 2014, Evaluation of the VIIRS and MODIS LST products in an arid area of Northwest China. Remote Sens. Environ. 142: 111–121.

Liang, L., & Gong, P., 2020, Urban and air pollution: a multi-city study of long-term effects of urban landscape patterns on air quality trends. Sci. Rep. 10(1), 18618. https://doi.org/10.1038/s41598-020-74524-9

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E., 2020, Environmental and health impacts of air pollution: a review. Front. Public Health 8, 14.

Moazzam, M.F.U., Doh, Y.H., & Lee, B.G., 2022, Impact of urbanization on land surface temperature and surface urban heat island using optical remote sensing data: A case study of Jeju Island, Republic of Korea. Build. Environ. 222, 109368. https://doi.org/10.1016/j.buildenv.2022.109368

Mwangi, P., 2024, Evaluating the spatio-temporal distribution of nitrogen dioxide, land surface temperature and NDVI in Nairobi City County. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. 10: 237–244.

Oskouei, E.A., Shobairi, S.O.R., Sadeghi, H., Shokouhi, M., Fatahi, E., Khazanedari, L., Lingxiao, S., Haiyan, Z., Chunlan, L., Jing, H., & Ayombekov, Q., 2024. Spatial and temporal monitoring of wildfires in Golestan province using remote sensing data. Ecological Questions 35(3): 17–32.

Parida, B.R., Bar, S., Roberts, G., Mandal, S.P., Pandey, A.C., Kumar, M., & Dash, J., 2021, Improvement in air quality and its impact on land surface temperature in major urban areas across India during the first lockdown of the pandemic. Environ. Res. 199, 111280.

Shobairi, Seyed Omid Reza, Lingxiao Sun, Haiyan Zhang, Chunlan Li, Jing He, Behnam Asghari Beirami, Samira Hemmati Roudbari, and Qorghizbek Ayombekov, 2024, Modeling process of the spatial-temporal changes of vegetation cover and its relationship with drivers in drylands and wetlands in Xianjiang (China). Transylvanian Review of Systematical and Ecological Research 26(1): 27–74.

Siddiqui, A., Chauhan, P., Halder, S., Devadas, V., & Kumar, P., 2022, Effect of COVID-19-induced lockdown on NO_2 pollution using TROPOMI and ground-based CPCB observations in Delhi NCR, India. Environ. Monit. Assess. 194(10), 714.

Stratoulias, D., Nuthammachot, N., Dejchanchaiwong, R., Tekasakul, P., & Carmichael, G.R., 2024, Recent developments in satellite remote sensing for air pollution surveillance in support of sustainable development goals. Remote Sens. 16(16), 2932. https://doi.org/10.3390/rs16162932

Zhang, L., et al., 2022, Direct and indirect impacts of urbanization on vegetation growth across the world's cities. Sci. Adv., 8(27), eabo0095.

Zhang, Q., & Seto, K.C., 2011, Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data. Remote Sens. Environ. 115(9): 2320–2329.

Zheng, Z., Yang, Z., Wu, Z., & Marinello, F., 2019, Spatial variation of NO_2 and its impact factors in China: An application of Sentinel-5P products. Remote Sens. 11(16), 1939.