The relationship between spatial patterns of urban land uses and air pollutants in the Tehran metropolis, Iran

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Abstract

Context Urban expansion has led to land use changes in metropolises, which in turn cause landscape pattern changes and ecological issues in urban areas.

Objective The main objective of this research is to investigate the relationship between different land use and air pollutants (NO₂, SO₂, CO, O₃) in the metropolis of Tehran.

Methods The Local Climate Zone scheme and Landsat 8 satellite images were used to extract urban land uses in Tehran. Additionally, Sentinel-5P satellite images were used to calculate and evaluate air pollutants in summer (2020) and winter (2021). Then, the relationship between the spatial composition and configuration of urban land uses and air pollutants was computed.

Results The results show that the correlation of the distribution or concentration of air pollutants is different from the spatial pattern of land use. The spatial composition and configuration of anthropogenic land uses, including the classes of compact mid-rise, compact low-rise, large low-rise, and heavy industry, had a positive correlation with NO₂ and SO₂ (P < 0.05). In contrast, the pollutant CO had a significant negative correlation with the green spaces of types A (dense trees) (P < 0.01) and B (scattered trees) (P < 0.05). Conversely, the spatial composition and configuration of anthropogenic land uses had a negative correlation with O₃ (P < 0.05) while had a positive correlation with green spaces (P < 0.05).

Conclusion Generally, the spatial pattern of the anthropogenic land uses had a direct and positive correlation in both spatial configurations with NO₂, SO₂, and CO and a negative correlation with O₃.

Keywords Land use · Air pollutants · Landscape metrics · Local climate zone · Tehran metropolis

Introduction

Climate warming is a global issue, which has become a serious threat to human health and the environment (Ou et al. 2013). One of the main reasons of climate warming is increasing trend in greenhouse gases emissions especially after industrialization era which has captured the attention of most of the
world’s nations (Parry et al. 2007). Urban centers are key players in generating greenhouse gases (Moghbel and Erfanian Salim 2017). The most common air pollutants in cities include carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen oxides (NOₓ), hydrocarbons (HC), suspended particulate matter (SPM, including PM10, PM2.5), ozone (O₃) (Hoek et al. 2002). Urban development and its structure, public facilities and traffic patterns are the main factors which can deteriorate urban air quality. In other word, land use and transportation modes have been changed due to urbanization so that significant increase in energy consumption and the massive emission of air pollutants have exacerbated air pollution (Hopke et al. 2008; Fang et al. 2015; She et al. 2017).

Rapid urbanization also results in expansion of small urban. Merging of small urban centers into each other cause formation of huge conurbations. In this regard, changes in land use along with traffic and industrial emissions, have also been identified as a main reason which can affect urban air quality (Romero et al. 1999; Weng and Yang 2006; Huang et al. 2013; Xu et al. 2016; Zahari 2016). Urban land use patterns are usually reflected via the dispersion of air pollutants and air quality in urban environments (Huang and Du 2018). In fact, distribution of pollutants depend on the activities of the land use (Halim et al. 2020). Therefore, changes in urban land use patterns reduce urban air quality and create various stresses (Du et al. 2010; Wei and Ye 2014; Tao et al. 2015; Huang and Du 2018; Hien et al. 2020).

Land use changes affect natural land cover surfaces directly or indirectly thereby affecting the transport/dispersion of air pollution (Halim et al. 2020). It has been well documented in previous studies that urban building layouts, urban planning patterns, building height, and other factors can affect the air quality in urban environments (Ng 2009; Gómez-Baggethun and Barton 2013). Hence, air pollution can concentrate in built-up lands (Weng and Yang 2006; Xian 2007; Zahari 2016; Wang et al. 2018). Accordingly, Weng and Yang (2006) have examined the impact of land use variables on air pollutants. They have showed a positive correlation between spatial trends of air pollutants with the density of built-up land in Guangzhou, China. Also, Ku (2020a, b) have illustrated that the annual averages NO₂ is increased by increase of built-up area in Tiachung city, Taiwan. Whereas inverse relationship was observed between the increase in forest connectivity and forest area and annual average of NO₂. Liu and Shen (2014) have indicated a negative correlation between green spaces and air pollution. Zhu et al. (2019) showed that concentrations of SO₂, CO and O₃ were all positively correlated with the cultivated land. Similarly, forests lead to decrease of SO₂ and CO concentration. Furthermore, a positive correlation has been found between cultivated land with many air pollutants by Huang and Du (2018), while Nowak et al. (2006) found low concentration of air pollutants in forested land. Base on the study by Nowak et al. (2000) local ozone concentrations can reduce by increasing of tree covers in urban area by a few parts per billion (ppb) by volume during daytime.

The studies mentioned above show that there is considerable relationship between urban land use and changes in air pollutants. However, most previous studies have examined this relationship using the maps of current urban land use conditions and data from air quality monitoring stations. Thus, to achieve a deeper understanding of the effectiveness of urban air quality improvement strategies (reducing air pollution), it is necessary to use integrated research methods such as the quantification of the spatial structure of urban patterns (composition and configuration) and the analysis of the correlation between air pollutants and landuse (Ku 2020a, b). Accordingly, the main objective of this research is to explain the relationship between different land use patterns and air pollutants in a spatial–temporal analysis framework in the summer and winter seasons. We modeled the relationship between the spatial structure of urban patterns (composition and configuration) and air pollutants by employing the Pearson correlation and multiple linear regression.

**Methodology**

In the present study, the Local Climate Zone (LCZ) scheme and Landsat 8 satellite images were used to extract urban land uses in Tehran (4 images for each season). Then, FRAGSTATS software (version 4.2.1) was used to calculate land use metrics based on spatial patterns (composition and configuration) of each land use. Air pollutants distribution were calculated by Sentinel-5P satellite images in summer (2020) and winter (2021). Finally, considering 22 districts of
Tehran, Pearson correlation coefficient and multiple linear regression were used to investigate the relationship between the spatial composition and configuration of urban land uses and air pollutants, respectively (Fig. 1). It is worth to note that land use maps were generated at the same scale used to generate the images for air pollutants, namely 1 km.

Study Area

Tehran as the most populous metropolis and capital of Iran is located in the geographical position of 35° 36′ 46′′ N and 51° 17′ 23″ E. The area of the city is equal to 730 square kilometers. With the population of about 9 million people, it has the population density of 12,910 people per square kilometer (Fig. 2). Due to the rapid population growth and increasing urbanization, the metropolis of Tehran includes various types of urban land uses. Additionally, the unique geographical location of the city, which is surrounded by Shemiran heights in the north, Damavand in the east, and Karaj in the west and is open only from the south, has led to the increased concentration of pollutants in this metropolis (Zebardast and Riazi 2015). The air in Tehran is among the most polluted in the world (Heger and Sarraf 2018). Thus, to investigate

Fig. 1 Analytical framework of the research

Metropolis of Tehran

Landuse Pattern

- The local climate zone used to extract land cover
- Fragstats used to calculate land use metrics based on spatial patterns of each land use

Air Pollution

- Monitoring of air pollution using sentinel satellite images
- Google Earth Engine in summer 2020 and winter 2021

Analysis of spatial composition of urban land uses and air pollution indices using Pearson Correlation method

Investigation of spatial configuration landuse and pollution indicators using multiple regression in summer and winter

The relationship between landuse patterns and air pollution
the relationship between urban land uses and air pollution, the metropolis of Tehran was considered as the study case in the present research.

Materials and methods

The local climate zone (LCZ) scheme was used to extract urban land uses. The LCZ scheme is currently considered a standard for linking landscape to air pollutants at an urban scale. Generally, this classification scheme can be applied in three areas: (1) study of urban heat islands (Emmanuel and Krüger 2012; Alexander and Mills 2014; Leconte et al. 2015; Lehnert et al. 2015), (2) Modeling (such as: Surface Urban Energy and Water Balance model (SUEWS), digital elevation model (DEM)) (Alexander et al. 2015; Bokwa et al. 2015; Geletič et al. 2016), and (3) Land cover mapping (Bechtel and Daneke 2012; Lelovics et al. 2014; Danylo et al. 2016). One of the advantages of LCZ classification is the complete description of land-use types in an urban environment because it meets the standards for measuring physical properties and urban morphology (Stewart and Oke 2012). Each class can be identified using structural features and land cover that influence air temperature at a height of 1–2 m above the ground (Das and Das 2020). One of the methods for generating a map based on the LCZ classification is the remote sensing imagery-based method (Bechtel et al. 2016; Zhongli and Hanqiu 2016). Using this method, we followed three basic steps of pre-processing Landsat-8 satellite images (Conrad et al. 2015), and digitized each class of land uses using Google Earth and by SAGA GIS software.

After producing the classification maps based on the LCZ schema, we compared them with contemporary Google Earth imagery using ENVI5.3 software. Classification accuracy is assessed using the kappa coefficient and overall accuracy. If the Kappa coefficient is above 85% and the overall accuracy is above 90% at this stage, the accuracy of the generated map can be considered acceptable (Kerle et al. 2004).

After generating land use maps, the characteristics of the land uses were quantified using landscape metrics computed by the FRAGSTATS 4.2.1 software. As Table 1 shows, 6 metrics with the following characteristics were selected: (1) significant role in theory and practice (Li and Wu 2004; Peng et al. 2010; Zhou et al. 2011), (2) Ease of calculation and high
interpretive power (Zhou et al. 2011; Li et al. 2012), and (3) The least exaggeration in the data (Riitters et al. 1995; Li and Wu 2004; Zhou et al. 2011).

Furthermore, the spatial and temporal variation of air pollutants was investigated using data from TROPOMI instruments on board of the Sentinel-5P satellite launched on 13 October 2017 by the European Space Agency for the global monitoring of the environment and the air pollutants such as carbon dioxide, nitrogen dioxide, ozone, and sulfur dioxide (Veefkind et al. 2012) with a resolution of 1 km*1 km. We accessed data using the Google Earth Engine launched by Google in 2010. The platform allows users to access GEE through an Internet-based

Table 1  Landscape metrics used in this study (McGarigal 2015)

| Categories                | Metrics (abbreviation) | Description                                                                 | Equation                                                                 |
|---------------------------|-------------------------|-----------------------------------------------------------------------------|--------------------------------------------------------------------------|
| Composition               | Class area (CA)         | Total class area(unit: Hectares)                                           | \[\sum_{j=1}^{n_i} a_{ij} (1/1000) \left( \sum_{k=1}^{n} a_{ik} / n_i \right) (1/10000)\] |
| Configuration             | Mean Patch Area (AREA_MN) | Total patch area divided by patch number (units: Hectares)                | \[\frac{\sum_{j=1}^{n_i} a_{ij}}{A} (10000)(100)\]                      |
| Patch Density (PD)        |                          | Number of patches divided by total landscape area (unit: number per km²)  | \[\frac{\sum_{j=1}^{n_i} c_{ij}}{A} (10000)\]                           |
| Edge density (ED)         |                          | Amount of edge relative to the landscape area at class level (unit: m/ha)  | \[\frac{\sum_{j=1}^{n_i} c_{ij}}{A} (100)\]                           |
| Largest Patch Index (LPI) |                          | Percent of the total landscape that is made up by the largest patch at class level (unit: %) | \[\frac{\sum_{j=1}^{n_i} h_{ijr}}{z} \left( \frac{a_{ij}}{\sum_{j=1}^{n_i} a_{ij}} \right)\] |
| Area-Weighted Radius of   |                          | The mean distance (m) between each cell in the patch and the patch centroid divided by the sum of patch areas (unit: Meters) | \[\frac{\sum_{j=1}^{n_i} \left( h_{ijr} / z \right) \left( a_{ij} / \sum_{j=1}^{n_i} a_{ij} \right)}{A} (100)\] |

\[a_{ij} = \text{area (m) of patch } ij; n_i = \text{number of patches}; A = \text{total landscape}; e_{ik} = \text{total}; h_{ijr} = \text{distance between cell } ijr; z = \text{number of cells}\]
Application Programming Interface (API) and an interactive web-based development environment (Amani et al. 2020) (Table 2). Finally, pearson correlation and multiple linear regression was used to investigate the relationship between the spatial pattern of urban land uses and air pollutants.

Results

Land uses and air pollutants in Tehran metropolis

Using Landsat 8 satellite, land use maps were generated with the help of LCZ schema for the summer 2020 and winter 2021. Land uses were classified into 8 types, including compact buildings of 3–9 stories and more (2), compact buildings of 1–3 stories (3), large industrial warehouses (8), industrial structures (10), dense coniferous/deciduous trees with green ground cover (A), scattered coniferous/deciduous trees with green ground cover (B), scattered bush and scrub with green ground cover (C), low plants without/with scattered bushes and green ground cover (mostly agricultural lands) (D). Kappa statistic and overall accuracy were obtained respectively to be 0.8603 and 87.23% for the map of summer 2020 and 0.8706 and 88.17%, for the map of winter 2021, indicating the accuracy of the maps generated. On the other hand, according to the measurement of air pollutants (Fig. 4), CO and O3 declined so that the maximum and minimum density of these pollutants were (0.0350), (0.1262) and (0.03295), (0.1238) mol/m², respectively. In contrast, changes in NO2 showed an increasing trend in summer, with a maximum density of 0.00046 and a minimum density of 0.00035 mol/m². In winter, changes in the three pollutants CO, SO2, and NO2, in contrast to O3, showed a sharply declining trend with the maximum density of 0.0033, 0.0008, and 0.058 mol/m² and the minimum density of 0.0001, 0.0004, and 0.0355 mol/m², respectively.

The relationship between the spatial composition of urban land uses and air pollutants

Pearson correlation coefficient was used to investigate the relationship between the spatial composition of urban land uses and air pollutants. Table 3 shows the correlation coefficients between the CA metric of the eight types of land uses defined for Tehran and the pollutants NO2, SO2, CO, and O3. The results showed that CO and NO2 had a significant positive correlation with built land uses (compact midrise (2), compact low-rise (3), large low-rise (8), and heavy industry (10)) at 95% and 99% confidence levels. In contrast, while having a significant negative correlation with green spaces of types A (dense trees) (P < 0.01) and B (scattered trees) (P < 0.05) in both seasons, the pollutant CO had a significant negative correlation with the green spaces of type D (low plants) (P < 0.05).

Table 2 Sentinel-5P satellite information about air pollutants

| Satellite   | Name | Description                                           | Source                                                                 | Min* | Max* | Unit     |
|-------------|------|-------------------------------------------------------|------------------------------------------------------------------------|------|------|----------|
| Sentinel-5p | CO   | highly poisonous, colorless and odorless, produced by incomplete combustion of carbon | produced by human activities and natural resources such as Motor vehicles, chemical industries, fuels such as gas, oil, coal and wood | −279 | 4.64 | mol/m²   |
|             | NO2  | a reddish brown gas With a pungent odor and a high reactivity | Caused by combustion processes such as vehicles, heating systems and power plants | −0.0006 | 0.0096 |          |
|             | SO2  | a non-flammable, colorless gas with a pungent odor   | produced by volcanoes, most industrial activities, Burning oil and coal | −48  | 0.24 |          |
|             | O3   | a pale blue gas and and toxic With high reactivity    | created by chemical reactions between nitrogen oxides (NOx) and volatile organic compounds (VOCs) in the presence of sunlight. These compounds are released into the air from a variety of sources, including Motor vehicle exhaust, industrial activities | 0.0047 | 0.272 |          |

*Values are estimated, Earth Engine Code Editor (google.com)(Chalupka 2005, Barn et al. 2011)
in summer. It should be noted that in addition to the negative correlations mentioned for CO, the pollutant NO$_2$ had also a significant negative correlation with the green spaces of type C (scattered bush and scrub) (P < 0.05) in summer.

The pollutant SO$_2$ had a significant positive correlation with compact buildings of 3–9 stories and more, large industrial warehouses, and industrial structures in both seasons, and it had a significant positive correlation with compact buildings of 1–3 stories (P < 0.05) only in winter. This pollutant had a significant negative correlation with green spaces including dense and scattered trees in both seasons and the lands including bushes, grasslands and agricultural lands in summer at 95% and 99% confidence levels. The correlations obtained in relation to the pollutant O$_3$ were in contrast to the correlations of other pollutants. This pollutant had a significant negative correlation with compact buildings of 3–9 stories, large industrial warehouses, and industrial structures (P < 0.05), and a significant positive correlation with green spaces including scattered trees and green ground cover in both seasons and the green spaces including dense trees, grasslands, and agricultural lands in summer. Among the pollutants, the average concentration of the pollutant O$_3$ in summer and the
average concentration of the pollutant CO in winter had the highest correlation with the composition of land uses.

Considering the land uses, the CA metric of lands with natural cover, (dense trees (A), scattered trees (B), bush and scrub (C), low plants (D)), had a negative correlation with the concentration of air pollutants except O3. In other words, the larger the area of these lands, the lower the concentration of air pollutants. In contrast, the CA metric of built and anthropogenic land uses (compact midrise (2), compact low-rise (3), large low-rise (8), and heavy industry (10)) had a positive correlation with the concentration of all pollutants except O3 so that the concentration of pollutants increased with the increase in the area of these land uses. It is worthy to note that the CA metric of compact midrise (summer) and heavy industry (winter) had the highest correlation with the concentration of air pollutants.

The relationship between the spatial configuration of urban land uses and air pollutants

The relationship between the spatial configuration of land uses and the air pollutants in Tehran was studied using 5 metrics of AREA_MN, PD, ED, LPI, and GYRATE_AM and multiple linear regression in which the dependent variable Y indicated the average change of air pollutants in summer and winter and the independent variable X indicated the metrics selected for different land uses. After examining the regression models that had reached a significant level, it was found that CO had a significant positive correlation with the AREA_MN, PD, and ED metrics of compact buildings of 1–3 stories, the AREA_MN, PD, and LPI metrics of industrial warehouses, and the PD, ED, LPI, and GYRATE_AM metrics of compact buildings of 3–9 stories and industrial structures in summer. This correlation was also seen for this pollutant in winter so that it had a significant positive correlation with the AREA_MN, PD, and LPI metrics of compact buildings of 3–9 stories, the AREA_MN and PD metrics of compact buildings of 1–3 stories, and the AREA_MN, PD, and LPI metrics of industrial structures. Regarding the relationship between this pollutant and natural land uses, it was recognized that CO had a negative correlation with AREA_MN, PD, and ED metrics of green spaces including dense and scattered trees in summer and winter. It had also the same relationship with the AREA_MN and GYRATE_AM metrics of agricultural lands in summer (see Appendix, (Table A–1)). The pollutant SO2

Table 3 Correlation coefficients between the CA metric and air pollutants

| Land use | CA of Summer 2020 | NO2 | O3 | CA of Winter 2021 | NO2 | O3 |
|----------|------------------|-----|----|------------------|-----|----|
| 2        | 0.487**          | 0.363* | 0.549** | −0.612** | 0.541** | 0.424* | 0.591** | −0.443* |
| Sig      | 0.006            | 0.048 | 0.002 | 0.00 | 0.002 | 0.002 | 0.001 | 0.014 |
| 3        | 0.407*           | 0.299 | 0.476** | −0.437* | 0.435* | 0.372* | 0.513** | −0.425* |
| Sig      | 0.026            | 0.108 | 0.008 | 0.016 | 0.016 | 0.043 | 0.004 | 0.019 |
| 8        | 0.381*           | 0.482** | 0.411* | −0.266 | 0.533** | 0.438** | 0.524** | −0.239 |
| Sig      | 0.038            | 0.007 | 0.024 | 0.156 | 0.002 | 0.015 | 0.003 | 0.196 |
| 10       | 0.482**          | 0.566** | 0.524** | −0.380* | 0.621** | 0.516** | 0.619** | −0.353* |
| Sig      | 0.007            | 0.001 | 0.003 | 0.038 | 0.00 | 0.004 | 0.00 | 0.047 |
| A        | −0.515**         | −0.520** | −0.519** | 0.379* | −0.482** | 0.487** | −0.525** | 0.459** |
| Sig      | 0.004            | 0.003 | 0.003 | 0.039 | 0.007 | 0.006 | 0.003 | 0.008 |
| B        | −0.395*          | −0.496** | 0.478** | 0.343* | −0.371* | −0.392* | −0.446* | 0.360* |
| Sig      | 0.034            | 0.005 | 0.008 | 0.047 | 0.044 | 0.032 | 0.013 | 0.043 |
| C        | −0.282           | −0.376* | −0.376* | 0.352* | −0.262 | −0.256 | −0.322 | 0.324* |
| Sig      | 0.138            | 0.041 | 0.042 | 0.041 | 0.162 | 0.173 | 0.083 | 0.044 |
| D        | −0.352*          | −0.532** | 0.368* | 0.493** | −0.174 | −0.299 | −0.272 | 0.187 |
| Sig      | 0.048            | 0.002 | 0.045 | 0.006 | 0.358 | 0.109 | 0.0147 | 0.305 |

** (P<0.01), * (P<0.05)
had a significant positive correlation with AREA_MN, PD, ED, and LPI metrics of compact buildings of 3–9 stories and industrial structures in both summer and winter. This pollutant had the same relationship with compact buildings of 1–3 stories so that it had a positive correlation with the AREA_MN and PD metrics in summer and the LPI metric in winter. It should be noted that SO2 had also a positive correlation with the LPI metric of large industrial warehouses in summer and the LPI and PD metrics of them in winter. AREA_MN and LPI metrics of scattered agricultural lands and grasslands had a negative correlation with SO2 in summer, which was also the case for the AREA_MN metric of scattered grasslands in winter. In addition to the above metrics, the PD and ED metrics of green spaces including trees (dense and scattered) had a negative correlation with SO2 in both seasons (Table A–2). The relationship between NO2 and the metrics defined for the configuration of land uses followed the same trends observed in relation to previous pollutants. However, the only difference was that AREA_MN, PD, and ED metrics of compact buildings of 3–9 stories and 1–3 stories and industrial structures had a positive correlation with this pollutant in summer. This correlation was in winter and the significant positive correlation could also be seen with regard to the LPI metric. Industrial warehouses also had a positive significant correlation with this pollutant in AREA_MN and PD metrics. The investigation of the relationship between this pollutant and green spaces demonstrated that the AREA_MN, PD, and GYRATE_AM metrics of green spaces including trees (dense and scattered) and the ED and LPI metrics of scattered agricultural lands and grasslands had a negative correlation with this pollutant in both seasons (Table A–3).

The relationships of configuration metrics with the studied pollutants were such that these metrics had positive relationships with anthropogenic land uses and negative relationships with air pollutants in natural uses. However, the correlations recognized for O3 were similar to what was observed regarding the spatial composition of land uses. Built land uses (ED, LPI, and GYRATE_AM metrics) had a negative correlation with this pollutant while the LPI and AREA_MN metrics of green spaces including trees (dense and scattered) and the AREA_MN, LPI, and GYRATE_AM metrics of agricultural lands had a positive correlation with O3 (Table A–4).

**Discussion**

The results of this study [like the studies by (Xu et al. 2016; Zhou et al. 2018; Halim et al. 2020)] indicate that the spatial patterns of built and anthropogenic land uses, including the compact midrise, compact low-rise, large low-rise, and heavy industry classes are all positively correlated with such pollutants as NO2, SO2, and CO so that the degree of correlation with these pollutants increases with the increase in the area (CA) of dense buildings with more floors. This is consistent with the findings of the study by Wang et al. (2018), which showed that the density, height, and other spatial patterns of buildings significantly affected wind direction, reduced in wind flow, and thus increased concentration of pollutants. Additionally, one of the main reasons for the positive correlation between built and anthropogenic land uses and the pollutant CO is the improper distribution of land uses and the increased travel demand, which lead to increased concentration of this pollutant (Ou et al. 2013). In the case of warehouses and heavy industries, due to the existence of heating systems, transportation of heavy equipment, and burning more fossil fuels, the increased area (CA) of these lands leads to an increase in pollutants NO2 and SO2 (King et al. 2014; McCarty and Kaza 2015; Rodríguez et al. 2016; Liu et al. 2018). In the discussion of spatial configuration metrics, PD and ED have almost a positive relationship with the built lands in both seasons. In other words, the increase in PD, AREA_MN, and LPI of these lands indicates the increased area, the enclosure, and thus the confinement of urban pollutants. There is a stronger positive correlation between the spatial pattern of built and anthropogenic land uses and air pollutants in winter. In general, due to preventing the pollutants from being diluted and causing the air not to rise, the phenomenon of air inversion in winter prevents the rise and dispersal of air pollutants (Pardyjak et al. 2009; Pope and Wu 2014). In addition, wind speed is often lower in autumn and winter than in spring and summer and this slows down the transfer of clean air to urban areas (Jiang et al. 2014; Hess et al. 2015). In contrast, these spaces are negatively correlated with the tropospheric ozone that is produced from terrestrial sources, and the ozone in the troposphere is considered a pollutant. This negative correlation is stronger in summer when the angle of the sun is more vertical.
A negative correlation has been recognized between spatial patterns of green and natural spaces (A: dense trees, B: scattered trees, C: bush, scrub, and D: low plants) and the pollutants NO₂, SO₂, and CO (Civerolo et al. 2000; Irga et al. 2015; Huang and Du 2018). As Ku (2020a, b) explains, the investigation of the spatial configuration of spaces demonstrates that the increase in PD and AREA_MN of trees, which indicates a decrease in fragmentation and an increase in connectedness and density in these spaces, leads to the reduced concentration of pollutants. This can be due to increased evapotranspiration as well as more photosynthesis of trees than other plants (Zhang et al. 2009; Cao et al. 2010). It should be noted that the increase in PD is interpreted as increased fragmentation and dispersion when the number of patches as well as the proximity of the patches increase. Otherwise, the increased PD and the decreased number of patches indicate the integration of lands and the formation of patches with a larger area. In general, green spaces with more trees have a stronger inverse relationship with the pollutants NO₂, SO₂, and CO in summer. However, similar to anthropogenic land uses, the relationship with O₃ is different from other pollutants. It should be noted that in agricultural lands, there is a negative relationship in summer due to the presence of various plants and this relationship is not established in winter due to absence of human activity and the lack of plant growth.

Conclusions

The ever-increasing population growth, uncontrolled urban expansion, and the lack of attention to the natural spaces lead to increased production of pollutants that have harmful effects on the urban populations. Thus, this study aimed to investigate and evaluate the relationship between spatial patterns of various urban land uses and the pollutants NO₂, SO₂, CO, and O₃ in summer 2020 and winter 2021 using landscape metrics, including Class area (CA), Mean Patch Area (AREA_MN), Patch Density (PD), Edge density (ED), Largest Patch Index (LPI), Area-Weighted Radius of Gyration (GYRATE_AM). This was done in the Tehran metropolis, where LCZ scheme was used to classify land uses, 2: Compact midrise, 3: Compact low-rise, 8: Large low-rise, 10: Heavy Industry, A: Dense trees, B: Scattered trees, C: Bush, scrub, and D: Low plants) Sentinel-5P datasets were used to collect data on the studied pollutants.

The results showed that the spatial pattern of the anthropogenic land uses, which included Compact midrise, Compact low-rise, Large low-rise, and Heavy industry classes had a direct and positive correlation with NO₂, SO₂, and CO and a negative correlation with O₃. The positive correlations were stronger in winter due to air inversion, especially for compact midrise and heavy industry. In green spaces and natural lands, which included the classes of Dense trees, Scattered trees, Bush, scrub, and Low plants, the relationships were inverse to those observed in anthropogenic land uses. In other words, these land uses had a negative correlation with NO₂, SO₂, and CO and a positive correlation with O₃ and these relationships were especially much stronger in summer and green spaces with dense trees due to the increased density and greenness of the plant and the photosynthesis.

Based on the models used, the relationship between the spatial pattern of urban lands and air pollutants became clearer. Findings indicate that quantitative results can help develop more complex strategies and scenarios in future research and urban planning. According to the results, the traffic volume, population density, enclosure (the ratio of building height to street width), access to public transportation, and climatic factors such as changes in temperature, rainfall, humidity, and wind flow should be considered in high-rise land uses and industrial areas. Additionally, to create urban green spaces, there should be land uses with dense trees. However, it is necessary to focus on one or more specific land uses to study more deeply the relationship between land uses and air pollutants.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.
Declarations

Competing interests  The authors have no relevant financial or non-financial interests to disclose.

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