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# Examining Relationships between Spatial Pattern of Green Infrastructure and Urban Heat Island (Case Study: Tehran Metropolis)

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**Abstract**
Green infrastructure (GI) is one factor that reduces the intensity of Urban Heat Islands (UHI). The research results related to the relationship between the spatial pattern (composition/configuration) of urban GI and UHI show contradictory results. Some researchers emphasized the negative relationship between MPS and ED criteria, while other researchers found positive results in these criteria. Based on this, this study was conducted in the metropolis of Tehran, which is located in the center of Iran and has undergone many changes. The method is based on Local Climate Zone (LCZ) classification, measuring the landscape metrics (CA, ED, MPS, LSPI), and analyzing the relationships through Pearson correlation and partial Pearson correlation. The results show: (1) Areas with tree cover in two types of green spaces A/B have a negative effect on Land Surface Temperature by 0.46 and 0.84 at the 95% and 99% confidence levels, respectively, (2) Mean patch size (MPS) and largest patch index (LPI) of type A were important factors in reducing LST by 0.458 and 0.481 respectively at 99% confidence level, (3) The value of Edge Density (ED) in GI, including B/C type, has positive effects on LST and is 0.519 and 0.33 at the 95% confidence level. These results showed that it is possible to influence the reduction of LST by planning suitable GI spatial patterns, So that urban planners and designers should focus on creating green infrastructure with dense trees in urban centers, and on the other hand, pay attention to air circulation flows in Tehran metropolis based on the height of buildings.
**Keywords:** Spatial Pattern, Green Infrastructure, Urban Heat Islands, Tehran Metropolis.

## 1. Introduction

The purpose of this article is to explain the relationship between urban green infrastructure and heat islands Population growth, These factors, together with globalization and urban population growth, cause rapid and informal urban development, change in land use, and an increase in infrastructure resources and transportation needs, is one of the main reasons for the increase in temperature (Dizdaroglu, 2022; Najah, Abdullah, & Abdulkareem, 2023). The increase in temperature caused by the Urban Heat Islands (UHI) and destruction of green spaces is effective in intensifying a wide range of negative environmental and social consequences, including deaths caused by heat (Dipeolu, Akpa, & Fadamiro, 2020; Hondula, Georgescu, & Balling Jr, 2014) Especially among workers who work outdoors (Di Blasi et al., 2023), changing the liveability of communities (McIntyre et al., 2001), and global warming (Karl et al., 1993; Santamouris et al., 2015). UHI expresses the phenomenon of higher temperature in urban areas compared to rural and suburban areas (Li, Zhou, & Ouyang, 2013), so with the increase of urbanization, the effects of UHI also intensify (Liu et al., 2007). The air temperature of UHI has a temporary quality and a wide time that can describe the temporary changes of the heat islands, but it is difficult to depict the spatial changes of this factor, and It is a difficult matter this difficulty can be solved by using the Land Surface Temperature (LST) which can show the temperature of the whole city at the same time (Weng, 2009).

One of the current approaches to reduce the effects of urban heat islands, increase air quality and control climate change is the expansion of green infrastructure. (Al-Dabbous & Kumar, 2014; Monteiro et al., 2016) that the relationship between types of land cover, especially green infrastructure and heat islands, and related strategies to reduce the effect of UHI have been continuously studied (Zhou et al., 2023). The important factor in this approach is the green space, which refers to the types of infrastructure related to vegetation and natural element, so that the green space has a great ability to reduce heat islands through the action of evaporation or absorption of short-wave radiation, and the proportional area of green space in a region is one of the effective factors in cooling (Chen et al., 2014; Kong et al., 2014; Li et al., 2012; Myint et al., 2013).

The research conducted on the relationship between green infrastructure and LST (Table 1), indicates the necessity of conducting more studies in this field. For example, some studies emphasized that the Class Area (CA) of GI has a negative relationship with the LST, while they showed different results in the case of Edge Density (ED), and Mean Patch Size (MPS) (Guo, Wu, & Chen, 2019; Li et al., 2012), or indicated that UHI intensity was negatively correlated with green infrastructure cores, holes, and rings, but positively correlated with small islands (Lin et al., 2023). Some authors show that the ED of green infrastructure in hot and humid climates has a negative effect on temperature, but the relationship of this metric in hot and dry climates was positive (Zhou, Wang, & Cadenasso, 2017). There is also research in evaluating the relationship between urban land use spatial pattern and LST with the help of the

Normalized Vegetation Index (NDVI) and Proportion Vegetation Cover (PVC), linear regression, and identification of susceptible areas based on their distribution and Population vulnerability refers to the negative relationship between the CA and ED of green infrastructure with the LST (Dugord et al., 2014; Li et al., 2011; Zhou, Huang, & Cadenasso, 2011). As it is known, there are contradictions in the results of this research. In other words, this research has shown different results about CA, MPS, NDVI, etc., while one of the causes of these contradictions is due to the lack of control of the influence of factors such as the area and density of trees and the type of GI surface cover. This can be one of the reasons for the contradiction between the ED and MPS metrics of the green infrastructure with the LST.

In the aforementioned studies, the same categories have been proposed for urban green infrastructure, and not much attention has been paid to the structural patterns of green infrastructure and their classification. Using the studies conducted in this field, to answer the research questions, a conceptual model based on the relationship between UHI and spatial pattern of green infrastructure has been used in the landscape ecology approach. Thus, this research was conducted to explain the correlation between the spatial patterns of green infrastructure and urban heat islands, and the Local Climate Zone (LCZ) method was used to classify GI in terms of the density of trees and their surface type and tries to answer these questions:

1) What is the relationship between the spatial pattern of green infrastructure and UHI?

2) What is the role of different types of urban green infrastructure in LST changing?

**Table 1.** Studies related to Investigating the Relationship between the Spatial Pattern and the LST

| Researchers | Case Study | Method | Results |
|---|---|---|---|
| **(Li et al., 2011)** | Shanghai, China | Analysis of LST in relation to NDVI, PVC | The negative linear relationship between the normalized index and the ratio of vegetation cover with the LST and the positive relationship between the impervious surfaces and the LST, as well as the more suitable reduction effect of the vegetation cover in summer than in early spring |
| **(Zhou, Huang, & Cadenasso, 2011)** | Baltimore, United States | Investigating the relationship between the spatial pattern of different land use and land cover and the LST using linear regression | Observing the negative relationship between the area of green infrastructure and LST |
| **(Li et al., 2012)** | Beijing, China | Investigating the spatial pattern of green infrastructure in three spatial resolutions (2.44 m, 10 m, 30 m) based on the images of Landsat TM, QuickBird, and SPOT satellites and using the Pearson correlation method to investigate the relationship between the patterns of green infrastructure and LST | Higher resolution images can more accurately determine the spatial pattern of green infrastructure, and the relationship between green infrastructure area and LST is consistently negative, but the relationship between its configuration parameters and LST is different at different spatial resolutions. |
| **(Dugord et al., 2014)** | Berlin, Germany | Investigating LST according to the land use pattern and identifying susceptible areas based on its distribution and population vulnerability | The more cooling effect of green infrastructure in the morning than in the evening |
| **(Zhou, Wang, & Cadenasso, 2017)** | Baltimore And Sacramento, United States | Investigating the relationship between the spatial pattern of green infrastructure and LST in several different scales and using Pearson correlation, partial Pearson, and multivariate regression methods | Mean Patch size (MPS) had significant positive effects on LST in Baltimore, but negative effects were found in Sacramento. In contrast, edge density (ED) has negative effects on LST in Baltimore, but positive effects in Sacramento. In addition, the results emphasize the necessity of controlling the effect of tree area metrics when quantifying the effects of their spatial configuration on LST, and the relationships between metrics Configurations and LST become stronger with increasing scale. |
| **(Guo, Wu, & Chen, 2019)** | Shenzhen, Guangzhou, Foshan, and | Measuring green infrastructure and LST data for summer and winter, then comparing statistical changes using a new method, a | The contribution of the spatial composition of green infrastructure parameters plays a more decisive role in determining LST, especially in summer. In addition, the effect of city heat |

| | | | |
|---|---|---|---|
| | Dongguan, China | combination of stepwise regression and hierarchical analysis | islands is not only reduced by increasing the area of green infrastructure but the optimization of the spatial configuration of green infrastructure should also be considered. |
| **(Najah, Abdullah, & Abdulkareem, 2023)** | Baghdad | The research emphasizes testing the selected case studies, to measure Surfaces in urban heat islands and Canopy layer UHI, and by adopting mathematical approaches. | The results show several factors associated with the change in land uses that aggravate UHI in terms of formation, land cover, and construction, including materials and colors. |
| **(Zhou et al., 2023)** | Hohhot, Beijing, Shanghai, and Haikou of China | The data used in this study includes four cloud-free Landsat 8 OLI/TIRS images. landscape indicators were selected that are capable of quantifying patch characteristics, vegetation abundance, planting structure, and the composition of the interior and surrounding landscape of urban green spaces patches (PSI, NDVI, Pland, NGP). Bivariate correlation analyses and regression analyses were conducted. | Local climate condition affects the cooling effect of urban green spaces. The cooling intensity of urban green spaces is weaker in cities with humid and hot summers than in cities with dry and hot summers. Patch characteristics, Pland and NGP, NDVI, and planting structure together can explain a significant proportion of the cooling intensity variations of urban green spaces. |
| **(Lin et al., 2023)** | Shenzhen, china | Morphological spatial pattern of green space, using machine learning methods. Analysis of morphological characteristics of green space based on MSPA. A linear relationship between UHI intensity and a set of potential influencing factors according to the correlation coefficient. The contribution of morphological factors to UHI intensity was measured based on a random forest. | UHI intensity was negatively correlated with green space. Therefore, a few large core areas of green spaces are better than many small islands. The fragmentation of the green space should be integrated or connected to increase the cooling capacity. |

## 2. Material and Methods

### 2.1. Local Climate Zone (LST) and measurement of landscape metrics

The method of this research is based on the use of the classification of GI through local climate zone (LCZ) and measurement of landscape metrics (Gheshlaghpoor, Abedi, & Moghbel, 2023). According to Figure 1, in this classification, urban land is divided into 17 different types of land use, of which 4 types are dedicated to green spaces (A-D). These 4 types are: A) Green spaces with dense trees and green fields, B) Green spaces with scattered trees and green fields, C) Green lands with bushes and soil, and D) Natural lands without trees and mostly agricultural (Stewart & Oke, 2012). After producing the classified map of the green infrastructure, the revealed data was compared with the Google Earth map related to the time taken in the ENVI 5.3 software, and the accuracy of the classification was checked using the Kappa coefficient and the overall accuracy. Eq.1 “overall accuracy” shows the percentage of correctly classified points to the total selected points and Eq.2 “Kappa coefficient” better defines the discrimination between the classes, and finally, if the overall accuracy and the Kappa coefficient are higher than 90% and 85%, respectively, the accuracy of the extracted maps is at its best (Imran et al., 2021). After the production of the classification map of GI in Tehran, the quantification of the features of green areas was done with the help of landscape parameters, and their calculation was done in Fragstats 4.2.1 software so that Table 2 shows features of the three selected metrics in term of spatial composition and configuration of green infrastructure. The characteristics of these metrics are 1. They play an important role in theory and practice (Li & Wu, 2004; Peng et al., 2010; Zhou, Huang, & Cadenasso, 2011), 2. Ease of calculation and high interpretability (Li et al., 2012; Zhou, Huang, & Cadenasso, 2011), 3. Minimal data exaggeration (Li & Wu, 2004; Riitters et al., 1995; Zhou, Huang, & Cadenasso, 2011). Finally, after calculating green infrastructure metrics and LST, an analysis of the relationship between GI patterns in the Tehran metropolis and its LST was done using SPSS 25 software and the Pearson correlation coefficient.

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified}}{\text{Total number of reference}} \times 100$$

$$\text{Kappa coefficient } = \frac{\text{The total sum of correct} - \text{ Sum of all the(row total } \times \text{column total)}}{\text{Total squared} - \text{Sum of all the(row total } \times \text{column total)}}$$

**Figure 1.** Urban (1–10) and natural (A–G) LCZ types and their characteristics (Stewart & Oke, 2012)

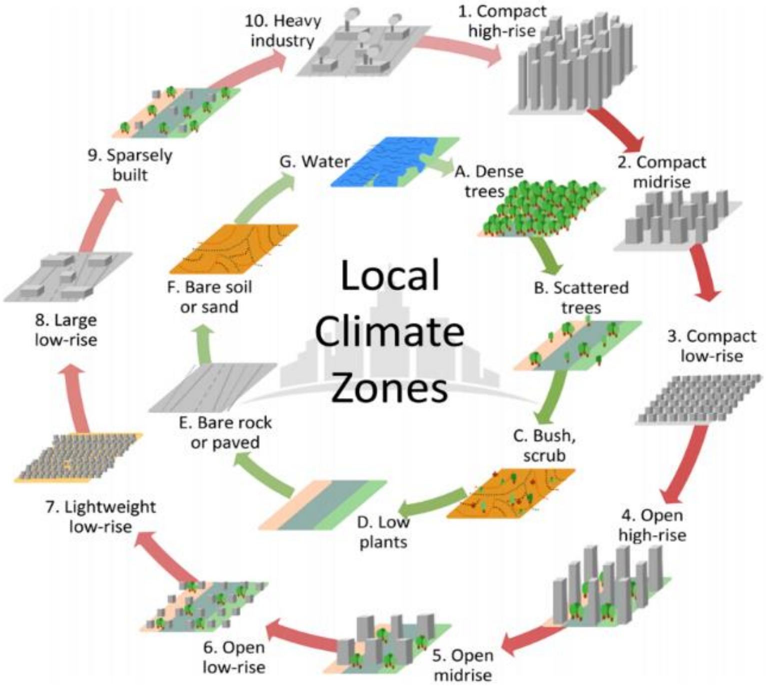


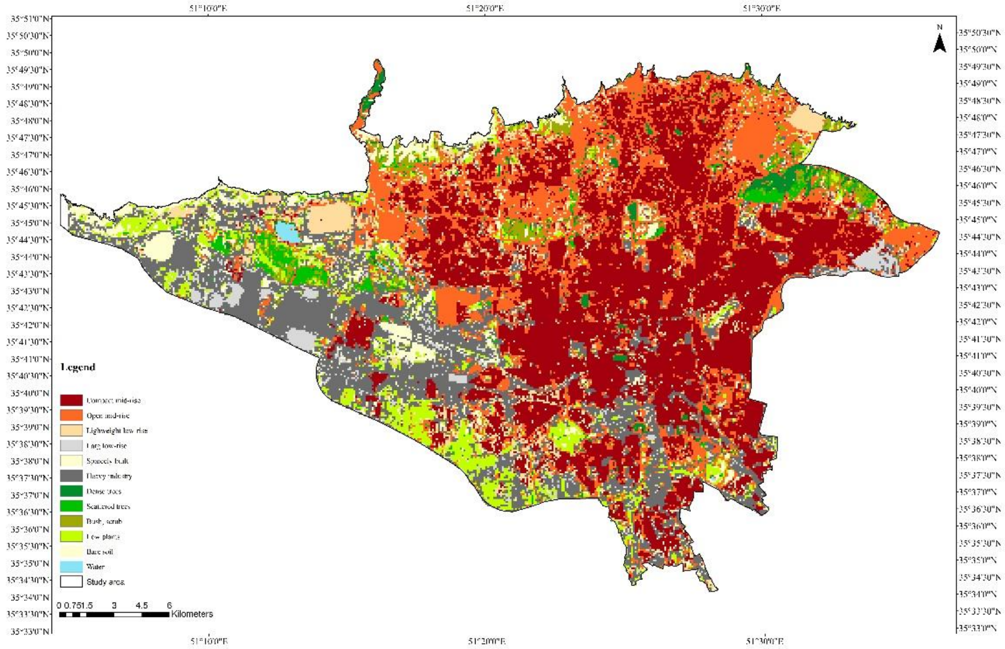

**Table 2.** Selected landscape variables in measuring the spatial patterns of green spaces

| Spatial pattern | Metrics | Unit | Description | References |
|---|---|---|---|---|
| Spatial composition | Class area (CA) | Ha | The area (square meters) of all patches related to a class type divided by 10,000 (to convert to hectares) | (Kong et al., 2014; Li et al., 2012; McGarigal, 2002) |
| Spatial configuration | Mean patch size (MPS) | Ha | The number of patches in a class and it calculates the average area of the patches. | (Kong et al., 2014; Li et al., 2012; McGarigal, 2002; Zhang et al., 2009) |
| | Edge density (ED) | $\frac{Meter}{Ha}$ | The total area of patches of one class per hectare | (Kong et al., 2014; McGarigal, 2002; Zhang et al., 2009; Connors et al., 2013; Maimaitiyiming et al., 2014) |
| | Largest Patch Index (LPI) | $\frac{\max(a_{ij})}{A}(100)$ | Percent of the total landscape that is made up by the largest patch at class level (unit: %) | (McGarigal, 2002) |

### 2.2. Study area

Tehran With approximately 8 million population, is the most populous city in Iran with a very distinct demographic difference than other cities (Center, 2011). This city within the longitudes of 51° to 51° 40′ E and the latitudes of 35° 30′ to 35° 51′ N, has an area of 730 square kilometers (Hosseini, Pourahmad, & Pajoohan, 2016) (Figure 2). Tehran metropolis is the 25th most populous city and the 27th largest city in the world, which has 22 districts. The rapid growth of the population and the increase in urbanization in the Tehran metropolis and the special geographical location of the city, which is not only limited from the south and is surrounded by the heights of Shemiran and Damavand from the north and east and by the Karaj metropolis from the west, has caused an increase in the pollutants concentration in this metropolis (Zebardast & Riazi, 2015).

**Figure 2.** Study area




### 2.3. Data collecting

The Landsat 8 satellite (Table 3) was used to extract the structural features and land cover that affect the atmospheric temperature at a height of 1-2 meters above the ground, so the data related to this satellite was received from the USGS then it was processed using ENVI 5.6 software.

**Table 3.** Features of Landsat 8 satellite

| satellite | Sensor | Year | Row | Path | UTM zone | datum |
|---|---|---|---|---|---|---|
| Landsat 8 | OLI | 2019 | 35 | 164 | 39 | WGS84 |

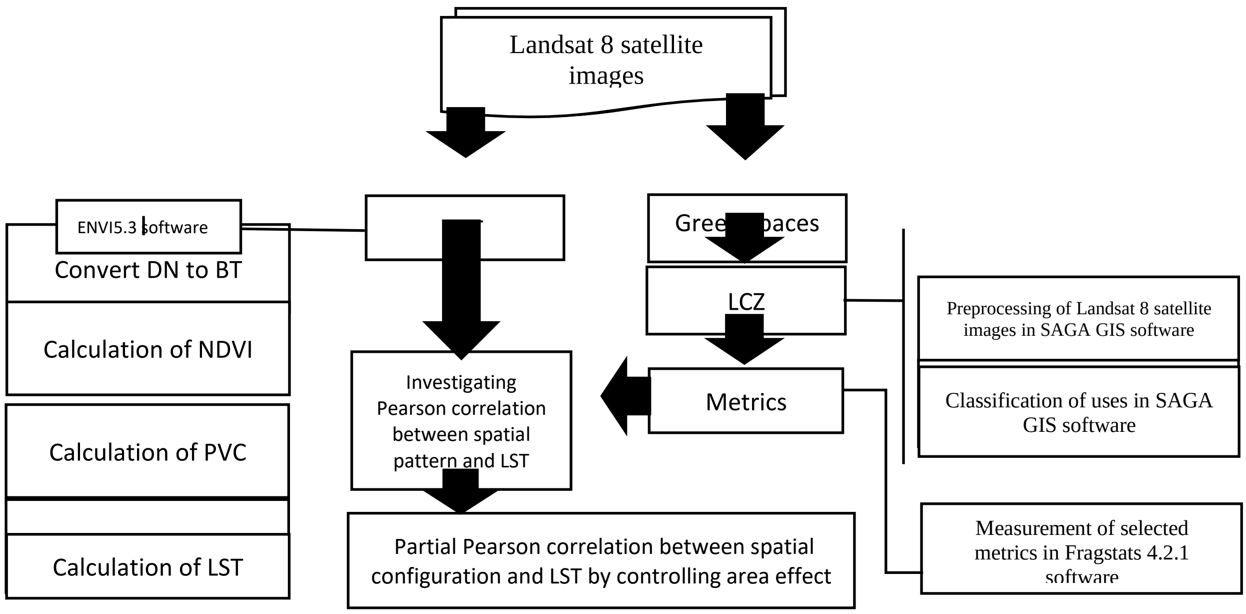
Based on Eq.3, the Land Surface Temperature (LST) of Tehran was calculated by brightness temperature (BT), normalized vegetation cover index (NDVI), proportion vegetation cover (PVC), and land surface emissivity (LSE) (Table 4). The statistical analysis methods of this research are using Pearson and partial Pearson correlation, It should be noted that since configuration metrics of each class are highly related to its area, Pearson correlation analysis may show deceptive relationships between LST and spatial configuration (Smith et al., 2011; Zhou, Huang, & Cadenasso, 2011). Therefore, we also used a partial Pearson correlation coefficient to examine the relationship between configuration metrics and LST after controlling for the effect of green space area as a controlled variable. All statistical analysis was done using SPSS 25 software. In general, Figure 3 shows the research process:

$$LST = BT/(1+(\lambda \times (BT/14380) \times a\log(\in)))$$

**Table 4.** LST of Tehran in 2019

| Year | Min temperature | Max temperature | Average temperature | standard deviation |
|---|---|---|---|---|
| 2019 | 19.32 | 49.52 | 36.18 | 3.86 |

**Figure 2.** Process of examining the relationship between green spaces and LST




**3. Results**

The green space map of Tehran metropolis in 2019 was prepared with the help of Landsat 8 satellite images and LCZ method. The Kappa coefficient and overall accuracy of this map was 0.8706, 88.172%, which confirms the accuracy of the production map. Pearson correlation analysis in the study of the relationship between the spatial composition of green infrastructure classes and LST (Table V) showed that the spatial composition or CA metric of dense and scattered trees, and low plants has a significant and negative correlation with LST. So that the highest negative relationship belongs to class B with scattered trees and green field and the lowest to class A with dense trees and green field. In contrast to this negative correlation, the correlation coefficient of bare soils (class C) with LST is positive and significant

In relation to the spatial configuration, the Pearson correlation of the average size of each class of green infrastructure (MPS) with the LST consistently has a significant negative relationship, although the size of these correlations is different among classes. However, this correlation between the ED and LPI of green infrastructure classes, in addition to its importance, size, and significance, is also different in terms of direction (Table 5). Class A shows a significant negative correlation with LST, but classes B and C show a significant positive correlation of ED with LST, on the other hand, the ED of class D does not have a significant correlation with LST.

**Table 5.** Correlation of spatial pattern of green space classes with LST

| **Spatial pattern** | **Metrics** | **A** | **B** | **C** | **D** |
|---|---|---|---|---|---|
| Spatial composition | CA | $-0.46^{*}$ | $-0.84^{**}$ | $+0.278^{*}$ | $-0.43^{**}$ |
| Spatial configuration | MPS | $-0.498^{**}$ | $-0.318^{*}$ | $-0.302^{*}$ | $-0.421^{*}$ |
| | ED | $-0.501^{**}$ | $+0667^{**}$ | $+0.766^{**}$ | -0.371 |
| | LPI | $-0.345^{*}$ | $-0.284^{*}$ | $+0.322^{*}$ | +0.131 |

$^{**}p < 0.01;\ ^{*}p < 0.05$

As stated, the CA metric of the GI classes (spatial composition) has a great impact on the configuration metrics of these classes, so this effect causes the correct correlation value of the configuration measures with temperature not to be displayed. Therefore, by using a partial Pearson correlation coefficient and controlling the effect of the CA metric, the relationships between configuration parameters and LST changed a lot (Table 6). In this way, metrics of MPS, ED, and LPI had a significant relationship with classes A and D, B and C, A and B, respectively, while before controlling the CA metric, almost all metrics have a significant correlation with LST.

**Table 6.** Correlation of spatial configuration of green space classes with LST after controlling CA metric

| | **Metrics** | **A** | **B** | **C** | **D** |
|---|---|---|---|---|---|
| Spatial configuration | MPS | $-0.458^{**}$ | -0.071 | -0.167 | $-0.368^{*}$ |
| | ED | -0.106 | $+0.519^{*}$ | $+0.33^{*}$ | -0.139 |
| | LPI | $-0.481^{**}$ | $-0.477^{**}$ | +0.157 | +0.127 |

$^{**}p < 0.01$; $^{*}p < 0.05$

**4. Discussions**

Investigating the correlation between the spatial composition of green infrastructure and the LST showed that the area of dense and scattered trees, and low plants had a negative and inverse relationship with the LST, which is similar to the results of previous researches (Kong et al., 2014; Li et al., 2011; Li et al., 2012; Zhou, Huang, & Cadenasso, 2011; Zhou, Wang, & Cadenasso, 2017). Class B has the highest negative correlation of the CA metric with LST, but it is mostly located in the eastern and western areas of Tehran and is not located in the main centers of the city, which have high temperatures, Class A, despite its spread in the east and center of the city, has the smallest area of the green infrastructure classes and its CA metric has the least negative relationship with the LST and at the 95% confidence level. Class D is located mostly in the south and west of the city and its area has a negative relationship with LST at the 99% confidence level, but it is worth mentioning that previous findings have shown that the effect of green spaces with few trees and grass fields to reduce the LST, It is less than green spaces with many trees (Myint et al., 2013). In general, it cannot be said that the area of class B has a stronger inverse relationship with LST, because class A, which represents green spaces with dense trees, is less in the Tehran metropolis and the number of observations of this class, despite being small compared to other classes, has shown a negative and significant effect on LST. In general, the spatial composition of natural lands has a negative and reducing effect on LST. The correlation of the spatial composition of class C in the northern half of the city is not like the other three classes and indicates a positive and significant relationship with the LST due to the presence of bushes and grasslands with low density, scattered shrubs, and soil. Because the presence of bushes has a positive effect in reducing LST, but the placement of this bush in the soil and the lack of relative humidity and proper air circulation have a positive effect on the increase of LST.

In relation to the partial Pearson correlation of spatial configuration metrics, mean patch size (MPS) and largest patch index (LPI) of class A (and B for LPI) shows a negative and significant relationship with LST at the 99% confidence level, so that an increase in MPS and LPI of green areas with dense trees causes an increase in evaporation and transpiration, and as a result of LST decrease (Cao et al., 2010; Yokohari et al., 1997; Zhongli & Hanqiu, 2016). But due to the sparseness and spread of this class of green spaces and the increase in temperature of Tehran, class A is not able to reduce that of the city. In addition, the MPS of low plants also has a negative correlation with the LST at the 95% confidence level, although its cooling effects are less. On the other hand, the edge density (ED) of scattered trees and bare soils at the 95% confidence level had a significant positive relationship with LST, and according to previous studies, the increase in ED causes an increase in shading and a decrease in temperature (Zhou, Wang, & Cadenasso, 2017), But in this type of green infrastructure classes, there are no trees in the majority, which causes a positive relationship between the ED of these classes and LST.

Considering the different relationships between the spatial patterns of green infrastructure classes in Tehran, to reduce the average temperature of the city, the urban planners and policymakers should increase the area of class B green spaces in the central and high-traffic areas of the city, And in addition to this class, they can also use class A, but these areas cannot be widely used in urban centers due to the high density of trees. On the other hand, it is possible to change the class C green spaces located inside the city to one of the mentioned classes, which will improve and reduce LST. Finally, one of the potential limitations of this research is the resolution scale of aerial images, which future studies should investigate. On the other hand, it is better to extract the characteristics of man-made spaces, including the height of buildings, their density, and type of use, and control their impact on natural lands.

**5. Conclusions**

Climate changes caused by the increase in the temperature of cities and the lack of attention to the effect of the spatial patterns of the green infrastructure structure on the decrease in temperature have led to the creation of heat islands in urban centers, which is important to intensify efforts that can promote a better understanding of the environment (Dipeolu, Ibem, & Oriola, 2022). In this research, green spaces were classified into 4 using the local climate zone method, including; A) Green spaces with dense trees and green fields, B) Green spaces with scattered trees and green fields, C) Green lands with bushes and soil, D) Natural lands without trees and mostly agricultural and the correlation of the spatial composition and configuration of each of them with the LST was investigated. The result of the spatial composition of these GI showed that the green space with trees in both conditions (high/low density) and even class D has a reducing effect on LST. In other words, the increase in the area of these lands will moderate and reduce Land Surface Temperature. The results regarding the spatial configuration show that MPS and LPI of the green areas with dense trees and plants with low height have a significant negative correlation with LST, and on the contrary, the green space with low density of trees and green lands including grasslands with low density in the relationship with the edge density metric had a significant positive relationship with LST. These relationships between the spatial configuration of natural lands and LST are caused by the presence of trees and their density in all kinds of green infrastructure, which causes shading and increases the humidity of the environment and, as a result, decreases the temperature. These results showed that it is possible to influence the reduction of LST by planning suitable GI spatial patterns, So that urban planners and designers should focus on creating green infrastructure with dense trees in urban centers, and on the other hand, pay attention to air circulation flows in Tehran metropolis based on the height of buildings.

**Conflict of Interests**

The authors declare no conflict of interest.

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