

## Article

# How Do Vegetation Biomass, Area, and Shape Attributes Influence the Cooling Effect of Urban Green Spaces?

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**Abstract:** Despite the increasing volume of research exploring the impact of various characteristics of urban green spaces (UGS) on land surface temperature (LST), findings remain inconsistent, particularly in arid climatic zones. In this research, we examined UGS change and their temperature and analyzed the relationship between pertinent variables of vegetation biomass, area, and shape of green patches and LST in Karaj city, an Iranian semi-arid urban area in 2000 and 2020. Linear regressions were used to model the relationship between green patches' variables and LST. The results showed that vegetation biomass of green patches was more effective in reducing temperature in comparison with area and shape complexity. Moreover, larger patches with more vegetation biomass and higher shape complexity showed lower temperatures. These results can guide urban landscape optimization by providing a clear understanding of which factors contribute most significantly to temperature mitigation in arid and semi-arid urban areas. For instance, areas identified as green but thermally not significantly cold need to be prioritized for improvements such as planting denser vegetation or introducing more heat resilient species.

**Keywords:** spatial pattern; landscape metric; urban green space; urban heat island; Karaj



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## 1. Introduction

Cities are highly vulnerable to the combined consequences of urbanization and climate change [1,2]. The synergistic effects of urban heating and global warming make adapting urban areas to climate change one of the most pressing challenges of the Anthropocene [3,4]. A growing number of major cities worldwide are becoming urban heat islands (UHIs), characterized by higher temperatures in urban areas than in surrounding rural areas [5,6]. These temperature disparities arise from human activities, rapid urbanization, and population growth [5,6]. High percentages of impermeable land cover types, such as concrete and asphalt, exacerbate UHI effects by promoting heat storage and reducing natural radiative cooling [7]. Factors such as the decline in vegetation cover, rising energy demands, and excess heat from vehicles and buildings further amplify the impact of UHIs [8–10]. Furthermore, the intensity of UHIs is influenced by various factors, including city size, urban morphology, biome, regional climate, seasonal weather variations, and vegetation cover [10].

In cities dominated by impervious materials and high thermal inertia, urban surface and near-surface air temperatures are significantly more persistent than in rural areas [11]. This disparity becomes particularly severe during heatwave conditions, where UHI effects amplify extreme heat, leading to complex repercussions for human health and the urban

environment [5]. The canopy layer UHI effect, marked by elevated near-surface air temperatures in urban locations, heightens the risk of heat stress for city dwellers, especially during heatwaves [12]. The persistence of urban warming significantly impacts outdoor thermal comfort, contributing to increased hospitalizations and mortality rates linked to heat stress [13,14]. Extreme temperatures, a major cause of weather-related morbidity and mortality worldwide, pose a growing threat to human health [15]. Given the severe consequences of UHIs on human well-being, mitigation strategies are imperative. As heat extremes have intensified dramatically in recent years [16], policies must adapt to address the challenges posed by climate change and focus on mitigating UHI effects.

Over the past five decades, researchers have primarily concentrated on UHI mitigation through strategies such as improving urban shading, expanding green spaces, and modifying surface material properties [17]. Among these strategies, urban green space has emerged as an essential component of the urban ecological infrastructure [18,19]. Urban green space (UGS) refers to any type of cover, encompassing forests, gardens, bushland, green ways, public parks, and agricultural land, that provides a multitude of ecosystem services [20]. UGS not only mitigates UHI effects and improves the urban thermal environment [21–23] but also contributes significantly to enhancing the city's resilience and improving the quality of life and well-being of its citizens [24–28]. Vegetation surface can moderate the temperature through shading, evapotranspiration, and air movement in cities [29–32]. Hence, the lower temperature of UGS than their surrounding built-up area is known as the cool island effect [29,33,34]. However, urbanization can alter UGS area and its spatial distribution, contributing to an intensified UHI effect [35–37]. Therefore, the planning of UGSs to mitigate the temperature has been considered vital, particularly in cities located in hot and dry climatic zones, where managing urban heat is particularly challenging.

In recent years, land surface temperature (LST) has been widely used as a reliable remotely based indicator when studying urban thermal environments, since there is a strong correlation between LST and air temperature [22,38]. Moreover, the Normalized Difference Vegetation Index (NDVI) is the most common tool to investigate green biomass or green abundance [39]. In addition, a large body of research has been conducted to investigate the influence of vegetation abundance on LST across different urban areas [33,40–42]. Beyond vegetation abundance, the spatial characteristics of UGS significantly affect the urban temperature [43–45]. The spatial characteristics of green patches can be described by compositional (i.e., patch area) and configurational (i.e., shape and adjustment) attributes that referred to the spatial pattern. Landscape metrics have been developed to quantify different aspects of the spatial pattern of a landscape [46]. These landscape metrics are used to facilitate comparisons among different landscapes, to quantify how landscapes change over time, especially in response to different types of disturbances or land-use change, as well as to investigate the relationship between landscape characteristics and ecological processes [47].

Although previous research provides a wealth of knowledge associated with the spatial pattern of UGS and their effect on LST, this type of study is still inadequate, particularly in the megacities within arid and semi-arid climates. Moreover, there is a huge inconsistency between the spatial pattern of UGS and their effect on LST due to the unique spatial forms of cities and different spatial analyses and scales [48]. Given that cities have unique spatial layouts and environmental factors, the relationship between UGS patterns and LST requires further exploration to ensure that findings are broadly applicable. Therefore, comparative-based research at different times and in different cities are essential to bridge the scientific gap in this area. In addition, there is a challenge in analyzing the relationship between landscape indices and LST. In other words, statistical significance varied between the different methods [49]. Ref. [50] highlighted the necessity of conducting more case studies

with different methods to achieve generalization in this area. As such, developing robust statistical models that predict LST in response to UGS spatial characteristics is critical in addressing the existing research gaps and to support more effective UGS planning in diverse urban environments [42]. Given these challenges, semi-arid cities like Karaj provide a critical context for studying the relationship between UGS spatial patterns and urban temperatures

The Karaj urban region has undergone extensive urbanization over recent decades, impacting both the extent and health of its vegetation cover [51]. This study aims to address key questions related to urban green spaces (UGS) and temperature in Karaj: (1) How have urban green spaces and their temperatures changed over a 20-year period?; (2) How do specific characteristics of green patches—namely, vegetation biomass, area, and shape—affect land surface temperature in both 2000 and 2020?; (3) How can statistical analysis be used to model the relationship between land surface temperature (LST) and the attributes of green patches?

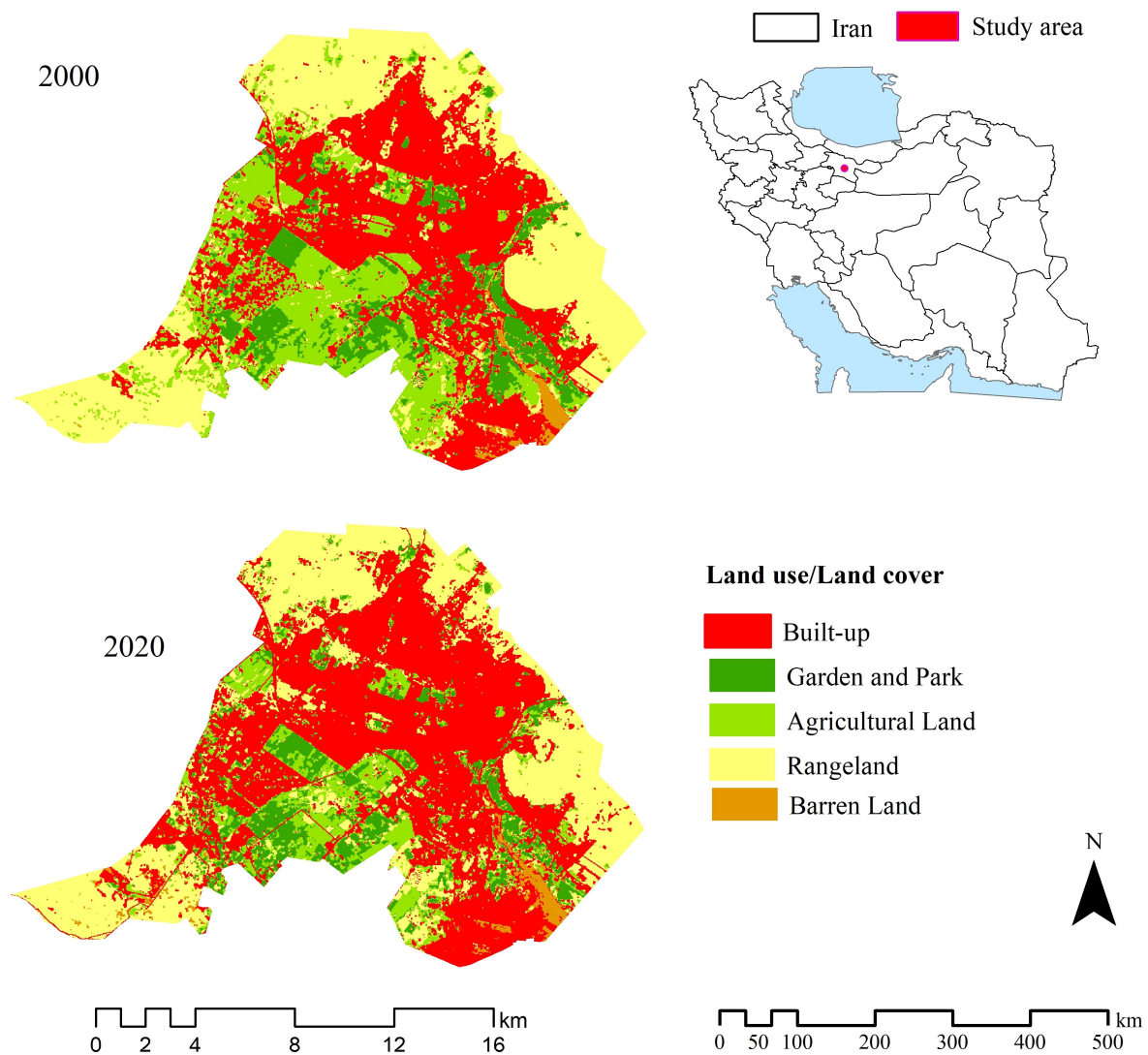
This research will highlight shifts in UGS distribution and provide insights into temperature fluctuations influenced by urban expansion and vegetation cover changes. In addition, understanding which attributes influence cooling effects the most can guide urban planning strategies that maximize temperature regulation. Developing a predictive model will support decision-making and help to anticipate the effects of urbanization on the urban thermal environment. Finally, the paper will explore areas for further research, particularly in refining methods for assessing the cooling potential of green spaces, improving data collection through advanced remote sensing techniques, and better understanding the broader implications of urban green space planning and design for climate adaptation in arid cities.

## 2. Materials and Methods

### 2.1. Study Area

The study area is considered an urban cluster, including Karaj as the core city and several adjacent cities of Kamalshahr, Mahdasht, Garmadreh, and Mohammadshahr, located in Alborz province to the west of Tehran and south of the Alborz Mountain range. The geographic extent of the area spans from 35.42° N, 50.50° E (southwest corner) to 35.53° N, 51.03° E (northeast corner), as illustrated in Figure 1. This urban area, with 48,000 hectares, accommodates approximately 87% of the Alborz province's population. With over two million inhabitants, it is the fourth-most populous urban district in the country [52]. According to De Martonne's climate classification scheme, the area is classified as arid and semi-arid [53]. The mean annual precipitation and temperature of the region are 247 mm and 14.4 °C, respectively. July, with a mean temperature of 34.6 °C, and February, with a mean temperature of 9.2 °C, are the warmest and coldest months of the year, respectively [52].

The study area experienced intense urbanization over the last twenty years; the gardens were destroyed and replaced with residential areas. Urban parks planted with tree-cover areas (gardens), fragmented croplands, and dense and sparse rangelands form the vegetation cover of the region [51].



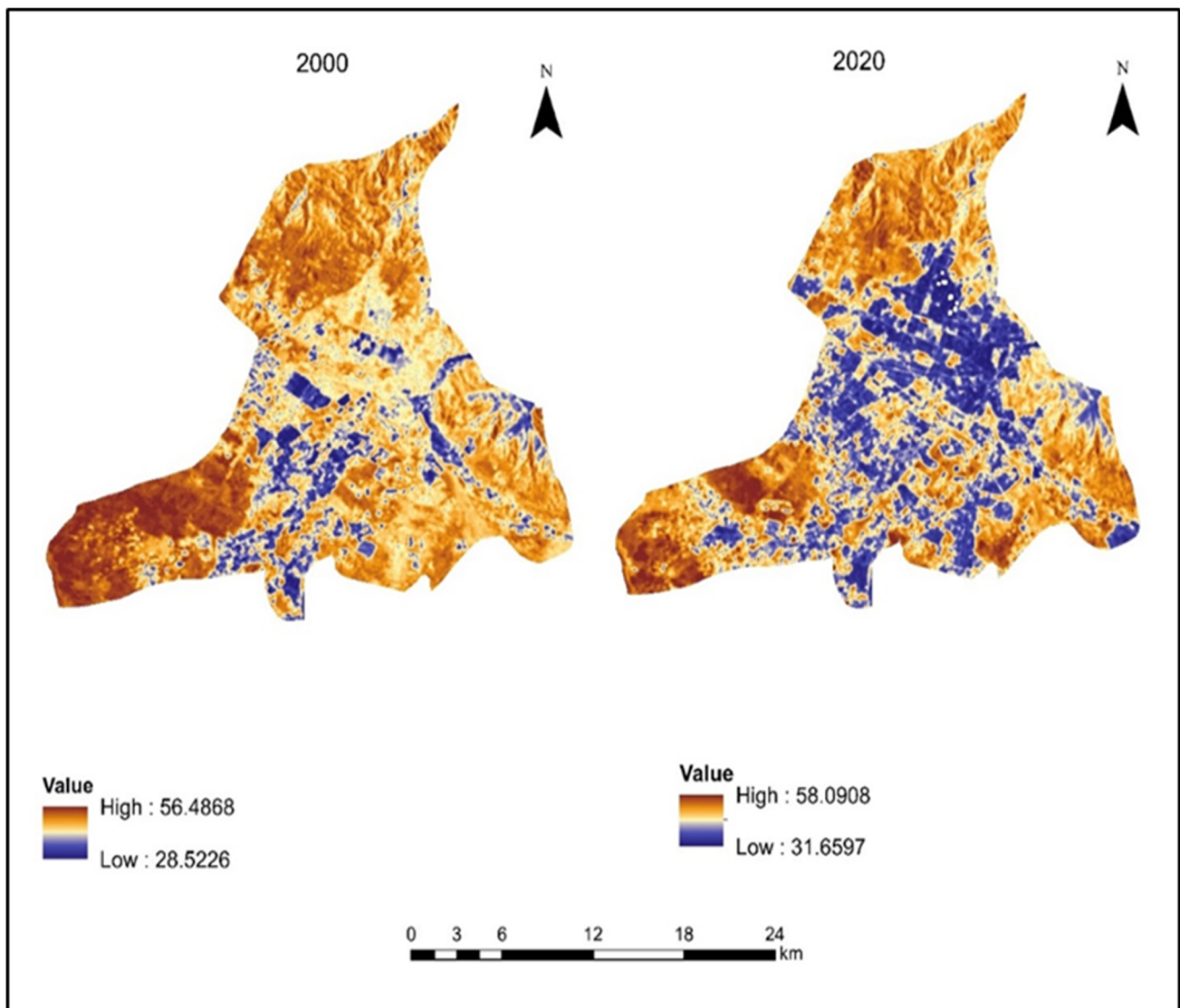
**Figure 1.** Land use/land cover map of the Karaj Urban Region in 2000 and 2020.

## 2.2. LST Retrieval

A Landsat 8 TIRS image taken on July 8 in 2020 and one image from Landsat 7 ETM+ taken on July 17 in 2000 were acquired from Google Earth Engine. The cloud threshold of the selected images was less than 10%. Due to a lack of suitable images on the same day for two different years, we used the closest dates for the images in the given years. LST maps (Figure 2) were produced using the Mono-Window algorithm following [54,55]. The Mono-Window algorithm was selected for LST retrieval due to its demonstrated accuracy in arid regions, as highlighted by [56]. Their comparison of multiple algorithms showed that the Mono-Window method provides reliable results when atmospheric transmittance and emissivity are accurately incorporated, making it suitable for the climatic conditions of the study area [56].

The LST values were measured from the thermal infrared bands of the Landsat satellite data using ENVI 5.3. There are three critical parameters in the MW algorithm: ground emissivity, atmospheric transmittance, and mean atmospheric temperature [55]. To retrieve LST, first, digital numbers of the thermal bands (Band 6 in Landsat TM and ETM+ and Band 10 Landsat OLI/TIRS) were converted to a top-of-atmosphere (TOA) radiance. Then, the radiance was used to derive the satellite brightness temperature of each pixel. The brightness temperature was corrected using NDVI to derive emissivity. Two atmospheric

parameters of transmittance and mean atmospheric were acquired from the meteorological database of the region.



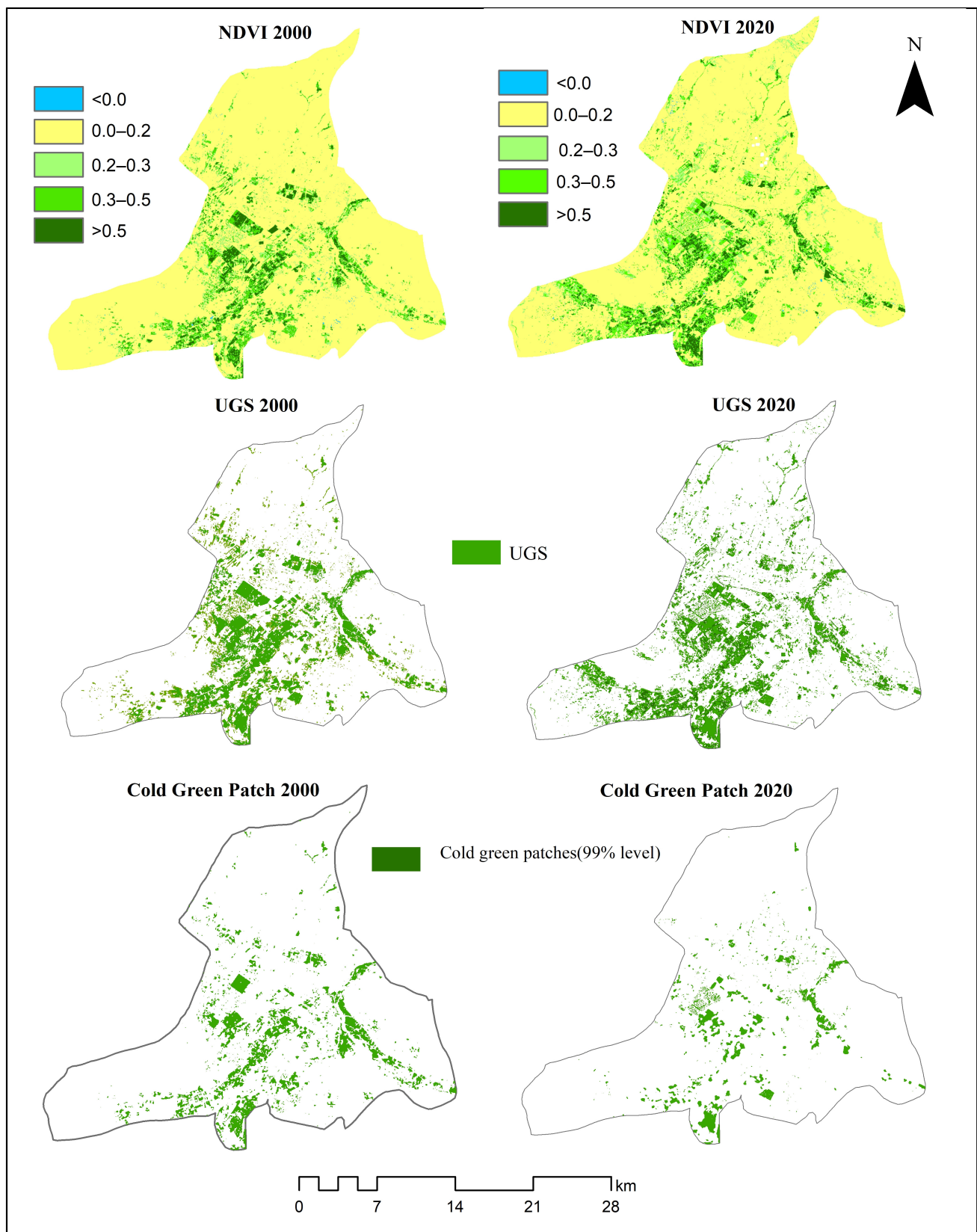
**Figure 2.** LST maps in 2000 and 2020.

### 2.3. Extraction of UGS

To extract the UGS layer, we first generated an NDVI map using visible (RED) and near infrared (NIR) reflectance bands from ETM+ and TRIS image data for 2000 and 2020 (Figure 3).

Given the importance of UGS identification, it was necessary to produce a highly accurate UGS map. To do so, 300 training points were collected from vegetation cover in parks, gardens, and agricultural lands, and 300 samples were surveyed from the built-up area and barren land using an array of Landsat false-color composites and Google Earth images. Then, the value of LST and NDVI was joined to the sample points for two years. A diagnosis test [57] was applied to identify the threshold value of each variable (i.e., NDVI and LST). In this research, the threshold value is a value of the variables that can diagnose the occurrence of a phenomenon (i.e., the presence of UGS). In the diagnosis test, the receiver operating characteristic (ROC) [58] was used to analyze the ability of input variables in distinguishing UGS from non-UGS. Then, in the ROC curve, the optimal NDVI and LST thresholds were calculated using true skill statistics or the Youden's index [58]

embedded in the ROCR package in R.3.5.2 and MedCalc version 13. The Youden index is a measure of the ROC curve, calculating the ability of a variable in distinguishing the sample points and identifying the optimal threshold value (i.e., cut-off point) of the variable.



**Figure 3.** NDVI maps, UGS maps, and cold green patches at 99% confidence level.

In ROC, the area under the curve (AUC) has a range of values, varying from 0.5 to 1.0 (poor to perfect performance). In addition, the performance of each variable in distinguishing green areas can be evaluated using the Sensitivity, Specificity, Correct classification and Miss classification criteria.

#### 2.4. Identification of Cold Green Patches

Green patches extracted by thresholding NDVI were thermally heterogeneous. To identify the significant green cold spots, we used the Hot Spot Analysis tool available in the ArcGIS ESRI 3.3.2 environment. This tool measures the Getis-Ord  $G_i^*$  statistic, which is an intensity degree of spatial clustering for each spatial unit relative to its neighbors. The  $G_i^*$  value is positive in areas with a cluster of high-intensity values and vice versa. The  $G_i^*$  statistic calculation for a feature converts to a z-score [59]. In this research, the LST map was analyzed using the z-score classification, with results varying from statistically significant negative to statistically significant positive at the different confidence levels of 99%, 95%, 90%, and not significant. Areas of high temperatures were identified as significant hot spots, whereas the areas with low temperatures were identified as significant cold spots. Considering the objective of this research, we analyzed only cold green patches (CGP) at a 99% confidence level.

#### 2.5. Analyzing Biomass, Area, and Shape

In addition, the green biomass of each cold green patch was calculated using the NDVI value. There have been numerous metrics developed to analyze the spatial pattern of a landscape; however, many of them describe similar aspects of the pattern [38,51,52]. Based on the previous studies amongst numerous metrics, the area and shape of green patches significantly affect LST [25,53–55]. In this study, we selected two metrics of size (AREA) and shape complexity (SHAPE). AREA represents the average size of all patches within a given landscape or study area, while SHAPE describes average complexity of the patch shape in a given area. These metrics were calculated for CGPs in 2000 and 2020 using FRAGSTATS v 4.3.1 software [35].

#### 2.6. Regression Analysis

First, the non-normal distribution of independent variables was normalized using the Box–Cox transformation technique [56]. The relationship between spatial metrics and LST was modeled using a simple linear regression relationship. To evaluate the efficiency of each model, the coefficient of determination, or “ $r^2$ ”, was used: the closer to one, the higher the power to interpret the LST at the patch level. In addition, multiple linear regression (MLR) was used to provide a comprehensive model of the relationship between LST and patch attributes.

### 3. Results

#### 3.1. Diagnostic ROC Test

The maps of NDVI and LST were provided to extract the UGS and GHS. NDVI minimum and maximum values were  $0.79 \pm 0.42$  in 2000 and  $0.82 \pm 0.31$  in 2020 (Figure 3). Minimum and maximum LST values were 28.5 and 56 °C in 2000 and 31 and 57 °C in 2020. To extract the UGS, the diagnostic ROC test was used. Table 1 shows the results of the test using several criteria, including Youden index, AUC, Sensitivity, Specificity, Correct classification, and Misclassification. In addition, the value of correct classification and misclassification confirms the better diagnosis performance of NDVI than LST in separating UGS from non-UGS in both years.

**Table 1.** Youden’s statistics for LST and NDVI (2000–2020).

| Criteria                   | 2000           |            | 2020         |            |
|----------------------------|----------------|------------|--------------|------------|
|                            | LST            | NDVI       | LST          | NDVI       |
| AUC                        | 0.846          | 0.922      | 0.822        | 0.983      |
| Significance level P       | <0.0001        | <0.0001    | >0.0001      | >0.0001    |
| Youden index J             | 0.6067         | 0.8200     | 0.5975       | 0.9375     |
| Correct classification     | 0.802          | 0.910      | 0.796        | 0.968      |
| Misclassification          | 0.198          | 0.090      | 0.204        | 0.032      |
| Sensitivity                | 0.74           | 0.877      | 0.902        | 0.988      |
| Specificity                | 0.867          | 0.943      | 0.688        | 0.948      |
| Associated threshold value | $\leq 42.7638$ | $> 0.2009$ | $\geq 41.87$ | $< 0.2683$ |

### 3.2. Temporal Change of Urban Green Space

As shown in Figure 3 the total area of UGS has decreased by 19% from 2000 to 2020. Moreover, from the Hot Spot analysis results, their temperature has changed dramatically over time. As such, the zonal statistics show that the area of cold green patches at 99% confidence level (i.e., CGP) decreased by 54% from 2000 to 2020 (Figure 3).

The results of spatial pattern and biomass of CGP showed that the mean area (AREA) of CGP decreased from 2000 to 2020 (Table 2). This means that the average area of green patches that were significantly cold decreased more than five times in twenty years. As is represented in Table 2, calculation of SHAPE indicated a gradual decrease for two decades. Moreover, the average biomass of CGP decreased from 0.5 to 0.4 over time (Table 2).

**Table 2.** Changes of spatial pattern and biomass of CGP (2000–2020).

| Variables     | 2000 | 2020   |
|---------------|------|--------|
| Green Biomass | 0.5  | 0.4    |
| SHAPE         | 1.41 | 1.34   |
| AREA (ha)     | 10.9 | 2.0766 |

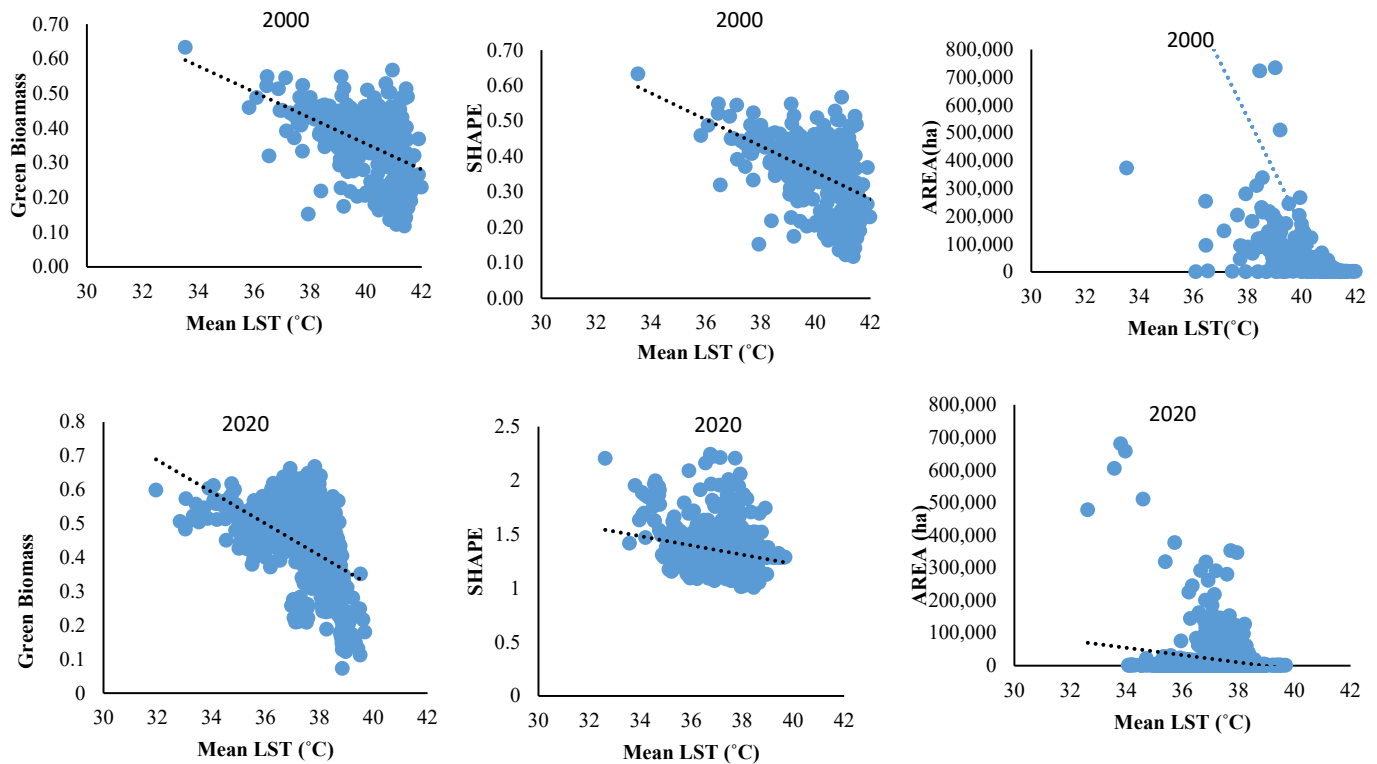
### 3.3. The Relationship Between LST and Green Patch Attributes

The scatter plots indicated a negative correlation of all three variables with mean LST in 2000 and 2020. In this way, with decreasing of NDVI values, mean LST decreased (Figure 4). When the shape increased, the temperature of the patches decreased. Regarding the AREA metric, with the increase in size of CGP, their LST decreased in 2000 and 2020.

Table 3 shows the formulas for simple linear regression, indicating the relationship between dependent variables (LST) and independent variables of green biomass, SHAPE, and AREA.

The coefficient of determination (R Square) in Table 3 indicated a significant relationship between all the parameters and LST. The highest  $r^2$  belonged to NDVI in both years (0.217 in 2000 and 0.293 in 2020). In 2000, the lowest  $r^2$  was acquired for SHAPE, while in 2020 the lowest  $r^2$  was seen for AREA. As such, the highest relationship was between LST and green biomass of the patches in both years.

Statistical parameters to create multiple regression in 2000 and 2020 are shown in Table 4. Multiple linear regression was significant in both 2000 and 2020 ( $p$ -value = 0.000). The coefficient of determination was 0.413 and 0.328, respectively, in 2000 and 2020. The parameters of the regression models for 2000 and 2020 are shown in Table 4.



**Figure 4.** Scatter plot between Green Biomass, SHAPE, AREA and LST in 2000 and 2020.

**Table 3.** Simple linear regression between LST and variables of green biomass, SHAPE, and AREA.

| Time | x             | Equation                        | R Square |
|------|---------------|---------------------------------|----------|
| 2000 | Green Biomass | $y = -0.0372x + 1.8439$         | 0.2177   |
|      | SHAPE         | $y = -0.1036x + 5.5411$         | 0.183    |
|      | AREA (ha)     | $y = -196,035x + 8 \times 10^6$ | 0.1907   |
| 2020 | Green Biomass | $y = -0.0468x + 2.184$          | 0.2931   |
|      | SHAPE         | $y = -0.045x + 3.0216$          | 0.1954   |
|      | AREA (ha)     | $y = -11,129x + 433,024$        | 0.1483   |

**Table 4.** Parameters of multiple linear regression models in 2000 and 2020.

| Model | Unstandardized Coefficients |                         | Standardized Coefficients | t       | Sig.   | Collinearity Statistics |       |
|-------|-----------------------------|-------------------------|---------------------------|---------|--------|-------------------------|-------|
|       | B                           | Std. Error              | Beta                      |         |        | Tolerance               | VIF   |
| 2000  | (Constant)                  | 43.498                  | 0.267                     | 163.143 | 0.000  |                         |       |
|       | NDVI                        | −4.611                  | 0.485                     | −9.514  | 0.000  | 0.952                   | 1.050 |
|       | SHAPE                       | −1.153                  | 0.165                     | −0.279  | −6.983 | 0.000                   | 1.123 |
|       | AREA (ha)                   | $-6.242 \times 10^{-7}$ | 0.000                     | −0.280  | −6.979 | 0.000                   | 1.133 |
| 2020  | (Constant)                  | 41.039                  | 0.261                     | 157.429 | 0.000  |                         |       |
|       | NDVI                        | −4.991                  | 0.291                     | −17.141 | 0.000  | 0.943                   | 1.060 |
|       | SHAPE                       | −1.021                  | 0.184                     | −0.150  | −5.544 | 0.000                   | 1.137 |
|       | AREA (ha)                   | $-2.830 \times 10^{-6}$ | 0.000                     | −0.174  | −6.371 | 0.000                   | 1.148 |

B-coefficients in Table 4 indicate the regression models as follows:

$$\text{LST}_{2000} = 43.498 - 4.611 \times \text{NDVI} - 1.153 \times \text{MSI} - 6.242\text{E}6 \times \text{AREA} \quad (1)$$

$$\text{LST}_{2020} = 41.039 - 4.991 \times \text{NDVI} - 1.021 \times \text{MSI} - 2.830\text{E}7 \times \text{AREA} \quad (2)$$

The final models predict LST from all independent variables simultaneously.

All parameters with 0.000  $p$ -value were negatively correlated to the LST of cold green patches. The values of the VIF index for all the parameters of the models were between 1.050 and 1.148 in both years, which shows that there is no relationship between the independent parameters.

MLR models were significant in 2000 and 2020 ( $p$ -value = 0.000). As is represented in Table 5, coefficient determination in 2000 and 2020 were 0.413 and 0.328, respectively, indicating the models' ability to predict LST. The MLR model showed a higher ability to predict LST than the simple model.

**Table 5.** The results of variance analysis and accuracy of the multiple linear regression models in 2000 and 2020.

| Time |            | Sum of Squares | dF   | Mean Square | F       | Sig.  | R     | R Square |
|------|------------|----------------|------|-------------|---------|-------|-------|----------|
| 2000 | Regression | 241.796        | 3    | 80.599      |         |       |       |          |
|      | Residual   | 343.000        | 412  | 0.833       | 96.812  | 0.000 | 0.643 | 0.413    |
|      | Total      | 584.795        | 415  |             |         |       |       |          |
| 2020 | Regression | 441.246        | 3    | 147.082     |         |       |       |          |
|      | Residual   | 902.678        | 1037 | 0.870       | 168.969 | 0.000 | 0.573 | 0.328    |
|      | Total      | 1343.925       | 1040 |             |         |       |       |          |

#### 4. Discussion

The results showed that the total area of UGS decreased by 19% from 2000 to 2020. Moreover, from the Hot Spot analysis results, their temperature has changed dramatically over time. As such, it can be stated that the area of cold green patches at a 99% confidence level or the area of cold green patches decreased by 54% from 2000 to 2020. Therefore, urban expansion affected both the quantity and quality of the UGS in the study area. The average area of cold green patches decreased from 2000 to 2020. In the study area, due to poor vegetation cover in hot season, some of the green patches were not significantly cold; in response, we analyzed only the change of cold green patches. Inspecting the Google Earth image and land use maps, the gardens and some public parks, primarily located in the southern parts of the city, recorded the highest NDVI. LST patterns were distributed unevenly across the region in both years due to the high heterogeneity of land use/land cover classes, so various types of vegetation cover, from sparse rangeland to dense gardens, substantially affected the LST. Observation showed that the barren land and degraded rangeland had the highest temperature while the densely built-up area and gardens had the lowest LST. Comparing the LST maps indicated that, in 2000, the UGS was the coldest, while in 2020, some vegetation cover lost its cooling effect (due to losing its quality), and the densely built-up area, mostly in the North and Central parts of the city, showed lower LST.

In this research, over the past two decades, the LST pattern of the region has changed due to land use/land cover transformation. The loss of green cover coupled with poor implementation of sustainable urban land use planning practices resulted in both qualitative and quantitative degradation of green covers. It not only reduced the cooling performance of the urban landscape but also caused high-LST bare lands to surround and further affect the thermal properties of built-up patches. Another substantial change in the LST pattern was seen in decreasing the temperature of the densely built-up area in 2020. Generally, this land use LST pattern has been frequently observed in urban regions located in arid and semi-arid climatic zones like central Iran, where the diurnal surface UHI effect often does not form in the built-up area (the reasons for this phenomenon are beyond the scope of the research) [60–65].

In terms of the relationship between the green patch attributes and their temperature, the results indicated that the vegetation biomass, area, and shape complexity negatively affected LST; this means that increasing these three parameters decreases the green patches' temperature. Other researchers indicated a negative relationship between NDVI and LST [57,58]. In this regard, the broad-leaved gardens with higher green biomass showed a lower temperature within the city.

In terms of patch shape complexity, the studies represented conflicting results. Similar to this research, [66,67] found a significant negative relationship between LST and the shape complexity index of the green patches in the megacities of Southeast Asia and Beijing. In addition, [68] showed that the cooling effect of green patches is better than simple shape [68]. Additionally, [48] revealed that a simpler shape is more effective in terms of UGS cooling capacity in Singapore. The reason for these contradictory results can be explained by various parameters of the urban regions, such as the climatic zone, urban structure, building density, material type, etc. In terms of the relationship between LST and the size of green patches, like many previous studies, the results showed that the larger the patch, the lower the temperature [48,60,68,69].

Regarding urban planning implications, constructing larger green patches with higher shape complexity and planting trees can be some of the most effective measures to mitigate temperature. The simple and multiple linear regression between LST as independent variable and SHAPE-AM, mean area, and green biomass as dependent variables were fitted to model their relationship. The coefficient determination of the MLR model was significantly higher than SLM since it considers more factors to predict LST.

#### *Strengths and Limitations of the Study*

This study provides important findings on the relationship between urban green spaces (UGS) and land surface temperature (LST) in arid urban environments, with a focus on long-term trends over the 2000–2020 period. The analysis of UGS area, biomass, and shape complexity using spatial data offers valuable contributions to understanding how these features can mitigate urban heat. The application of both Simple Linear Regression (SLR) and Multiple Linear Regression (MLR) models provides useful statistical approaches, although these models show only moderate predictive power, with  $R^2$  values of 0.413 for 2000 and 0.328 for 2020. This suggests that the models may not fully capture the complexity of LST dynamics, as they did not incorporate additional variables such as albedo, building materials, or anthropogenic heat, which could influence temperature outcomes. Moreover, while previous studies have found that the NDVI is effective in expressing vegetation status and quantifying vegetation attributes [70], the green biomass values derived from NDVI do not capture species-specific variations that may influence heat mitigation.

The analysis in this study is based on data for a single day (2000 and 2020), which introduces a limitation. Variations in meteorological and hydrological conditions, both on the specific days and during the days preceding the analysis, can influence the surface moisture levels and, consequently, the LST patterns observed. For instance, recent rainfall or changes in humidity might temporarily alter surface heat budgets and cooling effects from vegetation. Future studies using multi-temporal or seasonal data could provide a more comprehensive understanding of these dynamics and help to isolate the effects of land use change from short-term meteorological variability.

The study faces limitations related to the accuracy of LST retrieval methods. A comparative study by [56] highlights the challenges of accurately retrieving LST from satellite images, showing discrepancies of up to 5 °C between different retrieval algorithms [56]. These differences emphasize the importance of selecting appropriate LST retrieval methods and validation techniques. While the study utilizes established algorithms, the choice of

method can significantly influence results, with some algorithms (e.g., SW9) proving more accurate than others (e.g., MW2 and SW1) [56]. This variability in accuracy may impact the study's ability to reliably capture the effects of UGS on LST [56]. Additionally, the study only uses data from two time points (2000 and 2020), limiting the analysis of more rapid or short-term changes in UGS and LST. In addition, the findings are geographically specific, limiting their applicability to cities with different climatic conditions or urban morphologies. Further research should consider a multi-scalar and multi-temporal approach, incorporating advanced modeling techniques to improve the robustness of the conclusions.

## 5. Conclusions

Urbanization alters the quantity and quality of UGS, consequently affecting the thermal environment of cities. In this research, we analyzed the change of UGS pattern and their relationship with LST in Karaj urban area in 2000 and 2020. The investigation showed that the UGS area has decreased significantly in twenty years. Moreover, their area, shape, and green biomass changes were analyzed using landscape metrics and NDVI. The results showed a negative association between the area, shape, and green biomass of green patches and their temperature in both 2000 and 2020. The results showed that the LST of the green patches is more affected by the green biomass than patch area and shape. Considering these results in relation to urban planning, it is concluded that optimization of vegetation cover, area, and shape of green patches should be considered as an important strategy to improve the thermal environment of the Karaj urban region. Overall, this research offers insight to the urban planner when seeking to optimize the spatial pattern of the UGS from the patch-based perspective toward urban temperature mitigation.

This study is the first to investigate the specific ways in which vegetation biomass, area, and shape attributes influence the cooling effect of UGS in Karaj. This novel approach contributes to a more comprehensive understanding of the role these factors play in urban cooling. The implications of this research are significant. The development of a predictive model based on these factors could support urban planning and decision-making by providing tools to anticipate the thermal impacts of urbanization. Such a model would be invaluable for arid cities striving to achieve sustainable development goals, which seeks to make cities more resilient and adaptable to the challenges posed by climate change.

Our analysis of the urban green spaces in Karaj City can be applied to other cities facing similar urbanization trends. Many cities around the world are experiencing urban sprawl, which leads to the fragmentation of green spaces. The results from Karaj can provide insights into how cities can manage UGS to maintain or enhance environmental quality, such as cooling effects and biodiversity preservation. The challenges faced by Karaj, such as balancing urban growth with green space preservation, are common in many cities across Asia, Africa, and Latin America. In addition, our findings on the relationship between green space, biomass, and thermal regulation can provide guidance to planners and policymakers in these regions.

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