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The Structural Limits of Cooling: Fragmentation and Shape Inefficiency Constrain Green Infrastructure in an Arid Urban Heat Island

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ABSTRACT

The mitigation of the Urban Heat Island (UHI) effect necessitates a comprehensive understanding of how the spatial configuration of Green Infrastructure (GI) influences its thermal performance. Traditional metrics often fail to capture this functional relationship. This study addresses this gap by integrating the Green Space Thermal Effectiveness Index (GSTEI) with landscape ecology metrics to analyze GI in the rapidly urbanizing City of Qom, Iran. Using Landsat 9 Land Surface Temperature (LST) and Sentinel-2 NDVI data from the summer of 2023, the continuous GSTEI (net cooling in ∘C) was calculated and reclassified into four discrete thermal performance classes (Low: $0 - 2$∘C to Very High: > 10∘C). The FRAGSTATS analysis revealed that the overall urban GI landscape is highly fragmented, characterized by a high Edge Density (ED = 78.51 m/ha) and low patch dominance (LPI = 2.51%). Critically, thermal performance was found to be strongly configuration-dependent: the least effective GI (Low cooling class) exhibited the highest fragmentation (Patch Density = 243.21 per ha) and the lowest aggregation (Clumpiness = 0.5664). Conversely, higher-performing classes were significantly more clumped, demonstrating the thermal benefits of spatial consolidation. Paradoxically, the Very High cooling class (> 10 °C) was characterized by the smallest mean patch size (0.084 ha), suggesting that intensive, high-density vegetation can occasionally bypass the structural constraints of small area. Adjacency analysis further confirmed a strict thermal flow gradient, where low-performing patches had the highest interface with the heat-emitting built-up matrix. These findings confirm that fragmentation significantly compromises the cooling function of urban green space. The study provides a quantifiable framework for planners, emphasizing that while consolidation of fragmented patches is generally essential for UHI mitigation, small patches can achieve exceptional cooling through high-density design, offering a dual strategy for arid urban environments.

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1. Introduction

The relentless pace of global urbanization has profoundly altered the thermal balance of cities, leading to the pervasive phenomenon known as the Urban Heat Island (UHI) effect (Tian *et al*., 2021; L. Yang *et al*., 2016). The UHI effect, characterized by significantly elevated air and surface temperatures in urban centers compared to surrounding non-urban areas, poses substantial risks to public health, increases energy demand for cooling, and degrades overall urban liveability, particularly in arid and semi-arid climates like those prevalent in the Middle East (Tzyrkalli *et al*., 2024). Mitigating the UHI is therefore a critical priority for sustainable urban planning.

Urban Green Infrastructure (GI), including parks, urban forests, and street trees, represents the most effective passive cooling strategy available to cities (Saeedi *et al*., 2022; Shao & Kim, 2022). The biophysical processes of evapotranspiration and shading allow GI to substantially reduce Land Surface Temperature (LST) within and around their boundaries(Abdulateef & Al-Alwan, 2022). However, the degree of cooling benefit, often quantified using Land Surface Temperature (LST), is not solely dependent on the total area of vegetation. A substantial body of research confirms that the spatial structure and configuration of GI significantly modulate its thermal effectiveness (J. Liu *et al*., 2024; Y. Liu *et al*., 2018; Lyu *et al*., 2023).

Studies show that higher vegetation density and total biomass are supremely effective in reducing LST, often providing a greater cooling effect than the mere area or shape complexity of green patches alone(Huang *et al*., 2025; Li *et al*., 2023). This power stems from enhanced evapotranspiration and superior shading. Indeed, research on large urban parks has measured significant temperature reductions, with cooling effects observed up to 8.28 centigrade in areas characterized by dense vegetation and high biomass (Huang *et al*., 2025).

The spatial configuration of urban green spaces is another critical determinant of their effectiveness in heat mitigation. Research indicated that compact urban development, which supports a higher spatial concentration and better connectivity of green areas, significantly enhances cooling benefits and promotes heat mitigation (Bao *et al*., 2016; Jang & Jung, 2025). Crucially, the internal distribution of these spaces is equally important: evidence suggests that evenly distributed green spaces throughout the urban fabric are more effective in reducing temperatures compared to large, aggregated, or isolated green spaces (Bao *et al*., 2016).

The physical characteristics of green spaces, specifically their shape and size, are also crucial determinants of their cooling power. Generally, larger green spaces exert a more substantial and pronounced cooling effect on the surrounding urban environment (Bao *et al*., 2016; Tan & Li, 2013). A significant threshold appears to be around 10 hectares; green spaces exceeding this size demonstrate a close and reliable relationship with their cooling intensity, suggesting a predictable and strong thermal benefit. Conversely, smaller spaces exhibit much greater variability in their cooling effects (Tan & Li, 2013). Beyond size, shape is also important, with regularly shaped green spaces typically exhibiting higher Land Surface Temperature (LST) mitigation compared to irregularly shaped ones (Bao *et al*., 2016).

Some studies, primarily within the field of landscape ecology, have utilized landscape metrics for a precise assessment of the thermal performance of urban green spaces. Metrics such as the Percentage of Landscape (PLAND), Edge Density (ED), and Patch Density (PD) are identified as significant determinants of Land Surface Temperature (LST). Here is a summary of these research combined the metrics to demonstrates the capacity to explain the complexity of the relationships between GI pattern and temperature variance.

The recent study by Zhang *et al*., (2024)revealed a negative correlation between LST and

Edge Density (ED), Patch Density (PD), and the Area-weighted mean shape index, with correlation coefficients ranging from −0.388 to −0.469. This signifies that UGS with more complex shapes and greater fragmentation are more effective at cooling. Conversely, the Aggregation Index (AI) was found to be positively correlated with LST, indicating that highly clustered or aggregated green patches resulted in relatively higher surface temperatures. This contradiction where fragmentation appears beneficial in some studies likely stems from differences in regional climate and the specific nature of complexity. In temperate or humid climates, complex edges may facilitate greater heat exchange through air flow; however, in the extreme arid contexts, high edge-to-area ratios might lead to a thermal override where hot advection from the built-up matrix overwhelms the cooling core.

Another study by Govind & Ramesh, (2020) indicated that urban expansion has resulted in the circumferential increase of the urban core area and the spread of growth towards the outskirts beyond 15 km from the city center. Crucially, the thermal effects of this growth vary significantly between day and night: the urban expansion causes an expansive cooling effect during the daytime but an expansive heating effect at night in accordance with the growth in urban density (UD) in the suburban area.

Despite this growing body of knowledge, a significant research gap persists, particularly concerning arid cities. Existing studies have predominantly focused on temperate or mesic climates, where hydrological conditions and vegetation types differ substantially from arid environments (Azmeer *et al*., 2024; Okour & Shaweesh, 2024). The unique climatic constraints of arid regions, such as water scarcity, high evaporative demand, and different native vegetation, likely alter the relationship between GI spatial structure and its cooling function. Furthermore, research specific to arid zones has produced inconsistent results regarding the impact of Urban Green Spaces (UGS) on LST (Mokhtari *et al*., 2025), indicating a pressing need for focused, quantitative investigations in these vulnerable contexts.

Furthermore, a methodological shortcoming in much of the existing literature is the predominant reliance on class-level metrics (e.g., mean patch size for a whole class) to explain a phenomenon driven by individual green space units. This approach can obscure the critical, fine-grained relationships between a patch's specific geometry and its function. To address these gaps, this study conducts a spatially explicit analysis in the rapidly urbanizing, arid City of Qom, Iran. We integrate a functional cooling metric, the Green Space Thermal Effectiveness Index (GSTEI), with a comprehensive suite of FRAGSTATS landscape metrics across all three levels: patch, class, and landscape. This multi-scale approach allows us to answer a central research question: What are the most effective spatial forms of urban green spaces for reducing LST in an arid city? By quantitatively linking hierarchical spatial configuration to thermal performance, this research provides urban planners with an actionable, evidence-based framework for optimizing GI design from the individual patch to the entire network, maximizing its UHI mitigation potential in arid environments.

2. Methodology

The methodological framework for this study involved three primary stages: (1) Defining the study area and acquiring multi-sensor satellite data, (2) Calculating and classifying the Green Space Thermal Effectiveness Index (GSTEI), and (3) Quantifying the spatial configuration of the thermal classes using landscape metrics.

2.1. Study Area

The analysis focused on the City of Qom, Iran, which serves as a critical case study due to its large population, rapid urbanization, and significant vulnerability to the Urban Heat Island (UHI) effect. The official administrative boundary of Qom, derived from the FAO/GAUL Level 1 database and subsequently clipped to the municipal area, was used as the Area of Interest (Figure 1).

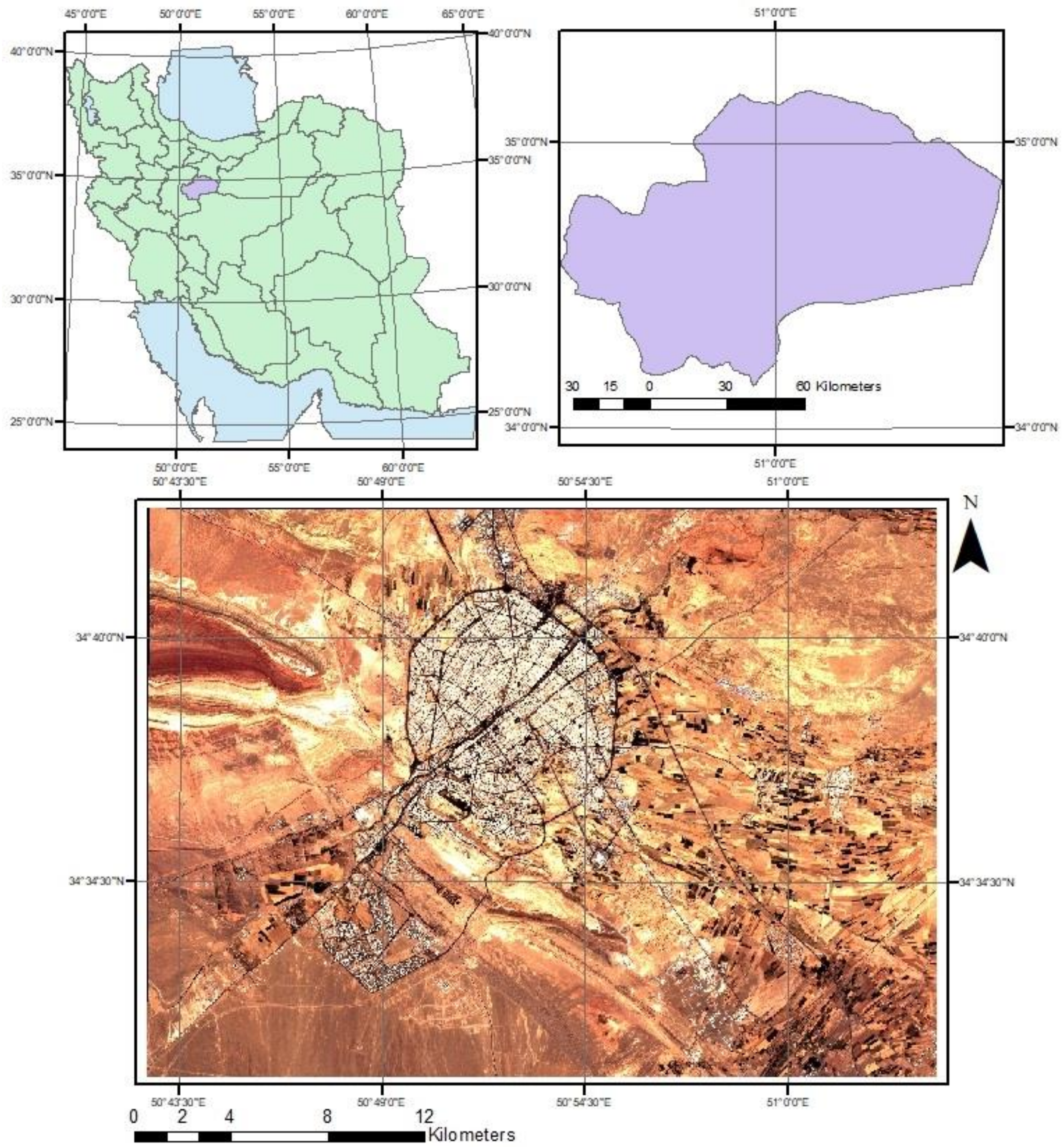

Figure. 1. The location of the study area

2.2. Satellite Data and Urban Mask

The analysis utilized data acquired during the peak summer period (June 15 to September 15, 2023) to capture maximum thermal stress. All image processing and analysis were conducted on the Google Earth Engine (GEE) cloud platform.

Land Surface Temperature (LST): Land Surface Temperature was derived from the Landsat 9 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS) (Collection 2, Tier 1, Level 2). The LST band (ST_B10), originally at 30m resolution, was corrected for atmospheric effects and converted from Kelvin to Celsius.

Vegetation Index (NDVI): The Sentinel-2 MSI (Level 2A, SR product) was used to derive the Normalized Difference Vegetation Index (NDVI) due to its high spatial resolution (10m). The NDVI was used to identify Urban Green Space (GI) based on a threshold of NDVI ≥ 0.25.

Urban Built-Up Mask: The Global Human Settlement Layer (GHSL), specifically the Built-Up Surface asset (GHS-BUILT-S), was used to restrict the study only to areas classified as built-up. This ensures the GI analysis is confined to the true urban matrix, filtering out peri-urban or rural vegetation.

All thermal and spectral images were processed to create cloud-masked median composites for the defined time frame and resampled to a consistent 10m resolution.

2.3. GSTEI Calculation and Classification

2.3.1. Green Space Thermal Effectiveness Index (GSTEI)

The GSTEI was calculated to quantify the relative cooling capacity of each GI pixel by comparing its LST to the mean LST of the surrounding non-vegetated built-up matrix (LSTBU). Built-Up Matrix Temperature (LST BU): To establish a baseline for the urban thermal environment, the mean LST of the built-up matrix was calculated as a city-wide average. This was achieved by masking the LST image to include only pixels where NDVI$\leq$0.10 and averaging these values across the entire administrative AOI. Consequently, the GSTEI in this study represents the thermal deviation of a green space unit from the urban mean rather than a localized microclimatic buffer. This approach allows for a standardized comparison of thermal performance across the disparate spatial configurations found throughout the city. STEI Calculation: The index was then computed for every GI pixel (LSTGS) as the difference between the average built-up temperature and the green space temperature (Equation 1):

Equation 1: $GSTEI = LSTBU - LSTGS$

A positive GSTEI value indicates a cooling effect (the GI is cooler than the urban matrix), with higher values representing greater thermal effectiveness. The final GSTEI raster was masked to include only GI within the GHSL urban boundary. To prepare the continuous GSTEI raster for categorical analysis in FRAGSTATS, the GSTEI values (expressed in degrees Celsius, ∘C) were reclassified into four discrete integer classes representing distinct thermal performance levels (Table 1):

Table 1. Reclassification parameters for four classes of GSTEI

Class ID	Cooling Performance	GSTEI Thresholds (Δ∘C)	Description
1	Low	$0 < GSTEI \leq 2$	Minimal cooling relative to the urban matrix.
2	Moderate	$2 < GSTEI \leq 5$	Average cooling capacity.
3	High	$5 < GSTEI \leq 10$	Strong cooling performance.
4	Very High	$GSTEI > 10$	Exceptionally strong thermal mitigation.

The resulting raster, containing integer values 1 through 4, was exported as for subsequent spatial analysis.

2.3.2. Spatial Configuration Analysis

The classified GSTEI raster was analyzed using the FRAGSTATS v4.2 software to quantify the spatial pattern of the GI thermal performance. The analysis was conducted at the landscape level, the class level, the patch level and the adjacency level (boundaries between categories). Table 2 illustrated the selected metrics to characterize the size, fragmentation, aggregation, and diversity of the thermal performance classes:

Table 2. Selected metrics and the definitions of them

Level	Metric	Abbreviation	Definition
Landscape	Total Area	TA	The total area of all GI patches across the entire landscape (in hectares).
Landscape	Largest Patch Index	LPI	The percentage of the total landscape area occupied by the single largest patch, used to assess dominance.
Landscape	Class Area	CA	The total area occupied by a specific GSTEI class (e.g., total area of High-cooling GI).
Landscape	Edge Density	ED	The total length of all patch boundaries (edge) divided by the total landscape area, measuring overall fragmentation.
Landscape	Shannon Diversity Index	SHDI	Quantifies the proportional abundance and distribution of the four GSTEI classes, reflecting the spatial complexity and evenness of thermal performance across the landscape.
Class	Patch Density	PD	The number of patches of a specific class per unit area (ha), indicating class-level fragmentation.
Class	Number of Patches	NP	The total count of individual patches belonging to a specific GSTEI.
Class	Clumpiness Index	CLUMPY	Measures the aggregation of a class, where positive values indicate the class is more aggregated or clumped than expected by chance.
Patch	Patch Area	AREA	Represents the typical size of a green space unit within each class.
Patch	Perimeter-Area	PARA	A measure of patch compactness and shape complexity.
Patch	Shape Index	SHAPE	Quantifies the regularity of a patch's shape
Patch	Contiguity Index	CONTIG	Measures the extent to which a patch's cells are interconnected and spatially clumped.

2.3.3. Adjacency Metrics

The Adjacency Matrix was generated to determine the spatial relationship between the different GSTEI classes. The matrix reports the total number of shared pixel boundaries between any two classes. This is critical for assessing the thermal flow gradient and the degree of interface between GI patches and the non-GI Background (urban matrix).

3. Results

The total area of the identified Urban Green Infrastructure (GI) within the study area was 840.03 hectares (ha). The landscape-level metrics (Table 3) revealed a fragmented and diverse thermal performance pattern across the GI. The Shannon Diversity Index (SHDI) for the four GSTEI classes was high (1.3619), indicating that the area of cooling performance was distributed relatively equitably among the Low (1), Moderate (2), High (3), and Very High (4) classes. However, the Edge Density (ED) was significantly high (ED = 78.51 m/ha), suggesting a fine-grained landscape structure characterized by numerous small patches and a large total perimeter relative to the area. This high edge-to-area ratio implies a significant exposure of GI patches to the warmer urban matrix.

The Largest Patch Index (LPI) was notably low at 2.51%, confirming the absence of a single dominant cooling patch and reinforcing the highly fragmented nature of the urban green spaces, regardless of their thermal performance category.

Table 3. Landscape-level spatial metrics of Urban Green Infrastructure (GI) thermal performance.

Metric	Definition	Value	Unit
TA	Total Area	840.03	ha
LPI	Largest Patch Index	2.5094	%
ED	Edge Density	78.5091	m/ha
SHDI	Shannon Diversity Index	1.3619	dimensionless

3.1. Distribution and Fragmentation of GSTEI Classes

Analysis at the class level (Table 4) showed substantial differences in area contribution and fragmentation among the four GSTEI performance categories.

Table 4. Class-level spatial metrics for GSTEI categories

Class ID	Cooling Performance	CA (ha)	NP	PD (ha−1)	LPI (%)	CLUMPY
1	Low (0 − 2∘C)	213.32	2043	243.21	0.89	0.5664
2	Moderate (2 − 5∘C)	234.83	1482	176.42	2.51	0.6333
3	High (5 − 10∘C)	255.03	1630	194.04	1.30	0.6214
4	Very High (> 10∘C)	136.85	1623	193.21	1.16	0.6179

Class Area (CA): The majority of the Urban GI area was concentrated in the higher cooling categories:

- The High cooling class (5 − 10∘C) contributed the largest area (CA = 255.03 ha).
- The Moderate cooling class (2 − 5∘C) followed closely (CA = 234.83 ha).
- The Low cooling class (0 − 2∘C) and Very High cooling class (> 10∘C) represented the smallest portions (CA = 213.32 ha and CA = 136.85 ha, respectively).

Fragmentation (NP and PD): A clear inverse relationship was observed between cooling effectiveness and fragmentation. The Low cooling class (1) was the most fragmented, exhibiting the highest number of patches (NP = 2043) and the highest Patch Density (PD) (PD = 243.21 per ha). This indicates that the least effective green spaces are typically the smallest and most spatially separated.

Aggregation (CLUMPY): All classes displayed a positive Clumpiness index (CLUMPY > 0.56), suggesting that patches of similar thermal performance tend to be aggregated. The Moderate cooling class (2) was the most spatially aggregated (CLUMPY = 0.6333), while the Low cooling class (1) was the least aggregated (CLUMPY = 0.5664). This suggests GI with better thermal performance forms more continuous, large blocks.

3.2. Patch Geometry and Thermal Effectiveness

Patch-level metrics revealed a strong and distinct relationship between the physical form of individual green spaces and their cooling function (Table 5). The mean area of patches varied substantially across the four performance classes. The highest thermal efficiency was concentrated in the Moderate ($2-5\circ C$) and High ($5-10\circ C$) classes, which share the largest mean patch sizes (0.158 ha and 0.156 ha, respectively). In stark contrast, the Low cooling class ($0-2\circ C$) had a significantly smaller mean area (0.104 ha), and the Very High class ($> 10\circ C$) showed the smallest mean size (0.084 ha), indicating that the strongest cooling is achieved by smaller, exceptionally dense parcels.

Analysis of patch geometry further clarified these performance differences. The Low cooling class (1) exhibited the poorest structural efficiency, characterized by the highest Mean Perimeter-Area Ratio (3497.10 m/ha) and the highest Mean SHAPE Index (1.31). This geometry signifies highly convoluted, complex boundaries and maximum exposure to the surrounding hot built-up matrix. Conversely, the High cooling class (3) displayed the most structurally compact form, featuring the lowest Mean PARA (2745.10 m/ha) and the lowest Mean SHAPE Index (1.14). The extremely low Mean CONTIG Index (0.07) for the Low class confirms severe perforation and isolation, which compromises its ability to establish a thermally buffered core.

Table 5. Patch-level spatial metrics for GSTEI categories

Class ID	Cooling Performance	Mean AREA (ha)	Mean PARA (m/ha)	Mean SHAPE	Mean CONTIG
1	Low (0–2 °C)	0.104	3497.10	1.31	0.07
2	Moderate (2–5 °C)	0.158	2694.99	1.19	0.31
3	High (5–10 °C)	0.156	2745.10	1.14	0.29
4	Very High (> 10 °C)	0.084	3028.72	1.11	0.23

A notable deviation from the general trend of 'larger is cooler' was observed in the Very High cooling class (Class 4). Despite achieving the highest thermal mitigation (> 10 °C), these patches exhibited the smallest mean area (0.084 ha) and the lowest mean perimeter (254.41 m) across all categories. However, this class also demonstrated the highest geometric efficiency, with a Mean SHAPE index of 1.11, indicating nearly perfectly compact or circular forms. This suggests a critical threshold in arid urban cooling where extreme geometric regularity and potentially higher biomass density can compensate for a lack of total surface area, allowing even micro-scale green infrastructure to achieve maximum thermal effectiveness.

3.3. Spatial Relationships and Thermal Transitions

The Adjacency Matrix (Table 6) illustrates the spatial connectivity and the prevalence of boundaries between different thermal performance classes. A clear and consistent thermal performance gradient was observed: classes only exhibited adjacency with the immediate nextlower or next-higher class in the GSTEI magnitude. For example, the Very High class (4) only borders the High class (3), and there were zero adjacencies between non-consecutive classes (e.g., Class 1 and Class 3).

The most frequent boundary transition occurred between the Moderate (2) and High (3) cooling classes (Total Adjacency = 2, 804). This boundary accounts for the largest area of transition in thermal effectiveness, highlighting it as the primary interface for cooling improvement or decline.

In terms of exposure to the non-GI matrix (Background), the Low cooling class (1) recorded the highest boundary count (26, 099 adjacencies). This metric reinforces the finding from the fragmentation analysis: low-performing GI patches are the most exposed to the urban heat matrix, likely contributing to their reduced thermal effectiveness.

Table 6. Adjacency matrix showing the number of shared pixel boundaries (adjacencies).

Class ID / ID	1 (Low)	2 (Moderate)	3 (High)	4 (Very High)	Background
1 (Low)	57, 330	1, 899	0	0	26, 099
2 (Moderate)	1, 899	68, 664	2, 804	0	20, 565
3 (High)	0	2, 804	74, 646	1, 892	22, 670
4 (Very High)	0	0	1, 892	36, 914	15, 934

4. Discussion

The analysis of the Green Space Thermal Effectiveness Index (GSTEI) for the City of Qom, quantified through landscape ecology metrics, provides critical insights into the relationship between the spatial configuration of Urban Green Infrastructure (GI) and its capacity to mitigate the Urban Heat Island (UHI) effect. The results consistently demonstrate that the thermal performance of GI patches is fundamentally constrained by fragmentation and isolation, particularly in the lower-performing categories.

The overall spatial structure of GI in Qom is characterized by high fragmentation and decentralization. The large Edge Density (ED = 78.51 m/ha) indicates a landscape composed of numerous small GI patches with high perimeter-to-area ratios. This structure is known to be thermally inefficient, as maximizing the perimeter exposes a larger surface area of the green space to the radiative heat and convective transfer from the adjacent hot built-up matrix, thereby promoting the edge effect and reducing the overall GSTEI(H. Yang *et al*., 2025).

Furthermore, the very low Largest Patch Index (LPI = 2.51%) confirms the absence of large, dominant green spaces. Large GI patches are essential for acting as cool islands that generate significant cool air advection, which can flow into adjacent urban areas (Pramanik *et al*., 2025). The lack of such dominant features suggests that the cooling benefits are localized, preventing effective thermal mitigation across larger urban neighborhoods.

4.1. Spatial Aggregation Drives Thermal Effectiveness

The class-level metrics establish a clear link between thermal performance and spatial aggregation. The combined area of the High and Moderate cooling classes (CA = 489.86 ha) makes up the majority of the GI, a positive finding that suggests a substantial portion of the city's green space is effectively functioning to cool the environment which is consistent with previous findings suggesting the role of urban green spaces in the cooling effects of the cities(Saaroni *et al*., 2018; Sanusi & Jalil, 2021; Shih & Mabon, 2021). Crucially, these higher-performing classes (Moderate and High) exhibit higher Clumpiness (CLUMPY > 0.62) compared to the Low-cooling class. This supports the general principle in thermal planning: aggregation enhances thermal efficiency. Clumped patches minimize the perimeter relative to their interior mass, creating thermally stable core areas that maintain cooler temperatures even under peak summer conditions (Amani-Beni *et al*., 2019; Song *et al*., 2020). Conversely, the Low cooling class (1) is defined by its low thermal output (GSTEI ≤ 2∘C) and its extreme spatial characteristics: it has the highest Patch Density (PD = 243.21 per ha) and the lowest Clumpiness (CLUMPY = 0.5664). This demonstrates that small, numerous, and highly isolated GI patches likely street-side plantings or small, fragmented plots are structurally incapable of overcoming the pervasive UHI effect, making their contribution to cooling negligible.

The patch-level analysis provides critical empirical evidence supporting the concept that the thermal performance of GI in Qom is a function of both area and structural compactness. The dominance of the Mean Area metric in the Moderate and High classes (0.15 ha) confirms that GI needs a critical minimum size to develop and maintain a cool core, effectively isolating it from the UHI. However, the data reveals a thermal trade-off:

1. Thermal Inefficiency due to Form: The Low cooling class (1) is thermally compromised primarily by its complex geometry, as shown by its highest PARA (3497.10) and SHAPE (1.31) values. This indicates that fragmentation and excessive boundary exposure are stronger determinants of thermal failure than mere patch size. These patches are often small, linear, or irregularly shaped, rendering their internal cooling effects negligible due to constant thermal exchange with the hot urban edge.

2. High-Intensity Small Patches: The anomalous finding that the Very High cooling class (4) has the smallest mean area (0.084 ha) suggests that these are not typical patches. These are likely small, intensively managed, high-density vegetation areas such as highly irrigated parks or dense tree groves where the evaporative cooling effect is maximized, successfully overcoming the geometric constraint of small size. While this finding points toward the efficacy of high-density vegetation, a primary limitation of this study is the reliance on NDVI (≥ 0.25) to define Green Infrastructure (GI). While NDVI is a robust proxy for vegetation vigor, it does not inherently distinguish between vertical structure (e.g., dense tree canopies vs. low-lying irrigated lawns) or specific management practices like intensive irrigation. Consequently, the high cooling observed in these small patches remains partly speculative without higher-resolution structural data. Future research should integrate Very High-Resolution (VHR) imagery or LiDAR data to differentiate between vegetation types and verify if the 'Very High' cooling class is driven by specific land uses, such as highly managed public parks or dense urban woodlots, which can maintain a stable microclimate despite their small spatial footprint.

The Adjacency Matrix provides strategic information for urban planning interventions. The highest recorded interface between GI and the non-GI Background was observed for the Low cooling class (1) (26, 099 adjacencies). This finding confirms that the least effective patches are the most exposed to the heat-emitting urban fabric. These low-performing patches represent the primary target for landscape intervention. Strategies should focus on:

Increasing Patch Size: Consolidating small, fragmented patches to reduce the perimeter-to-area ratio and generate functional core areas.

Enhancing Connectivity: Reducing the distance between Low-performing patches to promote the flow of cool air between them and leverage economies of scale in cooling.

Furthermore, the observation of a linear spatial gradient—where classes primarily share boundaries with those of adjacent thermal magnitude (e.g., Class 1 bordering Class 2)—characterizes the spatial organization of the urban thermal landscape. While this indicates a high degree of spatial autocorrelation, it should be interpreted as a description of current clustering patterns rather than a prescribed causal sequence for patch improvement. The lack of direct 'jumps' (e.g., Class 1 directly bordering Class 3) suggests that thermal transitions across the city are spatially gradual, likely influenced by the surrounding urban matrix which prevents extreme thermal contrasts between adjacent green units.

Based on these findings, urban planning strategies in Qom should shift focus from simply increasing the *quantity* of green space to improving the functional *quality* through geometric optimization. Specifically:

- Prioritize Geometric Correction: Investment should target the Low cooling class (1) patches. Since their PARA is highest, the goal must be to reduce the total perimeter relative to the area. This can be achieved by consolidating adjacent micro-patches into single, larger units or simplifying the boundaries of complex, finger-like patches to create more circular or block-shaped forms (like those observed in the optimal Class 3).
- Enhance Contiguity and Connectivity: The extremely low CONTIG in the Low class (0.07) highlights severe isolation. Planning must focus on establishing structural corridors between these small, isolated patches, which is vital for facilitating the movement of cool air (advection) across the urban environment.

5. Conclusion

This study successfully bridged a critical methodological gap in Urban Heat Island (UHI) research by integrating the functional metric of the Green Space Thermal Effectiveness Index (GSTEI) with the structural quantification of FRAGSTATS landscape ecology metrics. Focusing on the arid City of Qom, Iran, the analysis provides empirical evidence that the thermal performance of Urban Green Infrastructure (GI) is profoundly governed by its spatial configuration, size, and geometry.

The key findings are three-fold:

High Fragmentation Compromises Function: The overall GI network in Qom is highly fragmented, characterized by a high Edge Density (ED = 78.51 m/ha). This structural arrangement maximizes the thermal interface between cool green space and the hot built-up matrix, confirming that widespread fragmentation severely limits the potential for UHI mitigation across the city.

Geometric Inefficiency Drives Failure: The most critical finding stems from the patch-level analysis. The Low cooling class ($0 - 2\circ$C) is defined not only by its high patch count (

PD = 243.21 per ha) but, more critically, by its extremely poor geometry. This class exhibited the highest Mean Perimeter-Area Ratio (3497.10 m/ha) and highest Mean Shape Index (1.31). This configuration demonstrates that thermal inefficiency is driven by excessive boundary convolution and limited internal contiguity (CONTIG = 0.07), leaving the patches unable to establish a thermally buffered core.

Optimal Form is Simple and Consolidated: Conversely, the High cooling class ($5 - 10\circ$C) achieved superior performance with the largest mean size (0.156 ha) and the most compact, structurally efficient form (PARA = 2745.10 m/ha; SHAPE = 1.14). This class represents the optimal thermal geometry for GI in an arid environment.

The findings offer actionable and spatially explicit guidance for urban planners in Qom and other similar arid regions:

- Prioritize Geometric Consolidation over Mere Area Expansion: Future GI strategies must shift from simply increasing the total number of patches to aggressively consolidating small, low-performing patches (Class 1) into larger, more compact units. The primary goal should be the reduction of the Perimeter-Area Ratio (PARA) to protect the cooling core from the "thermal leaks" caused by the surrounding arid urban matrix.
- Strategic High-Density Interventions: While spatial consolidation is the preferred landscape-level strategy, the high performance of the "Very High" class despite its small mean size (0.084 ha) indicates that intensive, high-biomass, and well-maintained vegetation can compensate for size limitations. This offers a vital secondary strategy for land-scarce high-density districts where large-scale consolidation is physically impossible.
- Spatial Patterning for Thermal Resilience: The observed adjacency patterns suggest that thermal transitions are gradual across the urban fabric. Planners should focus on "buffering" low-performance clusters by incrementally improving the quality of neighboring land cover, rather than expecting isolated, micro-scale interventions to provide city-wide thermal relief.

This study utilized a single summer image for analysis, which captures peak thermal stress but does not reflect diurnal or seasonal variability. Future research should apply this GSTEI-FRAGSTATS framework across multiple time-series to assess the temporal stability of GI thermal performance. Furthermore, incorporating socio-economic variables will allow for a comprehensive environmental justice analysis, linking structural deficiencies in GI geometry to vulnerable urban populations.

Authors Contribution

Iman Saeedi: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration. The author has read and agreed to the published version of the manuscript.

Ethics approval and Consent to participate

The authors avoided from data fabrication and falsification.

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Competing Interests

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Data available on request from the author.

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