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Mapping Urban Heat Island Dynamics in Osijek, Croatia: Integrating Landsat Thermal Data with GIS-Based Land Cover Analysis

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ABSTRACT

Urban Heat Island (UHI) effects have become a significant environmental challenge driven by rapid urbanization and land use/land cover (LULC) changes. This study investigates the spatiotemporal dynamics of UHI in Osijek, Croatia, by integrating Landsat-derived thermal data with GIS-based LULC analysis from 2015 to 2025. Multi-temporal Landsat 8 and Landsat 9 imagery were used to derive Land Surface Temperature (LST), the Normalized Difference Vegetation Index (NDVI), and LULC classifications. Supervised maximum likelihood classification identified built-up areas, vegetation, water bodies, and bare surfaces, while Pearson correlation analysis examined the relationship between NDVI and LST. Results revealed substantial land cover changes, with vegetation decreasing from 43.41% in 2015 to 35.15% in 2025, accompanied by a marked increase in bare surfaces. Despite these changes, mean LST declined from 22.6 °C to 15.6 °C, and mean UHI intensity decreased from 13.09 °C to 0.95 °C over the study period. The NDVI–LST relationship showed a strong negative correlation in 2015 ($r = -0.579$, $p < 0.001$) but weakened considerably in subsequent years, suggesting that vegetation became less influential in regulating urban thermal conditions. These findings indicate that Osijek's thermal environment is shaped by complex interactions among vegetation, bare surfaces, built-up areas, and spatial land configuration rather than vegetation cover alone. The study emphasizes the need for integrated urban climate planning that combines vegetation enhancement, sustainable surface material management, and climate-sensitive urban design to mitigate UHI effects and promote sustainable environmental management in medium-sized European cities.

KEYWORDS Urban heat island (UHI), Land surface temperature (LST), Remote sensing, GIS, Osijek

1. Introduction

Urbanization has become one of the most significant drivers of environmental transformation globally, profoundly altering land surface characteristics and urban climate systems. The rapid conversion of natural landscapes into built-up environments modifies surface energy balance, reduces vegetation cover, and increases heat retention within cities. One of the most prominent consequences of these changes is the Urban Heat Island (UHI) phenomenon, where urban areas experience significantly higher temperatures than their surrounding rural regions. UHI has been linked to increased energy demand, deteriorating air quality, and adverse impacts on human health and ecosystem stability (Oke *et al.* 2017; Li *et al.* 2020; Zhao *et al.* 2014). Land Surface Temperature (LST) is widely recognized as a key indicator for assessing urban thermal environments and quantifying UHI intensity. The advancement of satellite remote sensing technologies, particularly the Landsat series, has enabled consistent monitoring of LST across spatial and temporal scales. When integrated with Geographic Information Systems (GIS), remote sensing provides a robust framework

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for analyzing the relationship between land use/land cover (LULC) changes and urban thermal dynamics. Numerous studies have demonstrated that impervious surfaces, such as concrete and asphalt, significantly contribute to elevated LST, whereas natural surfaces help regulate temperature (Weng *et al.* 2014; Guha *et al.* 2017; Estoque *et al.* 2017).

Vegetation plays a critical role in mitigating urban heat through processes such as evapotranspiration and shading. The Normalized Difference Vegetation Index (NDVI) is widely used as a proxy for vegetation health and density, enabling the assessment of its cooling effects in urban environments. Empirical studies consistently report an inverse relationship between NDVI and LST, indicating that areas with higher vegetation cover tend to exhibit lower surface temperatures. However, the strength and spatial variability of this relationship often differ depending on urban structure, seasonal variations, and land management practices, highlighting the need for localized and multi-temporal analyses. Recent advancements in geospatial techniques have further enhanced UHI research through the integration of multi-source datasets and advanced analytical methods. Machine learning approaches, spatial regression models, and cloud-based platforms such as Google Earth Engine have improved the accuracy and scalability of urban thermal studies (Amani *et al.* 2020; Phan *et al.* 2020). These innovations allow for a more comprehensive understanding of the complex interactions between anthropogenic activities, land cover dynamics, and thermal patterns in urban areas. Despite these advancements, much of the existing research has focused on large metropolitan cities, leaving medium-sized urban centers relatively underexplored. Cities like Osijek, Croatia, exhibit distinct patterns of urban growth and environmental change that may influence UHI dynamics differently. Understanding these localized processes is essential for developing effective, context-specific mitigation strategies and promoting sustainable urban planning.

Furthermore, while previous studies have examined LST, NDVI, and LULC independently, there is still a need for integrated, multi-temporal analyses that evaluate their interactions simultaneously. Such an approach is crucial for understanding the evolution of urban thermal environments and identifying the key drivers of UHI intensity over time. Addressing this gap will contribute to a more holistic understanding of urban climate dynamics and support evidence-based decision-making. Against this background, this study investigates the spatiotemporal dynamics of UHI in Osijek, Croatia, by integrating Landsat-derived thermal data with GIS-based LULC analysis over the period 2015–2025. Specifically, the study aims to: (i) analyze changes in land use/land cover patterns, (ii) assess spatial and temporal variations in land surface temperature, (iii) examine the relationship between LST and NDVI, and (iv) evaluate the evolution of urban heat island intensity. The findings of this study are expected to contribute to the growing body of knowledge on urban climate systems and provide practical insights for climate-responsive urban planning and environmental management.

2. Materials and Methods

2.1. Study Area

Osijek is a prominent urban center located in eastern Croatia, serving as the administrative and economic hub of the Osijek–Baranja County. Geographically, the city is situated between approximately 45°32′–45°36′ N latitude and 18°38′–18°44′ E longitude, along the right bank of the Drava River, a major tributary of the Danube. The study area covers approximately 5,911 hectares, as defined by the spatial extent of the analyzed satellite imagery. The city lies within the Pannonian Basin, characterized by relatively flat terrain with low elevation gradients, which facilitates urban expansion and land transformation. Its proximity to the Drava River and associated floodplains contributes to the presence of water bodies and riparian vegetation, both of which play significant roles in moderating local microclimatic conditions. Climatically, Osijek experiences a humid continental climate marked by distinct seasonal variations. Summers are typically warm to hot, with average temperatures ranging between 25 °C and 30 °C, while winters are cold, often with temperatures dropping below 0 °C. The mean annual temperature is approximately 11 °C, and the

region receives an average annual precipitation of about 650–700 mm, with rainfall peaks occurring during late spring and early summer. These climatic conditions significantly influence land surface temperature variability and the intensity of urban heat island effects (Zhao *et al.* 2014).

Rapid urbanization and land use changes over the past decade have led to notable transformations in the city's spatial structure. Expansion of built-up areas, reduction in vegetated surfaces, and modification of natural land cover have contributed to alterations in surface energy balance and thermal characteristics. Such changes make Osijek an ideal case study for examining the interactions between land use/land cover dynamics, vegetation indices, and urban heat island intensity. Furthermore, the city's moderate size and heterogeneous land cover composition—including urban fabric, agricultural land, water bodies, and green spaces—provide a representative framework for understanding UHI dynamics in medium-sized European cities. Unlike megacities that have been extensively studied, Osijek offers insights into localized urban climate processes that are increasingly relevant for sustainable urban planning and climate adaptation strategies.

2.2. Data Sources and Acquisition

This study utilized multi-temporal satellite imagery and ancillary geospatial data to analyze land surface temperature (LST), land use/land cover (LULC), and vegetation dynamics. Landsat imagery was selected due to its high spatial resolution (30 m) and long-term data availability, making it suitable for spatiotemporal analysis (Weng *et al.* 2014; Amani *et al.* 2020).

Three time periods were considered: 2015, 2020, and 2025, representing a decade of urban transformation. The datasets used include:

1. Landsat 8 OLI/TIRS for 2015 and 2020
2. Landsat 9 OLI/TIRS for 2025
3. Thermal Infrared Sensor (TIRS) bands for LST extraction
4. Operational Land Imager (OLI) bands for LULC classification and NDVI computation

All satellite images were obtained from the United States Geological Survey (USGS) Earth Explorer platform and selected based on minimal cloud cover (<10%) to ensure data quality.

2.3. Image Preprocessing

Preprocessing steps were conducted to ensure the accuracy and consistency of satellite data. These included:

1. Radiometric Correction – Conversion of digital numbers (DN) to Top of Atmosphere (TOA) spectral radiance.
2. Atmospheric Correction – Applied to reduce atmospheric interference and improve surface reflectance accuracy.
3. Geometric Correction – Ensured spatial alignment across multi-temporal datasets.
4. Cloud Masking – Removal of cloud and shadow pixels using quality assessment (QA) bands.

These preprocessing steps are essential for minimizing uncertainties in remote sensing-based temperature retrieval (Amani *et al.* 2020).

2.4. Land Use/Land Cover (LULC) Classification

LULC classification was performed using a supervised classification approach, specifically the Maximum Likelihood Algorithm, due to its robustness in handling multispectral data (Estoque *et al.* 2017).

The study classified land cover into four major categories:

1. Built-up area
2. Vegetation
3. Water bodies
4. Bare surfaces

Training samples were selected based on visual interpretation and high-resolution reference imagery. Classification accuracy was assessed using confusion matrices, and overall accuracy and Kappa coefficients were computed to validate classification performance.

2.5. Land Surface Temperature (LST) Retrieval

LST was derived from Landsat thermal bands using a standard radiative transfer approach. The procedure involved the following steps:

2.5.1. Step 1: Conversion of DN to Spectral Radiance

$$L_\lambda = M_L \times Q_{\text{cal}} + A_L \tag{1}$$

Where:

- L_λ = Spectral radiance
- M_L = Radiance multiplicative scaling factor
- A_L = Radiance additive scaling factor
- Q_{cal} = Quantized calibrated pixel value

2.5.2. Step 2: Conversion to Brightness Temperature

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \tag{2}$$

Where:

- T_B = Brightness temperature (Kelvin)
- K_1, K_2 = Calibration constants

2.5.3. Step 3: Land Surface Emissivity (LSE)

LSE was estimated using NDVI-based methods:

$$\varepsilon = 0.004 P_v + 0.986 \tag{3}$$

Where P_v is the proportion of vegetation derived from NDVI.

2.5.4. Step 4: Final LST Calculation

$$\text{LST} = \frac{T_B}{1 + \left(\frac{\lambda T_B}{\rho}\right)\ln(\varepsilon)} \tag{4}$$

Where:

- λ = Wavelength of emitted radiance
- $\rho = \frac{hc}{\sigma}$ (Planck's constant relationship)

This method is widely adopted in urban thermal studies due to its reliability and consistency (Weng *et al.* 2014; Li *et al.* 2020).

2.6. Normalized Difference Vegetation Index (NDVI)

NDVI was calculated to assess vegetation density and its influence on surface temperature:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \tag{5}$$

Where:

- NIR = Near-infrared band
- Red = Red band

NDVI values range from −1 to +1, with higher values indicating dense vegetation. This index is critical for analyzing the cooling effect of vegetation in urban environments.

2.7. Urban Heat Island (UHI) Analysis

UHI intensity was calculated by comparing urban LST values with reference non-urban (rural) areas:

$$\text{UHI} = \text{LST}_{\text{urban}} - \text{LST}_{\text{rural}} \tag{6}$$

Spatial distribution maps were generated to visualize thermal hotspots and their evolution over time. Areas with significantly higher LST values were identified as UHI zones.

2.8. Statistical and Correlation Analysis

To examine the relationship between LST and NDVI, Pearson correlation analysis was performed for each study year (2015, 2020, and 2025). Statistical measures including mean, standard deviation, and correlation coefficients were computed.

The strength of the relationship was interpreted as follows:

- Strong negative correlation: High vegetation reduces temperature
- Weak or no correlation: Influence of other urban factors

This approach helps quantify the role of vegetation in mitigating urban heat.

2.9. Data Analysis Tools

All spatial and statistical analyses were conducted using:

1. ArcGIS – Spatial analysis and mapping
2. ERDAS Imagine – Image processing
3. Google Earth Engine – Cloud-based analysis
4. SPSS / Excel – Statistical analysis

3. Results and Discussion

3.1. Land Use/Land Cover Dynamics

The spatial distribution and temporal changes in land use/land cover (LULC) are presented in Table 1 and Figure 1. As shown in Table 1, vegetation cover dominated the study area in 2015 (43.41%), followed closely by built-up surfaces (42.56%). However, by 2020, vegetation declined significantly to 33.36%, while bare surfaces increased sharply to 30.87%. By 2025, vegetation showed only slight recovery (35.15%), whereas bare surfaces remained substantially high (31.77%). The spatial patterns illustrated in Figures 1 and 2 further confirm the progressive fragmentation of vegetated areas and expansion of exposed surfaces across the study period. This transition reflects increasing land surface disturbance and possible urban restructuring processes. These findings align with studies such as Li *et al.* (2020) and Guha *et al.* (2017), which reported that rapid urban land transformation often leads to vegetation loss and increased surface exposure. The persistence of high bare-surface proportions in 2025 suggests incomplete urban consolidation, which can significantly influence surface thermal behavior.

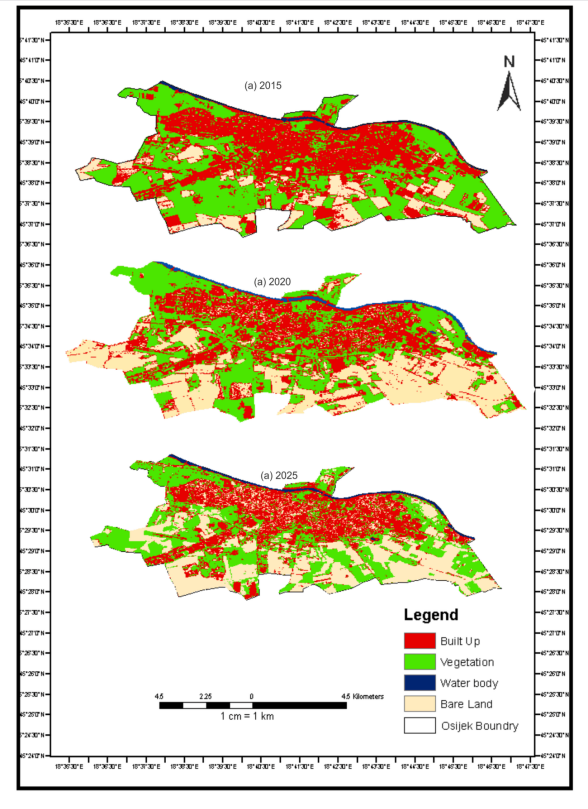

Figure 1. LULC of Osijek 2015-2025.

Table 1. LULC results of Osijek 2015 - 2025.

Class	LULC 2015		LULC 2020		LULC 2025	
LULC	Area ha	% Coverage	Area ha	% Coverage	Area ha	% Coverage
Vegetation	2566	43.41	1972	33.36	2078	35.15
Water Body	93	1.57	111	1.88	101	1.71
Built Up	2516	42.56	2003	33.89	1854	31.37
Bare Surface	736	12.45	1825	30.87	1878	31.77
Total	5911	100	5911	100	5911	100

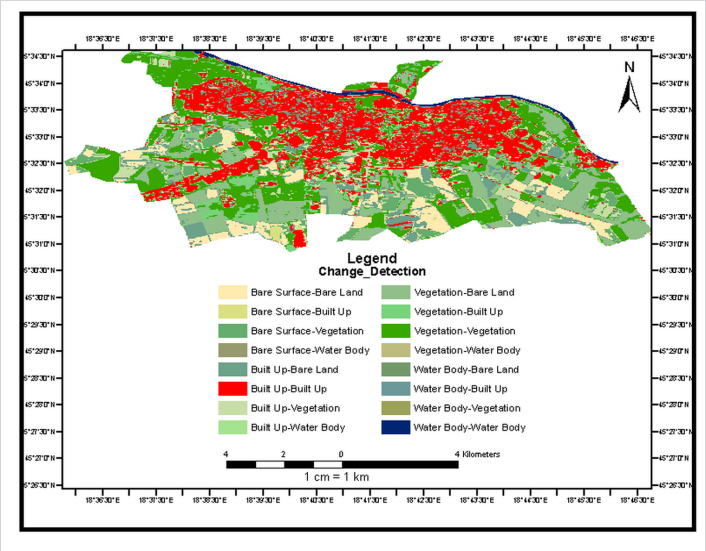

Figure 2. LULC change detection analysis of Osijek 2015-2025.

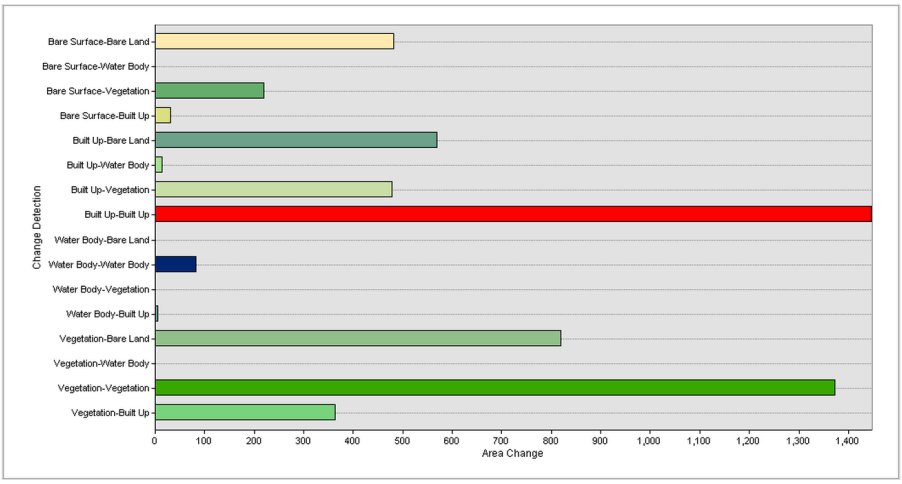

Figure 3. Graphic representation of LULC change detection analysis of Osijek 2015-2025.

Table 2. Osijek LULC change detection 2015 - 2025.

Changes Detected	Area Change km²	% Change
Vegetation-Built Up	364.369987	6.17427
Vegetation-Vegetation	1373.836397	23.27974
Vegetation-Water Body	0.875302	0.01483
Vegetation-Bare Land	821.338561	13.91763
Water Body-Built Up	7.643252	0.12952
Water Body-Vegetation	0.421745	0.00715
Water Body-Water Body	84.289155	1.42828
Water Body-Bare Land	0.114624	0.00194
Built Up-Built Up	1448.175062	24.53941
Built Up-Vegetation	479.586117	8.12662
Built Up-Water Body	15.270847	0.25877
Built Up-Bare Land	570.169991	9.66156
Bare Surface-Built Up	32.480226	0.55038
Bare Surface-Vegetation	220.230814	3.73182

Table 2. (continued)

Changes Detected	Area Change km²	% Change
Bare Surface-Water Body	0.00277	0.00005
Bare Land - Bare Land	482.620435	8.17803
Total	5901.425285	100

3.2. Spatiotemporal Variation in Land Surface Temperature

The descriptive statistics of LST are summarized in Table 3, while the spatial distribution is presented in Figure 4. As indicated in Table 3, mean LST decreased from 22.6 °C in 2015 to 20.7 °C in 2020 and further to 15.6 °C in 2025. Similarly, maximum LST declined from 30.17 °C to 21.8 °C over the study period. Figure 4 shows a noticeable reduction in high-temperature hotspots, particularly in densely built-up zones. The decline in standard deviation (from 2.4 in 2015 to 1.06 in 2025) suggests increasing thermal uniformity across the landscape. This observed cooling trend contrasts with the widely reported urban warming patterns in many global cities (Zhao *et al.* 2014), but may be explained by local land surface changes, increased surface moisture, or reduced impervious density. Similar localized cooling effects have been documented in urban transition zones where vegetation recovery or land abandonment occurs.

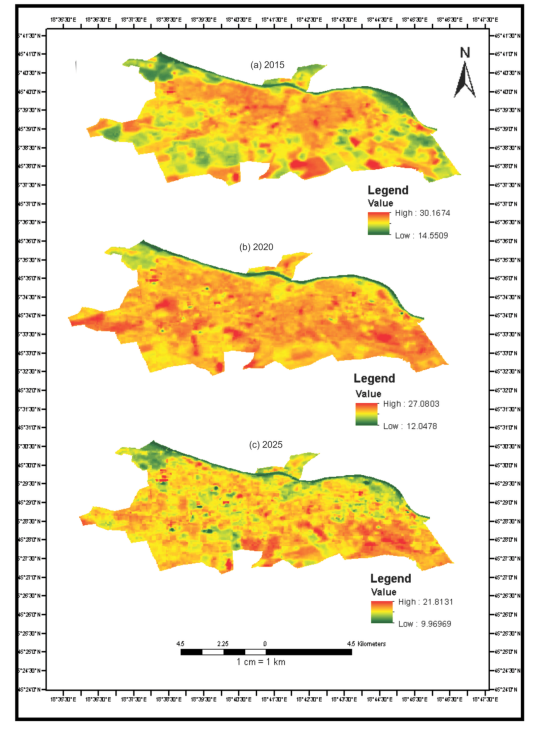

Figure 4. LST of Osijek 2015-2025.

Table 3. LST of Osijek 2015 - 2025.

Variables	LST 2015	LST 2020	LST 2025
Minimum LST	14.56	12.05	9.96
Maximum LST	30.17	27.08	21.8
Mean LST	22.6	20.7	15.6
Standard Deviation	2.4	1.73	1.06

3.3. Vegetation Dynamics and NDVI Analysis

The NDVI statistics presented in Table 4 indicate a decline in vegetation health and density between 2015 and 2020, followed by slight stabilization in 2025. Mean NDVI decreased from 0.2649 in 2015 to 0.158 in 2020, with minimal recovery to 0.163 in 2025. The reduction in NDVI variability (standard deviation decreasing from 0.134 to 0.088) suggests homogenization of vegetation cover. However, the slight recovery observed in 2025 may indicate localized greening or vegetation regrowth, as also noted by Mas'uddin *et al.* (2023).

Table 4. NDVI of Osijek 2015 - 2025.

Variables	NDVI 2015	NDVI 2020	NDVI 2025
Minimum	−0.069	−0.114	−0.0898
Maximum	0.57	0.508	0.59
Mean	0.2649	0.158	0.163
Standard Deviation	0.134	0.094	0.088

3.4. Urban Heat Island (UHI) Intensity

The UHI intensity results are presented in Table 5 and Figure 5. Table 5 shows a substantial decline in mean UHI intensity from 13.087 in 2015 to 0.95 in 2025. Maximum UHI values also decreased significantly, indicating reduced thermal contrast between urban and surrounding areas. Figure 5 further illustrates the shrinking extent of high UHI zones over time. Notably, the presence of negative UHI values in 2025 suggests localized cooling effects where urban areas are cooler than their rural counterparts. This trend deviates from the conventional understanding of persistent urban heat islands (Li *et al.* 2020), but similar reductions have been observed in cities undergoing land-use restructuring or increased vegetation integration (Kasniza Jumari *et al.* 2023). The findings suggest a weakening of urban thermal intensity rather than complete elimination of the UHI effect.

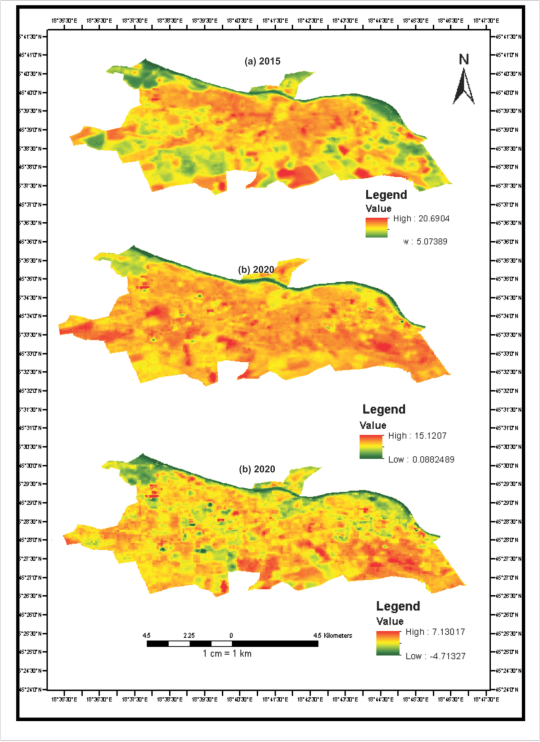

Figure 5. UHI of Osijek 2015-2025.

Table 5. UHI of Osijek 2015 - 2025.

Variables	UHI 2015	UHI 2020	UHI 2025
Minimum	5.073	0.088	−4.71
Maximum	20.69	15.12	7.13
Mean	13.087	8.73	0.95
Standard Deviation	2.38	1.73	1.065

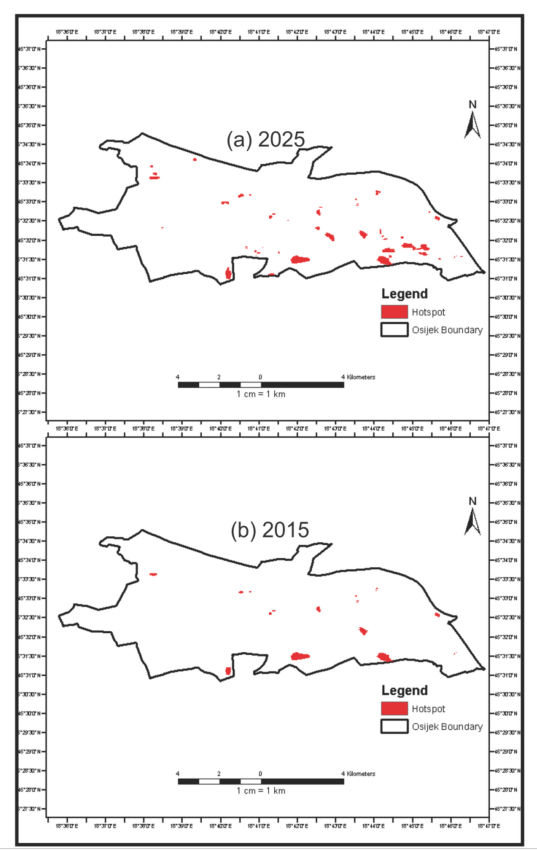

Figure 6. Urban heatmap of Osijek 2015-2025.

3.5. Relationship Between LST and NDVI

The correlation results summarized in Tables 7, 9 and 11 indicate a strong negative relationship between NDVI and LST in 2015 ($r = -0.579$, $p < 0.001$), confirming the cooling effect of vegetation. However, this relationship weakened significantly in 2020 ($r = -0.036$) and remained weak in 2025 ($r = -0.117$). This pattern suggests that vegetation played a dominant role in temperature regulation in 2015 but became less influential in later years. The weakening relationship may be attributed to increased dominance of other surface characteristics such as bare soil and built-up materials. This indicates that LST variability is controlled by multiple interacting factors beyond vegetation alone.

Table 6. Descriptive statistics Osijek 2015.

	Mean	Std. Deviation	N
NDVI	.2611004	.13196617	502
LST	22.5952852	2.40973370	502

Table 7. Correlations Osijek 2015.

		NDVI	LST
NDVI	Pearson Correlation	1	-.579**
	Sig. (2-tailed)		.000
	N	502	502
LST	Pearson Correlation	-.579**	1
	Sig. (2-tailed)	.000	
	N	502	502

**. Correlation is significant at the 0.01 level (2-tailed).

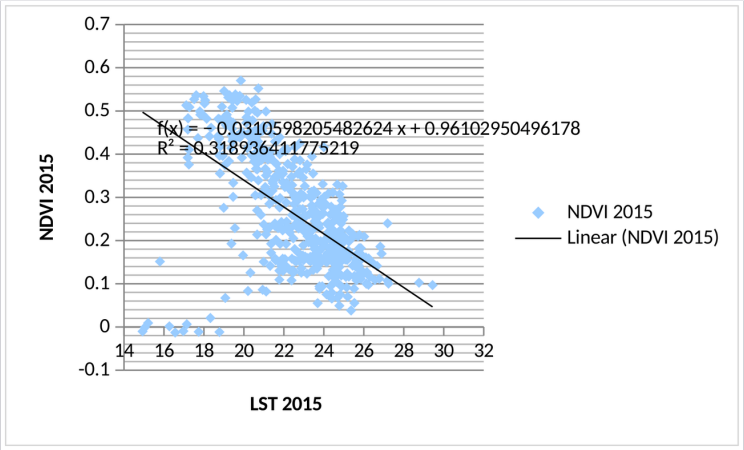

Figure 7. Correlation between LST and NDVI 2015.

Table 8. Descriptive statistics Osijek 2020.

	Mean	Std. Deviation	N
LST	20.71	1.714	503
NDVI	.15	.091	503

Table 9. Correlations Osijek 2020.

		LST	NDVI
LST	Pearson Correlation	1	-.036
	Sig. (2-tailed)		.422
	N	503	503
NDVI	Pearson Correlation	-.036	1
	Sig. (2-tailed)	.422	
	N	503	503

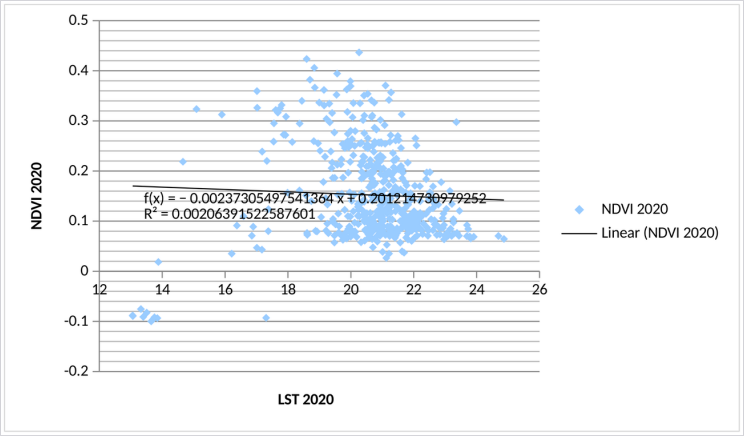

Figure 8. Correlation between LST and NDVI 2020.

Table 10. Descriptive statistics Osijek 2025.

	Mean	Std. Deviation	N
LST	15.68	1.049	502
NDVI	.16	.087	502

Table 11. Correlations Osijek 2025.

		LST	NDVI
LST	Pearson Correlation	1	-.117**
	Sig. (2-tailed)		.009
	N	502	502
NDVI	Pearson Correlation	-.117**	1
	Sig. (2-tailed)	.009	
	N	502	502

**. Correlation is significant at the 0.01 level (2-tailed).

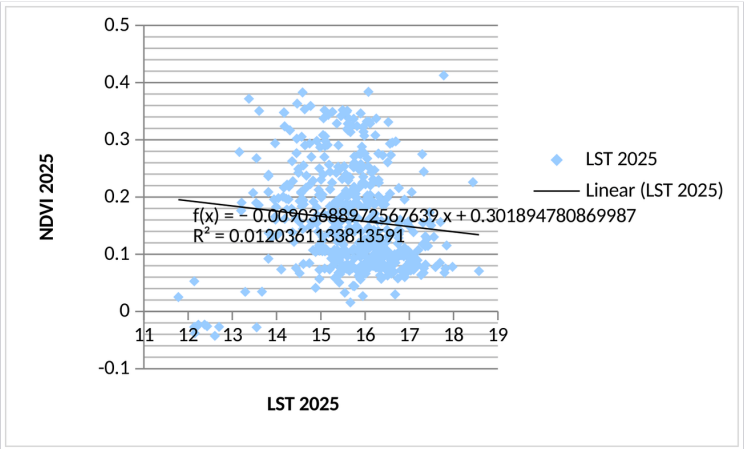

Figure 9. Correlation between LST and NDVI 2025.

3.6. Discussion

The integrated analysis of LULC (Table 1; Figure 1), LST (Table 3; Figure 4), NDVI (Table 4), and UHI intensity (Table 5; Figure 5) reveals a complex and non-linear interaction between land surface transformation and urban thermal dynamics. Collectively, the results indicate that while the study

area experienced substantial vegetation decline and expansion of bare surfaces between 2015 and 2025, this was paradoxically accompanied by a progressive reduction in mean LST and UHI intensity. This finding challenges the conventional expectation that vegetation loss directly translates into increased urban warming. Typically, numerous studies have established that reductions in vegetation cover intensify urban heat due to diminished evapotranspiration and shading effects (Li *et al.* 2020; Zhao *et al.* 2014). However, the results presented in Tables 3 and 5 show a consistent decline in both LST and UHI intensity across the study period, suggesting that additional controlling factors played a significant role in modulating the thermal environment. One plausible explanation lies in the increase in bare surfaces (Table 1), which, depending on soil moisture conditions, albedo, and compaction, may not always behave as strong heat-retaining surfaces compared to dense impervious materials such as asphalt and concrete. In some cases, exposed soils with higher reflectivity or moisture content can contribute to localized cooling effects, particularly in transitional urban landscapes.

Furthermore, the observed decline in built-up area between 2015 and 2025 (Table 1) provides an additional explanation for the reduction in thermal intensity. Built-up surfaces are widely recognized as primary contributors to urban heat islands due to their high heat storage capacity and low albedo (Guha *et al.* 2017). The reduction in impervious surfaces may therefore have offset the thermal impact of vegetation loss, resulting in an overall cooling trend. This supports the argument that urban heat dynamics are not solely dependent on vegetation but are strongly influenced by the balance between different surface types. The weakening of the NDVI–LST relationship further reinforces this complexity. As shown in Tables 7, 9 and 11, the strong negative correlation observed in 2015 ($r = -0.579$) weakened significantly in 2020 and remained weak in 2025. This indicates that vegetation was a dominant control on surface temperature in the earlier period but became less influential over time. The results therefore suggest a transition from vegetation-dominated thermal regulation to a more complex multi-factor system.

Another important insight from the analysis is the reduction in thermal variability, as indicated by the decreasing standard deviation of LST and UHI intensity (Tables 3 and 5). This suggests that the study area is becoming more thermally homogeneous over time, which may be attributed to the spatial redistribution of land cover types and the reduction of extreme thermal hotspots. While this may appear beneficial in terms of reduced peak temperatures, it also indicates a loss of thermal diversity, which can have ecological and climatic implications, particularly in terms of urban microclimate regulation. The spatial patterns illustrated in Figures 4 and 5 further confirm that high-temperature zones became less pronounced and more dispersed over time. This redistribution of thermal hotspots suggests that urban heat is no longer concentrated solely in densely built-up areas but is influenced by a broader spatial configuration of land surfaces.

From a theoretical perspective, the findings contribute to the growing body of evidence that challenges the traditional linear relationship between urbanization and thermal intensification. Instead, the results support a systems-based understanding of urban climate, where interactions between vegetation, built-up areas, bare surfaces, and microclimatic conditions collectively determine thermal outcomes. This aligns with recent advances in urban climate research that advocate for integrated, multi-variable approaches to understanding and mitigating urban heat (Kasniza Jumari *et al.* 2023). From a planning and policy standpoint, the implications are significant. The results clearly demonstrate that increasing vegetation alone may not be sufficient to mitigate urban heat, particularly in environments where other surface characteristics play dominant roles. Instead, effective urban heat mitigation requires a holistic land management strategy that simultaneously addresses vegetation enhancement, reduction of impervious surfaces, stabilization of bare lands, and optimization of urban spatial configuration. In particular, the persistence of large bare-surface areas (Table 1) highlights the need for targeted interventions, as these surfaces can either exacerbate or mitigate heat depending on their physical properties and environmental context.

In summary, the integrated findings underscore that urban thermal dynamics in the study area are governed by complex, non-linear, and multi-factor interactions. The decline in LST and UHI intensity, despite vegetation loss, highlights the importance of considering the combined effects of land-cover composition, spatial arrangement, and surface properties. This reinforces the need for integrated urban climate planning frameworks that move beyond single-factor solutions and adopt a more comprehensive approach to sustainable urban development.

4. Conclusion, Policy Implications, and Recommendations

4.1. Conclusion

This study provides a comprehensive spatiotemporal assessment of land use/land cover (LULC) dynamics, land surface temperature (LST), normalized difference vegetation index (NDVI), and urban heat island (UHI) intensity across the study period (2015–2025). Drawing on the integrated analysis presented in Tables 1–11 and Figures 1–9, the findings reveal a complex and non-linear urban thermal response to land surface transformations. The results demonstrate that vegetation cover declined significantly between 2015 and 2020, with only marginal recovery by 2025, while bare surfaces expanded and remained dominant in later years. Despite this reduction in vegetative cover, mean LST and UHI intensity exhibited a consistent decline over the study period. This apparent contradiction suggests that urban thermal dynamics in the study area are not solely controlled by vegetation extent but are influenced by a broader combination of surface characteristics, including bare soil exposure, land-use restructuring, and spatial configuration of urban elements.

Furthermore, the relationship between NDVI and LST was found to be non-stationary. While a strong and significant negative correlation was observed in 2015, indicating the cooling role of vegetation, this relationship weakened considerably in 2020 and remained weak in 2025. This finding highlights the increasing complexity of urban thermal systems, where vegetation alone may no longer be a sufficient predictor of surface temperature patterns. Overall, the study contributes to the growing body of literature emphasizing that urban heat dynamics are governed by multi-factor interactions rather than single-variable controls, reinforcing conclusions drawn by recent studies (Li *et al.* 2020; Zhao *et al.* 2014). The results underscore the importance of adopting integrated approaches to urban climate analysis and planning.

4.2. Policy Implications

The findings of this study have important implications for urban planning, environmental management, and climate adaptation strategies. First, the observed decline in UHI intensity suggests that urban thermal conditions can be moderated through land surface changes, even in the absence of large-scale vegetation expansion. This implies that policymakers should not rely solely on greening initiatives but should also consider surface material management and land-use configuration as critical components of urban heat mitigation. Second, the persistence of high proportions of bare surfaces highlights a key vulnerability in the urban landscape. Bare soils and exposed lands can significantly influence thermal behavior, often acting as transitional heat sources depending on moisture conditions. Therefore, reducing unmanaged open surfaces through controlled development or ecological restoration should be prioritized. Third, the weakening relationship between NDVI and LST indicates that traditional green-based planning strategies may have diminishing returns if implemented in isolation. This calls for a multi-dimensional planning framework that integrates vegetation, built form, and surface materials, consistent with findings from recent urban climate studies (Kasniza Jumari *et al.* 2023).

Finally, the spatial redistribution of thermal patterns observed in the study suggests that urban heat mitigation should be spatially targeted rather than uniformly applied. Identifying and prioritizing thermal hotspots remains essential for effective intervention.

4.3. Recommendations

Based on the findings, the following recommendations are proposed to enhance urban thermal resilience and support sustainable land management:

1. Integrated Urban Greening Strategies: Urban vegetation should be enhanced not only in quantity but also in spatial continuity and structure. Green corridors, urban forests, and interconnected open spaces should be prioritized to maximize cooling efficiency.
2. Management of Bare Surfaces: Large expanses of exposed land should be minimized through land reclamation, controlled development, or conversion into functional green or permeable spaces. Stabilizing bare surfaces can reduce thermal variability and improve environmental quality.
3. Adoption of Climate-Sensitive Urban Design: Urban planning policies should incorporate heat mitigation principles such as reflective materials, permeable surfaces, and optimized building layouts to reduce heat absorption and enhance ventilation.
4. Spatially Targeted Heat Mitigation: Thermal hotspot mapping (as shown in Figure 6) should guide intervention strategies. Priority should be given to areas with historically high LST and UHI intensity.
5. Multi-Factor Urban Climate Modeling: Future urban climate assessments should integrate additional variables such as albedo, soil moisture, and building density to better capture the complexity of LST dynamics.
6. Continuous Monitoring Using Remote Sensing: The use of multi-temporal satellite data (e.g., Landsat, MODIS) should be institutionalized for continuous monitoring of urban thermal environments and land-use changes.

4.4. Future Research Directions

While this study provides valuable insights, further research is recommended to:

1. Incorporate higher temporal resolution datasets to account for seasonal variability in LST
2. Apply advanced machine learning models to improve LST prediction accuracy
3. Investigate socio-economic drivers of land-use change and their thermal implications
4. Explore micro-scale urban climate dynamics using in-situ measurements

Declarations

Author contributions. Francis Ezinwanne Onuegbu: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Writing (original draft), Project administration, Resources, Software, Funding acquisition. Geraldine Nkechinyere Okeudo: Writing (review and editing), Visualization, Validation, Supervision, Resources.

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Generative AI. there was none if there was none.

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