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VEGETATION AND TEMPERATURE RELATIONSHIPS ACROSS URBAN AND PERI-URBAN LANDSCAPES: A TWO-PERIOD COMPARISON OF ORAN AND NOVI SAD (2015 AND 2024)

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Abstract: This study examines two-period change, between 2015 and 2024, in the statistical relationship between land surface temperature (LST) and vegetation density, expressed as the Normalized Difference Vegetation Index (NDVI), across the urban and peri-urban study areas of Oran, Algeria and Novi Sad, Serbia. Landsat Collection 2 Level 2 imagery was processed in Google Earth Engine using pixel-level quality masking, thermal uncertainty filtering, water-body exclusion, and aggregation to a fixed 100 m grid. Pearson correlation analysis of 3,000 random land pixels per city and year shows contrasting LST–NDVI associations. In Novi Sad, the correlation weakened from $r = -0.78$ in 2015 to $r = -0.69$ in 2024, but remained strongly negative, indicating that higher NDVI values were still statistically associated with lower LST. In Oran, the already weak relationship declined from $r = -0.23$ to $r = -0.08$, meaning that NDVI explained less than 1% of LST variance in 2024. The two-period pixel-wise comparison showed warming and vegetation decline in both study areas, with stronger thermal amplification in Oran. ERA5-Land meteorological data and Dynamic World built-up data are used as contextual variables for each city, without treating precipitation differences between the two climatic settings as direct causal evidence. The findings highlight the need for locally adapted urban heat mitigation strategies.

Keywords: land surface temperature; NDVI; urban heat island; vegetation cooling; Google Earth Engine

1. Introduction

Urban areas globally are facing increasing thermal challenges due to the combined effects of anthropogenic climate change and the urban heat island (UHI) phenomenon, which exacerbate the frequency and intensity of extreme heat events (Cheval et al., 2024). As cities expand with dense infrastructure, the substitution of natural landscapes with impervious materials significantly alters the surface energy balance, leading to trapped heat and elevated land surface temperatures (LST; Illán-Fernández et al., 2025; Oke, 1982). The Intergovernmental Panel on Climate Change has highlighted that these thermal extremes pose severe risks to public health, economic stability, and urban sustainability (Dubash et al., 2022), with vulnerability particularly pronounced in densely populated cities of the Global South (Zitouni et al., 2025).

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Urban heat mitigation has therefore become an important objective for city planners and environmental policymakers, with increasing research attention to climate adaptation strategies and nature-based solutions such as green infrastructure (An & Dedekorkut-Howes, 2025). Urban forests, parks, and street trees can reduce ambient and surface temperatures through shading and evapotranspiration (Kucera & Jenerette, 2023; Soltanifard & Amani-Beni, 2025). Evidence from temperate and continental climates supports this approach. For example, Schwaab et al. (2021) showed that urban trees can provide substantial cooling benefits across European cities. Increasing urban canopy cover is therefore frequently promoted as a UHI mitigation strategy, although its effectiveness may depend on local climatic, hydrological, and land-cover conditions (Alonzo et al., 2025; Ma et al., 2026).

The temperature-mitigation role of urban vegetation is context-dependent and vulnerable to environmental stressors (Tang et al., 2025). In hot and semi-arid climates, such as the Mediterranean region, severe summer water deficits force trees into hydraulic stress. Under water stress, stomatal closure can limit transpiration and reduce the potential cooling contribution of vegetation (Kinzinger et al., 2025; Mas et al., 2024). Recent global assessments confirm this limitation, revealing that in arid environments, the cooling effect of vegetation weakens and can even transition into a net warming effect due to low albedo and absent evaporative cooling (Guo et al., 2026; Ibsen et al., 2021). In coastal cities, the powerful thermodynamic influence of sea breezes can overshadow the localized microclimatic benefits of green spaces, rendering standard afforestation strategies less effective (Alomar-Garau & Grimalt-Gelabert, 2022; Burkart et al., 2016).

A significant knowledge gap persists regarding how the relationship between LST and the Normalized Difference Vegetation Index (NDVI) varies across distinct climatic and spatial contexts, particularly when findings from European urban settings are applied to Global South cities (Tiepolo et al., 2023). To address this gap, this study examines two-period change from 2015 to 2024 in the statistical relationship between LST and NDVI across the urban and peri-urban study areas of Novi Sad, Serbia and Oran, Algeria. Novi Sad represents a humid continental setting in which previous work has shown the relevance of urban greenery for microclimatic conditions (Simović et al., 2025), whereas Oran represents a semi-arid Mediterranean coastal setting. Rather than inferring direct biophysical causation, the analysis compares the strength and spatial pattern of LST–NDVI associations in each study area and discusses them in relation to local climatic, land-cover, and urban-structure conditions.

2. Case studies

This study examines two cities selected to represent contrasting climatic, geographic, and urban-structural regimes: Novi Sad, a humid continental riverine city with abundant, physiologically active vegetation, and Oran, a semi-arid Mediterranean coastal city of the Global South where summer water deficits constrain vegetation function (Figure 1). This pairing was chosen to test whether the vegetation–temperature associations reported for temperate European cities remain valid under water-limited Mediterranean conditions, thereby addressing the knowledge gap concerning the transferability of urban-greening strategies between these two climatic domains. Oran is a major coastal city in northwestern Algeria, located on the Mediterranean coast (35.70°N, 0.63°W), and represents a semi-arid Mediterranean urban setting. According to the 2008 national census, the commune of Oran had 609,940 inhabitants (Office National des Statistiques, 2008). Novi Sad is the second-largest

city in Serbia and is located on the Danube River (45.25°N, 19.84°E). According to the 2022 Census, the City of Novi Sad had 368,967 inhabitants, while the Novi Sad settlement had 260,438 inhabitants (City of Novi Sad, 2022). These demographic figures are used only as contextual information because administrative population units do not correspond exactly to the raster-based analytical extent used in this study.

For each city, the analytical study extent was defined as an approximately 30 × 30 km area centered on the urban core, generated using a 15 km buffer around a central geographic point. This extent intentionally includes a broad urban–peri-urban land-cover gradient, from dense built-up areas to transitional, agricultural, natural, coastal, or riverine surfaces. Such variability is necessary for the pixel-level analysis because the LST–NDVI statistical relationship requires sufficient variation in both vegetation density and surface temperature across the sampled pixels. For Novi Sad, the study extent includes the southern portion of Fruška Gora, which provides a natural vegetation reference within the wider analytical area. For Oran, the study extent includes the coastal zone and inland semi-arid surfaces. Therefore, the descriptive statistics reported in Table 1 represent averages across the full analytical study extent and should not be interpreted as describing the urban core alone.

Although the built-up areas within the two analytical extents are relatively similar in size, the cities differ substantially in population size, urban density, coastal or riverine setting, and built-up morphology. These differences may influence surface heat emissions, anthropogenic pressure, ventilation, and LST patterns, and they are therefore considered when interpreting the comparative results. Built-up area within each study extent, derived from the Dynamic World land-cover dataset (Brown et al., 2022), comprised 130.38 km² for Oran and 116.00 km² for Novi Sad in the 2016 baseline.



Figure 1. Location map of the study areas.
Note. Panel A: Oran, Algeria. Panel B: Novi Sad, Serbia.

3. Methodology

Data were acquired from Landsat 8 and Landsat 9 Level 2 Science Products, which provide atmospherically corrected surface reflectance and surface temperature archives (Cook et al., 2014; Masek et al., 2020). The temporal scope encompasses the period from June 1 to September 30 for the years 2015 and 2024. For the 2015 baseline, only Landsat 8 imagery was available, while for 2024, both Landsat 8 and Landsat 9 were merged to maximize temporal density. This combination is justified because both sensors share near-identical radiometric and spectral characteristics and are processed through the same Collection 2 atmospheric correction pipeline, ensuring inter-sensor consistency (Masek et al., 2020). The merging effectively doubles the available temporal sampling, reducing residual cloud contamination in the median composites. This temporal window captures representative warm-season surface conditions while minimizing intra-annual phenological variability (Gao et al., 2020). All processing was conducted within the Google Earth Engine cloud computing platform (Gorelick et al., 2017). Scene-level cloud filtering was not applied to maximize data retention. Instead, a rigorous pixel-level masking protocol was applied using the QA_PIXEL bitmask band, generated by the CFMask algorithm (Foga et al., 2017), to remove fill values (bit 0), dilated clouds (bit 1), cirrus (bit 2), clouds (bit 3), and cloud shadows (bit 4). Cirrus exclusion is critical, as their optically thin but thermally cold nature can introduce radiometric bias in LST retrievals. Thermal retrieval uncertainty was further constrained using the ST_QA band; all pixels exceeding a 3.5 K uncertainty threshold were excluded.

The NDVI was computed from the scaled surface reflectance bands as the normalized ratio of the near-infrared band (Band 5) and the red band (Band 4), following the standard formulation established by Tucker (1979) and Rouse et al. (1974). NDVI values range from -1 to $+1$, with higher positive values indicating denser and more photosynthetically active vegetation. The median composite of all valid acquisitions within the June–September window was generated for each year, providing a representative warm-season surface while reducing the influence of residual atmospheric noise and transient cloud contamination.

A fundamental methodological challenge in multi-sensor urban thermal studies involves the spatial resolution disparity between native optical bands (30 m) and the Thermal Infrared Sensor, which acquires data at a native resolution of 100 m but is resampled to 30 m in the distributed Level 2 products (Cook et al., 2014). To address this and enable physically valid temporal subtraction, a strict spatial framework was implemented using coordinate reference system anchored analysis locked at a 100 m grid. For Oran, UTM Zone 30N (EPSG:32630) was applied, while for Novi Sad, UTM Zone 34N (EPSG:32634) was employed, ensuring minimal spatial distortion within each study area (Stal et al., 2022). Spatial aggregation was performed in Google Earth Engine using the *reduceResolution* function with a mean reducer to aggregate both NDVI and LST to the target 100 m spatial unit. This fixed grid approach ensures that extracted thermal signatures represent the aggregate conditions within each analysis unit, eliminating mixed-pixel artifacts and allowing exact pixel-to-pixel comparison over the ten-year period (Wu et al., 2021).

To prevent artificial depression of thermal statistics by aquatic surfaces, permanent water bodies were excluded using the Joint Research Centre Global Surface Water dataset v1.4 (Pekel et al., 2016). Pixels with water occurrence exceeding 90% at the native 30 m resolution were flagged as permanent water. This water mask was then aggregated to the 100 m analytical grid as the proportion of permanent water within each cell, and cells with 50% or more permanent

water coverage were excluded. This approach substantially excludes open-water surfaces such as the Mediterranean Sea and the main Danube channels while preserving mixed coastal and riverbank pixels.

Full raster enumeration was avoided because adjacent raster cells are not statistically independent; spatial autocorrelation implies that nearby observations tend to be more similar than distant ones, consistent with Tobler's First Law of Geography (Institut national de la statistique et des études économiques, 2018; Tobler, 1970). Instead, a spatially lagged random sampling approach was employed. A fixed random sample of 3,000 valid land pixels was drawn for each city-year, with a minimum spacing of 200 m between sample points. This spacing is informed by the spatial resolution hierarchy of the input data: because the thermal infrared sensor acquires data at a native 100 m resolution and both variables were aggregated to a 100 m grid, the 200 m lag ensures that each sampled pixel is separated from its nearest neighbor by at least two native thermal resolution cells. This spacing aligns with the operational scale of urban thermal variability identified by Weng et al. (2004), who demonstrated through fractal analysis that the spatial complexity of LST peaks between 120 and 240 m, beyond which thermal signals become spatially smoothed. While this design does not eliminate spatial dependence entirely, it substantially reduces its influence on the correlation estimates and improves the plausibility of independence assumptions (Institut national de la statistique et des études économiques, 2018).

Pearson product-moment correlation coefficients and coefficients of determination were computed between NDVI and LST for each sample, serving as effect-size metrics of the LST–NDVI statistical relationship. Negative values indicate inverse relationships where higher vegetation density is associated with lower surface temperatures, with the magnitude reflecting the strength of this statistical association. It should be noted that Pearson correlation quantifies the strength of the linear statistical association between NDVI and LST but does not establish a causal relationship; observed negative correlations are interpreted as LST–NDVI statistical associations that may be consistent with vegetation cooling mechanisms documented in the literature, rather than as proof of direct causation. Pearson correlation was chosen as the primary metric because it provides a directly interpretable, standardized measure that facilitates comparison across cities and time periods, and because visual inspection of the scatter plots (Figure 7) confirms that the relationship is predominantly linear within the observed NDVI range for both cities (Soltanifard & Amani-Beni, 2025). Linear regression equations were fitted to quantify the rate of thermal change per unit increase in vegetation density.

To assess whether the observed decadal changes in correlation strength were statistically significant, a Fisher z-transformation test (Fisher, 1921) was applied to compare the Pearson coefficients between 2015 and 2024 for each city. The Fisher z-transformation is appropriate in this context because the 2015 and 2024 samples are drawn as separate random samples (each $n = 3,000$) from their respective temporal composites, satisfying the assumption of independent correlations. In addition, to account for potential dependence between year-specific correlations when computed from the same pixel locations, a matched-pixel sensitivity analysis was conducted using 3,000 pixels with valid data in both temporal composites. The difference between the 2015 and 2024 NDVI–LST correlations was tested using Steiger's (1980) test for dependent nonoverlapping correlations, implemented with the *cocor* package in R (Diedenhofen & Musch, 2015). The consistency between the independent-sample correlations

(Table 3) and the matched-pixel estimates (Section 4.3.) provides additional empirical support for the robustness of the reported associations. To complement sample-based correlation estimates, population-level descriptive statistics—including mean LST, mean NDVI, standard deviation, and valid pixel counts—were extracted for each study area and year using a regional reducer applied over the full study area with comprehensive masking.

To contextualize the observed thermal and vegetative changes within their broader climatic setting, ancillary meteorological and land cover data were extracted independently of the Landsat pipeline. Mean air temperature and total precipitation were derived from the ERA5-Land monthly aggregated reanalysis dataset (Muñoz-Sabater et al., 2021) for the same June to September temporal window across both study years. Urban expansion was quantified using the Google Dynamic World land use and land cover dataset (Brown et al., 2022), from which the total built-up area was computed for the baseline period (2015/2016) and for 2024.

Temporal change was quantified through pixel-wise subtraction of the 2015 composites from the 2024 composites for both LST and NDVI. To ensure spatial consistency, the subtraction operation inherently restricts the analysis to pixels containing valid data in both the 2015 and 2024 composites, resulting in 61,221 overlapping valid pixels for Oran and 87,150 for Novi Sad. The resulting difference images (Δ LST and Δ NDVI) were analyzed using a regional reducer to compute the mean change values, along with the percentage of the study area experiencing thermal amplification (Δ LST > 0) and vegetation degradation (Δ NDVI < 0).

Several methodological limitations should be acknowledged. The present analysis compares two temporal snapshots (2015 and 2024) and therefore captures net decadal change rather than continuous temporal dynamics; intermediate trends and non-linear trajectories between these years cannot be resolved. The 100 m grid may overlook finer building-scale UHI variability (Stewart & Oke, 2012) and June–September median compositing together with Landsat’s 16-day revisit interval may smooth short-term thermal events (Wetherley et al., 2018). NDVI may also saturate in dense canopies, suggesting future use of alternative indices. Although random sampling with 200 m spacing reduces spatial autocorrelation, it may underrepresent rare land-cover classes; stratified sampling and formal spatial diagnostics such as Moran’s I on regression residuals should be incorporated in future studies, alongside spatial regression models where warranted. Pearson correlation assumes linearity, so nonlinear approaches should also be considered to detect threshold effects. Regarding thermal uncertainty, the ST_QA 3.5 K threshold ensures retained pixels have individual uncertainties below this value, and multi-date median compositing is expected to further reduce, but not eliminate, this uncertainty. To quantify statistical uncertainty, 95% confidence intervals for sample-based correlations were computed using the Fisher z-transformation.

4. Results and discussion

4.1. Regional thermal and vegetative characterization

The population-level spatial analysis over the study period reveals clear thermal and vegetative changes, particularly in the Mediterranean context (Table 1). The spatial distributions of LST and NDVI for the baseline year 2015 are presented in Figures 2 and 3, respectively; pixel-wise changes are shown in Figure 4, and the 2024 distributions are presented in Figures 5 and 6.

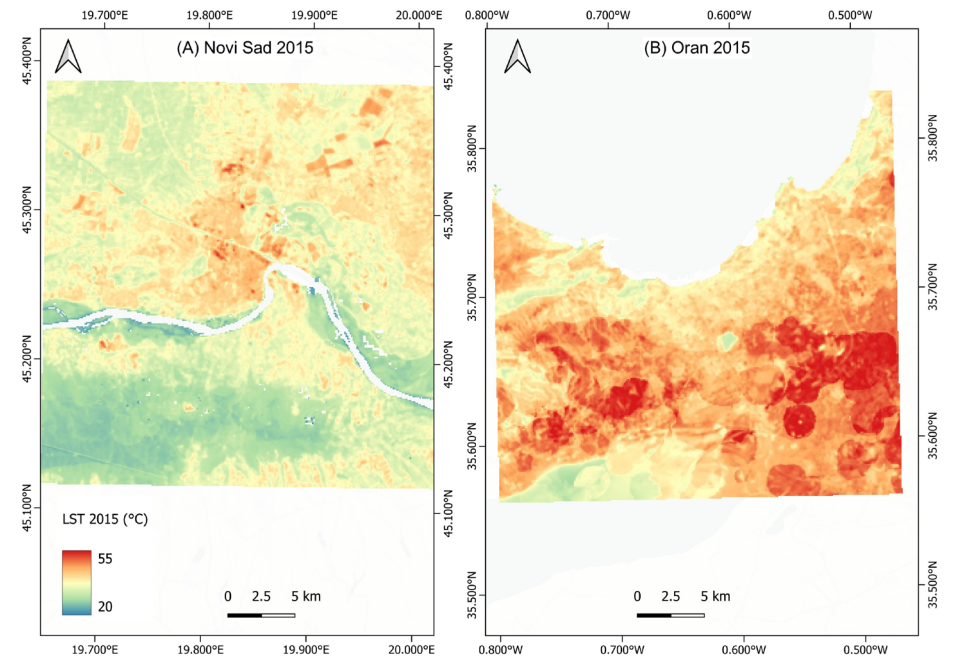


Figure 2. June–September median LST for 2015 at 100 m resolution.

In Oran, the study-area mean LST increased from 44.62 °C ($SD = 5.17$) in 2015 to 46.76 °C ($SD = 3.90$) in 2024, a rise of 2.14 °C. Pixel-by-pixel change detection showed that 72.37% of the study area experienced thermal amplification, with a mean LST increase of 2.28 °C (Figure 4A). Mean NDVI declined from 0.215 ($SD = 0.124$) to 0.188 ($SD = 0.080$), with vegetation degradation affecting 71.30% of the study area (Figure 4B). The lower standard deviation of both variables in 2024 suggests increasing spatial homogenization, consistent with the replacement of heterogeneous vegetated surfaces by more thermally uniform impervious materials. In the Novi Sad study area, mean LST increased modestly by 0.57 °C, from 35.62 °C ($SD = 4.64$) to 36.19 °C ($SD = 4.66$) at 100 m resolution, with 59.19% of the area experiencing thermal amplification. Mean NDVI declined from 0.679 ($SD = 0.167$) to 0.576 ($SD = 0.178$), affecting 85.88% of the study area, yet this vegetation decline did not produce a proportionate increase in thermal loading. It should be noted that these study-area means integrate both urban and non-urban pixels, including the forested Fruška Gora Mountain. The spatial pattern of LST change (Figure 4A) reveals notable heterogeneity, with parts of the urban core exhibiting localized cooling while peri-urban zones show warming. This localized cooling should not be interpreted as contradicting previous Novi Sad heat-island studies (Simović et al., 2025), because Figure 4A represents a two-period LST change signal rather than the absolute thermal hierarchy of the city. Previous research on Novi Sad has shown that dense, high-activity tree canopies can reduce local air temperature by up to 2 °C, and that vegetation structure is more important for microclimatic cooling than green-area size alone (Simović et al., 2025). This heterogeneity may reflect differences in atmospheric conditions across the Landsat acquisition dates composited for 2015 versus 2024, potential

changes in urban surface albedo or construction materials, and residual atmospheric or aerosol effects not fully captured by the Level 2 atmospheric correction. The concurrent NDVI decline in parts of the study area (Figure 4B) may reflect phenological variability between the June–September composite windows, while precipitation during the same window was higher in 2024 (213 mm) than in 2015 (179 mm). A supplementary stratified analysis using Dynamic World built-up masks revealed that urban pixels in Novi Sad experienced a mean cooling of $-0.33\text{ }^{\circ}\text{C}$ (95% CI: -0.56 to -0.10 , $p = 0.006$, $n = 242$), while non-urban areas warmed by $+0.78\text{ }^{\circ}\text{C}$ (95% CI: 0.67 – 0.90). This urban-specific cooling, despite concurrent NDVI decline, suggests that changes in surface albedo or construction materials, combined with inter-annual atmospheric variability, are the most plausible explanations for the localized cooling pattern visible in Figure 4A.

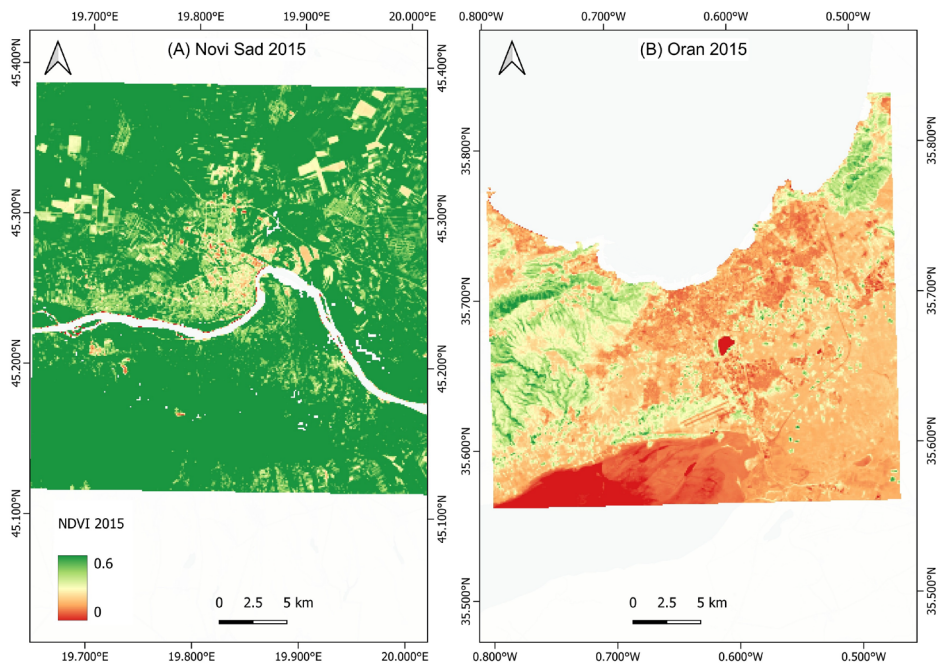


Figure 3. June–September median NDVI for 2015 at 100 m resolution.

Table 1. Population-level descriptive statistics for Oran and Novi Sad (2015 and 2024)

City	Year	Valid pixels	Mean LST ($^{\circ}\text{C}$)	<i>SD</i> LST	Mean NDVI	<i>SD</i> NDVI
Oran	2015	61,599	44.62	5.17	0.215	0.124
Oran	2024	62,747	46.76	3.90	0.188	0.080
Novi Sad	2015	87,797	35.62	4.64	0.679	0.167
Novi Sad	2024	87,801	36.19	4.66	0.576	0.178

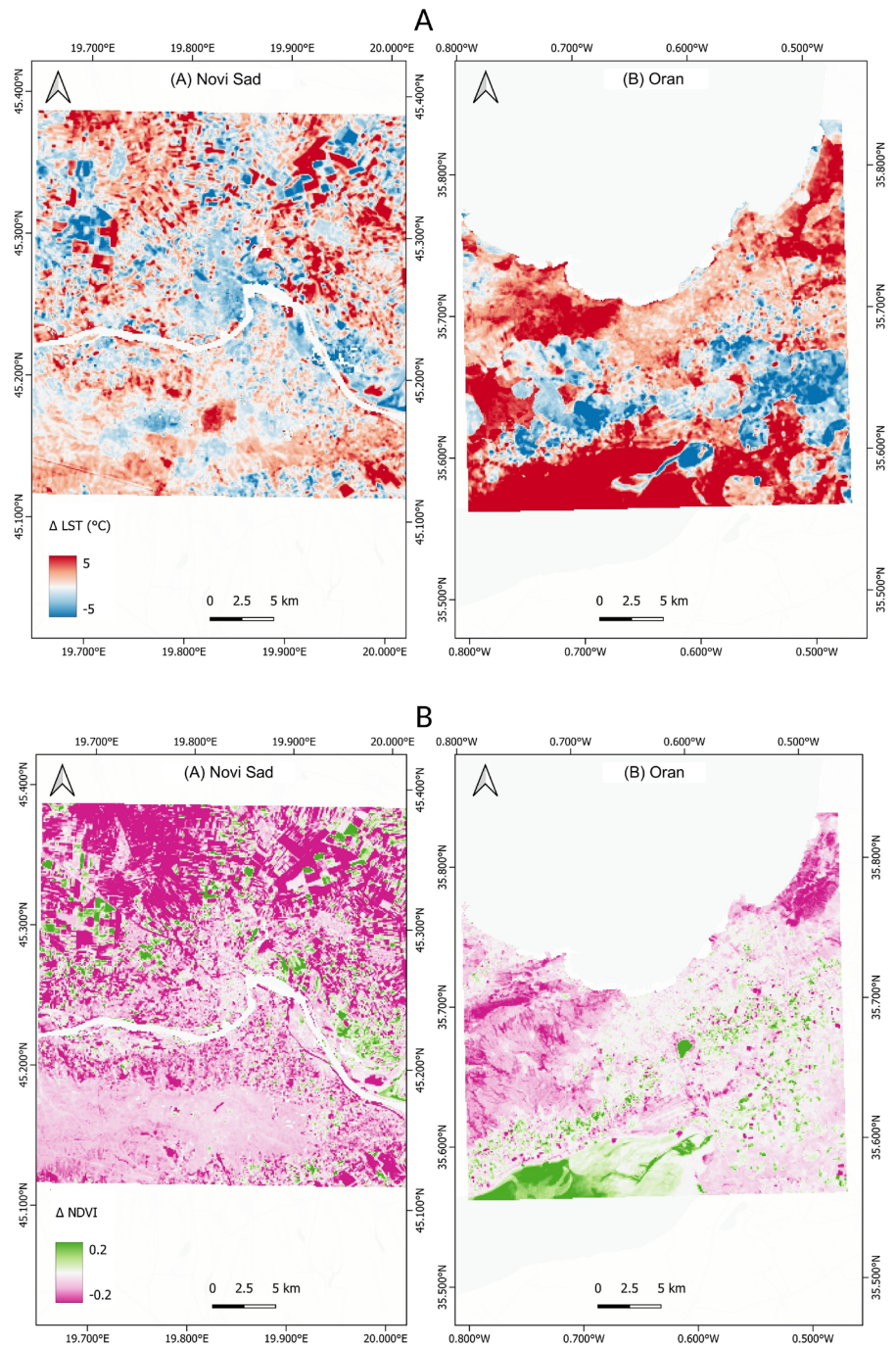


Figure 4. Temporal change (2024 minus 2015).
Note. Panel A: LST. Panel B: NDVI.

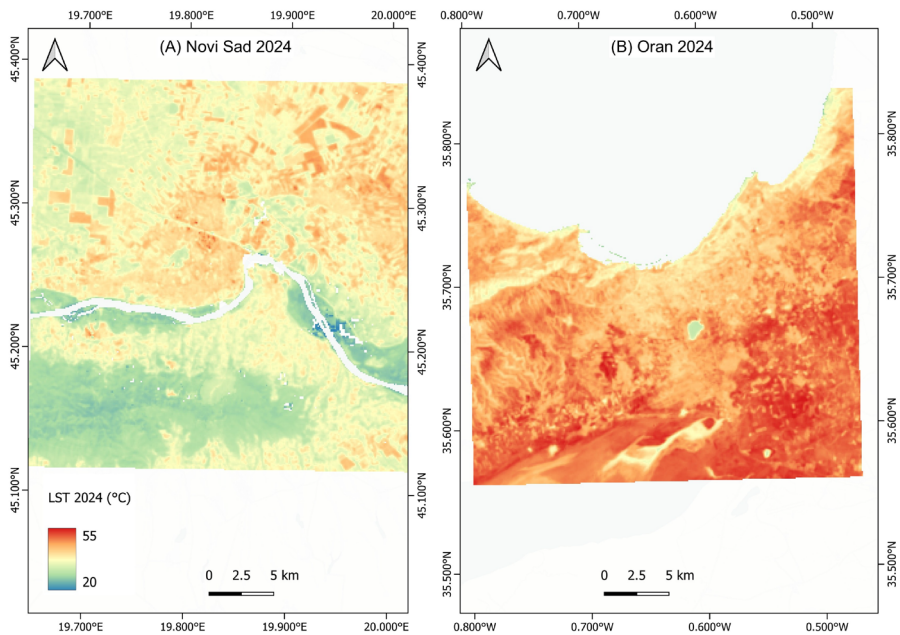


Figure 5. June–September median LST for 2024 at 100 m resolution.

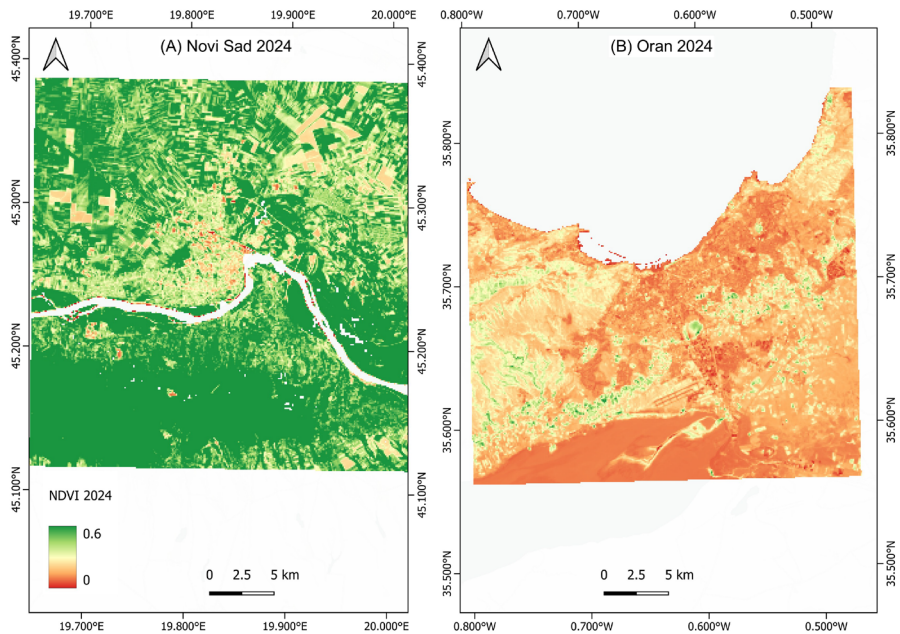


Figure 6. June–September median NDVI for 2024 at 100 m resolution.

For the pixel-wise change analysis reported in this section, population-level 95% confidence intervals for mean change values were computed from the full overlap pixel set. For Oran, mean Δ LST was +2.28 °C (95% CI: 2.24–2.31, n = 61,221) and mean Δ NDVI was –0.027 (95% CI: –0.028 to –0.026). For Novi Sad, mean Δ LST was +0.57 °C (95% CI: 0.56–0.59, n = 87,150) and mean Δ NDVI was –0.104 (95% CI: –0.105 to –0.103). Although statistically significant, the mean LST change in Novi Sad should be interpreted cautiously because it remains within the per-pixel LST uncertainty threshold.

4.2. Meteorological and land cover context

Meteorological data from the ERA5-Land reanalysis dataset and land cover metrics from the Dynamic World dataset were extracted for both cities (Table 2). These variables are used as contextual descriptors for the two composite windows and should not be interpreted as evidence of long-term climatic trends. In Novi Sad, mean air temperature over the June–September window increased from 23.20 °C in 2015 to 24.51 °C in 2024, while total precipitation over the same window was 179.13 mm in 2015 and 213.14 mm in 2024. These values provide meteorological context for the Landsat composites but are not used to infer a long-term precipitation trend.

For Oran, mean air temperature over the June–September window increased from 25.36 °C in 2015 to 25.73 °C in 2024, while total precipitation over the same window was 15.96 mm in 2015 and 22.18 mm in 2024. Concurrently, satellite-derived land cover data reveal that the built-up area in Oran expanded from 130.38 km² in 2016 to 137.11 km² in 2024, representing an expansion of approximately 6.73 km² of impervious surface. In Novi Sad, built-up area expanded more substantially from 116.00 km² to 132.87 km², an increase of 16.87 km². These land-cover and meteorological variables provide contextual information for interpreting the contrasting LST–NDVI statistical associations, while avoiding direct causal inference from two-year meteorological differences.

Table 2. Meteorological and land cover context for Oran and Novi Sad

City	Year	Mean air temperature (°C)	June–September precipitation (mm)	Built-up area (km ²)	Built-up change (km ²)
Oran	2015	25.36	15.96	130.38*	
Oran	2024	25.73	22.18	137.11	+6.73
Novi Sad	2015	23.20	179.13	116.00*	
Novi Sad	2024	24.51	213.14	132.87	+16.87

Note. *Built-up area for 2015 corresponds to the 2016 baseline from Dynamic World, which commenced coverage in late 2015.

4.3. Quantitative assessment of the LST–NDVI relationship

A pixel-level statistical analysis based on 3,000 random samples per city per year was conducted to quantify the decadal shift in the LST–NDVI relationship (Figure 7; Table 3). In Novi Sad, the inverse correlation remained strong, but weakened from r = –0.78 (p < 0.001, R^2 = 0.608) in 2015 to r = –0.69 (p < 0.001, R^2 = 0.481) in 2024; this decline was statistically significant according to Fisher’s z -transformation (z = 7.35, p < 0.001). Despite this reduction, vegetation retained a substantial cooling association with surface temperature.

In Oran, the relationship was already weak in 2015 (r = –0.23, p < 0.001, R^2 = 0.053) and declined further in 2024 (r = –0.08, p < 0.001, R^2 = 0.007), with the deterioration also

significant by Fisher's z-transformation ($z = 5.87$, $p < 0.001$). Although statistically significant because of the large sample size ($n = 3,000$), the 2024 relationship in Oran was practically negligible, as vegetation density explained less than 1% of LST variance. These contrasting trajectories are consistent with the wetter conditions in Novi Sad and the more arid conditions in Oran (Table 2). A matched-pixel sensitivity analysis produced the same overall pattern. Using 3,000 spatially coincident pixels valid in both composites, Steiger's (1980) test for dependent nonoverlapping correlations confirmed a significant weakening of the relationship in both Oran ($r = -0.229$, 95% CI: -0.26 to -0.20 ; $r = -0.104$, 95% CI: -0.14 to -0.07 , $p < 0.001$) and Novi Sad ($r = -0.780$, 95% CI: -0.79 to -0.77 ; $r = -0.693$, 95% CI: -0.71 to -0.67 , $p < 0.001$). The matched-pixel correlations are broadly consistent with the independent-sample estimates reported in Table 3, with minor differences attributable to the restriction to pixels with valid data in both temporal composites.

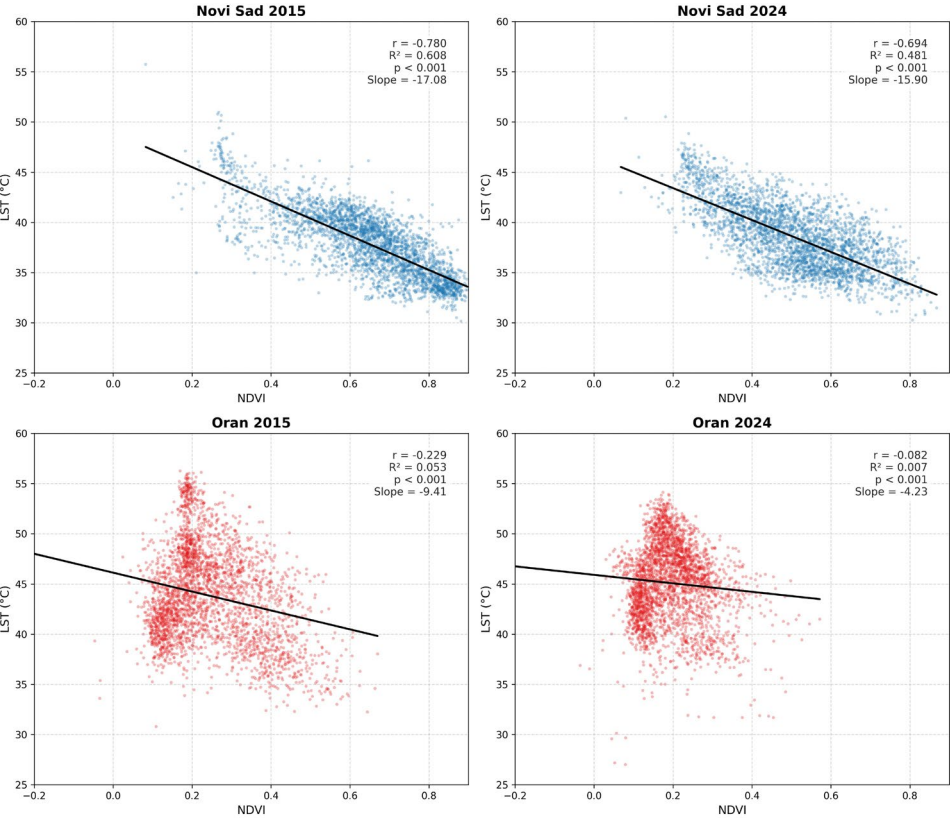


Figure 7. Scatter plots of LST versus NDVI for 3,000 random samples per city per year with regression lines.

Table 3. Pearson correlation coefficients, linear regression parameters, and Fisher z-transformation results for the LST–NDVI relationship based on 3,000 random pixel samples per city per year

City	Year	r	p	R^2	Slope (β_1)	Intercept (β_0)	Fisher z (p)
Novi Sad	2015	−0.780	< 0.001	0.608	−17.08	48.91	7.35 (< 0.001)
Novi Sad	2024	−0.694	< 0.001	0.481	−15.90	46.59	
Oran	2015	−0.229	< 0.001	0.053	−9.41	46.12	5.87 (< 0.001)
Oran	2024	−0.082	< 0.001	0.007	−4.23	45.90	

4.4. Vegetation density categorical analysis

The 3,000-pixel random samples were classified into NDVI density categories (Table 4). This categorical analysis reveals the contrasting vegetative compositions of the two cities and their decadal trajectories. In Novi Sad, the number of densely vegetated pixels (NDVI > 0.5) declined from 2,526 in 2015 to 1,581 in 2024, a reduction of 37.4%, while semi-barren pixels (NDVI 0.1 to 0.3) increased from 92 to 279. Despite this substantial shift in vegetation density, the landscape remained overwhelmingly green, with the majority of sampled pixels maintaining NDVI values above 0.3. In Oran, the vegetative decline was far more pronounced. Dense vegetation pixels declined from an already marginal 71 in 2015 to merely 5 pixels in 2024, while semi-barren pixels increased from 2,022 to 2,590, dominating the landscape. This very limited representation of densely vegetated surfaces in the 2024 Oran sample corroborates the statistical decoupling observed in the correlation analysis and provides additional evidence of the extensive vegetation degradation in the Mediterranean context.

Table 4. Categorical distribution of NDVI density classes within the 3,000-pixel random samples for each city and year

City / Year	Dense vegetation (NDVI > 0.5)	Semi-barren (NDVI 0.1–0.3)	Other
Novi Sad 2015	2,526	92	382
Novi Sad 2024	1,581	279	1,140
Oran 2015	71	2,022	907
Oran 2024	5	2,590	405

Note: The “Other” category primarily comprises moderate vegetation with NDVI between 0.3 and 0.5, and highly reflective built-up surfaces with NDVI < 0.1.

4.5. Climate-dependent vegetation cooling and continental resilience

Results indicate contrasting LST–NDVI statistical associations across the two study areas. In Novi Sad, the strong inverse LST–NDVI relationship ($r = -0.78$ in 2015; $r = -0.69$ in 2024) aligns with evidence of substantial tree cooling in temperate and continental settings (Schwaab et al., 2021) and is consistent with previous evidence of vegetation-related microclimatic cooling in Novi Sad (Simović et al., 2025). Despite NDVI declining from 0.679 to 0.576 and mean air temperature over the June–September window increasing from 23.20 °C to 24.51 °C, the correlation remained strongly negative, suggesting that higher vegetation density continued to be associated with lower LST in Novi Sad. In contrast, Oran’s LST–NDVI coupling weakened sharply from $r = -0.23$ in 2015 to $r = -0.08$ in 2024 (Fisher $z = 5.87$, $p < 0.001$; Table 3). This finding challenges the universal applicability of urban greening strategies and supports

evidence that cooling benefits are constrained in hot, arid environments (Ibsen et al., 2021; Kucera & Jenerette, 2023; Soltanifard & Amani-Beni, 2025). Overall, the contrast suggests that cooling depends not only on vegetation quantity, but also on whether vegetation remains physiologically functional under local hydroclimatic conditions. These differences should not be attributed to climate alone. The two study areas also differ in population size and density, built-up morphology, coastal versus riverine setting, surrounding land-cover gradients, and the structure and maturity of urban vegetation. These factors may also influence LST patterns and should be considered when interpreting the contrast between Oran and Novi Sad.

4.6. Weakening of the LST–NDVI association under water-limited conditions

The weakened LST–NDVI association observed in Oran is consistent with both canopy loss from land conversion and water-limited stress affecting the remaining vegetation, although stomatal conductance was not directly measured in this study. ERA5-Land data indicate very low precipitation in Oran during the June–September windows of the two analyzed years, with 15.96 mm in 2015 and 22.18 mm in 2024. Under such water-limited conditions, urban trees may face hydraulic stress (Savi et al., 2016), and stomatal closure may suppress transpiration, reducing cooling efficiency (Kinzinger et al., 2025; Mas et al., 2024). This interpretation is consistent with Oran’s severe loss of dense vegetation (NDVI > 0.5 declined from 71 to 5 pixels; Table 4). This weakening of the LST–NDVI association is consistent with the combined influence of land-cover change and water-limited conditions in the Oran study area (Illán-Fernández et al., 2025). This interpretation is also consistent with global evidence that vegetation cooling weakens in arid environments and may even shift toward a net warming effect when limited evapotranspiration is outweighed by other surface properties (Guo et al., 2026). Likewise, severe drought can force trees to prioritize survival over microclimate regulation by shifting root water uptake toward deep reserves (Kinzinger et al., 2025), thereby reducing their cooling function (Oberleitner et al., 2022).

4.7. Coastal dynamics and governance implications

The geographic setting also shapes thermal behavior. In Oran, Mediterranean maritime influence appears to control spatial surface temperature patterns more strongly than neighborhood-scale greening, although sea breezes do not prevent the observed 2.28 °C increase in LST. Coastal studies show that sea-breeze systems can act as dominant cooling mechanisms, often overshadowing localized canopy effects (Alomar-Garau & Grimalt-Gelabert, 2022; Burkart et al., 2016). By contrast, landlocked Novi Sad depends more directly on internal green infrastructure for heat mitigation (Simović et al., 2025).

Urban expansion alone cannot explain the divergent thermal trends. Although Novi Sad’s built-up increase exceeded Oran’s (16.87 km² vs. 6.73 km²; Table 2), its warming remained modest at 0.57 °C. Built-up area alone does not fully describe urban pressure or thermal behavior. The two cities also differ in the demographic, morphological, and ventilation characteristics noted earlier. Therefore, similar or even larger built-up expansion values may produce different thermal responses depending on the spatial structure and intensity of land use within each city. Oran’s 6.73 km² expansion represents only approximately 1% of the study area, suggesting that built-up expansion alone is insufficient to explain the 2.28 °C increase in LST. Instead, Oran’s warming is more plausibly linked to macro-climatic forcing and widespread loss of evaporative cooling capacity, affecting 71.30%

of the landscape, while urban expansion indirectly replaced functional vegetation with impervious surfaces.

These findings suggest that urban heat adaptation should be tailored to local biophysical conditions (An & Dedekorkut-Howes, 2025; Dubash et al., 2022). For semi-arid cities such as Oran, directly importing water-intensive European greening models may be ineffective and hydrologically unsustainable. More suitable responses include drought-resistant xeriscaping, urban design that improves sea-breeze penetration, and high-albedo materials (Falasca et al., 2019).

5. Conclusion

This study examined two-period change in the statistical relationship between LST and NDVI across the Oran and Novi Sad study areas between 2015 and 2024. In Novi Sad, the Pearson correlation weakened from $r = -0.78$ to $r = -0.69$, but remained strongly negative, indicating that higher NDVI values continued to be associated with lower LST. In Oran, the relationship weakened from $r = -0.23$ to $r = -0.08$, a change confirmed by the Fisher z -transformation ($z = 5.87$, $p < 0.001$), and by 2024 NDVI explained less than 1% of LST variance. Pixel-wise change analysis further showed stronger thermal amplification and vegetation degradation in Oran, while Novi Sad displayed a more heterogeneous spatial pattern, including localized cooling in parts of the urban area and warming in peri-urban zones.

These findings suggest that urban vegetation–temperature relationships are highly context-dependent and should not be generalized across cities without considering local climatic setting, urban morphology, population pressure, land-cover structure, and coastal or riverine conditions. For semi-arid coastal settings such as Oran, heat mitigation strategies may need to combine drought-resistant vegetation, careful urban design, and high-albedo materials rather than relying only on conventional tree-planting approaches.

The findings should be interpreted in light of several limitations. The analysis compares only two temporal snapshots, 2015 and 2024, and therefore does not establish long-term climatic trends. The 30×30 km analytical extents include both urban and non-urban pixels, so the results should not be interpreted as describing the urban core alone. In addition, Pearson correlation identifies statistical association but does not prove causation, and physiological processes such as stomatal closure were not directly measured. Future research should use longer multi-year time series, urban-core and land-cover-stratified analyses, and additional field or meteorological observations to better separate the roles of vegetation structure, urban form, atmospheric variability, and water availability.

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