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Remote Sensing Analysis of Urban Heat Island Dynamics Using NDVI, NDBI, and LST in Constantine, Algeria (2005–2024)

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Research Article

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Remote Sensing Analysis of Urban Heat Island Dynamics Using NDVI, NDBI, and LST in Constantine, Algeria (2005–2024)

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Abstract

The intensification of the Urban Heat Island (UHI) effect represents a major environmental challenge in rapidly expanding semi-arid cities, where vegetation loss and the growth of impervious surfaces significantly alter the urban thermal environment. This study analyses the spatiotemporal evolution of vegetation cover, built-up surface characteristics, and land surface temperature (LST) in Constantine, Algeria, over the period 2005–2024, using multi-temporal Landsat imagery integrated within a Geographic Information System (GIS) framework. Biophysical indices, namely the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI), were derived to characterise land cover dynamics and examined in relation to LST retrieved from thermal bands through radiometric calibration and emissivity-based correction methods. The results indicate pronounced land surface transformations, marked by a substantial decline in vegetated areas and a significant increase in built-up–related spectral responses over the study period. Regression analyses reveal a consistent negative relationship between NDVI and LST, confirming the cooling role of vegetation, with the strongest association observed in 2015 ($R^2 \approx 0.26$), followed by a notable weakening in 2024 ($R^2 \approx 0.08$). Conversely, NDBI exhibits a positive relationship with LST, highlighting the warming influence of built-up surface intensity, with regression slopes increasing from approximately 9.8 °C in 2005 to 29 °C in 2024, despite moderate explanatory power ($R^2 = 0.29–0.42$). Spatial analysis of UHI patterns further demonstrates the growing dominance of high-LST zones (24–30 °C) in 2024 compared with cooler thermal conditions in 2005.

Key words: Urban Heat Island (UHI); Land Surface Temperature (LST); NDVI; NDBI; Remote Sensing; Urbanization; Algeria

1. Introduction

The world is experiencing an unprecedented pace of urbanisation, with more than half of the global population now residing in urban areas (Qiu et al., 2025). This rapid expansion has profoundly transformed terrestrial landscapes and led to the emergence of a distinct climatic phenomenon known as the Urban Heat Island (UHI) (Oke, 1982; Yang et al., 2017; Qiu et al., 2025). The UHI effect is characterised by elevated air and land surface temperatures in urban environments relative to their surrounding rural areas (Zhou et al., 2018; Yao et al., 2019; Vinayak et al., 2022). It primarily results from the replacement of natural land cover with impervious surfaces such as asphalt and concrete, which exhibit high heat absorption and storage capacities (Sarif et al., 2022; Shahfahad et al., 2022). Additional contributing factors include urban morphology, reduced vegetation cover, and anthropogenic heat emissions associated with human activities (O'Malley et al., 2014; O'Malley et al., 2015; Kim & Brown, 2021). The consequences of UHIs are multifaceted, encompassing increased energy demand for cooling, deterioration of air quality, and adverse impacts on human health and thermal comfort (Rasul et al., 2017; Bouketta, 2023).

The investigation of UHIs has been significantly advanced by developments in remote sensing and Geographic Information Systems (GIS), which enable consistent monitoring of urban thermal environments across large spatial extents and long temporal scales (Sharma & Joshi, 2016; Almeida et al., 2021). In particular, Landsat satellite data provide a valuable archive for analysing Land Surface Temperature (LST) dynamics and their relationship with land cover characteristics (Weng, 2009; Weng et al., 2014; Parastatidis et al., 2017; Li et al., 2023). To explore the interactions between urbanisation, vegetation, and surface temperature, a range of spectral indices has been widely applied (Qin et al., 2017; Li et al., 2023). The Normalized Difference Vegetation Index (NDVI) is commonly used as an indicator of vegetation presence and condition (Tucker, 1979), whereas the Normalized Difference Built-up Index (NDBI) is employed to characterise built-up and impervious surface features (Ouma et al., 2021; Bhomi et al., 2024).

A substantial body of literature reports a negative relationship between NDVI and LST, reflecting the cooling effect of vegetation through shading and evapotranspiration, alongside a positive relationship between NDBI and LST, highlighting the warming influence of built-up surfaces (Zhang et al., 2009; Guha et al., 2018; Sharma & Joshi, 2016). For example, Zhang et al. (2009) demonstrated strong associations between impervious surface fraction, NDBI, and LST, while Guha et al. (2018) confirmed similar patterns in Italian cities using Landsat-derived indices. The combined use of NDVI and NDBI has therefore proven effective for analysing the spatial structure of UHIs and the underlying land surface processes driving urban thermal variability. Comparable approaches have been successfully applied to assess the environmental impacts of rapid urbanisation in diverse geographical contexts, including large metropolitan regions in India (Sharma & Joshi, 2016; Anaud, et al, 2025).

In arid and semi-arid regions, such as much of North Africa and Algeria, UHI studies are of particular relevance due to high solar radiation levels, limited vegetation cover, and pronounced seasonal contrasts, all of which may intensify urban thermal responses (Bourbia & Boucheriba,

2010; Sahnoune et al., 2021; Jaber, 2023). In Algeria, several studies have examined UHI characteristics in major cities using remote sensing techniques to relate LST patterns to land cover and surface indices (Chraïr et al., 2020; Selka et al., 2024; Bendib & Boutrid, 2024). Selka et al. (2024), for instance, employed Google Earth Engine to analyse Landsat imagery from 1989 to 2019 in Tlemcen, integrating NDVI, NDBI, and NDLI with random forest classification to evaluate the thermal impacts of land-use change. Similarly, Chraïr et al. (2020) investigated the influence of land cover dynamics and seasonal variability on LST in the Oued Fekan sub-watershed.

Constantine, a rapidly expanding city characterised by a semi-arid climate and complex topography, represents a particularly relevant case for advancing the understanding of UHI dynamics in Algerian cities (Benlakhlef & Bergel, P. 2016; Khellaf & Saliha, 2021; Benoumeldjadj et al., 2023). Although previous studies have provided initial insights into urban thermal patterns in Constantine, a comprehensive spatiotemporal analysis focusing on the combined behaviour of NDVI, NDBI, and LST over multiple decades remains limited. In particular, there is a need to better characterise how vegetation decline and the intensification of built-up surface characteristics have jointly influenced the evolution of surface urban heat islands in this semi-arid urban context.

Accordingly, this study aims to analyse the surface Urban Heat Island in Constantine, Algeria, by examining the relationships between Land Surface Temperature (LST), the Normalized Difference Vegetation Index (NDVI), and the Normalized Difference Built-up Index (NDBI) over the period 2004–2024. The specific objectives are to: (1) estimate LST using multi-temporal Landsat data; (2) compute and map NDVI and NDBI to characterise land surface dynamics; and (3) analyse spatial correlations between LST, NDVI, and NDBI in order to identify areas most affected by the UHI effect and to better understand the relative influence of vegetation and built-up surface characteristics on the urban thermal environment. The results are intended to provide scientifically robust insights to support urban planning strategies and climate-sensitive decision-making in semi-arid cities (Li & Chen, 2023).

2. Study area

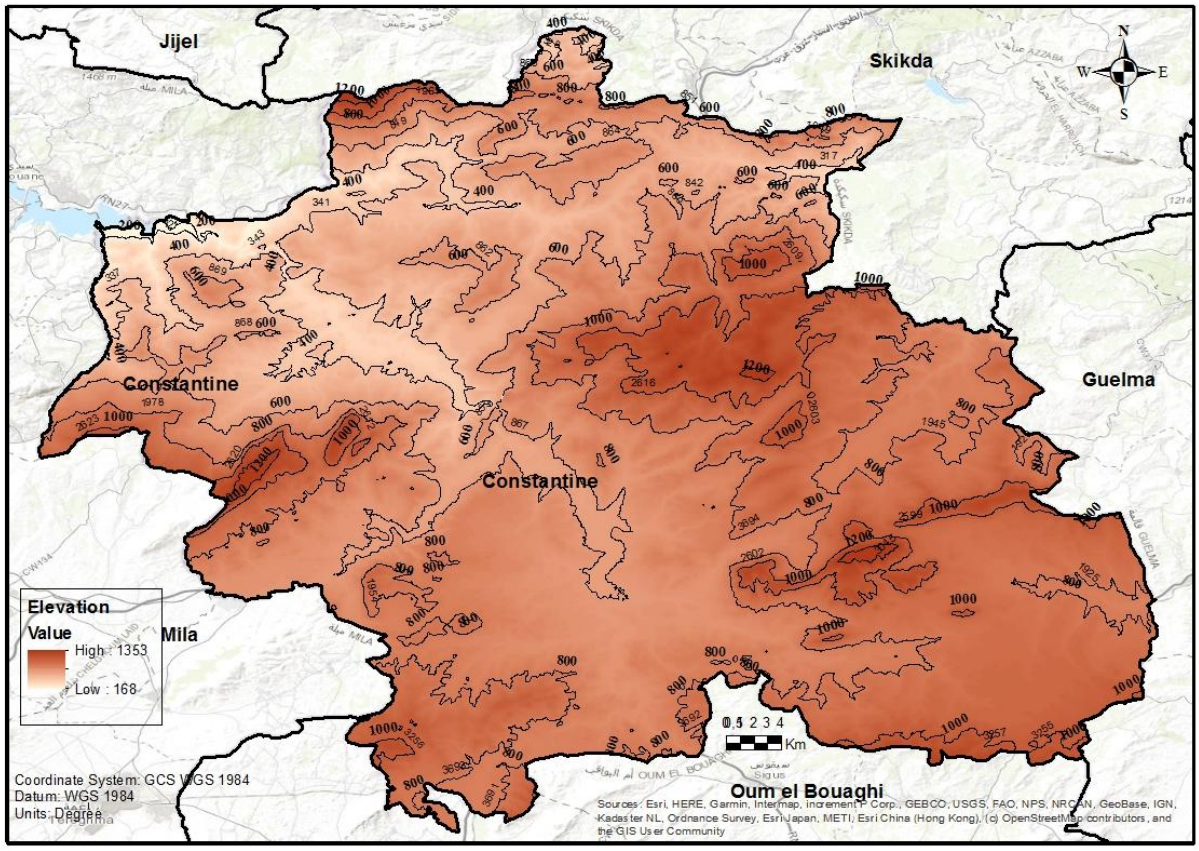
The study area is the city of Constantine, located in northeastern Algeria (36°21′ N, 6°36′ E), approximately 320 km east of Algiers. Commonly referred to as the “City of Bridges,” Constantine is situated on a rocky plateau deeply incised by the Rhumel River gorge, resulting in a highly contrasted and complex urban topography (Diaf et al., 2023). Administratively, the municipality covers an area of approximately 2,297 km² and hosts more than 940,000 inhabitants, ranking among the major urban centres of Algeria.

Climatically, Constantine is characterised by a Mediterranean semi-arid regime (Köppen–Geiger classification Csa), with hot, dry summers and relatively mild, wetter winters. Mean annual air temperatures range between 16 °C and 18 °C, while average annual precipitation varies from 600 to 700 mm (Meskaldji, 1994; Khellaf & Saliha, 2021). Summer conditions are marked by high thermal stress, with mean daily maximum temperatures reaching approximately 35.0 °C in July and 34.6 °C in August. In contrast, winter temperatures are considerably lower,

with mean daily minima of around 2.3 °C in January and 2.5 °C in February. These climatic conditions, combined with limited soil moisture availability during the dry season, constrain evapotranspiration processes and reduce the natural cooling capacity of vegetated surfaces, thereby enhancing surface thermal sensitivity.

Over the past two decades, Constantine has undergone rapid demographic growth and pronounced urban expansion, particularly in peripheral districts such as Ali Mendjeli and Aïn Smara (Diaf, 2025). This urban growth has been accompanied by a substantial reduction in vegetation cover and a marked increase in impervious surfaces, processes that are widely recognised as key drivers of Urban Heat Island intensification. The conjunction of complex topography, a semi-arid climatic context, and accelerated land-use transformation makes Constantine a particularly suitable case study for analysing the interactions between vegetation dynamics, built-up surface characteristics, and land surface temperature patterns in semi-arid urban environments.

Fig.1: map of localisation of Constantine city



3. Data and methods

3.1 Data sources and image selection

This study is based on multi-temporal Landsat imagery acquired for the years 2004, 2014, and 2024 in order to capture long-term changes in land surface characteristics and urban thermal patterns in Constantine (table 1). Landsat 5 Thematic Mapper (TM) data were used for 2004,

while Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) data were employed for 2014 and 2024. These sensors provide a consistent and widely validated archive for land surface temperature (LST) and land cover analysis at a spatial resolution suitable for urban-scale studies.

Table 1: Landsat 5 TM and Landsat 8 OLI/TIRS Band Designations for UHI Analysis

Sensor	**Band No.**	**Band Name**	**Wavelength (µm)**	**Spatial Resolution (m)**	**Application in UHI Analysis**
Landsat 5 TM	3	Red	0.63–0.69	30	NDVI
	4	Near Infrared (NIR)	0.76–0.90	30	NDVI
	5	SWIR1	1.55–1.75	30	NDBI
	6	Thermal Infrared (TIR)	10.40–12.50	120 (resampled to 30)	LST estimation
Landsat 8 OLI/TIRS	4	Red	0.64–0.67	30	NDVI
	5	Near Infrared (NIR)	0.85–0.88	30	NDVI
	6	SWIR1	1.57–1.65	30	NDBI
	10	Thermal Infrared (TIR)	10.60–11.19	100 (resampled to 30)	LST estimation

To ensure interannual comparability, images were selected under similar seasonal conditions, prioritising cloud-free scenes acquired during the summer period (June to September) as shown in table 2, when the Urban Heat Island effect is typically most pronounced. Additional selection criteria included low cloud cover, stable atmospheric conditions, and minimal synoptic wind influence. All images were resampled to a common spatial resolution of 30 m to allow pixel-by-pixel comparison across the study period. While differences in sensor characteristics between Landsat 5 and Landsat 8 may introduce slight systematic biases, the use of standardised preprocessing and retrieval procedures helps to minimise their influence on relative spatial and temporal patterns.

Table 2: Characteristics of Landsat Scenes Used in the Study (2005–2024)

Study Period	**Landsat Sensor**	**Acquisition Date**	**Cloud Cover (%)**	**Solar Azimuth (°)**	**Solar Elevation (°)**
Period 1 (Reference)	Landsat 5 TM	July 2005	0.0	112.3	61.7
Period 2 (Transition)	Landsat 8 OLI/TIRS	July 2015	0.0	121.0	65.4
Period 3 (Recent)	Landsat 8 OLI/TIRS	July 2024	0.0	122.5	66.2

3.2 Pre-processing and radiometric correction

All Landsat images were subjected to a standardised pre-processing workflow to convert raw digital numbers (DNs) into physically meaningful quantities. This process included radiometric calibration, atmospheric correction, and conversion to top-of-atmosphere (TOA) reflectance for optical bands and brightness temperature for thermal bands. These steps are essential to ensure consistency across sensors and acquisition dates and to reduce atmospheric and illumination-related artefacts.

Thermal infrared bands (TM Band 6 for Landsat 5 and TIRS Band 10 for Landsat 8) were processed following established procedures to derive brightness temperature, which was subsequently corrected for land surface emissivity (LSE). Emissivity values were estimated using an NDVI-based approach that accounts for vegetation proportion, enabling improved LST retrieval over heterogeneous urban surfaces.

Two widely used spectral indices were computed to characterise land surface properties and urbanisation-related features:

Normalized Difference Vegetation Index (NDVI) (Indice de Végétation par Différence Normalisée): Widely applied to quantify vegetation cover and health Tucker (1979).

$$NDVI=(NIR-RED)/(NIR+RED)$$

Normalized Difference Built-up Index (NDBI) (Indice de Bâti par Différence Normalisée): Utilized for mapping urban areas and impervious surfaces (Zha et al. 2003).

$$NDBI=(SWIR-NIR)/(SWIR+NIR)$$

NDVI values range from −1 to +1, with higher values indicating denser vegetation cover, whereas positive NDBI values generally correspond to surfaces exhibiting built-up or impervious characteristics. In semi-arid environments, however, it is recognised that bare soils and sparsely vegetated areas may display spectral behaviour similar to impervious surfaces; therefore, NDBI results are interpreted as indicators of built-up spectral intensity rather than direct measures of urban land extent.

The table 3 show the spectral indices and parameters used for land surface temperature retrieval and UHI analysis. Land Surface Temperature (LST) was retrieved from thermal infrared data using a multi-step procedure adapted to each sensor. First, spectral radiance was computed from calibrated digital numbers, followed by the calculation of brightness temperature using sensor-specific calibration constants. Land surface emissivity was then estimated based on the proportion of vegetation derived from NDVI, and LST was obtained by applying emissivity-corrected algorithms appropriate for Landsat 5 and Landsat 8 sensors (Sobrino et al., 2004; Weng & Schubring, 2004). Final LST values were converted from Kelvin to degrees Celsius to facilitate interpretation and comparison across years.

Although absolute LST values derived from different Landsat sensors may be subject to residual uncertainty, the adopted methodology ensures that relative spatial patterns and interannual trends remain robust for comparative analysis.

Spatial analyses were conducted to examine the distribution and evolution of NDVI, NDBI, and LST across the study area. Urban Heat Island intensity was assessed by classifying LST into thermal classes, enabling the identification of high- and low-temperature zones and their spatial expansion over time. Statistical relationships between LST and the biophysical indices were explored using linear regression analysis. Separate regressions were performed for NDVI–LST and NDBI–LST for each study year to assess temporal variations in the strength and direction of these relationships. The regression slope and coefficient of determination (R^2) were used to evaluate the magnitude of vegetation cooling effects and built-up warming influences. While more advanced spatial or non-linear models may capture additional heterogeneity, the linear framework provides a transparent and interpretable baseline for interannual comparison and consistency with previous UHI studies.

Table 3: Spectral indices and parameters used for land surface temperature retrieval and UHI analysis

Index/Parameter	**Equation**	**Applicable Sensor**	**Key Variables/ Constants**	**Reference**
Normalized Difference Vegetation Index (NDVI)	(NIR−RED)/(NIR+RED)	Both	NIR, RED	(Tucker, 1979)
	(Band4−Band3)/(Band4+Band3)	Landsat 5 TM	Band 3, Band 4	
	(Band5−Band4)/(Band5+Band4)	Landsat 8 OLI	Band 4, Band 5	
Normalized Difference Built-up Index (NDBI)	(SWIR−NIR)/(SWIR+NIR)	Both	SWIR, NIR	(Zha et al. 2003)
	(Band5−Band4)/(Band5+Band4)	Landsat 5 TM	Band 4, Band 5	
	(Band6−Band5)/(Band6+Band5)	Landsat 8 OLI	Band 5, Band 6	
Proportion of Vegetation (Pv)	((NDVI−NDVImin)/(NDVImax −NDVImin))2	Both	NDVI, NDVImin, NDVImax	(Weng & Schubring, 2004)
Land Surface Emissivity (LSE)	$\epsilon=\epsilon v\times Pv+\epsilon s\times(1-Pv)+C$	Both	ϵv, ϵs, Pv, C	(Sobrino et al, 2004)
TOA Spectral Radiance (Lλ)	ML×Qcal+AL	Both	ML, Qcal, AL	
Brightness Temperature (BT)	K2/ln((K1/Lλ)+1)	Both	K1, K2, Lλ	(Sobrino et al, 2004)
Land Surface Temperature (LST) (MW/SC)	BT/(1+(λ×BT/C2)×ln(ϵ))	Both	BT, λ, C2, ϵ	(Weng & Schubring, 2004)
	Landsat 5: λ=11.45μm (Band 6)	Landsat 5 TM		
	Landsat 8: λ=10.8μm (Band 10)	Landsat 8 TIRS		
LST (Celsius)	LST Kelvin−273.15	Both	LST Kelvin	(Sobrino et al, 2004)

4. Results

4.1 Vegetation and Built-up Indices (NDVI and NDBI)

The analysis first focused on the spatiotemporal evolution of vegetation and built-up surface characteristics in Constantine between 2005 and 2024, as derived from the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI). These indices were used to characterise changes in surface properties associated with vegetation dynamics and urban development intensity over the study period.

Fig 2: the spatial distribution of NDVI and NDBI (2005-2024)

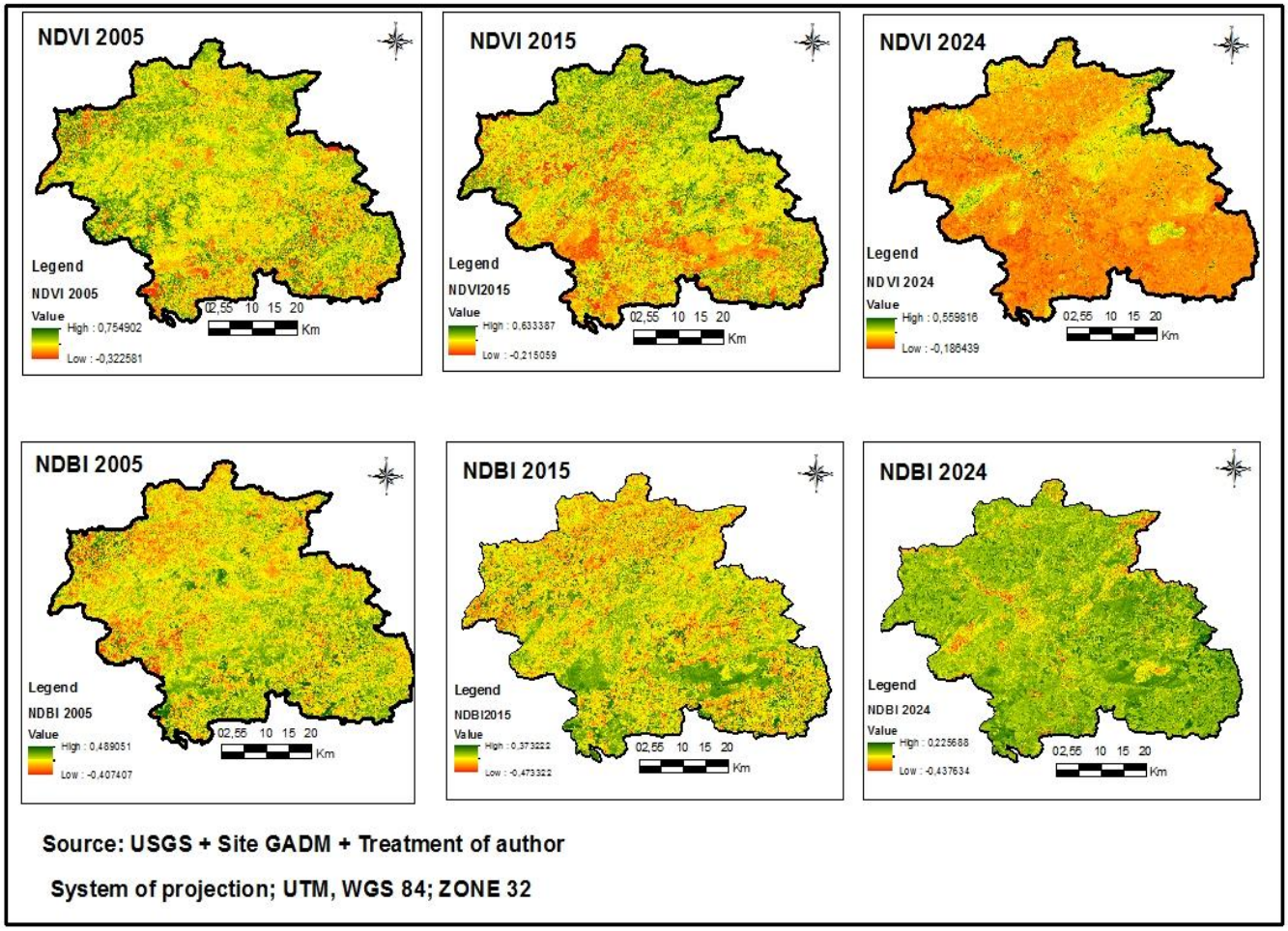


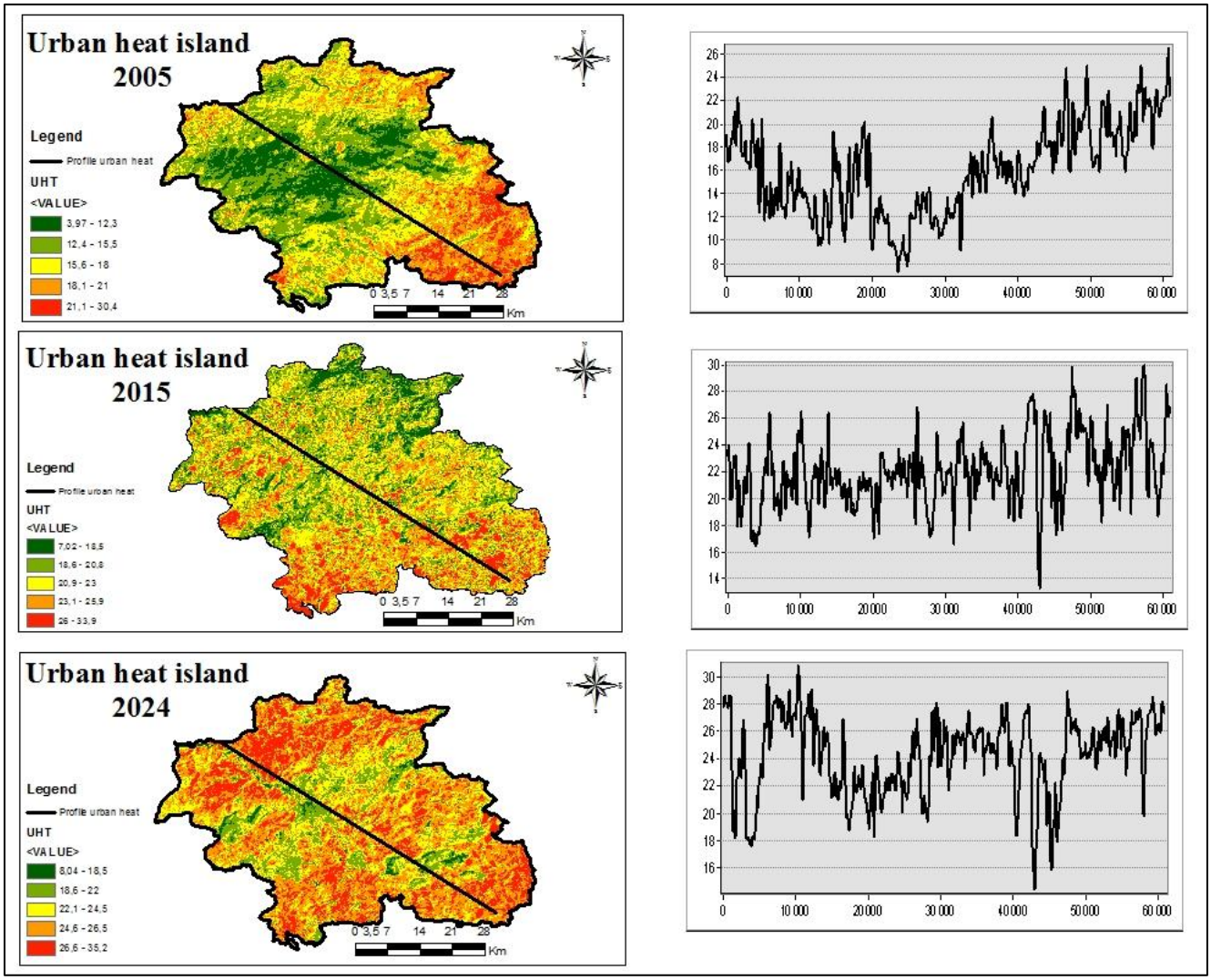
Fig.2 illustrates the spatial distribution of NDVI and NDBI for the years 2005, 2015, and 2024. The NDVI maps reveal a clear reduction in vegetated surface signals over time. In 2005, relatively high NDVI values were observed across large portions of the study area, with maximum values reaching approximately 0.75, indicating extensive vegetation cover. By contrast, in 2024 the maximum NDVI values declined to around 0.56, while large areas exhibited low or near-zero NDVI values, reflecting a substantial reduction in vegetated surfaces. Conversely, the NDBI maps display an expansion of surfaces exhibiting built-up–related spectral characteristics. In 2005, positive NDBI values were spatially limited and primarily concentrated around the historic urban core, with maximum values of approximately 0.48. By 2024, although the maximum NDBI values decreased to around 0.22 likely reflecting

increased surface heterogeneity the spatial extent of positive NDBI values expanded markedly. These areas became increasingly dominant around the central urban zone of Constantine and along major development corridors, indicating a pronounced intensification of built-up surface characteristics.

4.2.Urban Heat Island Dynamics in Constantine

The spatial and temporal analysis of the Urban Heat Island (UHI) effect in Constantine between 2005 and 2024 reveals a clear intensification of Land Surface Temperature (LST) patterns across the study area. Classified LST maps (Fig. 3) show a progressive expansion of high-temperature zones, indicating an increasing spatial extent of surface UHI conditions over time.In 2005, low-temperature classes (4–18 °C) dominated large portions of the study area, particularly in the central and northern sectors of the city. High-temperature zones exceeding 21 °C were spatially limited and mainly confined to the southeastern part of Constantine. By 2015, moderate- to high-temperature classes (18–26 °C) expanded considerably, occupying a larger proportion of the urban landscape.

Fig 3: Urban Heat Island Profiles (2005–2024)



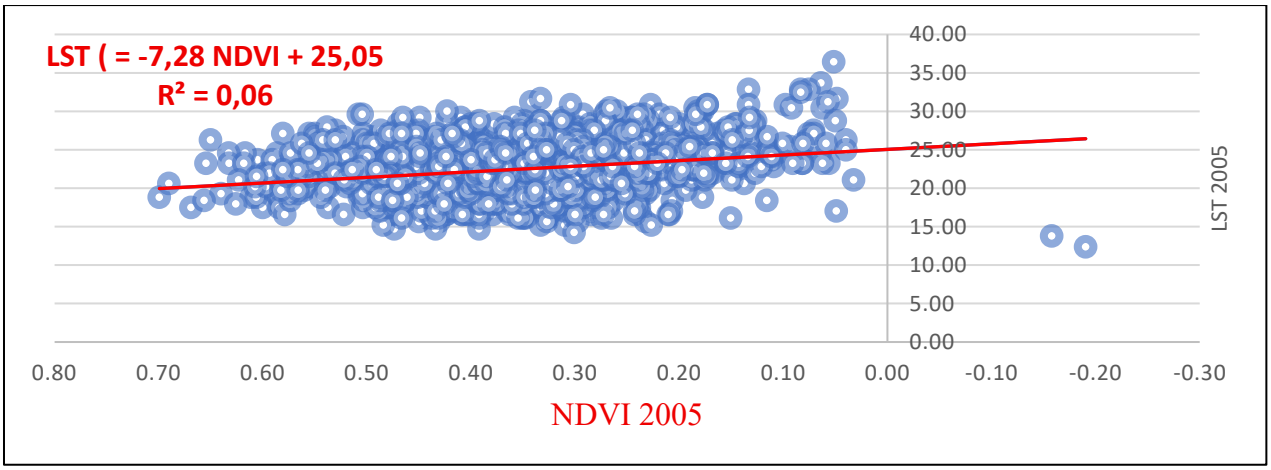
These higher-temperature zones became more spatially continuous and were no longer restricted to isolated areas. In 2024, the thermal structure of the city was characterised by the predominance of high-temperature classes, with LST values ranging from approximately 24 to 30.4 °C across extensive areas. Cooler temperature zones became increasingly fragmented and spatially marginal, indicating a substantial modification of the surface thermal environment over the study period.

The spatial patterns observed in the classified LST maps are further supported by temperature profiles extracted along a diagonal transect across the study area. In 2005, LST values along the transect ranged from approximately 8 °C to 22 °C, with limited thermal variability and a small number of localised peaks corresponding to urbanised sectors. In 2015, the transect profile exhibited increased thermal variability, with more frequent temperature fluctuations and peak values reaching up to approximately 28 °C. This pattern reflects a more heterogeneous surface thermal structure compared to 2005. By 2024, the transect profile displayed consistently elevated LST values, with temperatures rarely falling below 20 °C and sustained peaks exceeding 26 °C across large portions of the transect. The reduction in low-temperature intervals and the persistence of high-temperature values indicate a marked rise in baseline surface temperatures throughout the urban and peri-urban areas of Constantine.

4.3.Correlation NDVI with LST

The regression analysis for 2005 shows a weak negative relationship between NDVI and LST (fig.4). The regression equation was LST(°C) = −7.28 × NDVI + 25.05, with a slope of −7.28. This indicates that for each unit increase in NDVI, LST decreased by approximately 7.3 °C, reflecting the cooling role of vegetation. The intercept of 25.05 °C represents the predicted surface temperature in areas where NDVI approaches zero, corresponding to bare or sparsely vegetated land surfaces. The coefficient of determination (R^2 = 0.06) suggests that NDVI explained only about 6% of the variation in LST in 2005.

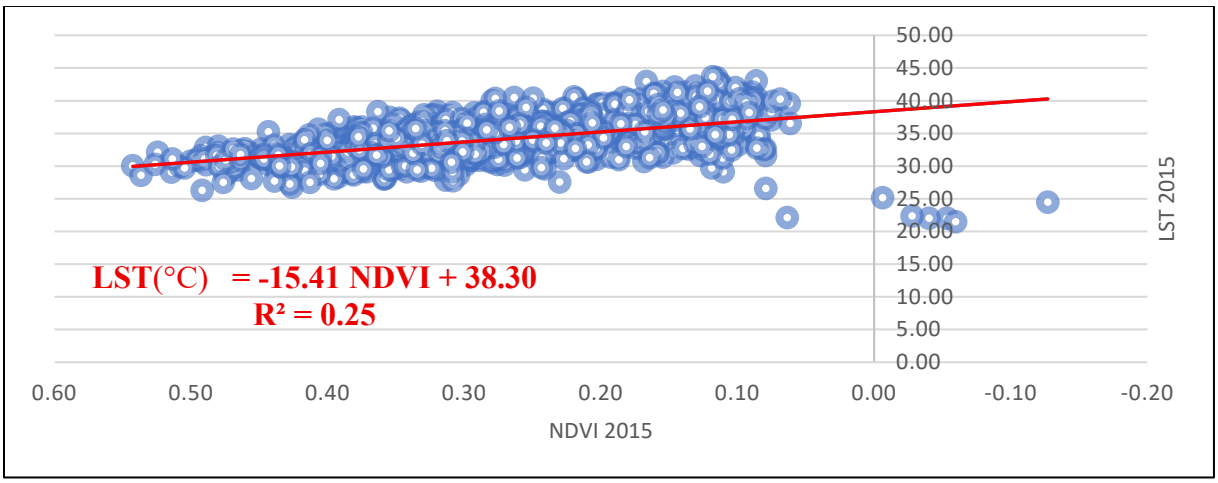
Fig 4: correlation of NDVI with LST 2005



For 2015, the NDVI–LST regression (Fig. 5) exhibits a stronger negative relationship, expressed by the equation: **LST (°C) = −15.41 × NDVI + 38.30**

The regression slope (−15.41) indicates an increased magnitude of the NDVI–LST relationship compared to 2005. The coefficient of determination (R^2 = 0.25) shows that NDVI explains approximately 25% of the variation in LST during this year.

Fig 5: correlation of NDVI with LST 2015

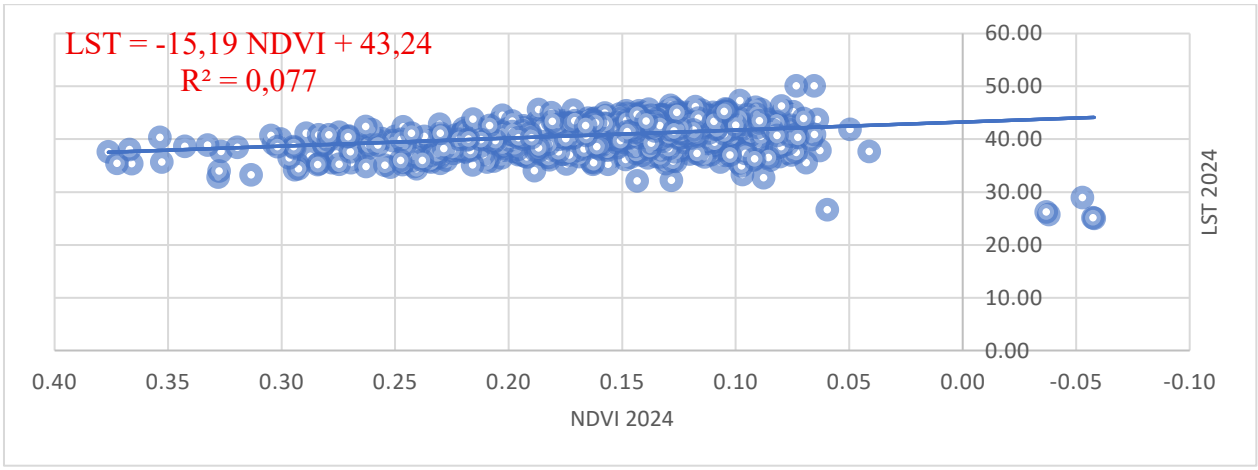


In 2024, the regression analysis (Fig. 6) maintains a negative slope similar in magnitude to that observed in 2015:

LST (°C) = −15.20 × NDVI + 43.24

However, the coefficient of determination decreases substantially (R^2 = 0.077), indicating a weak explanatory power of NDVI with respect to LST in 2024. The intercept value (43.24 °C) reflects higher baseline surface temperatures for areas with low NDVI values compared to previous years.

Fig 6: correlation of NDVI with LST 2024



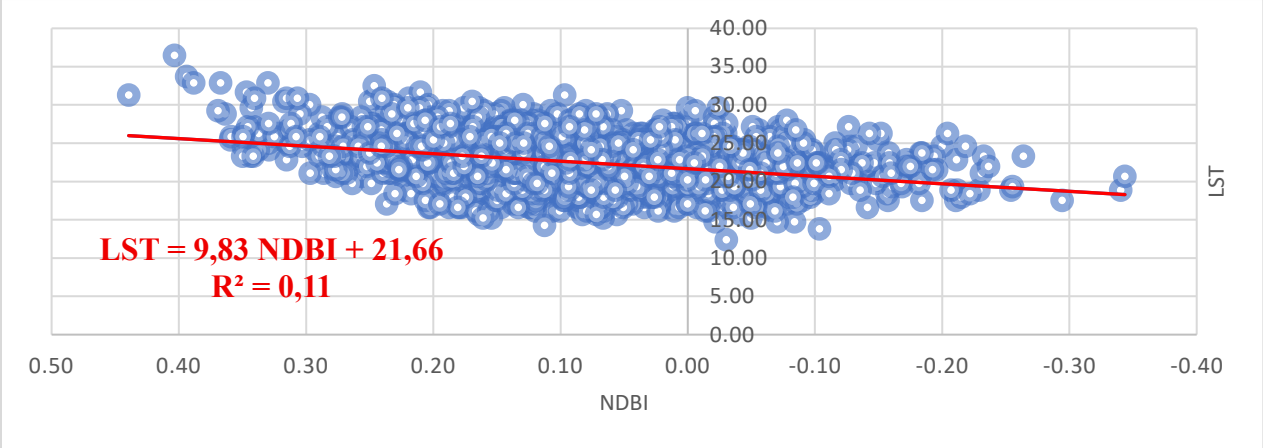
Correlation NDBI with LST

The regression analyses between NDBI and LST for 2005, 2015, and 2024 reveal a consistent positive relationship between built-up–related spectral characteristics and surface temperature. In 2005 (Figure 7), NDBI values ranged from approximately −0.35 to +0.40, with corresponding LST values between about 15 °C and 38 °C. The regression equation is:

LST (°C) = 9.84 × NDBI + 21.66

The positive slope (9.84) indicates increasing LST with higher NDBI values. The coefficient of determination (R^2 = 0.11) suggests that NDBI explains approximately 11% of the spatial variability in LST for this year.

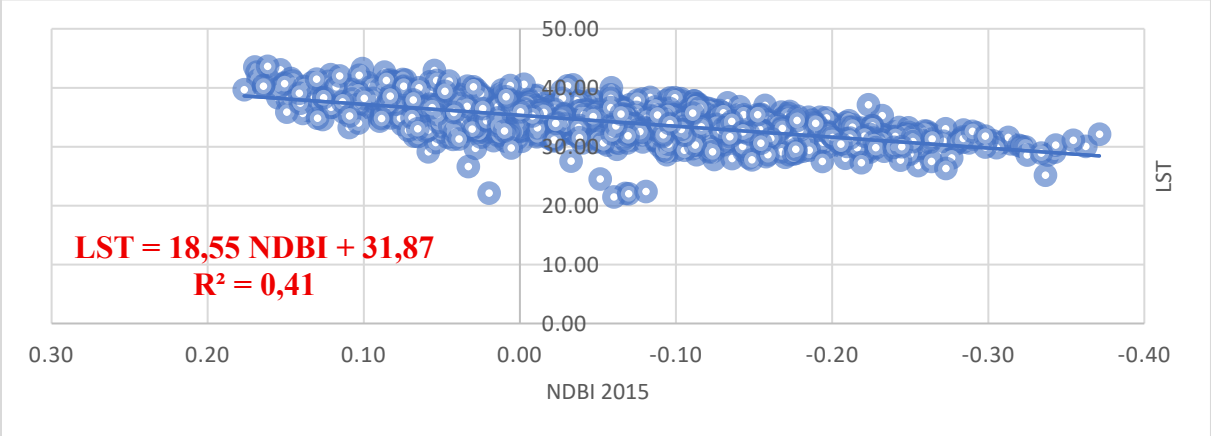
Fig 7: correlation of NDBI with LST 2005



By 2015 (Figure 8), the strength of the relationship increased markedly, with the regression expressed as: **LST (°C) = 18.55 × NDBI + 31.87**

The slope nearly doubled compared to 2005, and the coefficient of determination increased to R^2 = 0.41, indicating a substantially stronger association between NDBI and LST.

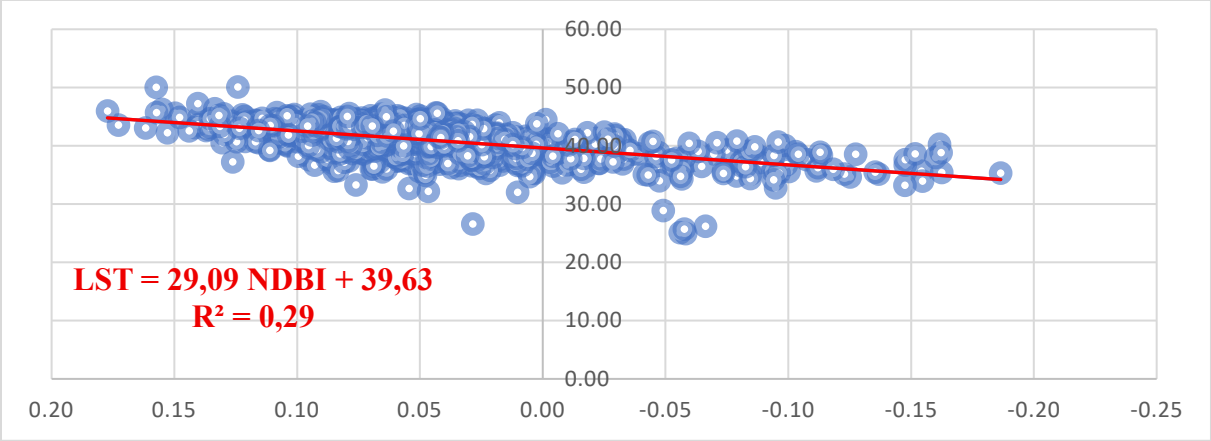
Fig 8: correlation of NDBI with LST 2015



In 2024 (Figure 9), the regression equation is: **LST (°C) = 29.09 × NDBI + 39.63**

The slope reaches its maximum value, while the coefficient of determination decreases to R^2 = 0.29. Despite the reduced explanatory power compared to 2015, the results indicate a continued strong positive relationship between NDBI and LST.

Fig 9: correlation of NDBI with LST 2024



5. Discussion

Urban Heat Islands (UHIs) represent a major environmental challenge in the context of accelerating global urbanisation and climate change. A comprehensive review by Kim and Brown (2021), based on 51 UHI-related studies, highlights the need for accurate estimation of UHI intensity and magnitude, emphasising the importance of considering three-dimensional urban form and refined classification schemes to improve the understanding of urban thermal dynamics. Complementing this perspective, Almeida et al. (2021) reviewed remote sensing–based approaches for UHI analysis and underlined the effectiveness of satellite data for monitoring urban thermal environments, while also calling for greater methodological standardisation to enhance inter-city and inter-regional comparability. Within this framework, the present study contributes to the growing body of remote sensing–based UHI research by providing a long-term, spatially explicit analysis of land surface thermal dynamics in a semi-arid urban context, using consistent Landsat-derived indices.

The results of this study reinforce the well-established inverse relationship between vegetation cover, as represented by NDVI, and Land Surface Temperature (LST). This cooling effect of vegetation was particularly evident in 2015, when NDVI exhibited its highest explanatory power with respect to LST. Such findings are consistent with global-scale analyses showing that negative NDVI–LST relationships dominate urban environments worldwide. For example, Ahmed et al. (2025) report that approximately 80% of statistically significant pixels globally exhibit negative NDVI–LST correlations. At the city scale, Duan et al. (2025) analysed Okara (Pakistan) and found a strong inverse NDVI–LST relationship, with coefficients of determination ranging from approximately 0.55 to 0.69. Similarly, Anaud et al. (2025) reported NDVI–LST correlation coefficients of −0.481 in 2013 and −0.426 in 2022 for a northern Indian city, confirming the persistence of this negative relationship across different climatic and urban

contexts. A recent global synthesis of satellite-based studies covering the period 2000–2024 further confirms this pattern, showing that approximately 80.4% of significant NDVI–LST correlations worldwide are negative (Rahimi et al., 2025). Together, these studies provide robust quantitative evidence that higher vegetation density is systematically associated with lower surface temperatures, underscoring the critical role of urban vegetation in mitigating UHI effects.

In contrast to vegetation, built-up surface characteristics exhibit a consistently positive relationship with LST. The present study demonstrates an increasingly strong NDBI–LST relationship over time, reflecting the growing thermal influence of impervious surfaces. This finding aligns closely with previous empirical studies. In Okara (Pakistan), Duan et al. (2025) reported strong positive correlations between NDBI and LST, with R^2 values ranging from approximately 0.62 to 0.69, indicating that built-up intensity was a dominant driver of surface warming. Comparable results have been observed in cities such as Kayseri (Türkiye), where areas with higher NDBI values consistently correspond to elevated LST.

The thermal dynamics observed in Constantine reflect broader regional trends reported across North Africa and Algeria. In Tlemcen, long-term analyses spanning 1989–2019 have revealed strong and persistent negative correlations between NDVI and LST across multiple biophysical indices (Selka et al., 2024). Similarly, Oran has experienced rapid urban expansion and significant loss of agricultural and vegetated land between 1984 and 2024, resulting in a marked intensification of the urban thermal environment (Soufiane et al., 2025).

The results of the present study confirm that Constantine follows a comparable trajectory, characterised by vegetation loss and the expansion of built-up surfaces. In the absence of effective vegetation-based mitigation measures, such land cover transformations are likely to accelerate UHI intensification in semi-arid cities. Taken together, these findings highlight the urgent need for climate-sensitive urban planning strategies in semi-arid urban environments. Integrating green infrastructure, such as urban parks, green corridors, and vegetated buffers, alongside the use of reflective or permeable building materials, can help restore the thermal buffering capacity of urban landscapes. Such approaches are widely recommended in the literature as effective tools for UHI mitigation (Santos et al., 2022) and are particularly relevant for cities like Constantine that are experiencing rapid urban growth under climatic constraints.

6. Conclusion

This study investigated the spatiotemporal evolution of land surface characteristics and Urban Heat Island (UHI) dynamics in Constantine, Algeria, over the period 2005–2024 using multi-temporal Landsat imagery and GIS-based analysis. By integrating Land Surface Temperature (LST) retrieval with biophysical indices (NDVI and NDBI), the research provides a comprehensive assessment of how vegetation dynamics and built-up surface characteristics have shaped the urban thermal environment in a semi-arid city context.

The results reveal a pronounced decline in vegetation-related surface signals and a substantial expansion of built-up surface characteristics, accompanied by a marked intensification and spatial expansion of surface UHI conditions. Regression analyses demonstrate a persistent

negative relationship between NDVI and LST, confirming the cooling influence of vegetation, although its explanatory power weakened over time. In contrast, NDBI exhibited a consistently positive and increasingly strong relationship with LST, highlighting the growing thermal dominance of impervious surfaces as urbanisation progressed.

These findings indicate that while vegetation continues to moderate surface temperatures at local scales, its overall capacity to regulate urban thermal variability has diminished in the face of rapid land cover transformation. The strengthening influence of built-up surfaces underscores the critical role of land-use change in driving UHI intensification in semi-arid environments. The observed patterns in Constantine are consistent with trends reported in other Algerian and North African cities, suggesting that similar thermal trajectories may be expected in rapidly urbanising regions with comparable climatic constraints.

From a broader perspective, this study demonstrates the value of multi-temporal satellite data for monitoring long-term UHI dynamics and assessing the thermal implications of urban growth. The results emphasise the importance of integrating vegetation preservation, green infrastructure development, and climate-sensitive urban design into planning strategies to mitigate increasing thermal stress. Future research incorporating higher-resolution thermal observations, urban morphological parameters, and anthropogenic heat indicators would further enhance understanding of UHI processes and support more effective mitigation and adaptation strategies in semi-arid cities.

Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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