Examination of the Relationship Between Surface Temperature and Spectral Land Cover Indices for Different Köppen Climate Classes

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Abstract

Land Surface Temperature (LST) serves as a critical parameter for evaluating urban climate dynamics and surface energy exchanges. This study examines the relationships between LST and four spectral land cover indices—Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI), and Normalized Difference Bareness Index (NDBaI)—across four Köppen–Geiger climate zones: Kars (Dfb – Humid Continental), Kilis (Csa – Hot-Summer Mediterranean), Cairo (BWh – Hot Desert), and Malanje (Aw – Tropical Savanna). Using Landsat 8 OLI/TIRS Collection 2 Level-2 imagery acquired in September 2023 (and 2020 for Kars), LST and spectral indices were extracted and analyzed through pixel-based Pearson correlation analysis. The results revealed diverse climatic dependence in the LST–index interactions. In Kars, LST showed a strong positive correlation with NDBI ($r = 0.63$) and a moderate correlation with NDBaI ($r = 0.39$). In Kilis, NDVI exhibited a moderate negative relationship with LST ($r = -0.47$), while NDBI correlated weakly ($r = 0.22$). Cairo displayed weak overall relationships, with LST–NDBI ($r = 0.38$) and LST–NDVI ($r = -0.22$) reflecting the dominance of impervious and arid surfaces. Conversely, Malanje demonstrated the strongest vegetation–temperature interaction, where LST–NDVI correlation reached $r = -0.75$, LST–NDWI $r = 0.72$, and LST–NDBI $r = 0.53$. Across all cities, built-up and bare areas consistently increased LST, while vegetation showed cooling effects that intensified in warmer, more humid climates. These findings highlight that the magnitude and direction of LST–land cover correlations are strongly controlled by regional climate regimes, emphasizing the necessity of climate-specific urban heat mitigation strategies.

1. Introduction

Land Surface Temperature (LST) is one of the main indicators for urban climatology because it governs surface energy balance, environmental quality, public health, and energy consumption (Sobrino et al. 2004; Sekertekin & Bonafoni, 2020). The spatial and temporal variation of LST emerges from various elements with Land Use Land Cover (LULC) changes being the primary factor (Ramzan et al., 2022). The study of LST and land surface characteristics enables scientists to understand thermal dynamics in different environments, since it helps explain how these factors interact during global warming and urbanization. Remote sensing technology enables exceptional monitoring of these changes across extensive areas and multiple climate zones through its ability to use satellite sensors, which provide imagery in various resolutions for climate-informed multi-temporal analysis. The Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Bareness Index (NDBaI) are most commonly used spectral indices from multispectral satellite imagery that determine vegetation abundance, water presence, impervious surface area, and bare soil coverage, respectively (Sekertekin et al. 2020; Kaur & Pandey, 2022; Delaney et al., 2025).

Previous studies have proven that these spectral indices show strong relationships with LST (Garai et al. 2022; Naga Rajesh et al.,2023; Rahimi et al., 2025; Alademomi et al. 2022; Hussain et al., 2023; Ma & Peng, 2022; Tiwari & Kanchan, 2024; Morsy & Hadı, 2022; Badugu et al., 2024). The majority of these studies focus on a single city or metropolitan area, often within a specific climatic zone. Different climatic settings produce varying effects on how land cover affects surface temperature through its strength, direction, and even its fundamental characteristics. Thus, this study posits that a comprehensive understanding of the LST-land cover dynamic requires a comparative analysis across diverse climatic backgrounds. To address this research gap, this study carries out a multi-city comparative analysis to examine LST relationships with NDVI, NDWI, NDBI, and NDBaI spectral indices in four different Köppen-Geiger climate zones:

- Kars, Türkiye (Dfb - Humid Continental): The climate features large seasonal temperature swings and a hot summer.
- Kilis, Türkiye (Csa - Hot-Summer Mediterranean): Featuring dry, hot summers and mild, wet winters.
- Cairo, Egypt (BWh - Hot Desert): Arid, with extremely low precipitation and high temperatures.
- Malanje, Angola (Aw - Tropical Savanna): Defined by a distinct wet and dry season.

2. Study Areas and Materials

2.1 Study Areas

This research examines four locations which span different Köppen climate zones including Kars (Dfb - Humid Continental) and Kilis (Csa - Hot-Summer Mediterranean) in Türkiye, Cairo (BWh - Hot Desert) in Egypt, and Malanje (Aw - Tropical Savanna) in Angola (Figure 1). Taken together, these four test sites provide an ideal framework for assessing how land cover characteristics along with climate variability influence surface temperature patterns.

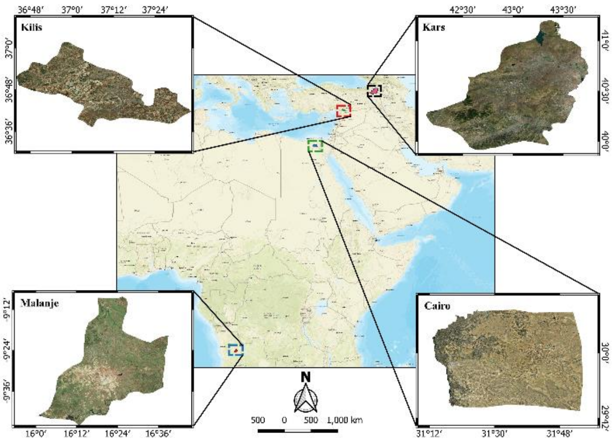

Figure 1. Location map of the test sites.

2.2 Materials

This study analyzed LST and spectral index relationships through Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) imagery data. The Landsat 8 satellite delivers multispectral data at 30 m spatial resolution for reflective bands and thermal bands at 100 m resolution which is resampled to 30 m for regional climate and land-cover research. Cloud-free images acquired in September were considered for the consistency throughout the research period. The exact acquisition dates for Malanje (Aw), Cairo (BWh), Kilis (Csa), and Kars (Dfb) are 12 September 2023, 16 September 2023, 18 September 2023, and 20 September 2020, which were selected based on recent cloud-free situation. The selected imageries were subsequently processed to extract spectral indices along with LST derived available surface temperature product.

3. Methodology

The methodology of this study involves two main components: (i) LST retrieval and (ii) calculation of spectral land cover indices. The Landsat Collection 2 Level-2 products served as the basis for all image processing operations to maintain uniformity across study areas. After these two steps, scatterplots and correlation coefficients were extracted for the relationship analysis.

3.1 Land Surface Temperature (LST) Retrieval

For LST, we utilized the Surface Temperature (ST) product available in the Landsat Collection 2 Level-2 dataset. Since this product provides LST in scaled units, only the recommended scaling factor was applied to convert the digital numbers (DN) to temperature values in Kelvin (www.usgs.gov/landsat-missions/landsat-collection-2-surface-temperature).

3.2 Spectral Indices Calculation

To analyze the relationship between LST and land cover characteristics, we computed four widely used spectral indices (NDVI, NDWI, NDBI, and NDBaI) using the Surface Reflectance (SR) bands from the same Collection 2 Level-2 dataset as described below.

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

$$NDWI = \frac{G - NIR}{G + NIR} \tag{2}$$

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \tag{3}$$

$$NDBaI = \frac{SWIR1 - TIRS}{SWIR1 + TIRS} \tag{4}$$

Where NIR, G, R, SWIR1, and TIRS represent near infrared, green, red, shortwave infrared 1, and thermal infrared band (band 10) of the Landsat 8 dataset. All indices were calculated on a pixel-by-pixel basis using the corresponding SR bands and then co-registered with the LST dataset for further analysis.

4. Results

The LST and spectral index maps of Cairo are presented in Figure 2. Based on the pixel-based analysis, the spectral indices of Cairo showed various relationships with the LST (Figure 3). The strength of the relationship between LST and NDBI was r=0.38, which demonstrated a positive correlation. The relationship between NDVI and LST showed a weak negative correlation with r=−0.22 which indicated that rising temperatures are linked to decreased vegetation density but the relationship remained weak. The NDBal and LST correlation shows a weak positive relationship (r=0.27). The NDWI revealed a very weak negative correlation with the LST, with r=−0.01, suggesting no significant relationship between LST and open water bodies in this region.

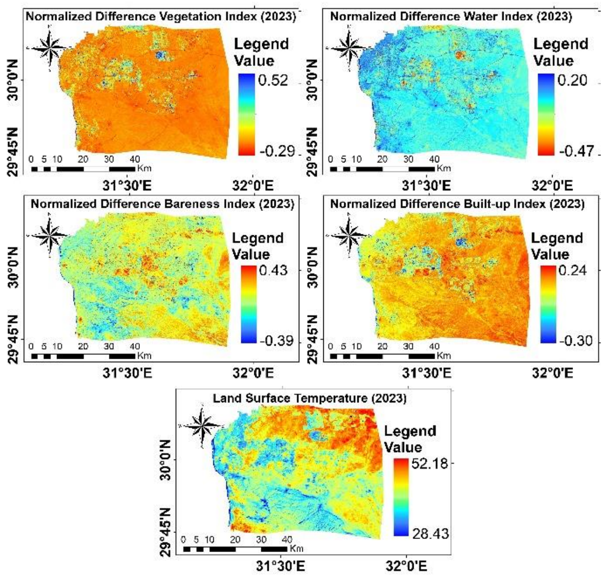

Figure 2. The LST and spectral index maps of Cairo.

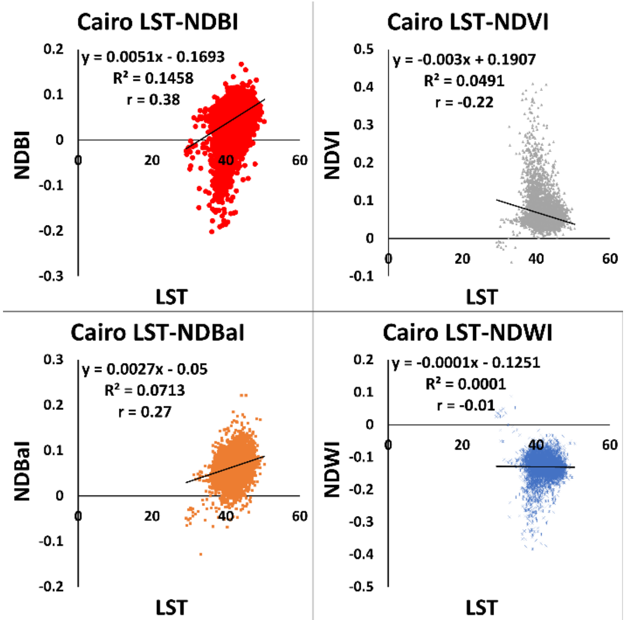

Figure 3. Scatterplots showing the relationship between LST and spectral land cover indices in Cairo.

The LST and spectral index maps of Kars are presented in Figure 4. The LST and NDBI showed a high correlation in Kars with r=0.63 (Figure 5). The NDVI and LST correlation showed a negative relationship with r=−0.34. The NDBaI and LST correlation is positive and moderate, with r=0.39. The NDWI presented a weak positive correlation with the LST, with r=0.13.

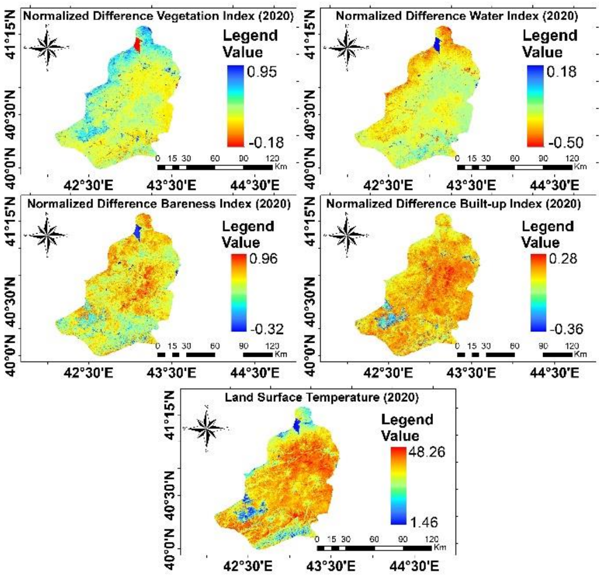

Figure 4. The LST and spectral index maps of Kars.

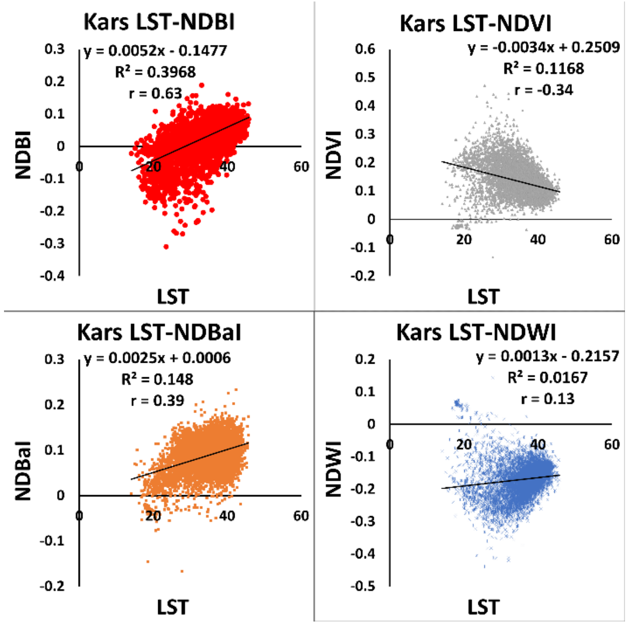

Figure 5. Scatterplots showing the relationship between LST and spectral land cover indices in Kars.

The LST and spectral index maps of Kilis are presented in Figure 6. The Mediterranean climate of Kilis showed a weak positive relationship between LST and NDBI with r=0.22 (Figure 7). The analysis revealed that NDVI and LST have a moderate negative relationship with r=−0.47. The NDBaI and LST correlation was negative, with r=−0.19, indicating a very weak inverse relationship between temperature and bare land or areas with low vegetation. The NDWI demonstrated a weak positive relationship with the LST (r=0.29).

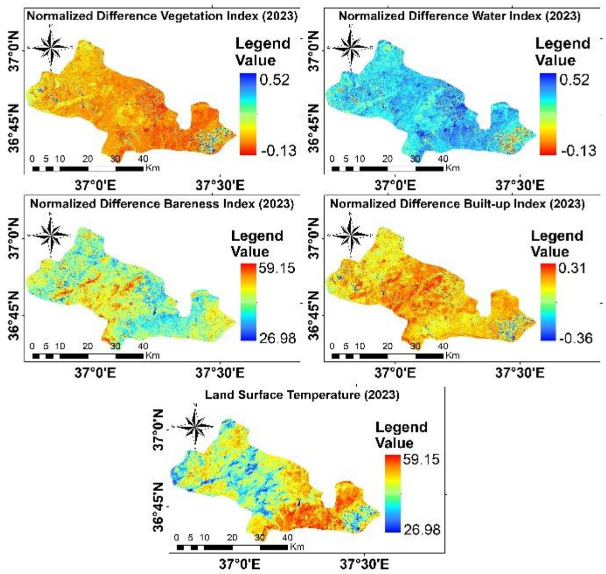

Figure 6. The LST and spectral index maps of Kilis.

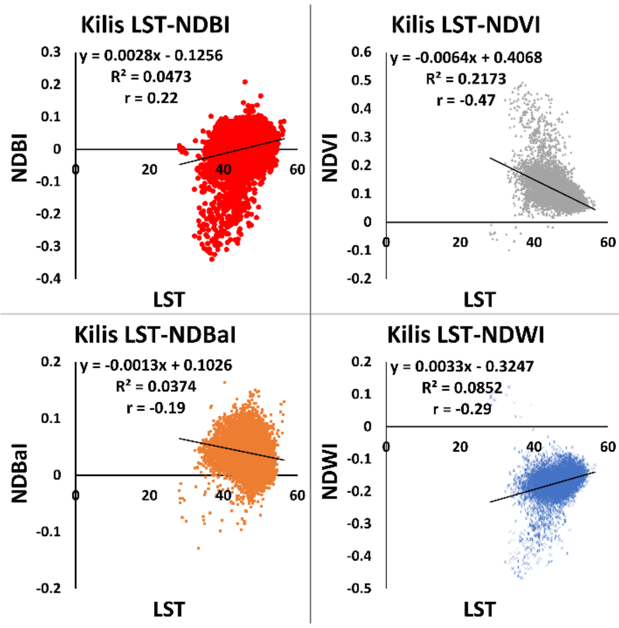

Figure 7. Scatterplots showing the relationship between LST and spectral land cover indices in Kilis.

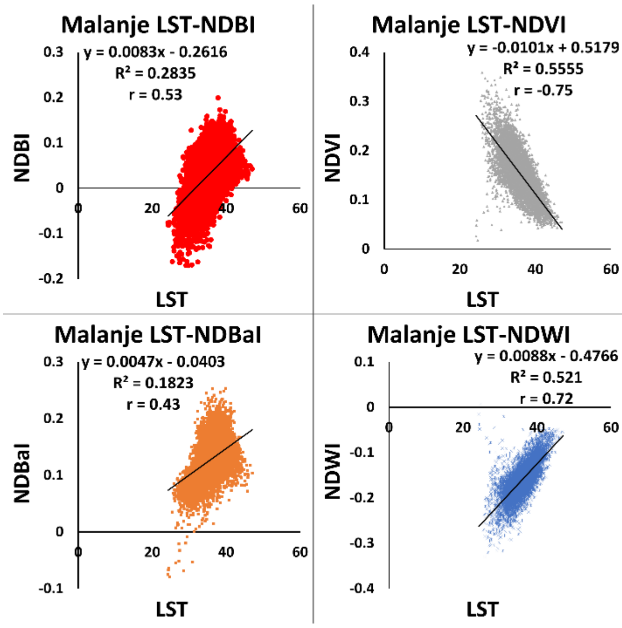

Figure 9. Scatterplots showing the relationship between LST and spectral land cover indices in Malanje.

The LST and spectral index maps of Malanje are presented in Figure 8. The tropical climate of Malanje showed the strongest relationship between LST and spectral indices (Figure 9). The relationship between LST and NDBI demonstrated a moderate strength through r=0.53. The NDVI and LST correlation revealed a strong negative relationship with r=−0.75 which shows that LST increases in this tropical region resulted in reduced vegetation development. The NDBaI and LST correlation was positive and moderate, with r=0.43. The NDWI showed a strong positive correlation with LST, with r=0.72.

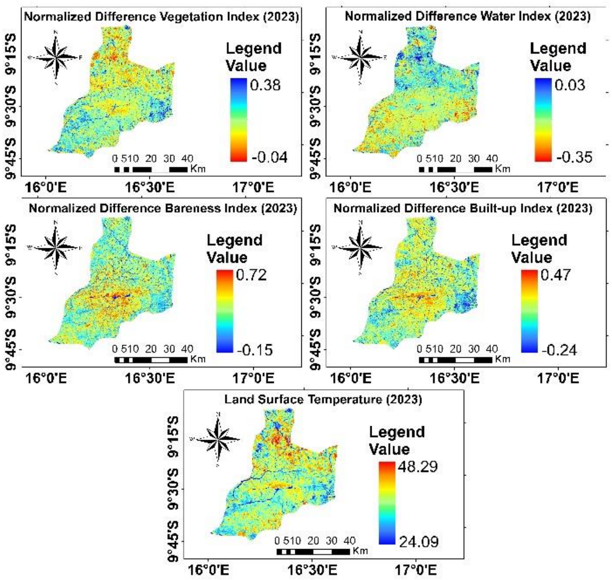

Figure8. The LST and spectral index maps of Malanje.

The scatterplots between the four cities demonstrate distinct climate-related patterns according to the analyses. The tropical region of Malanje experiences rising LSTs, which lead to decreased vegetation (low NDVI) and increased bare land exposure (high NDBaI) and expanded open water areas (high NDWI) because of the combination of hot weather, wet conditions, and plant destruction.

The LST in temperate Kars shows a strong relationship with urbanization (high NDBI) and a moderate relationship with bare land (NDBaI) yet the changes in vegetation and water body expansion are less than in tropical regions because seasonal patterns control land cover changes.

The Mediterranean Kilis area shows moderate vegetation reduction and temperature increase because of its hot, dry summer conditions yet its low NDBI value and moderate NDWI value indicate a combination of different land uses and irrigation systems which reduce LST variations.

Finally, the desert region of Cairo shows weak relationships between vegetation, bare land, and water bodies because its arid environment remains mostly unchanged by warming LSTs except for noticeable rises in urban heat signatures (NDBI).

The scatterplots presented above provide correlations between LST and spectral indices. On the other hand, Figure 10 illustrates the correlation heat map, showing the correlations between all variables. Apart from the LST-spectral index interpretations, the other important correlations for each city are as follows:

- Strong negative relationships between NDVI–NDWI (r = -0.84) and NDBI–NDVI (r = -0.72) have been observed in Cairo.
- Strong negative relationship between NDVI and NDWI (r = -0.95) in Kars may reflect contrasting spatial patterns between vegetation and water surfaces, typical in temperate regions where vegetation thrives away from water bodies.
- Strong negative correlations between NDVI and NDWI (r = -0.92) and NDBI–NDVI (r = -0.75) in Kilis again

highlight the inverse spatial patterns of vegetation and urbanization.

- Moreover, extremely strong negative correlations between NDVI and NDWI (r = -0.96) and strong positive correlation between NDBI and NDBaI (r = 0.87) in Malanje underline the clear separation between vegetated and built-up/bare surfaces typical of tropical urban–rural mosaics.

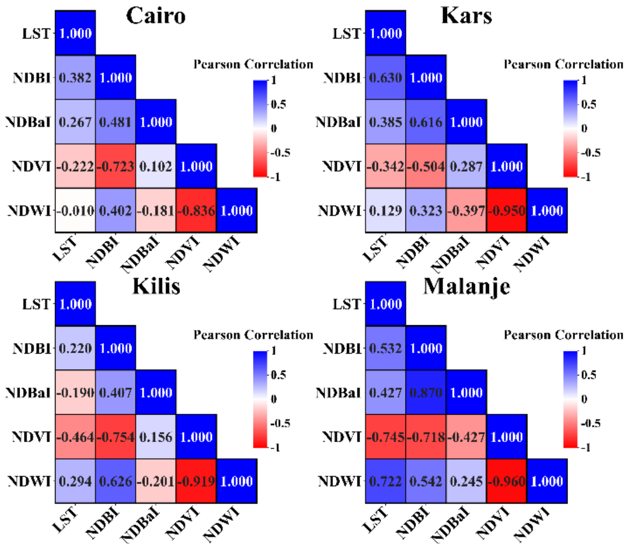

Figure 10. The correlation heat map, showing the correlations between all variables for each city.

Comparing the four cities reveals how climatic context governs the strength and direction of land surface relationships. In arid Cairo, thermal patterns are dominated by impervious and bare surfaces, while vegetation and water play minor roles. In temperate Kars, urban areas exhibit strong thermal contrasts against cooler vegetated surroundings, resulting in the highest LST–NDBI correlation. The Mediterranean Kilis demonstrates the moderating influence of vegetation, weakening the link between urbanization and heat while strengthening the cooling role of vegetation. In tropical Malanje, dense vegetation exerts a strong cooling effect, but both urban and bare surfaces exhibit pronounced heating, reflecting the complex energy balance in humid environments.

Overall, these patterns indicate that as climate becomes warmer and more humid, the relationship between LST and vegetation strengthens (more negative), while the association between LST and urban/bare surfaces remains consistently positive but varies with land cover composition. This emphasizes the importance of climate-specific strategies for mitigating surface heat through vegetation management and urban planning.

5. Conclusion

This study investigated how LST relates to spectral land cover indices, namely, NDBI, NDVI, NDBaI, and NDWI across four cities that span different climate zones including desert Cairo, temperate Kars, Mediterranean Kilis, and tropical Malanje. The research shows that environmental conditions produced different levels of strength and direction between these relationships.

The built-up areas of NDBI demonstrated the highest positive relationship with LST in temperate (Kars) and tropical (Malanje) regions because they generate significant surface heating in these climate zones. The NDVI data shows that vegetation loss occurred most intensely in Malanje's tropical area because heat reduced vegetation cover but Cairo's arid conditions already had minimal vegetation so the effect was less noticeable. The extent of bare land (NDBaI) expanded with LST increases mainly in tropical and temperate regions yet Kilis in the Mediterranean showed a minimal negative trend. The NDWI values of open water bodies in Malanje showed the most significant LST response because of the tropical climate conditions with hot temperatures and abundant rainfall. The desert city of Cairo did not show any connection between LST and NDWI values because of its limited water resources.

The research demonstrates that rising LSTs affect land cover characteristics through mechanisms which depend on specific climate conditions. The strongest LST–land cover interactions took place in tropical and temperate areas yet desert and Mediterranean regions showed either no effect or limited effects. The research findings demonstrate that scientists need to understand local climate patterns when studying how rising LSTs affect urban growth, vegetation, bare land, and water resources.

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