

The Thermal Footprint of Urbanisation: Surface Urban Heat Island and Land-Use Dynamics in Sakarya Province

Serdar Tüzün¹, Samiullah Serat², Mahnaz Gümrükçüoğlu Yiğit³, Hülya Karabaş⁴

^{1,2,3,4}Department of Environmental Engineering, Sakarya University, Sakarya, Türkiye

DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150900120>

Received: 28 September 2026; Accepted: 03 October 2026; Published: 19 October 2026

ABSTRACT

This study investigates the spatial and temporal variation in Surface Urban Heat Island (SUHI) intensity and its relationship with land use across the districts of Adapazarı, Serdivan, Erenler, and Arifiye in Sakarya Province, Türkiye. The analysis draws on Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS Collection 2 Level-2 imagery acquired under comparable day-and-time conditions during June, July, and August of 2000, 2006, 2012, 2018, and 2024. Using geographic information systems (GIS), median composites were generated for each study period in the Google Earth Engine environment. Land Surface Temperature (LST), the Normalized Difference Vegetation Index (NDVI), and the Normalized Difference Built-up Index (NDBI) were then calculated at a spatial resolution of 30 m. SUHI intensity was determined as the difference between the mean LST values of urban and rural areas. The findings show that built-up areas expanded over the study period, while agricultural and forested areas became increasingly fragmented. Mean LST increased from 31.77 °C in 2000 to 38.15 °C in 2024, whereas urban LST rose from 34.79 °C to 45.38 °C. Over the same period, rural LST increased from 29.84 °C to 36.11 °C, and SUHI intensity rose from 4.95 °C to 9.27 °C. The negative correlation between mean LST and NDVI ($r=-0.42$) and the positive correlation between mean LST and NDBI ($r=0.48$) highlight the contrasting effects of vegetation cover and built-up surfaces on the thermal environment. These findings underscore the need to conserve land cover, strengthen green infrastructure, and promote climate-sensitive urban development that accounts for the thermal impacts of the built environment in rapidly urbanizing, medium-sized cities. Future research using datasets with higher temporal resolution may yield more precise results. Nevertheless, this study provides a useful case study for examining SUHI dynamics and developing climate-resilient planning approaches in medium-sized cities with similar characteristics.

Keywords: Surface urban heat island, land surface temperature, Landsat, NDVI, NDBI, green spaces.

INTRODUCTION

In an increasingly warming world, 45% of the global population, which has reached 8.2 billion, lives in cities, 36% in towns, and 19% in rural areas. By 2050, two-thirds of global population growth is projected to occur in cities [WUP2025]. Similarly, in Türkiye, rapid population growth and increasing migration from rural to urban areas are accelerating the urbanization process. Land-use changes associated with rapid urbanization, together with global warming, alter the local climates of cities, causing urban areas to become warmer than their rural surroundings. Increasing building density, the expansion of impervious surfaces, the widespread use of low-albedo construction materials, and the decline of natural vegetation and agricultural land modify the surface energy balance, increase temperatures, and create urban heat islands (UHIs) (Zhou et al., 2021; Rao et al., 2023). This process has significant adverse consequences for thermal comfort, energy consumption, human health, and environmental sustainability. Monitoring urban development dynamics and changes in UHI conditions over time is therefore critically important for urban sustainability (Weiting et al., 2025).

International studies have shown that increases in impervious surfaces intensify Surface SUHI effects, whereas the loss of vegetation weakens evaporative cooling. They have also demonstrated that LST is

positively associated with building density and negatively associated with vegetation cover (Zng et al., 2021; Feng et al., 2024; Sinha & Banerjee, 2025). Multi-temporal analyses of Asian and European cities indicate that temperature increases associated with urban expansion are particularly pronounced in densely built-up areas (Weiting, 2025; Rose & Kucharik, 2026). For example, Southeast Asian capitals experienced rapid urban expansion between 1990 and 2024, largely at the expense of vegetation and surface water. In cities such as Hanoi and Jakarta, substantial increases in urban land cover showed a strong positive relationship with rising mean LST (Ng et al., 2025). In Türkiye, studies conducted in Konya, Niğde, Erzurum, Istanbul, and Ankara have demonstrated that surface temperatures are closely associated with land cover, the proportion of impervious surfaces, building density, and urban morphology (Sinha & Banerjee, 2025; Gümüş & Gümüş, 2025; Güller & Toy, 2024; Karaçam et al., 2026; Aydın & Özuduru, 2025). These findings highlight the importance of examining rapidly urbanizing, medium-sized cities using long-term satellite data to support sustainable planning and climate change adaptation (Ünsal, 2025; Şahin, 2025). Evaluating areas with different patterns of urban development together also allows for a more comprehensive analysis of the relationship between land-cover change and surface temperature. Previous heat-island assessments have also been conducted across Sakarya, and the warming trend identified in the present study is consistent with the findings of earlier research (Gümrukçüoğlu, 2015).

This study aims to determine the spatial and temporal variation in SUHI intensity in Sakarya Province using multi-temporal Landsat imagery covering the 2000–2024 period. To this end, the relationships between LST, the Normalized Difference Vegetation Index (NDVI), and the Normalized Difference Built-up Index (NDBI) are analyzed to assess the effects of urban growth on the thermal environment. By providing a long-term spatiotemporal analysis of SUHI dynamics in a rapidly urbanizing, medium-sized city, the study contributes to the existing body of urban climate research. It also evaluates the relationships between LST and land-cover indicators at multiple spatial scales, including the district level, thereby accounting for the effects of spatial aggregation. Furthermore, the findings offer directly applicable insights for climate-sensitive urban planning, enabling decision-makers in Sakarya and other cities experiencing similarly rapid urban growth and rising temperatures to assess current conditions and develop forward-looking strategies.

Study Area

Sakarya Province is located in northwestern Türkiye, between 29°57'–30°53' E and 40°17'–41°13' N. As a rapidly growing province, its population has nearly doubled since 2011 and now exceeds one million (TÜİK, 2024). The region generally experiences mild and rainy winters, while its summers are neither as hot nor as dry as those typical of the Mediterranean climate. Winter and spring are mild and rainy, whereas summer is warm and relatively dry. The province has an average elevation of approximately 31 m above sea level. Agricultural land accounts for 50% of its total area, while forests and shrublands cover 42%.

The central districts of Adapazarı, Serdivan, Erenler, and Arifiye were selected as the study areas. These districts were chosen because they encompass different forms of urban development representative of Sakarya's spatial growth, are subject to rapid urbanization pressure, and exhibit clearly observable land-use changes. In these districts, where population, development, and urban activities are concentrated, built-up areas expanded into natural and agricultural land, particularly between 2011 and 2024. Selecting these districts allows the study to move beyond a uniform analysis of the urban environment and instead examine how different urban forms, land-cover compositions, and development corridors influence thermal behavior.

Adapazarı, which encompasses a substantial part of the city center, is characterized by high building density, extensive transportation networks, and concentrated commercial activity, all of which contribute to a high proportion of impervious surfaces. Serdivan represents the principal urban growth corridor and has experienced the most dynamic expansion over the past two decades, with agricultural and semi-natural areas rapidly converted into residential development. The university campus and new housing projects have contributed to rapid population growth and extensive land-use transformation within the district.

Erenler is one of the districts in Sakarya where industrial and logistics activities are concentrated. Industrial facilities, storage areas, and transportation infrastructure developed near organized industrial zones have

created extensive concrete and asphalt surfaces. Arifiye, by contrast, is a transition zone where urban expansion is interwoven with agricultural land and where rural and urban characteristics coexist. The presence of agricultural land alongside newly developing residential and industrial areas makes it possible to analyze the spatial effects of land-use transformation. In particular, the conversion of rural land into built-up areas has caused substantial changes in land cover, potentially affecting local microclimatic conditions (Figure 1).

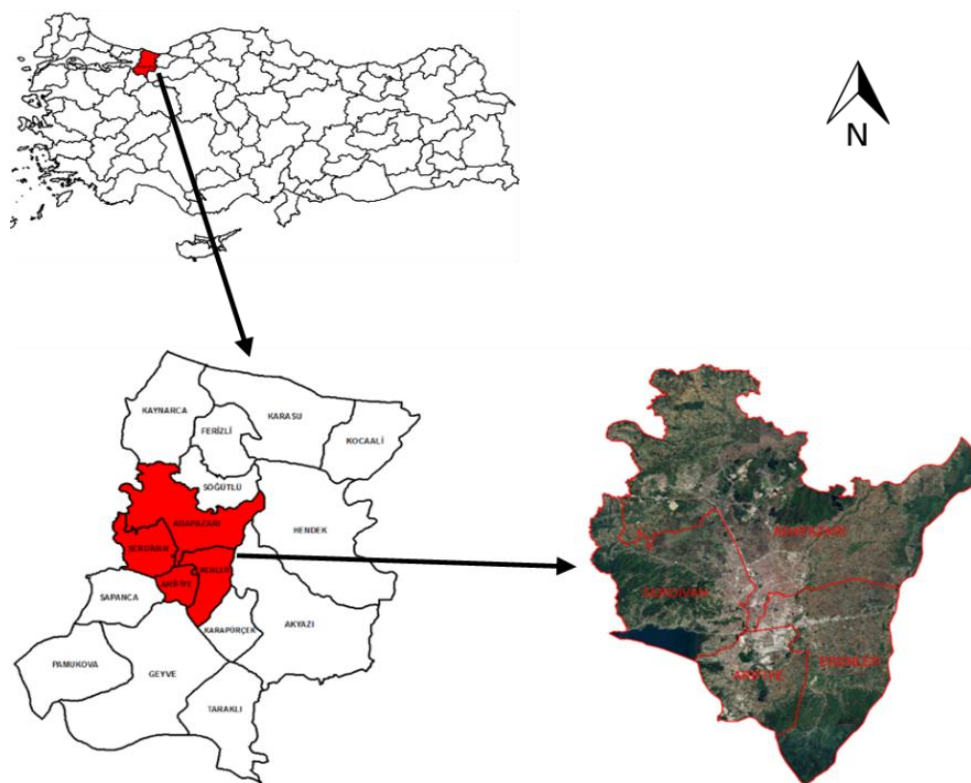


Figure 1. The study area comprising the central districts of Sakarya.

MATERIAL AND METHOD

Landsat Collection 2 Level-2 surface reflectance and surface temperature products were used in this study. Landsat 5 TM imagery was used for 2000 and 2006, Landsat 7 ETM+ imagery for 2012, and Landsat 8 OLI/TIRS imagery for 2018 and 2024. The satellite imagery was obtained from the United States Geological Survey (USGS) archive. All image-processing procedures were performed on the Google Earth Engine (GEE) platform, which provides direct access to the Landsat archive and enables the efficient, large-scale processing of satellite imagery without requiring local computational resources. To ensure temporal consistency throughout the study period, sensor selection was based on the year of image acquisition (Table 1).

Table 1. Summary of dataset

Dataset	Source / Product	Spatial Resolution	Temporal Coverage	Purpose in Study
Landsat 5 TM Collection 2 Level-2	USGS via Google Earth Engine	30 m	2000, 2006 (Summer: June–August)	Surface reflectance and thermal data (SR_B3, SR_B4, SR_B5, ST_B6) for NDVI, NDBI, and LST calculation
Landsat 7 ETM+ Collection 2 Level-2	USGS via Google Earth Engine	30 m	2012 (Summer: June–August)	Surface reflectance and thermal data (SR_B3, SR_B4, SR_B5, ST_B6) for NDVI, NDBI, and LST calculation
Landsat 8	USGS via Google Earth	30 m	2018, 2024	Surface reflectance and thermal data

OLI/TIRS Collection 2 Level-2	Engine		(Summer: June–August)	(SR_B4, SR_B5, SR_B6, ST_B10) for NDVI, NDBI, and LST calculation
FAO GAUL 2015 Level-2 Administrative Boundaries	FAO (GEE dataset: FAO/GAUL/2015/level2)	Vector	Static	Delineation of Sakarya Province – Merkez District study area
NDVI (Derived)	Calculated from Landsat SR bands (sensor-specific NIR & Red)	30 m	2000, 2006, 2012, 2018, 2024	Identification of vegetated (rural) areas (NDVI > 0.3) and vegetation dynamics
NDBI (Derived)	Calculated from Landsat SR bands (sensor-specific SWIR & NIR)	30 m	2000, 2006, 2012, 2018, 2024	Identification of built-up (urban) areas (NDBI > 0.1)
Land Surface Temperature (LST) (Derived)	Landsat thermal bands (ST_B6 for Landsat 5/7 ST_B10 for Landsat 8)	30 m	2000, 2006, 2012, 2018, 2024	SUHI intensity calculation (Urban LST – Rural LST) and spatial UHI mapping

Meteorological data were used to assess whether the observed changes in land surface temperature across the province were associated with interannual climatic variability. To capture the warmest period of the year, satellite imagery was restricted to the period between 1 June and 31 August. For the selected reference years, temperature data particularly maximum temperatures recorded during June, July, and August, when the highest temperatures typically occur were obtained from the Adapazarı meteorological station. These data were used as a reference to distinguish variations in land surface temperature associated with urbanization processes from those attributable to meteorological temperature variability (Table 2).

Table 2. Maximum temperature values for the average June–August period.

Year	Summer Average (°C)
2000	37.5
2006	37.3
2012	37.8
2018	34.1
2024	37.5

The study workflow consisted of image preprocessing, the generation of seasonal composites, the derivation of NDVI, NDBI, and LST, the delineation of urban and rural reference areas, and the calculation of SUHI intensity. The analyses were conducted for 2000, 2006, 2012, 2018, and 2024, representing different stages of urban development. Preprocessing, compositing, index calculation, masking, and zonal statistical analyses were performed using the GEE JavaScript API. The spatial outputs were exported in GeoTIFF format and cartographically processed in ArcGIS 10.1.

To generate the seasonal composites (June 1–August 31), a total of 7, 5, 12, 12, and 12 Landsat scenes were utilized for the 2000, 2007, 2014, 2019, and 2024 study years, respectively. No scene-level cloud cover threshold was applied. Because the study utilizes a median compositing approach, image quality was ensured purely through rigorous pixel-level screening using bits 3 and 4 of the QA_PIXEL band to eliminate clouds and cloud shadows before calculating the pixel-wise median. No temperature-range or outlier filtering was applied beyond the cloud and cloud-shadow masks.

The composites were clipped to the study area using the FAO GAUL 2015 Level 2 administrative boundary dataset available in GEE. The ST_B6 band was used as the thermal data source for Landsat 5 and 7, whereas ST_B10 was used for Landsat 8. All analyses were conducted at a spatial resolution of 30 m. NDVI was

calculated using the SR_B4 and SR_B3 bands for Landsat 5 and 7 and the SR_B5 and SR_B4 bands for Landsat 8. NDBI was calculated using SR_B5 and SR_B4 for Landsat 5 and 7 and SR_B6 and SR_B5 for Landsat 8. Furthermore, urban and rural reference areas were delineated strictly using spectral index-based masking ($\text{NDBI} > 0.1$ for built-up areas and $\text{NDVI} > 0.3$ for dense vegetation) to isolate thermal responses; this method functions as a binary spatial filter for LST extraction rather than a formal supervised Land Use/Land Cover (LULC) classification.

It does not constitute a formal supervised or unsupervised Land Use/Land Cover (LULC) classification. Consequently, no training samples, class accuracy assessment, overall accuracy, or Kappa coefficient were calculated. Figure 2 therefore illustrates the spatial distribution of these threshold-based urban and rural masks rather than a multi-class LULC map.

LST was derived from the Landsat Collection 2 Level-2 surface temperature products (Sharmin et al., 2024). The digital numbers of the thermal bands were converted to degrees Celsius using the scale and offset coefficients provided in the product metadata. District-level SUHI intensity was calculated as the difference between the mean LST values of the urban and rural reference areas (Zhou et al., 2018). The rural mask based on the NDVI threshold combines surfaces with different types of vegetation cover including forests, grasslands, and agricultural land into a single reference class.

Therefore, the calculated rural temperature does not represent an agricultural surface temperature differentiated by crop pattern, irrigation conditions, or soil moisture. This limitation was considered when interpreting the rural reference temperature and SUHI intensity. Spatially explicit, satellite-derived surface temperature anomalies were calculated by subtracting the corresponding rural reference mean from the LST value of each pixel. Positive values indicate surfaces warmer than the rural reference mean, whereas negative values represent cooler surfaces.

Mean NDVI, NDBI, and LST values were calculated for the five reference years using zonal statistics within district boundaries at a spatial resolution of 30 m. District-level SUHI values and pixel-based SUHI anomaly maps were also produced for the same years. Comparisons among the study periods were limited to the selected seasonal composites covering June, July, and August.

Statistical Analysis: The temporal changes in LST and SUHI intensity were examined using linear regression analysis. Year was used as the independent variable, while LST and SUHI intensity were separately treated as dependent variables. Model fit was evaluated using the coefficient of determination (R^2). The relationships between LST and NDVI and between LST and NDBI were examined using Pearson's correlation coefficient. The resulting correlation coefficient (r) indicates both the direction and strength of the relationship between the variables. Correlation coefficients range from -1 to $+1$, with values close to $+1$ indicating a strong positive relationship and those close to -1 indicating a strong negative relationship. Statistical significance was assessed at $p < 0.05$.

The Mann–Kendall test was used to determine the direction of monotonic changes in mean LST and SUHI intensity, while Sen's slope estimator was applied to quantify the magnitude of these changes. Sen's slope estimates provided a quantitative measure of the direction and magnitude of change, whereas the Mann–Kendall test was used to assess whether the observed monotonic changes were statistically significant. Because the statistical analyses were based on only five reference years, the Mann–Kendall, Sen's slope, and regression results were interpreted as exploratory indicators of change across the selected periods rather than as evidence of continuous long-term trends.

RESULTS

The analysis of multi-temporal Landsat composites for June, July, and August in 2000, 2006, 2012, 2018, and 2024 revealed a marked transformation in the thermal environment of the selected districts of Sakarya. The spatial distribution of land-use classes indicates that built-up areas expanded around the central urban zones, while agricultural and forested areas became increasingly fragmented (Figure 2).

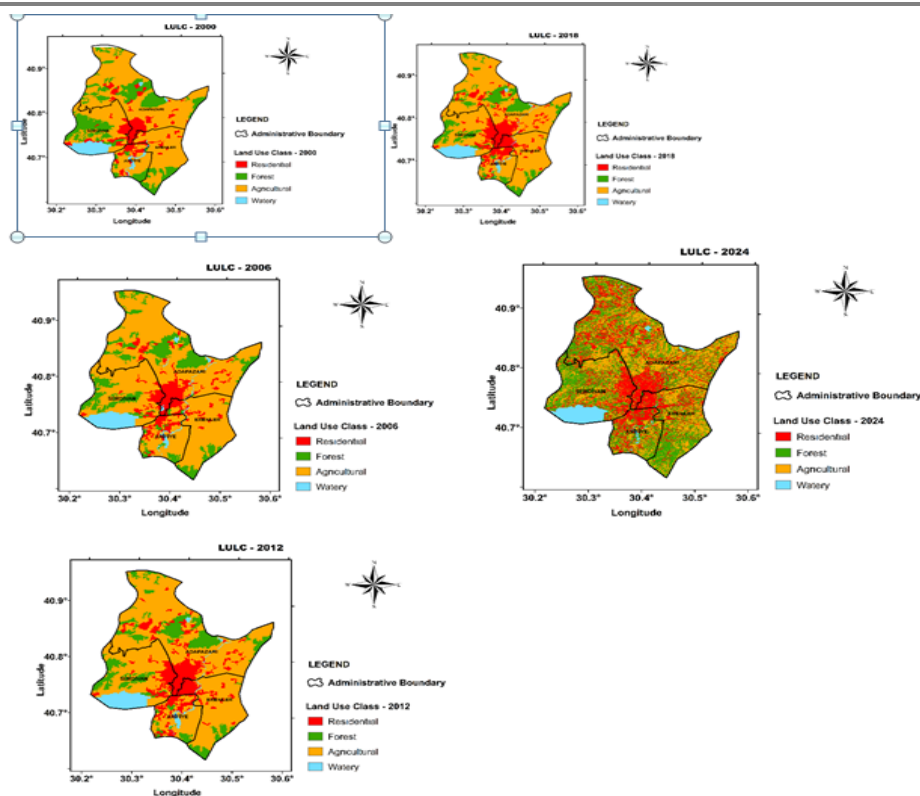


Figure 2. Spatiotemporal distribution of Land Use and Land Cover (LULC) classes in the central districts of Sakarya for the benchmark years 2000, 2006, 2012, 2018, and 2024.

The LST and SUHI distributions associated with these land-cover changes are presented in Figures 3 and 4, respectively. Mean LST was relatively lower in 2012 and 2018 than in 2006, before reaching its highest value of the study period in 2024. Areas characterized by high temperatures expanded markedly outward from the central urban core (Figure 3).

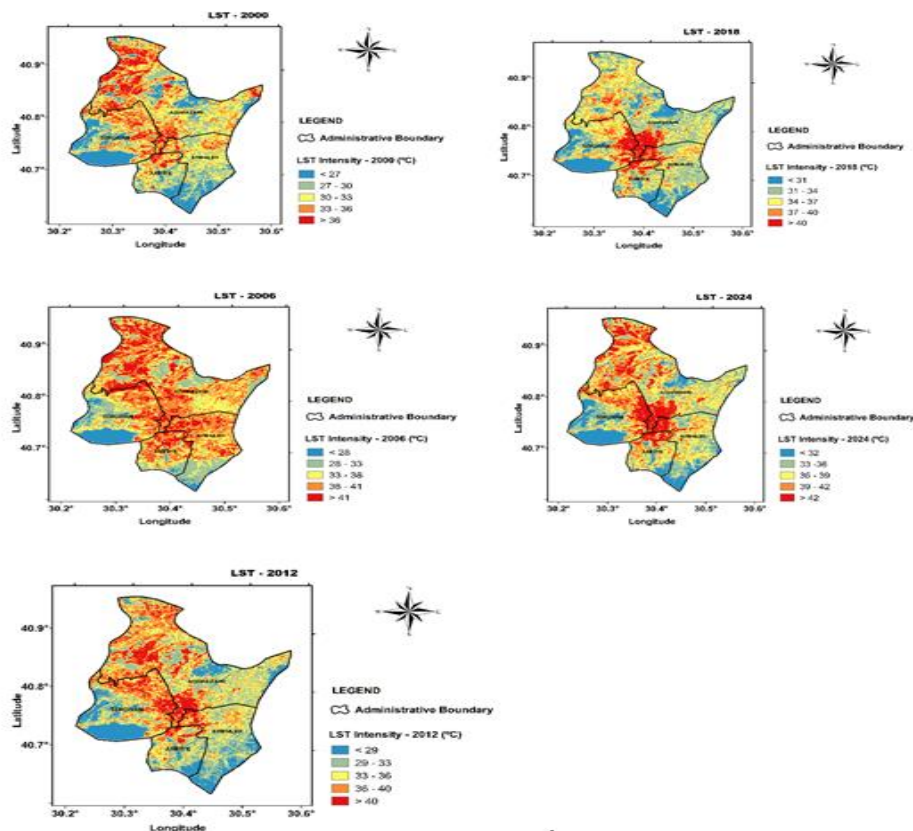


Figure 3. Spatiotemporal distribution of LST in the Merkez district of Sakarya for the years 2000, 2006, 2012,

2018, and 2024, derived from Landsat thermal infrared data.

Urban surfaces were warmer than rural surfaces in all reference years. Urban LST increased from 34.79 °C in 2000 to 45.38 °C in 2024, representing a rise of 10.59 °C. Over the same period, rural LST increased from 29.84 °C to 36.11 °C. SUHI intensity, calculated as the difference between urban and rural LST, increased from 4.95 °C in 2000 to 8.68 °C in 2006 and was estimated at 8.90 °C in 2012, 9.01 °C in 2018, and 9.27 °C in 2024. Thus, the urban–rural thermal contrast nearly doubled over the study period, while the thermal core both intensified and expanded spatially (Table 3). The increase in mean LST from 31.77 °C in 2000 to 38.15 °C in 2024 indicates an overall warming pattern. However, this increase was not linear over time. Mean LST rose to 37.79 °C in 2006, declined to 33.98 °C in 2012, and was calculated as 34.62 °C in 2018 and 38.15 °C in 2024. These fluctuations indicate that the increase during 2000–2024 occurred through periodic variations rather than as a continuous and consistent trend.

Table 3. Descriptives of thermal parameters for benchmark years (2000–2024).

Year	Mean LST (°C)	Urban LST (°C)	Rural LST (°C)	SUHI Intensity (°C)
2000	31.77	34.79	29.84	4.95
2006	37.79	42.57	33.89	8.68
2012	33.98	40.55	31.65	8.9
2018	34.62	42.53	33.52	9.01
2024	38.15	45.38	36.11	9.27

Satellite-derived high surface-temperature and SUHI clusters were particularly pronounced in the densely built-up areas of Adapazarı and Serdivan districts (Figure 4). This pattern indicates that the thermal core both intensified and expanded spatially.

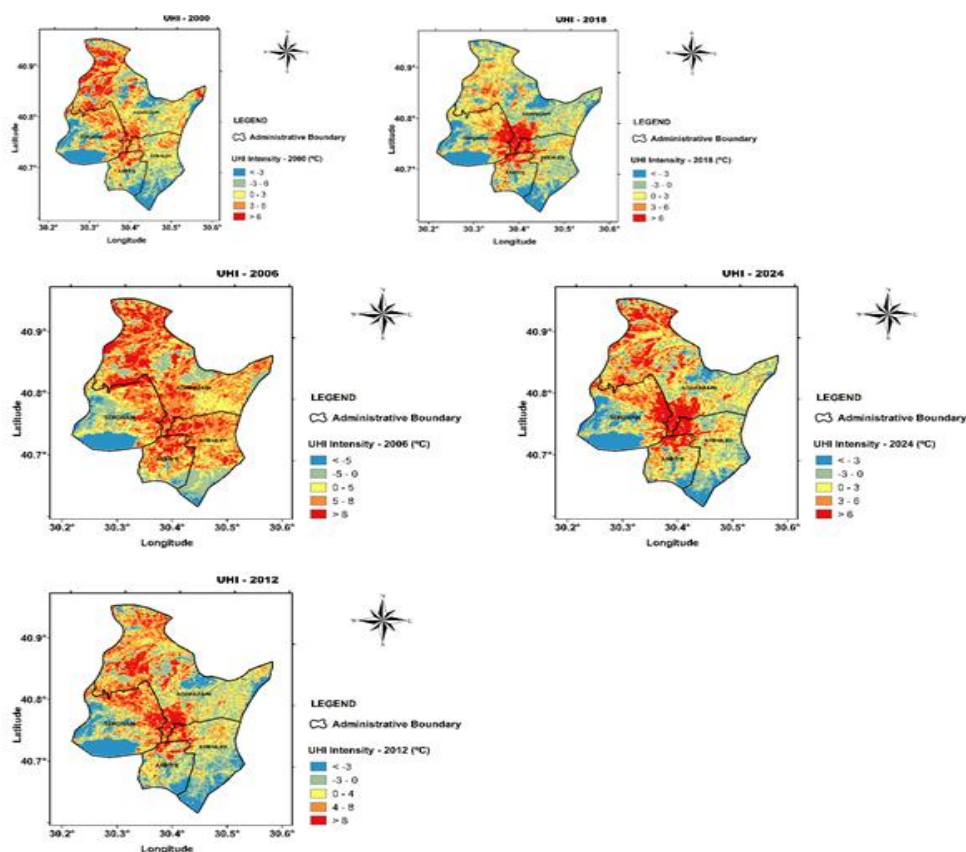


Figure 4. Evolution of Surface Urban Heat Island (SUHI) intensity in the Merkez district of Sakarya across

the five study periods (2000–2024). The color gradient represents the thermal differential (°C) between urbanized zones and the surrounding rural baseline.

Statistical Trends

The Mann–Kendall test results indicated positive trends in urban LST and SUHI intensity. However, the positive trend in rural LST was not statistically significant at the 95% confidence level ($\tau = 0.2130$, $p = 0.1412$; Sen's slope = 0.0768 °C/year). No significant monotonic trend was identified for mean LST ($\tau = -0.0067$, $p = 0.9814$). These findings indicate that thermal change did not occur uniformly across the study area and that pronounced warming was concentrated on urban surfaces. For urban LST, Kendall's tau coefficient was 0.4130 , with a Sen's slope of 0.2179 °C/year ($p = 0.0041$). A stronger monotonic increase was identified in SUHI intensity ($\tau = 0.5600$, $p < 0.0001$), with a Sen's slope of 0.1129 °C/year (Table 4).

Table 4. Results of the non-parametric trend test and Sen's slope analysis (2000–2024).

Parameter	Mann–Kendall ()	value	Sen slope (°C/yr)
Mean LST	–0,0067	0,9814	–0,0010
Urban LST	0,4130	0,0041	0,2179
Rural LST	0,2130	0,1412	0,0768
SUHI intensity	0,5600	<0,0001	0,1129

Linear regression analysis yielded an R^2 value of 0.430 ($p = 0.0003$) for temporal variation in urban LST and 0.440 ($p = 0.0003$) for SUHI intensity. The rural LST model had lower explanatory power ($R^2 \approx 0.18$), indicating greater temporal variability in rural temperatures than in urban temperatures. The Mann–Kendall trend test and Sen's slope estimates quantitatively characterized both the direction and magnitude of the trends, demonstrating that urbanization-related thermal increases were statistically significant. The absence of a clear trend in mean LST, in contrast to the increases observed in urban indicators, suggests that changes in the latter exhibited a more systematic and measurable signal.

Biophysical Variables

Pearson correlation analysis revealed a strong negative relationship between mean LST and NDVI ($r = -0.42$, $p = 0.48$, $n = 5$) and a strong positive relationship between mean LST and NDBI ($r = -0.42$, $p = 0.48$, $n = 5$) (Figure 6). Given the sample values, these coefficients should be considered indicative rather than definitive relationships. Accordingly, surface temperature tended to decrease as vegetation density increased and to rise with increasing built-up density. This finding is consistent with the cooling effects of vegetated surfaces through evapotranspiration and shading, whereas impervious surfaces increase heat storage (Voogt & Oke, 2003). The NDBI results further support the relationship between changes in the urban fabric and thermal conditions.

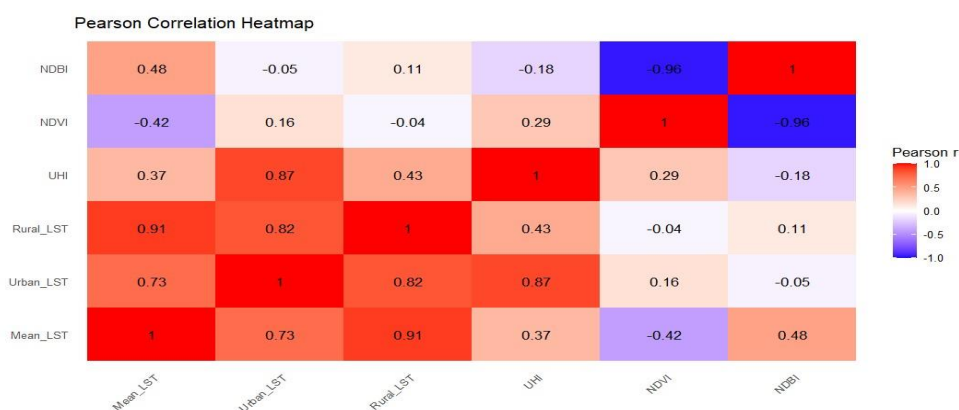


Figure 6. Pearson correlation heatmap displaying the relationships between thermal variables (Mean LST,

Urban LST, Rural LST, SUHI) and biophysical indices (NDVI, NDBI). The color scale represents the correlation coefficient (r), ranging from blue (negative) to red (positive).

SUHI intensity exhibited a strong positive correlation with urban LST ($r=0.87$). In contrast, the relationships between SUHI intensity and NDVI ($r=0.29$) and NDBI ($r=-0.18$) were weak. This indicates that SUHI intensity cannot be explained solely by mean spectral indices across the study area, but is also influenced by the relative thermal contrast between urban and rural reference areas. This finding is consistent with previous studies showing that urban areas tend to exhibit higher surface temperatures when vegetated surfaces are replaced by impervious materials such as asphalt and concrete (Voogt & Oke, 2003). These materials substantially alter the surface energy balance by reducing evapotranspiration and increasing heat storage. However, because the NDVI threshold-based rural mask encompasses agricultural land, forests, and other vegetated surfaces, variability in rural LST cannot be attributed solely to the amount of vegetation. Factors such as crop type, irrigation, soil moisture, harvest timing, surface albedo, and differences in evapotranspiration may influence the rural reference temperature and, consequently, the calculated SUHI intensity. Therefore, these variables should also be measured and incorporated into the analysis.

DISCUSSION

The main finding of this study is the divergence between the thermal changes observed in urban and rural surfaces. The increase in SUHI intensity indicates that warming was not evenly distributed across the study area. Although regional climate variability may affect both surface types, the more pronounced increase in urban areas points to the influence of local land-cover change on the thermal environment. This pattern is consistent with studies showing that replacing natural surfaces with materials that have limited evapotranspiration capacity, such as asphalt and concrete, alters the surface energy balance (Weng, 2001).

The results of this study demonstrate a distinct divergence in surface temperature trends between urban and rural areas in Sakarya; in other words, warming did not occur with the same intensity or direction across the entire study area. This disparity indicates that urbanization significantly intensifies thermal conditions beyond the effects of general climate variability. While regional climate change may contribute to the overall warming to some extent, the stronger and statistically significant rise observed in urban areas reveals that local land-surface transformations are the primary driving force.

This finding aligns with the results of previous studies. It is evident that the replacement of vegetation with impervious surfaces (such as asphalt and concrete) fundamentally alters the surface energy balance reducing evaporation and increasing heat storage thereby leading to higher surface temperatures. Unlike most research, which typically focuses on large metropolises, this study demonstrates that mid-sized cities undergoing rapid urbanization can experience similarly strong and intensifying urban heat island effects. The most pronounced temperature increase occurred between 2000 and 2006. This rise can be attributed to the combined impact of post-earthquake reconstruction, accelerated land-use changes, and industrial activities. These changes may have altered the surface energy balance and land-cover characteristics. However, because quantitative land-cover change analysis was not performed for the 2000–2006 interval, this association is presented as an interpretation rather than a confirmed causal relationship.

The positive relationship between NDBI and mean LST indicates that the expansion of built-up surfaces occurred alongside rising surface temperatures. The limited evapotranspiration capacity and heat-storage properties of impervious surfaces are the main physical mechanisms underlying this relationship. Urban morphology, building density, building height, and sky-view factor may also influence the amount of heat stored and the length of time it remains near the surface (Mekonnen et al., 2025; Sinha & Banerjee, 2025). This finding is consistent with studies showing that a higher proportion of impervious surfaces is associated with elevated LST and that urban expansion at the expense of green areas contributes to surface warming (Ng et al., 2025).

In contrast, the weak relationship between SUHI intensity and NDBI suggests that SUHI intensity is not determined solely by the proportion of built-up land. Although NDBI may help explain changes in absolute

surface temperature, SUHI is a relative measure based on the temperature difference between urban and rural reference surfaces. Consequently, simultaneous changes in rural temperature, the spatial arrangement of land cover, urban geometry, aerodynamic roughness, and boundary-layer processes may alter this relationship (Zhou et al., 2018; Mekonnen et al., 2025). The fact that absolute LST may increase while SUHI intensity declines in some cities further supports this distinction.

The spatial overlap between high SUHI values and areas dominated by dense development and transport-related land uses also points to the combined thermal effects of buildings and transport infrastructure. However, determining the independent contribution of transport would require direct measurements of traffic intensity and anthropogenic heat emissions. The negative relationship between NDVI and mean LST is consistent with the cooling effects of vegetation through shading and evapotranspiration (Weng, 2001; Guha & Govil, 2021). Previous studies have similarly reported an inverse relationship between NDVI and LST and have shown that the cooling effect of tree-dominated green spaces may become stronger under conditions of high heat stress (Gunawardena et al., 2017).

Satellite-derived LST is a different thermal variable from near-surface air temperature. Estimates of urban heat island intensity based on surface temperature and air temperature may differ, particularly under maximum and minimum temperature conditions (Sun et al., 2020; Ünsal, 2025). Integrating LST with meteorological records of air temperature, precipitation, and humidity would therefore help distinguish more clearly between the effects of regional climate variability and urbanisation.

Future Research

Although SUHI is a difference-based indicator that inherently reduces the influence of regional-scale climate variability, incorporating surface air temperature and precipitation datasets into future research would strengthen urban heat island assessments and help distinguish the effects of urbanisation more clearly from broader climatic trends. Such integration would support more robust causal inferences and contribute to the development of climate-resilient urban planning strategies.

The study is limited to satellite imagery acquired between June and August. Extending the analysis to multi-seasonal datasets would improve the generalisability of the findings by revealing whether SUHI intensification persists throughout the year or is concentrated in specific periods. Future research should also recognise that the SUHI estimates presented here are derived from satellite-based land surface temperature data and may therefore differ from those based on near-surface air temperature measurements.

CONCLUSION

This study assessed the temporal and spatial variation in the SUHI across the central districts of Sakarya using Landsat imagery acquired between June and August in 2000, 2006, 2012, 2018, and 2024. The analysis showed that SUHI intensity increased over the study period, indicating a growing thermal contrast between urban and rural surfaces. The positive relationship between LST and NDBI ($r = 0.48$) and the negative relationship between LST and NDVI ($r = -0.42$) support the respective roles of built-up surfaces and vegetation in surface warming and cooling processes.

The findings indicate that the relationship between urban development and the thermal environment should not be assessed solely in terms of rising surface temperatures. Instead, the expansion of built-up surfaces, changes in vegetation cover, and the increasing thermal contrast between urban and rural areas should be considered together. Accordingly, connected green corridors and vegetated buffer zones should be developed in industrial areas, transport corridors, and densely built residential districts. In addition to protecting vegetated surfaces, the size, connectivity, and spatial distribution of existing green areas should be carefully considered, as they may not be sufficient on their own to fully offset the thermal effects of expanding built-up surfaces. These results highlight the need for urban development plans and policies aimed at improving thermal comfort to protect existing vegetation, increase green-space provision, account for surface

characteristics in densely built-up areas, and promote integrated blue-green infrastructure connected to water bodies.

Overall, the study demonstrates that SUHI dynamics in rapidly growing, medium-sized cities are multidimensional and should be examined in relation to land cover, urban form, and the variable thermal characteristics of rural reference surfaces. Unlike research focusing primarily on large metropolitan areas, this study shows that medium-sized cities experiencing rapid urbanisation may also exhibit strong and increasingly intense urban heat island effects. Finally, the methodological framework developed in this study—which combines median composite generation, threshold-based classification of urban and rural areas, and both pixel-level and aggregated correlation analyses within Google Earth Engine—can be directly applied to rapidly growing cities in regions with similar characteristics.

REFERENCES

1. Arsiso, B. K. (2025). Urban land cover transformations and thermal dynamics through integrated LULC, UHI, and ecological vulnerability assessment using remote sensing indices in the City of Addis Ababa, Ethiopia. *Sustainable Cities and Society*, 107017. 10.1016/j.scs.2025.107017
2. Aydın, B. H. K., & Özüduru, B. H. (2025). Urban heat island effect of large-scale residential areas: A spatiotemporal analysis of Etimesgut district in Ankara. *Bitlis Eren Üniversitesi Fen Bilimleri Dergisi*, 14(1), 435–463. <https://doi.org/10.17798/bitlisfen.1596470>
3. Feng, L., Hussain, S., Pricope, N., Arshad, S., Tariq, A., Feng, L., & Mubeen, M. (2024). Seasonal Dynamics in Land Surface Temperature in Response to Land Use Land Cover Changes Using Google Earth Engine. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 17, 17983–17997. 10.1109/JSTARS.2024.3466191
4. Guha, S., Govil, H. An assessment on the relationship between land surface temperature and normalized difference vegetation index. *Environment, Development and Sustainability* 23, 1944–1963 (2021). <https://link.springer.com/article/10.1007/s10668-020-00657-6>
5. Gunawardena, K. R., Wells, M. J., & Kershaw, T. (2017). Utilising green and bluespace to mitigate urban heat island intensity. *Science of the total environment*, 584, 1040–1055.
6. Güller, C., & Toy, S. (2024). The Impacts of Urban Morphology on Urban Heat Islands in Housing Areas: The Case of Erzurum, Turkey. *Sustainability* 2024, 16(2), 791; <https://doi.org/10.3390/su16020791>
7. Gümrükçüoğlu, M., 2015 Urbanization Effect on Urban Heat Island, A Case Study: Sakarya International journal of energy and environment Volume 9, 83–89.
8. Gümüş, S. & Gümüş, M. (2025). Assessment of the impact of impervious surface increase on urban heat island and vegetation by remote sensing and statistical analysis: the case of Türkiye/Niğde city center (2013–2024). *Turkish Journal of Remote Sensing* 7(1):69–90. 10.51489/1663695
9. Karaçam, M., Kabadayı, E.M., Akar, F.İ. et al. (2026). Spatial and temporal patterns of daytime surface urban heat Islands in Istanbul, Türkiye: insights from a decade of google earth engine analysis. *Med. Geosc. Rev.* 8, 55–70. <https://doi.org/10.1007/s42990-026-00219-4>
10. Mekonnen, G. T., Berlie, A. B., Legesse, S. A., & Anteneh, M. (2025). Identifying the prominent cause of urban heat Island of Gondar City, Ethiopia: using GIS, Mann-Kendall test, Oke's algorithm and regression analysis. *Theoretical and Applied Climatology*, 156(6), 316.
11. Ng, Y.L., Lim, M.H., Huang, Y.F. et al. Thermal intensification and urban land cover change in Southeast Asian capitals: over three decades of satellite observations and trend analysis. *npj Urban Sustain* (2025). <https://doi.org/10.1038/s42949-025-00315-8>
12. Rao, P., Tassinari, P., Torreggiani, D., (2023). Exploring the land-use urban heat island nexus under climate change conditions using machine learning approach: A spatio-temporal analysis of remotely sensed data. *Heliyon*, 10.1016/j.heliyon.2023.e18423
13. Rose, R. & Kucharik, C., (2026). Diverging temperature and apparent temperature-based urban heat island of a midsize city. *Urban Climate*, 10.1016/j.uclim.2026.103054.
14. Sharmin, T., Chappell, A., & Lannon, S. (2025). Spatio-temporal analysis of LST, NDVI and SUHI in a coastal temperate city using local climate zone. *Energy and Built Environment*. 6 (6), 1142–115.

15. Sinha, S., & Banerjee, A. (2025). A systematic review of land use and land cover changes and their influence on urban heat island dynamics. *Discover Geoscience*, 3(1), 253.
16. Sun, T., Sun, R., & Chen, L. (2020). The trend inconsistency between land surface temperature and near surface air temperature in assessing urban heat island effects. *Remote sensing*, 12(8), 1271. 10.3390/rs12081271
17. Şahin, M. T., Hadimli, H., Çakır, Ç., Yasak, Ü., & Genişyürek, F. (2025). The role of urban landscape on land surface temperature: The case of Muratpaşa, Antalya. *Land*, 14(4), 663. <https://doi.org/10.3390/land14040663>
18. TÜİK. (2024). Address-based population registration system results, 2024. Turkish Statistical Institute. <https://www.tuik.gov.tr>
19. Ünsal, Ö. (2025). Land use change in Türkiye and determination of priority areas for urban heat island studies. *Coğrafi Bilimler Dergisi*, 23(1), 1–21.
20. Weiting, X., Qianlei, W., Junheng, Q., Jingbo, L., Sijie, Z., Bing, Q. (2025). Spatiotemporal dynamics of land surface temperature and its drivers within the local climate zone framework. *Sustainable Cities and Society*. 10.1016/j.scs.2025.106859
21. Weng, Q. (2001). A remote sensing/GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. *International Journal of Remote Sensing*, 22(10), 1999–2014. <https://doi.org/10.1080/713860788>
22. Voogt, J. A., & Oke, T. R. (2003). Thermal remote sensing of urban climates. *Remote sensing of environment*, 86(3), 370-384. 10.1016/S0034-4257(03)00079-8
23. Zhou, D., Xiao, J., Bonafoni, S., Berger, C., Deilami, K., Zhou, Y., ... & Sobrino, J. A. (2018). Satellite remote sensing of surface urban heat islands: Progress, challenges, and perspectives. *Remote Sensing*, 11(1), 48. <https://doi.org/10.3390/rs11010048>
24. Zhou, D., Zhao, S., Liu, S., Zhang, L., & Zhu, C. (2021). Surface urban heat island in China's 32 major cities: Spatial patterns and drivers. *Remote Sensing of Environment*, 10.1016/j.rse.2014.05.017