



Landsat and Random Forest Reveal Urban Heat Island Expansion in Can Tho City

Vu Khanh Tuong Van

Ho Chi Minh University of Natural Resources and Environment, Viet Nam

* Corresponding Author: **Vu Khanh Tuong Van**

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Abstract

Urban heat island assessment is increasingly important for rapidly urbanizing delta cities where built-up expansion, water networks and fragmented vegetation interact to shape surface thermal conditions. This study investigates the spatiotemporal variation of land surface temperature and urban heat islands in Can Tho City, Viet Nam, from 2015 to 2025 using Landsat 8 and Landsat 9 Collection 2 Level 2 imagery, Google Earth Engine and Random Forest regression. Annual median composites were generated after cloud and saturation masking, and three land-cover indicators were derived to represent vegetation, built-up surfaces and water bodies. A standardized urban heat island index was calculated from land surface temperature, and 33,542 sample points were extracted for machine-learning analysis. Results show that built-up surfaces expanded from the central urban core toward Cai Rang, Binh Thuy and major transport corridors, while vegetation became more fragmented and the cooling function of minor canals was locally weakened. The citywide mean land surface temperature reached about 35.06 C. Random Forest explained approximately one third of the observed thermal variability, with an error of 2.4 C. Built-up intensity was the strongest driver, accounting for 46.5 percent of feature importance, followed by water and vegetation. The results provide evidence for heat-sensitive urban planning in riverine delta cities.

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Keywords: Can Tho City, Google Earth Engine, land surface temperature, Random Forest, remote sensing, urban heat island

1. Introduction

Urban heat islands are among the most visible environmental consequences of rapid urbanization because artificial surfaces alter the urban energy balance, reduce evapotranspiration and store sensible heat. The physical basis of the urban heat island has been established through urban climatology research, which shows that surface materials, urban morphology and anthropogenic heat modify the exchange of radiation, heat and moisture between land and atmosphere^[1,2]. Remote sensing has extended this field from point-based air-temperature observations to spatially continuous surface thermal analysis, enabling the identification of intra-urban hotspots and their association with land-cover patterns^[3,4].

Land surface temperature derived from thermal infrared imagery is not identical to near-surface air temperature, but it provides a consistent indicator of surface thermal conditions and is particularly useful for mapping daytime surface urban heat islands. Previous studies have shown that built-up and impervious surfaces tend to increase land surface temperature, whereas vegetation and water bodies reduce it through shading, evaporation and moisture availability^[4,5,12]. Landscape configuration also matters because the spatial pattern of urban land cover can influence local thermal contrasts beyond the total area of each land-cover type^[18].

Satellite-derived indices are widely used to quantify these surface controls. The Normalized Difference Vegetation Index represents vegetation condition, the Normalized Difference Built-up Index has been used to identify built-up surfaces, and the Modified Normalized Difference Water Index enhances open-water features while suppressing built-up noise^[7,8]. Together, these indices provide a parsimonious but effective representation of the main surface components that regulate urban thermal environments in tropical cities.

Machine-learning methods have strengthened urban heat research by handling non-linear relationships between remote-sensing variables and temperature. Random Forest is particularly suitable because it combines multiple decision trees, is resistant to overfitting and can estimate variable importance^[9,10]. The availability of Google Earth Engine further enables long-term processing of large Landsat archives without local data-storage constraints^[11]. These capabilities are important for medium-sized cities where urban expansion is rapid but long-term monitoring remains limited.

In Viet Nam, urban heat island studies have focused mainly on large metropolitan areas and selected delta cities. For Can Tho, urban sprawl has been linked with local temperature change using Landsat data^[13], and subsequent studies have monitored surface urban heat island variation during 2014-2020 and analyzed current UHI conditions and influencing factors^[15,16]. Studies in other Vietnamese cities have also emphasized the role of built-up expansion and vegetation reduction in raising land surface temperature^[14]. However, three gaps remain: limited extension to the recent Landsat 9 period, insufficient integration of long-term standardized UHI mapping with machine-learning attribution, and limited production of journal-ready spatial evidence for planning-oriented interpretation.

This study addresses these gaps by developing a Landsat 8 and Landsat 9 based workflow for Can Tho City from 2015 to 2025. The specific contributions are: (i) generation of a

consistent time-series of land-cover indicators and land surface temperature; (ii) construction of a standardized UHI index to reveal heat anomalies within the city; (iii) use of Random Forest regression to quantify the relative roles of built-up surfaces, water bodies and vegetation; and (iv) translation of the results into implications for heat-sensitive urban development in a riverine delta city.

2. Materials and Methods

2.1. Study Area

Can Tho City is the largest urban center in the Vietnamese Mekong Delta and is located approximately between 9 degrees 55 minutes and 10 degrees 19 minutes north latitude and 105 degrees 13 minutes and 105 degrees 50 minutes east longitude. The city covers about 1,440 square kilometers and is bordered by An Giang, Dong Thap, Vinh Long, Hau Giang and Kien Giang provinces. Its low-lying deltaic terrain, dense river and canal network, and tropical monsoon climate make the city a suitable case for assessing interactions between urbanization and surface thermal conditions.

Urban development has accelerated around Ninh Kieu, Cai Rang, Binh Thuy and major transport corridors, while peri-urban districts such as Phong Dien and Vinh Thanh still contain substantial vegetation and water-related landscapes. This combination of compact urban cores, riverine cooling corridors and agricultural fringes creates a heterogeneous thermal environment.

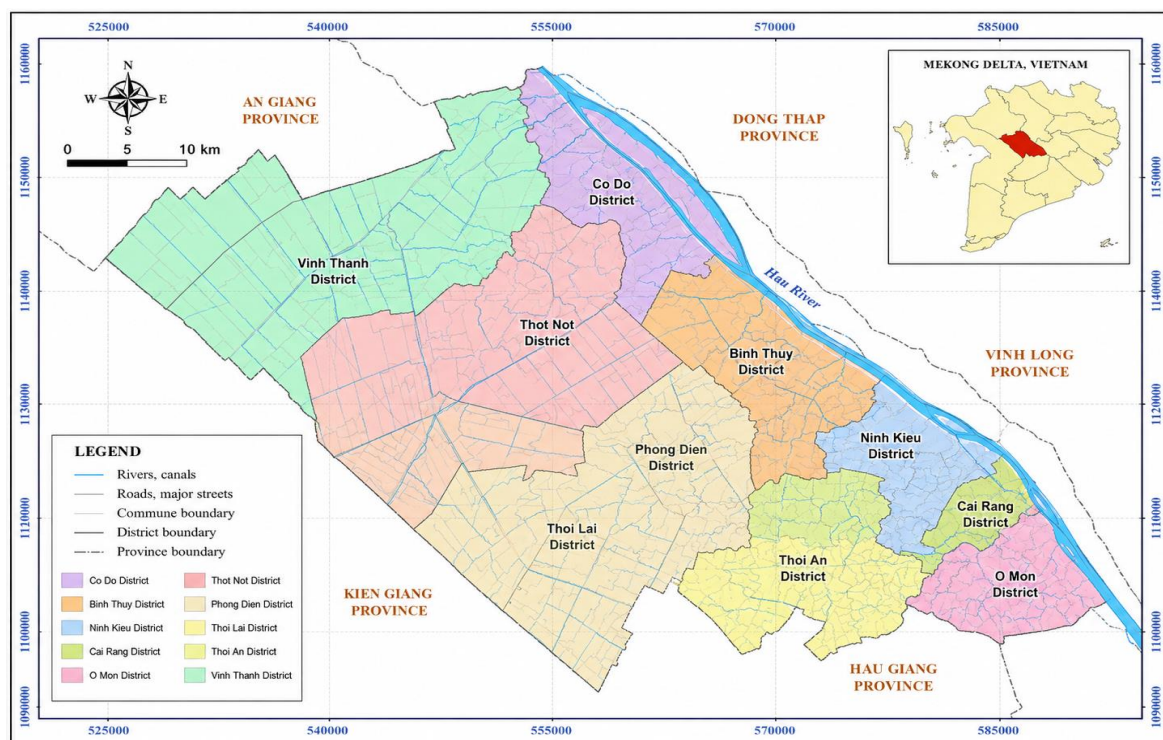


Fig 1: Study area and administrative divisions of Can Tho City.

2.2. Data Sources and Pre-Processing

The primary data source was Landsat Collection 2 Level 2 imagery from Landsat 8 OLI/TIRS and Landsat 9 OLI-2/TIRS-2. Level 2 data provide atmospherically corrected surface reflectance and surface temperature bands suitable for environmental analysis. The image archive was filtered by the Can Tho boundary and by acquisition years from 2015 to 2025. Cloud and saturation masking were implemented using

quality-assessment bands, and annual median composites were generated to reduce cloud contamination and short-term atmospheric noise.

Google Earth Engine was used for data retrieval, image filtering, masking, compositing, raster calculation, layer stacking and sample extraction. The final raster layers were clipped to the administrative boundary of Can Tho City and exported for map compilation and statistical analysis.

Table 1: Data sources and analytical roles.

Data layer	Source / derivation	Role in analysis
Landsat 8 and Landsat 9 Collection 2 Level 2	USGS archive processed in Google Earth Engine	Annual surface reflectance and surface temperature composites
Administrative boundary of Can Tho City	Vector boundary used in Google Earth Engine and GIS	Spatial clipping and sample constraint
NDVI, NDBI and MNDWI	Band-ratio indices derived from annual composites	Represent vegetation, built-up surfaces and water bodies
Land surface temperature	Scaled Landsat surface temperature band converted to Celsius	Response variable and basis for UHI calculation
Random sample points	33,542 points extracted from stacked raster layers	Model training and statistical evaluation

2.3. Remote-Sensing Indicators and Land Surface Temperature

Three indices were derived from annual surface reflectance composites. NDVI was used to characterize vegetation, NDBI to represent built-up intensity, and MNDWI to emphasize water surfaces. The indices were calculated as follows:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}). \quad (1)$$

$$\text{Ndbi} = (\text{Swir} - \text{Nir}) / (\text{Swir} + \text{Nir}). \quad (2)$$

$$\text{MNDWI} = (\text{Green} - \text{SWIR}) / (\text{Green} + \text{SWIR}). \quad (3)$$

For Landsat Collection 2 Level 2 surface temperature, the thermal band value was scaled according to the product specification and converted from Kelvin to Celsius:

$$\text{LST} = \text{DN} \times 0.00341802 + 149.0 - 273.15. \quad (4)$$

where DN is the pixel value of the surface temperature band. The resulting LST layer represents the surface thermal state of each pixel and was used to map the spatial distribution of heat across the city.

2.4. Standardized UHI Index

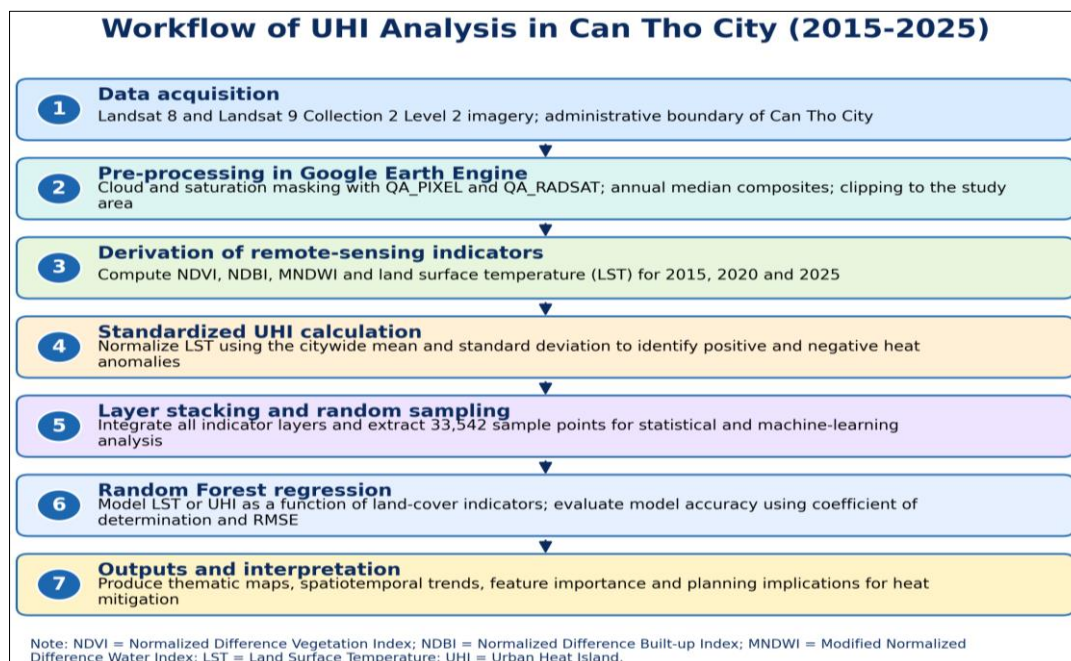
A standardized UHI index was calculated from the LST layer to identify areas that were warmer or cooler than the citywide thermal background. The index was defined as:

$\text{UHI} = (\text{LST} - \text{mean LST}) / \text{standard deviation of LST}$. (5)
Positive UHI values indicate pixels warmer than the city average, whereas negative values indicate cooler areas. This standardization allows comparison of thermal anomalies across years even when absolute temperature ranges vary among image composites.

2.5. Random Forest Regression and Model Evaluation

Random Forest regression was applied to model the relationship between land-cover indicators and LST or UHI. In regression mode, the prediction is the average value from an ensemble of decision trees. NDVI, NDBI and MNDWI were used as explanatory variables, while LST or the standardized UHI index was used as the response variable depending on the analytical step.

Model performance was evaluated using the coefficient of determination and root mean square error. Feature importance was used to quantify the relative contribution of each land-cover indicator to the prediction. This helped convert the model from a purely predictive tool into an interpretable assessment of the drivers of urban heat.

**Fig 2:** Workflow for UHI analysis in Can Tho City from 2015 to 2025.

3. Results

3.1. Spatiotemporal Variation of Built-Up, Vegetation and Water Indicators

The NDBI maps reveal an increasing and spatially expanding built-up signal during 2015-2025. High-NDBI areas were initially concentrated around the core urban area, especially Ninh Kieu. By 2020 and 2025, stronger built-up signals extended toward Cai Rang, Binh Thuy and major transportation corridors. The spatial pattern indicates that the surface materials associated with urban development expanded outward from the traditional urban core.

NDVI patterns show a fragmentation of vegetation cover, particularly in areas affected by urban growth. Some

peripheral and riverine zones still retained higher vegetation values, especially in Phong Dien and along parts of the Hau River corridor. However, the continuity of green patches near the urban fringe appeared weakened by new settlement clusters and road-oriented development.

The MNDWI maps confirm that the main river and canal network remained a distinctive cooling component of Can Tho City. Nevertheless, some small canals and water-related features appeared less prominent in the inner urban landscape, suggesting that local loss or narrowing of water surfaces may reduce the cooling function of blue infrastructure.

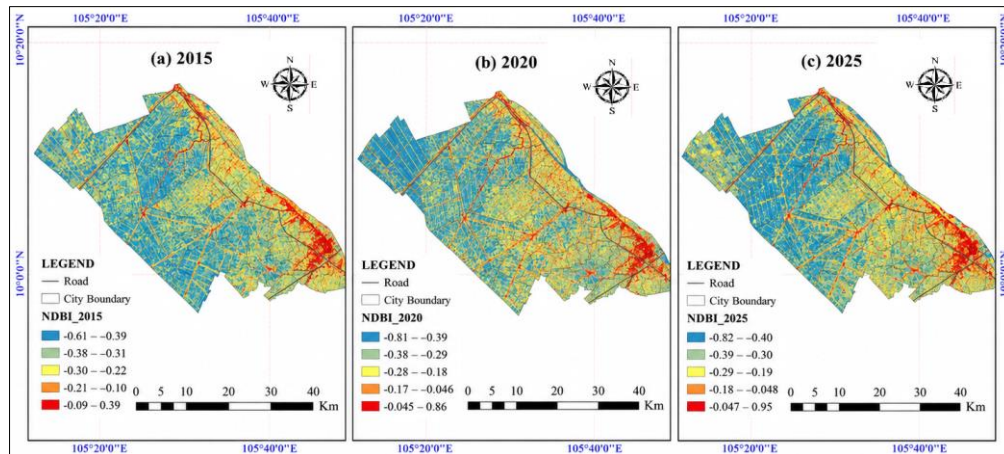


Fig 3: Spatiotemporal variation of NDBI in Can Tho City from 2015 to 2025.

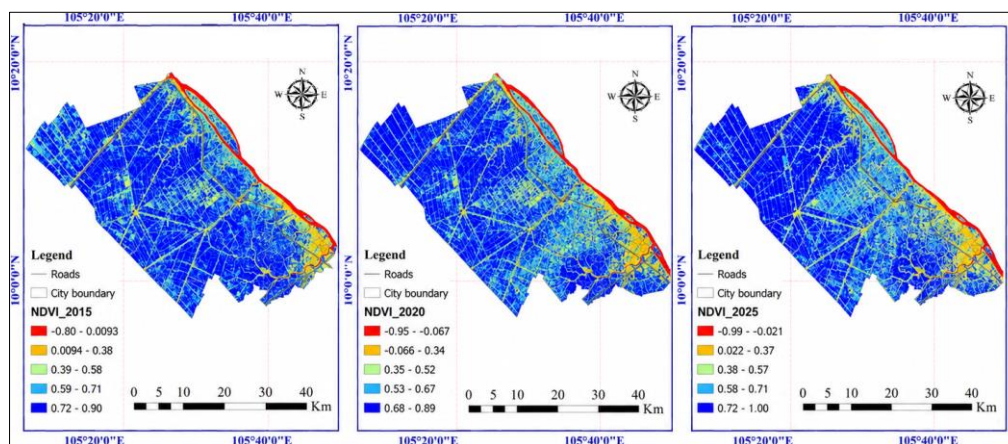


Fig 4: Spatiotemporal variation of NDVI in Can Tho City from 2015 to 2025.

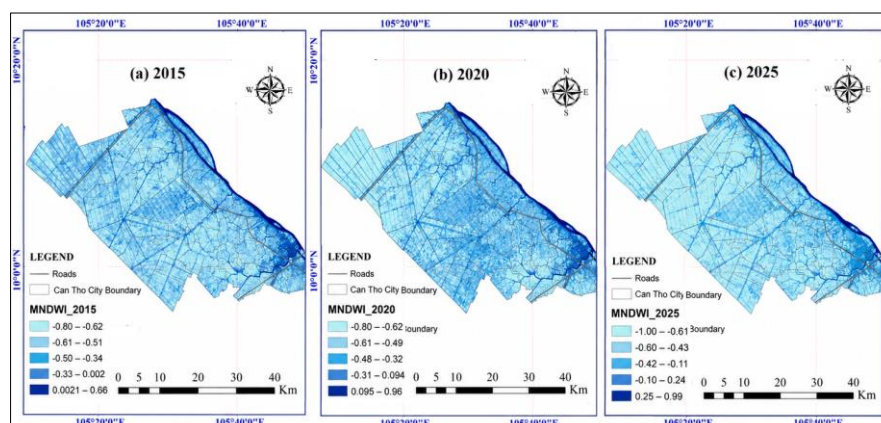


Fig 5: Spatiotemporal variation of MNDWI in Can Tho City from 2015 to 2025.

3.2. Land Surface Temperature and UHI Patterns

The LST maps show distinct thermal contrasts between built-up areas and the surrounding rural, vegetated and water-dominated landscapes. Hot spots were concentrated in the urban core and in newly urbanizing belts, while cooler surfaces were associated with water bodies, agricultural land and green corridors. The spatial distribution of high temperature broadly followed the expansion of NDBI, confirming the role of built-up surfaces in generating heat

accumulation. Based on 33,542 sample points, the mean LST of the city was approximately 35.06 C. High-temperature pixels locally exceeded 45 C and reached the highest ranges in the most intense built-up zones. This distribution indicates that the urban thermal environment is not uniform; it is structured by the interaction among impervious materials, vegetation cover and water networks.

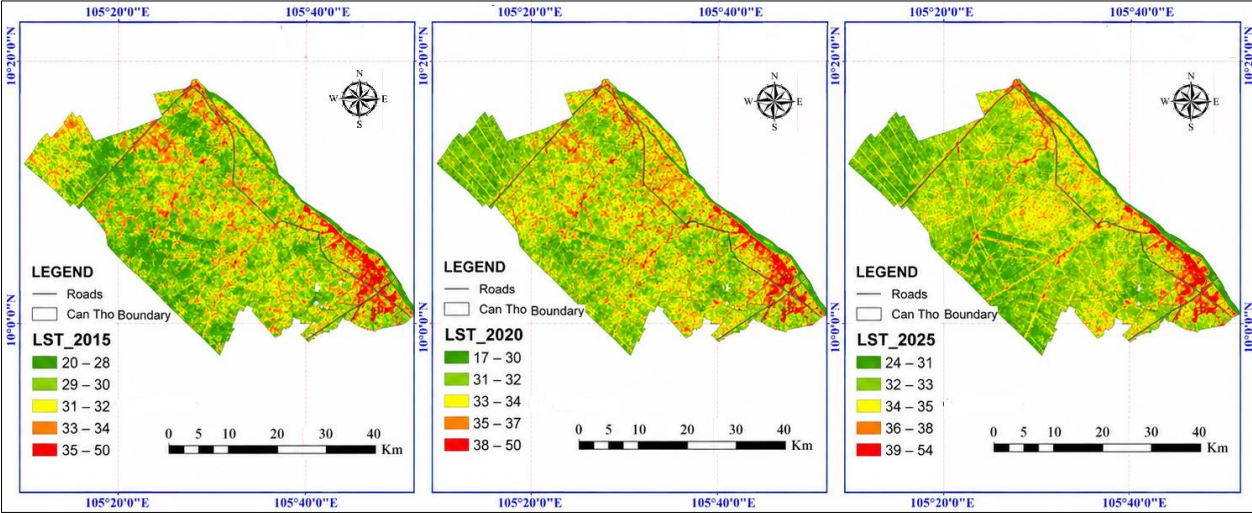


Fig 6: Spatiotemporal variation of land surface temperature in Can Tho City from 2015 to 2025.

3.3. Random Forest Model Performance and Feature Importance

The Random Forest model produced a coefficient of determination ranging from 0.32 to 0.35 and an RMSE of approximately 2.4 C. For a heterogeneous urban and peri-urban delta landscape, this level of explanatory power is meaningful because the model used only three surface indicators while LST is also affected by meteorological conditions, acquisition time, surface moisture, building

geometry and anthropogenic heat. Feature importance indicates that NDBI was the most influential predictor, accounting for 46.5 percent of the model contribution. NDWI ranked second with 27.2 percent, closely followed by NDVI with 26.3 percent. These values imply that built-up expansion is the dominant driver of surface heating, while water and vegetation have comparable cooling roles in Can Tho City.

Table 2: Summary of model performance and thermal statistics.

Metric / variable	Value	Interpretation
Sample size	33,542 points	Large citywide sample extracted from stacked raster layers
Coefficient of determination	0.32-0.35	Land-cover indicators explain about one third of LST variability
RMSE	2.4 C	Moderate error for Landsat-based surface temperature modeling
Mean LST	35.06 C	Average surface thermal condition of the city sample
Dominant predictor	NDBI	Built-up surfaces are the main driver of high LST

Table 3: Feature importance derived from the Random Forest model.

Predictor	Surface meaning	Feature importance (%)	Thermal implication
NDBI	Built-up and impervious surfaces	46.5	Increases heat storage and surface heating
NDWI	Water-related surfaces	27.2	Represents blue infrastructure and cooling corridors
NDVI	Vegetation cover	26.3	Represents evapotranspiration and shading effects

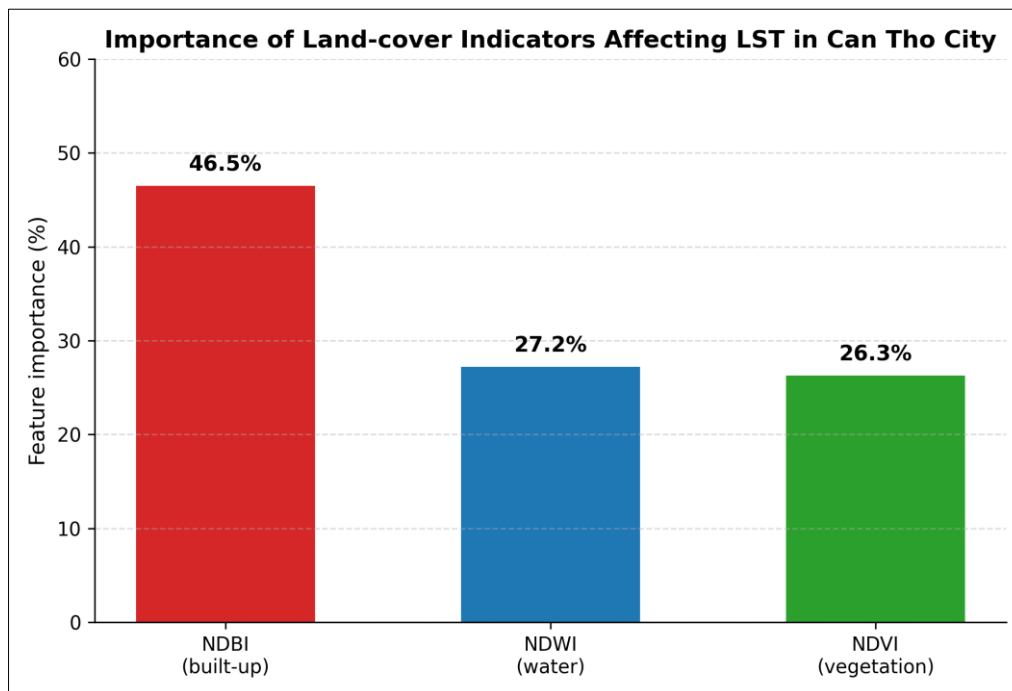


Fig 7: Feature importance of land-cover indicators from the Random Forest model.

4. Discussion

The results confirm the theoretical expectation that built-up surfaces intensify surface warming while vegetation and water moderate it. This finding is consistent with the broader remote-sensing literature, which identifies impervious surfaces as a major source of high LST and vegetation abundance as a cooling factor ^[4,5,12,18]. In Can Tho City, the dominance of NDBI is particularly important because urban growth is occurring in a low-lying delta landscape where surface materials are rapidly changing along road corridors and peri-urban development zones.

Compared with previous Vietnamese studies, this research contributes an updated Landsat 8 and Landsat 9 assessment through 2025 and combines spatial UHI mapping with Random Forest attribution. The pattern of expanding hot spots is consistent with previous evidence for Can Tho, where urban sprawl and surface urban heat island effects have been identified using Landsat data ^[13,15,16]. The present study extends that evidence by emphasizing the relative roles of built-up, water and vegetation indicators in a unified machine-learning framework.

The importance of water is a distinctive feature of Can Tho. Although vegetation is usually emphasized in urban heat mitigation, NDWI ranked slightly higher than NDVI in the Random Forest results. This reflects the riverine character of the city and suggests that canals, river edges and blue corridors are not only drainage or transport infrastructure but also thermal-regulation assets. Protecting narrow canals and avoiding excessive infilling in inner urban areas should therefore be considered a climate-adaptation priority.

The moderate coefficient of determination should be interpreted carefully. LST is controlled not only by land-cover indices but also by surface moisture, wind, air temperature, solar geometry, building height, urban canyon structure and anthropogenic heat. The model therefore captures a substantial but incomplete share of thermal variability. Future work should integrate urban morphology, population density, meteorological variables, local climate zones and field measurements to improve model performance

and strengthen the link between satellite-derived LST and human heat exposure.

From a planning perspective, the findings support three practical directions. First, high-NDBI corridors should be prioritized for heat mitigation through tree shading, reflective materials and permeable surfaces. Second, the remaining green patches in peri-urban districts should be protected as part of a connected green network. Third, water bodies and canal corridors should be incorporated into urban cooling strategies rather than treated only as drainage channels. These strategies are especially relevant for Can Tho because urban heat, flood risk and water management interact within the same deltaic urban system.

5. Conclusion

This study demonstrates that an integrated Landsat and Random Forest workflow can provide a practical basis for monitoring urban heat islands in a rapidly urbanizing Mekong Delta city. The approach converts long-term satellite observations into spatially explicit evidence about where heat accumulates, which land-cover components explain the thermal pattern, and how urban growth changes the balance between heat-generating and cooling surfaces.

The most important message is not only that Can Tho City has warmer built-up zones, but that the structure of future urban development will determine whether surface heat becomes more concentrated or can be moderated by green and blue infrastructure. Built-up expansion should therefore be managed together with vegetation continuity, canal protection and urban design measures that reduce heat storage. The proposed workflow is transferable to other delta cities where field measurements are limited but satellite archives are available.

Future research should move beyond three basic indices by incorporating building morphology, local climate zones, air-temperature observations and socio-economic exposure data. Such integration would allow urban heat research to support not only environmental monitoring but also public-health protection and climate-resilient planning.

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