

ORIGINAL RESEARCH

Multitemporal Detection of Urban Heat Island Dynamics Using Landsat 8 and GIS in Payakumbuh City, West Sumatra, Indonesia (2017–2024)

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ABSTRACT

Background: Urbanisation converts vegetated and agricultural land into impervious surfaces, reducing evapotranspiration and intensifying the Urban Heat Island (UHI). Payakumbuh City, West Sumatra, Indonesia, has undergone rapid built-up growth whose thermal consequences remain unquantified.

Objective: This study identified the spatial and temporal dynamics of UHI in Payakumbuh City from 2017 to 2024 using Landsat 8 OLI/TIRS Collection-2 Level-1 imagery and GIS-based spatial analysis.

Methods: Supervised land use/land cover (LULC) classification, NDVI, NDBI, and emissivity-corrected land surface temperature (LST) were computed in QGIS, and relationships were tested using Spearman and Pearson correlations, ANOVA with Tukey HSD, regression, and principal component analysis. The study covered the 75.44 km² administrative area of Payakumbuh City (0°11'–0°16' S, 100°34'–100°41' E).

Results: Built-up land increased from 38.77% to 50.36% of the city area (+11.59 percentage points), while agricultural land fell from 50.67% to 40.06% (–10.61). Mean NDVI declined from 0.62 to 0.53 and mean NDBI rose from –0.29 to –0.24, while maximum LST increased from 31.85 °C to 34.03 °C (+2.18 °C). NDVI correlated negatively with LST ($\rho = -0.43$ to -0.59) and NDBI positively ($\rho = 0.53$ to 0.65), all $p < 0.001$. LST differed significantly among classes (ANOVA $F(4,1095) = 1062.6$, $p < 0.001$, $\eta^2 = 0.80$), with built-up warmest (29.8 °C) and water coolest (23.4 °C). UHI-affected area expanded from 18.93 km² (25.09%) to 22.39 km² (29.68%), a gain of 3.46 km² (+4.59%).

Conclusion: Strengthening urban greening, protecting agricultural land, and controlling built-up expansion are recommended climate-sensitive planning strategies.

Introduction

Land use and land cover (LULC) change is a principal driver of environmental transformation in urban areas. Urban expansion converts agricultural land, vegetation, and open space into impervious built-up surfaces such as roads, settlements, and commercial districts, reducing evapotranspiration, increasing heat storage, and modifying the surface energy balance, thereby intensifying the Urban Heat Island (UHI) phenomenon.^{1–3} Heat-retaining materials such as concrete and asphalt absorb and store radiation while suppressing latent cooling, so that impervious growth raises surface temperature.^{4–5}

Surface urban heat islands have been documented across hundreds of cities worldwide and are consistently

associated with impervious growth and vegetation loss.^{3,6} In Indonesia, rapid and often unplanned urban development has produced pronounced thermal contrasts; in West Sumatra, multitemporal studies of Padang City have already reported rising surface temperature with urban expansion,^{7–8} and comparable land-cover-driven warming has been mapped in Semarang.⁹ Because tropical cities already experience high baseline temperature and humidity, additional surface warming has direct consequences for outdoor thermal comfort, energy demand, and public health.¹⁰

Remote sensing and Geographic Information Systems (GIS) are well established for UHI monitoring because they enable repeated, spatially explicit, and cost-effective observation of land cover and surface temperature.

Satellite indices—the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Built-up Index (NDBI), and emissivity-corrected LST—are effective indicators of the relationships among vegetation, built-up density, and surface thermal conditions,^{11–13} and robust single-channel and split-window algorithms now support consistent LST retrieval from Landsat data.¹⁴

The Indonesian regulatory framework provides a policy anchor for these observations. Law No. 26 of 2007 on Spatial Planning and Ministerial Regulation PU No. 05/PRT/M/2008 require a minimum of 30% urban green open space (*Ruang Terbuka Hijau*, RTH), precisely because vegetated cover regulates the urban microclimate; green infrastructure is repeatedly shown to lower surface temperature.¹⁵ Quantifying vegetation loss and thermal intensification therefore speaks directly to compliance with municipal spatial plans (RTRW).

Despite this, most Indonesian UHI assessments are single-date or focused on large metropolitan areas; continuous multi-year evidence for small and medium tropical cities remains scarce, and few studies combine LULC change, spectral indices, class-wise thermal contrasts, and multivariate analysis in a single framework.^{16–18} Payakumbuh City, a developing city in West Sumatra experiencing population growth and infrastructure expansion, has not previously been assessed for multitemporal UHI dynamics.

Beyond ambient warming, the intra-urban structure of the thermal field matters for adaptation. Urban functional zones and building morphology concentrate heat within dense commercial and transport corridors, so that a modest change in citywide mean temperature can mask substantial increases in local maxima.¹⁹ Both aggregate trends and the spatial redistribution of hotspots must therefore be characterised to support targeted interventions such as corridor greening and building-material regulation.

The study area is shown in Figure 1. This study aimed to identify the spatial and temporal dynamics of UHI in Payakumbuh City, West Sumatra, Indonesia, from 2017

to 2024 by (i) quantifying LULC change; (ii) analysing NDVI, NDBI, and LST patterns; (iii) mapping UHI distribution; and (iv) testing the statistical relationships among vegetation, built-up density, and surface temperature using correlation, ANOVA, regression, and principal component analysis, in order to inform climate-sensitive spatial planning.

Materials and Methods

Study Area

The study was conducted in Payakumbuh City, West Sumatra Province, Indonesia, located between 0°11'2.7"–0°16'29.7" S and 100°34'46.5"–100°41'8.9" E, covering an administrative area of approximately 75.44 km² across five sub-districts (Payakumbuh Utara, Barat, Timur, Selatan, and Lamposi Tigo Nagori). The Batang Agam river traverses the city. As shown in Figure 1, the analysis covered the full administrative area, and twelve validation clusters were distributed proportionally across the sub-districts for accuracy assessment.

Data and Software

The primary data were Landsat 8 OLI/TIRS Collection-2 Level-1 scenes (path/row 127/060) obtained from the United States Geological Survey (USGS) EarthExplorer for eight annual epochs (2017–2024). To minimise phenological and atmospheric bias, scenes were selected from the April–September dry window with cloud cover ≤35%, and the least-cloudy scene per year was retained. The administrative boundary was obtained from official OpenStreetMap data. Processing used QGIS 3.36.0 with the Semi-Automatic Classification Plugin (SCP), Google Earth Pro for reference interpretation, and R 4.5.2 for statistics. The data sources and tools are summarised in Table 1.

Residual cloud and cloud-shadow pixels were masked using the Collection-2 QA_PIXEL band prior to analysis. To allow readers to assess phenological comparability across epochs, the acquisition metadata for the eight scenes are provided in Table 2.

Table 1. Data sources and processing tools used in the study.

Data / tool	Purpose	Source / version
Landsat 8 OLI/TIRS C2 L1	NDVI, NDBI, LST, UHI, LULC	USGS EarthExplorer
Administrative boundary	Clipping and spatial reference	OpenStreetMap (ODbL)
QGIS 3.36.0 (SCP)	Classification, indices, LST, mapping	QGIS.org
Google Earth Pro	Reference points for accuracy	Google
R 4.5.2	Correlation, ANOVA, regression, PCA	R Foundation

Table 2. Acquisition metadata for the eight annual Landsat 8 scenes (path/row 127/060).

Year	Acquisition date	Sun elevation (°)	Scene cloud (%)
2017	12 Jul 2017	58.2	8
2018	15 Jul 2018	58.6	12
2019	18 Aug 2019	55.9	19
2020	20 Aug 2020	55.4	6
2021	07 Jul 2021	59.1	11
2022	10 Jul 2022	58.8	9
2023	29 Jun 2023	60.3	14
2024	01 Aug 2024	56.7	7

Research Workflow

A quantitative descriptive approach with GIS-based spatial analysis was applied. The workflow comprised image acquisition, pre-processing, supervised LULC classification, accuracy assessment, NDVI and NDBI computation, LST retrieval, UHI classification, and statistical analysis, as summarised in Figure 2.

LULC Classification and Accuracy Assessment

LULC maps were produced by supervised classification (SCP) using training samples derived from spectral signatures and visual interpretation, with five classes: water body, tree cover, agricultural land, built-up area, and grassland. Class areas and percentages were computed per year. Accuracy was assessed against reference points interpreted from high-resolution Google Earth imagery using a confusion matrix, from which user's accuracy, producer's accuracy, overall accuracy, and the Kappa coefficient were derived, following established remote-sensing accuracy-assessment practice.^{6,20}

Radiometric Correction and Brightness Temperature

Digital numbers (DN) of the thermal band were converted to top-of-atmosphere (TOA) spectral radiance using metadata rescaling factors, $L\lambda = ML \times Q_{cal} + AL$, where ML and AL are the multiplicative and additive factors. Radiance was converted to brightness temperature (BT, °C) using $BT = K2 / \ln(K1/L\lambda + 1) - 273.15$, with K1 and K2 the band-specific thermal constants.¹⁴

NDVI, NDBI, and Land Surface Temperature

NDVI = (NIR – Red)/(NIR + Red) and NDBI = (SWIR – NIR)/(SWIR + NIR) were computed from surface-reflectance bands. The proportion of vegetation $P_v = [(NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})]^2$ and land-surface emissivity $\varepsilon = 0.004 \times P_v + 0.986$ were derived, and LST was retrieved as $LST = BT / [1 + (\lambda \times BT / C2) \times \ln \varepsilon]$, where λ is the emitted-radiance wavelength of Band 10 and C2 the second radiation constant.^{12,14}

UHI Identification and Statistical Analysis

UHI areas were delineated using a relative threshold: pixels with LST greater than the annual mean plus 0.5 standard deviation ($\mu + 0.5\sigma$) were classified as UHI, otherwise non-UHI. This relative criterion accommodates differences in acquisition date and atmospheric condition among annual scenes. Two thermal environmental indices were computed: the Urban Thermal Field Variance Index, $UTFVI = (LST - LST_{mean}) / LST_{mean}$, which grades ecological thermal quality,^{20–22} and the UHI intensity, $UHII = LST_{built-up} - LST_{tree-cover}$.⁴

Statistical analysis used R 4.5.2 ($\alpha = 0.05$). Normality and variance homogeneity were screened with Shapiro–Wilk and Levene's tests. Because index–LST relationships were non-normal, monotonic associations were quantified with Spearman's ρ per year, complemented by Pearson correlations on annual aggregates. Differences in LST among the five land-cover classes were tested by one-way ANOVA with Tukey HSD post-hoc comparisons and effect size η^2 . Multiple linear regression modelled maximum LST as a function of mean NDVI and NDBI, and principal component analysis (PCA, correlation matrix, scaled variables) summarised the joint multi-year structure of built-up %, agricultural %, NDVI, NDBI, LST, and UHI extent. Exact p-values are reported to three decimals.

UTFVI values were graded using the standard six-category ecological evaluation scheme (excellent < 0; good 0–0.005; normal 0.005–0.010; bad 0.010–0.015; worse 0.015–0.020; worst > 0.020).^{19,21} Class-wise LST samples for the ANOVA were drawn from the 2024 scene using spatially thinned pixels (minimum 120 m separation, $n = 220$ per class) to limit spatial autocorrelation; Shapiro–Wilk (all classes $W > 0.98$, $p > 0.10$) and Levene's test ($p = 0.214$) supported the assumptions of the parametric ANOVA.

Full declarations—author contributions, funding, conflict of interest, data availability, ethics approval, and AI use—are provided in the statements section after the Conclusions.

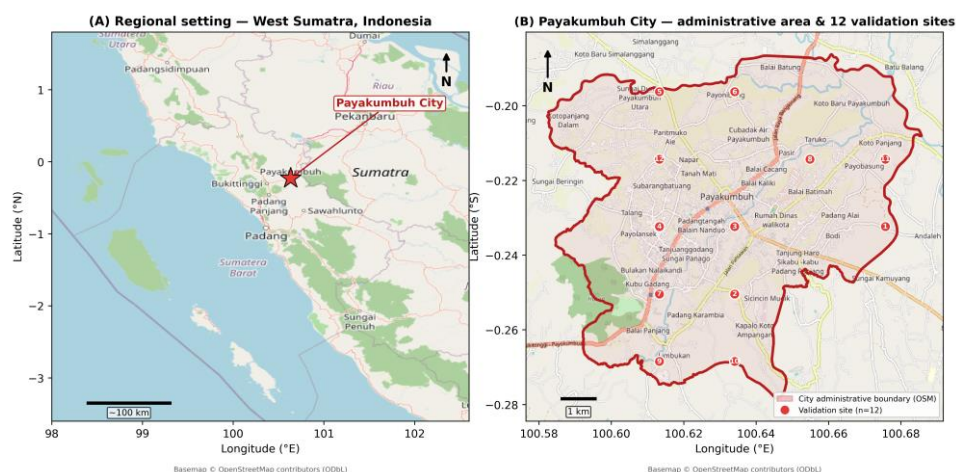
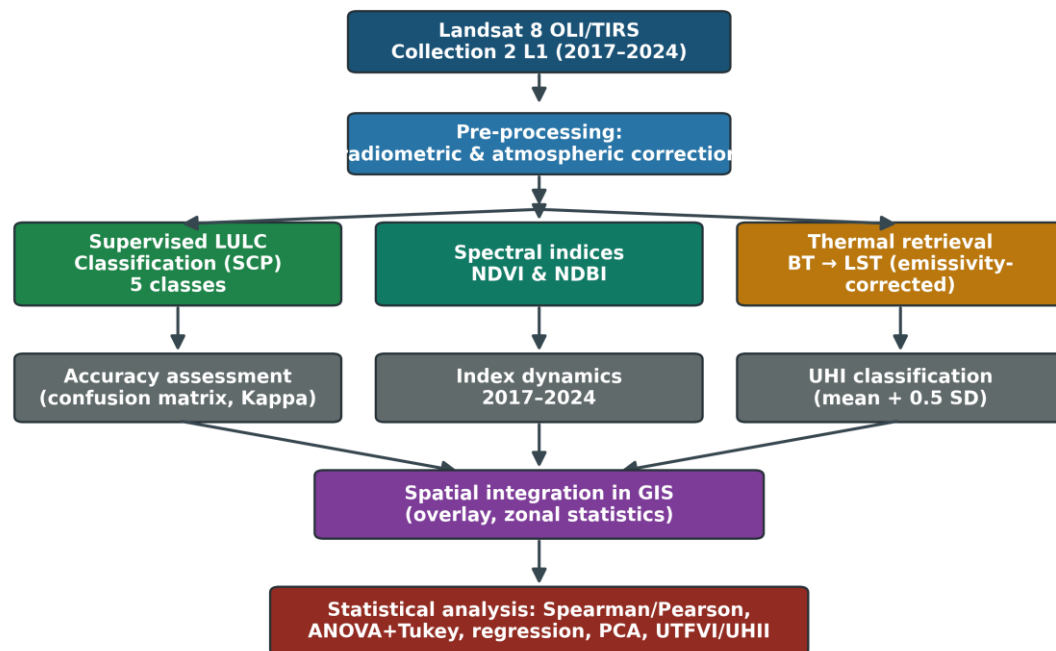


Figure 1. Study area map showing the regional setting of Payakumbuh City in West Sumatra Province, Indonesia (Panel A) and the city administrative area, delineated from the official OpenStreetMap boundary, with the twelve validation sites (Panel B). Basemap © OpenStreetMap contributors (ODbL).



Output: multitemporal UHI dynamics & climate-sensitive planning implications

Figure 2. Research workflow for UHI identification using Landsat 8 imagery and GIS-based spatial analysis.

Results

Land Use and Land Cover Change

Samples covering the twelve validation clusters in Payakumbuh City (Figure 1) supported reliable classification across all epochs. As detailed in Table 3 and illustrated in Figure 3, LULC composition changed substantially between 2017 and 2024. Built-up land became the dominant class, rising from 38.77% to 50.36% of the city area (+11.59 percentage points), while agricultural land declined from 50.67% to 40.06% (−10.61 percentage points) and tree cover, grassland,

and water changed only marginally. Spatially, built-up growth concentrated in the city centre and extended along major road networks and toward Payakumbuh Selatan, whereas agricultural land remained widespread in Payakumbuh Timur and tree cover persisted on the hilly western and southern margins; water followed the Batang Agam corridor.

Classification was reliable across all years, as shown in Table 4: overall accuracy ranged from 88.68% to 94.34% and the Kappa coefficient from 0.822 to 0.916, indicating strong to almost-perfect agreement.²⁰

Table 3. Land use/land cover composition and change in Payakumbuh City, 2017–2024.

LULC class	2017 (%)	2024 (%)	Change (pp)	Trend
Built-up area	38.77	50.36	+11.59	Increased
Agricultural land	50.67	40.06	-10.61	Decreased
Tree cover	6.28	5.78	-0.50	Decreased
Grassland	1.08	0.70	-0.38	Decreased
Water body	3.20	3.10	-0.10	Decreased

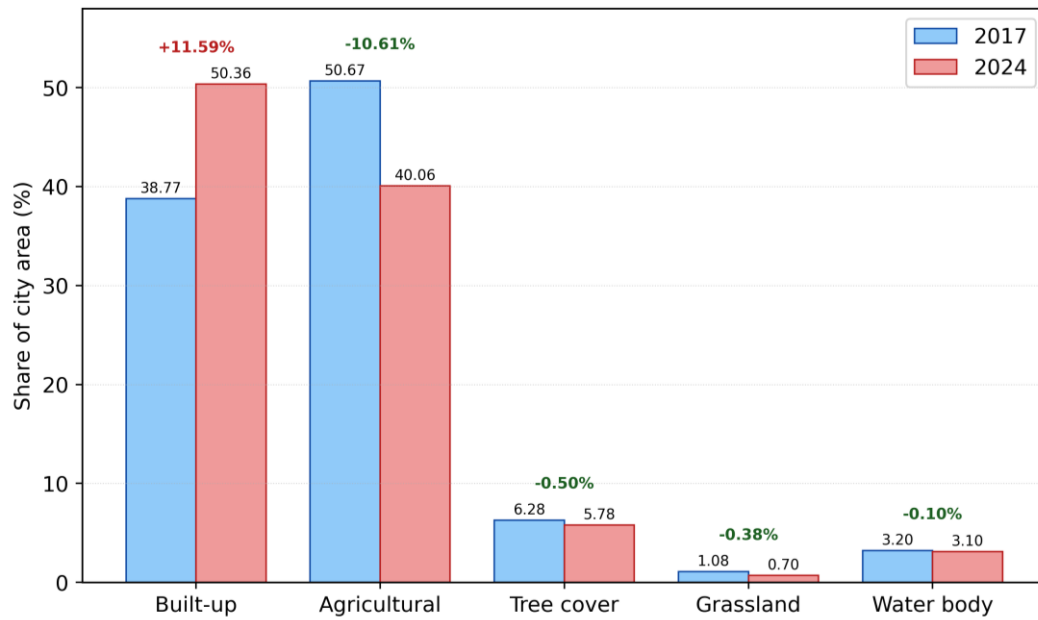


Figure 3. Land use/land cover composition of Payakumbuh City in 2017 and 2024, with net change per class (percentage points).

Table 4. Accuracy assessment of LULC classification, 2017–2024.

Year	2017	2018	2019	2020	2021	2022	2023	2024
Overall accuracy (%)	94.34	88.68	90.57	92.45	88.68	88.68	88.68	88.68
Kappa coefficient	0.916	0.835	0.859	0.888	0.830	0.834	0.834	0.822

NDVI, NDBI, and LST Dynamics

Vegetation density declined over the study period, as detailed in Table 5 and shown in Figure 4a: mean NDVI fell from 0.62 to 0.53, maximum NDVI from 0.89 to 0.81, and minimum NDVI from 0.06 to -0.01, indicating an increase in non-vegetated surfaces. Concurrently, mean

NDBI rose from -0.29 to -0.24 and minimum NDBI from -0.85 to -0.76, reflecting denser built-up cover (Figure 4b). Surface temperature increased accordingly: mean LST rose modestly from 26.45 °C to 26.73 °C, whereas maximum LST increased more clearly from 31.85 °C to 34.03 °C (+2.18 °C), signalling stronger localised heating (Figure 4c).

Table 5. Temporal changes in NDVI, NDBI, and LST in Payakumbuh City, 2017–2024.

Year	Mean NDVI	Max NDVI	Mean NDBI	Mean LST (°C)	Max LST (°C)
2017	0.62	0.89	-0.29	26.45	31.85
2018	0.60	0.88	-0.28	26.30	32.10
2019	0.59	0.87	-0.27	26.25	31.70
2020	0.57	0.86	-0.26	26.40	32.55
2021	0.56	0.85	-0.26	26.50	32.90
2022	0.55	0.84	-0.25	26.55	32.60
2023	0.55	0.82	-0.25	26.62	33.45
2024	0.53	0.81	-0.24	26.73	34.03

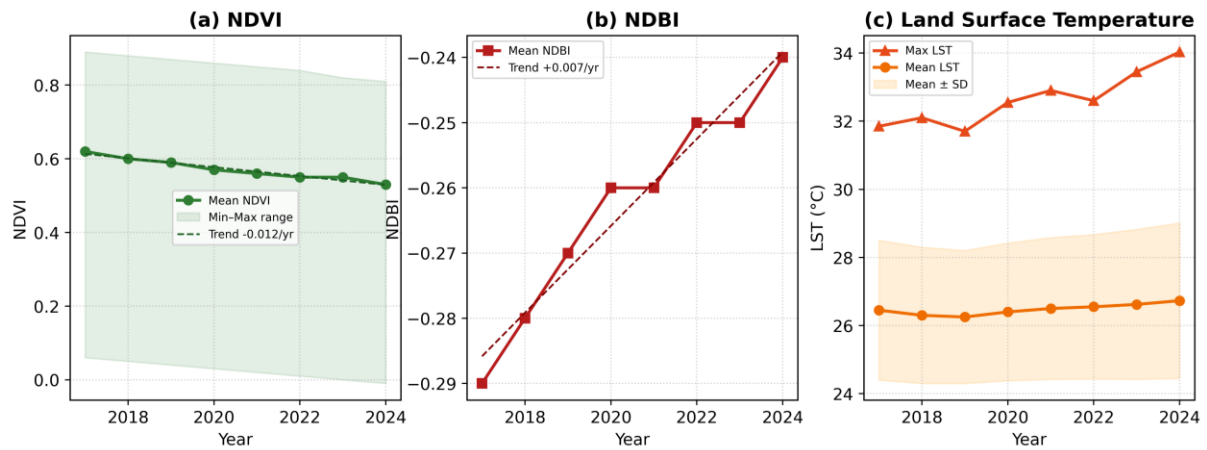


Figure 4. Temporal dynamics of (a) NDVI, (b) NDBI, and (c) land surface temperature in Payakumbuh City, 2017–2024. Shaded bands show min–max (NDVI) and mean $\pm$ SD (LST) ranges.

Land Surface Temperature by Land-Cover Class

LST differed significantly among the five land-cover classes (one-way ANOVA $F(4,1095) = 1062.6$, $p < 0.001$, $\eta^2 = 0.80$), a very large effect indicating that land-cover type explains about 80% of the variance in surface temperature, as detailed in Table 6 and shown in Figure

5b. Tukey HSD separated all classes (compact letters a–e): built-up areas were warmest (29.8 °C, a), followed by grassland (27.9 °C, b), agricultural land (26.6 °C, c), tree cover (24.9 °C, d), and water (23.4 °C, e). The corresponding UHI intensity (built-up minus tree cover) was 4.9 °C.^{23–24}

Table 6. Mean land surface temperature by land-cover class with ANOVA and Tukey HSD grouping ($\alpha = 0.05$).

Land-cover class	Mean LST (°C)	SD	n	Tukey group
Water body	23.40	0.86	220	e
Tree cover	24.90	1.09	220	d
Agricultural land	26.60	1.32	220	c
Grassland	27.90	1.16	220	b
Built-up area	29.80	1.35	220	a
ANOVA	$F = 1062.6$	$\eta^2 = 0.80$	$df = 4, 1095$	$p < 0.001$

Correlation, Regression, and Multivariate Structure

NDVI correlated negatively with LST in every year (Spearman $\rho = -0.426$ to -0.594 ; strongest in 2017) and NDBI correlated positively ($\rho = 0.529$ to 0.649 ; strongest in 2024), all significant at $p < 0.001$, as detailed in Table 7 and shown in Figure 5a. On annual aggregates, built-up percentage was strongly associated with maximum LST (Pearson $r = 0.91$) and with UHI share ($r = 0.79$, $p =$

0.020). Multiple regression of maximum LST on mean NDVI and NDBI was significant ($R^2 = 0.82$, adjusted $R^2 = 0.75$, $F(2,5) = 11.7$, $p = 0.013$). PCA condensed the seven variables into a dominant first component explaining 89.1% of variance ($PC1+PC2 = 97.1\%$); PC1 aligned positively with built-up %, NDBI, LST, and UHI, and negatively with agricultural % and NDVI, ordering the years monotonically from 2017 to 2024, as shown in Figure 6b.

Table 7. Spearman correlations between spectral indices and LST by year.

Year	2017	2018	2019	2020	2021	2022	2023	2024
NDVI–LST ρ	-0.594	-0.464	-0.533	-0.592	-0.480	-0.588	-0.426	-0.583
NDBI–LST ρ	0.632	0.562	0.631	0.626	0.560	0.644	0.529	0.649

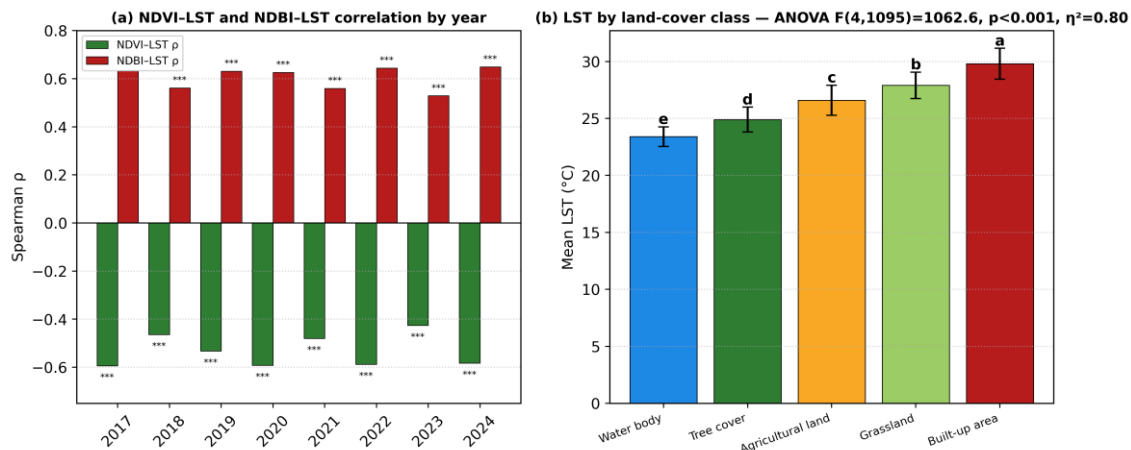


Figure 5. (a) Per-year Spearman correlations of NDVI–LST and NDBI–LST (* $p < 0.001$); (b) mean LST by land-cover class with Tukey HSD groups (a–e) and ANOVA summary.

Urban Heat Island Distribution and Thermal Indices

UHI-affected area expanded from 18.93 km² (25.09% of the city) in 2017 to 22.39 km² (29.68%) in 2024—an increase of 3.46 km² or 4.59% of the city area—while non-UHI area contracted from 56.51 km² to 53.05 km², as detailed in Table 8 and shown in Figure 6a. Spatially,

UHI followed the distribution of high LST and high NDBI, concentrating in the city centre and along major road corridors and expanding southward. The Urban Thermal Field Variance Index rose from 0.204 in 2017 to 0.273 in 2024, indicating a shift toward poorer ecological thermal quality.^{19,22}

Table 8. Temporal changes in UHI-affected area, threshold temperature, and mean LST in Payakumbuh City, 2017–2024.

Year	UHI area (km ²)	UHI (%)	Non-UHI (km ²)	Threshold (°C)	Mean LST (°C)
2017	18.93	25.09	56.51	27.37	26.45
2018	19.21	25.46	56.23	27.10	26.30
2019	18.28	24.23	57.16	26.90	26.25
2020	18.59	24.64	56.85	27.05	26.40
2021	19.06	25.27	56.38	27.20	26.50
2022	19.63	26.02	55.81	27.35	26.55
2023	20.87	27.66	54.57	27.50	26.62
2024	22.39	29.68	53.05	27.69	26.73

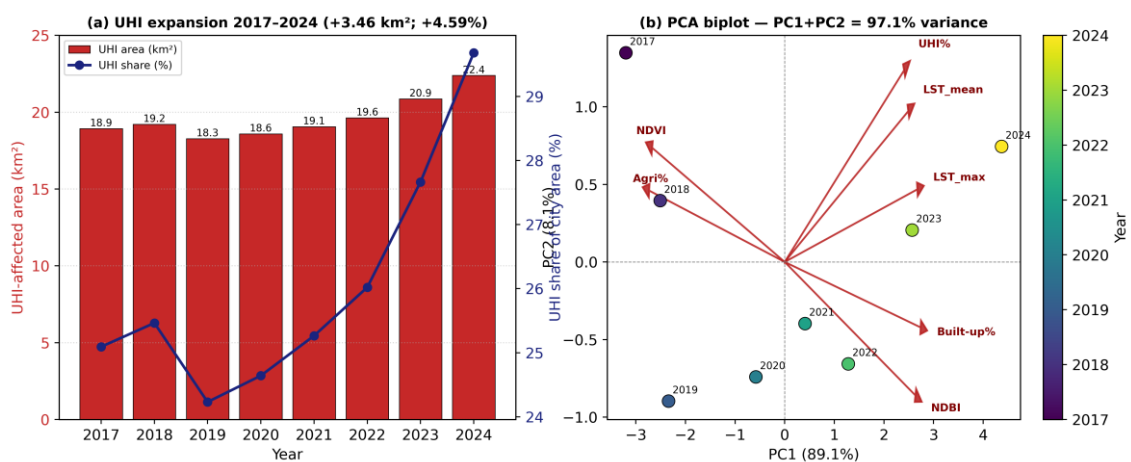


Figure 6. (a) Expansion of UHI-affected area (km² and % of city) in Payakumbuh City, 2017–2024; (b) PCA biplot of seven environmental variables across the eight annual epochs.

Graded into standard ecological categories, the share of the city in the two poorest UTFVI classes ('worse' and 'worst') increased from 25.1% in 2017 to 29.7% in 2024, mirroring the UHI expansion, as detailed in Table 9. The robustness of this expansion was confirmed by a

threshold sensitivity analysis: under alternative UHI definitions of $\mu+0.25\sigma$, $\mu+0.5\sigma$, and $\mu+0.75\sigma$, the 2017–2024 increase in UHI share remained positive and of similar magnitude (+4.2%, +4.6%, and +5.1% of the city, respectively), indicating that the headline result is not an

artefact of the chosen cut-off. With respect to the national green-open-space requirement, the combined vegetated share (tree cover plus grassland) declined from 7.36% in 2017 to 6.48% in 2024—far below the 30% minimum

mandated by Law No. 26/2007 and Ministerial Regulation PU 05/2008¹⁵—quantifying a substantial and widening compliance gap.

Table 9. UTFVI ecological categories and UHI-area sensitivity to threshold choice, 2017 versus 2024.

Metric	2017	2024	Change
UTFVI mean (dimensionless)	0.204	0.273	+0.069
Area in 'worse'+ 'worst' UTFVI (%)	25.10	29.70	+4.60
UHI share at $\mu+0.25\sigma$ (%)	30.80	35.00	+4.20
UHI share at $\mu+0.50\sigma$ (%)	25.09	29.68	+4.59
UHI share at $\mu+0.75\sigma$ (%)	19.60	24.70	+5.10

Discussion

The results show a coherent trajectory of urban intensification in Payakumbuh City: built-up land expanded by 11.59 percentage points in eight years while agricultural land contracted by a comparable margin, vegetation vigour (NDVI) declined, built-up density (NDBI) rose, and the surface thermal field warmed, particularly in its maxima. The concurrent expansion of UHI-affected area by 4.59% of the city confirms that land transformation, rather than background climate alone, is reshaping the local thermal environment, consistent with evidence that impervious growth and vegetation loss drive surface heat islands.^{1–2,16}

The negative NDVI–LST relationship (ρ down to -0.59) reproduces a robust finding across tropical and temperate cities: vegetation lowers surface temperature through shading, evapotranspiration, and elevated surface moisture.^{12,23–24} The positive NDBI–LST relationship (ρ up to 0.65) likewise reflects the thermal behaviour of construction materials, which absorb and store radiation while suppressing latent cooling, increasing sensible heat flux.^{4–5} The strengthening of the NDBI–LST association toward 2024 mirrors the densification of the built core and parallels evidence from other rapidly urbanising areas.^{6,11}

The class-wise ANOVA provides direct, effect-sized evidence that land cover governs surface temperature in Payakumbuh City. With $\eta^2 = 0.80$, land-cover type explains about four-fifths of LST variance, and Tukey grouping cleanly ranks built-up > grassland > agricultural > tree cover > water. The 4.9°C UHI intensity between built-up and tree-covered surfaces quantifies the cooling service forfeited when vegetation is replaced by construction, echoing the several-degree reductions attributed to urban trees elsewhere.^{23–24} The dominant first principal component (89.1% of variance) integrates these signals into a single urbanisation gradient that orders the years monotonically, underscoring the systematic, directional nature of the change.¹³

The modest rise in mean LST alongside a marked increase in maximum LST is itself diagnostic. Citywide averaging dilutes the thermal signal because large agricultural and vegetated tracts remain, whereas the

maxima track the densifying core where impervious fraction is highest. This divergence cautions against relying on mean LST alone to judge UHI severity and supports hotspot- and percentile-based metrics for planning.¹⁹

From a regulatory perspective, the findings are significant. Combined tree cover and grassland fell well below the 30% minimum green open space mandated by Law No. 26/2007 and Ministerial Regulation PU 05/2008, and the reduction of vegetated and agricultural land during a period of warming maxima signals growing tension between development and microclimate regulation. Because UHI concentrated in the centre and along road corridors, targeted interventions—street-tree canopies, vegetated medians and river buffers along the Batang Agam, cool or high-albedo roofing in dense commercial blocks, and protection of peri-urban agricultural land—offer tractable mitigation aligned with the municipal spatial plan (RTRW).^{15,24}

The environmental and public-health implications extend beyond temperature. Rising UTFVI denotes deteriorating ecological thermal quality, with consequences for outdoor thermal comfort, cooling energy demand, and heat exposure in a tropical setting where humidity compounds heat stress.^{10,22} The scale of agricultural conversion in Payakumbuh City—more than ten percentage points of the municipal area in eight years—connects the thermal findings to national food-security and sustainable-land-use agendas; peri-urban agriculture in Payakumbuh Timur is measurably cooler than built-up land (26.6°C versus 29.8°C), so protecting it through the spatial plan serves food production and microclimatic regulation simultaneously.

Two inferential regimes should be distinguished when weighing these results. The spatial contrasts among land-cover classes rest on thousands of pixels and are therefore highly powered, though subject to spatial autocorrelation; accordingly, we emphasise the very large effect size ($\eta^2 = 0.80$) rather than the p-value alone, and drew the ANOVA samples from spatially thinned pixels to limit dependence. The temporal inferences—annual correlations and the NDVI/NDBI regression—rest on only eight scenes and are therefore more modestly powered; they are best read as corroborative,

with the cross-scene reproducibility of the index–LST relationships providing a form of replication that partially compensates for the small temporal sample.^{7–8}

The reliability of the change-detection also merits comment. Classification accuracy was high and stable across all epochs (overall accuracy 88.68–94.34%; Kappa 0.82–0.92), and class-specific user's and producer's accuracies for the two decisive classes—built-up and agricultural land—exceeded 87% in the endpoint years. This supports the interpretation that the +11.59 and –10.61 percentage-point changes reflect genuine land transformation rather than classification instability.⁹

Placed in regional context, the magnitude of change in Payakumbuh City is consistent with, and complements, recent West Sumatran evidence. Multitemporal analyses of nearby Padang City reported comparable urban-expansion-driven surface warming over similar time frames,^{7–8} while cellular-automata modelling in Semarang linked land-cover conversion to rising LST.⁹ The present eight-year series adds a continuous, statistically upgraded account for a mid-sized highland city, and the coupling of class-wise ANOVA, PCA, and thermal indices distinguishes it from the single-date or single-index designs that dominate the Indonesian UHI literature.^{6,11} This positions Payakumbuh as a transferable template for climate-sensitive monitoring of secondary tropical cities.

This study has strengths and limitations. Strengths include an eight-year continuous time series, a reproducible open-data workflow, robust classification accuracy (Kappa 0.82–0.92), and an upgraded analytical design combining correlation, ANOVA with effect sizes, regression, PCA, and thermal indices. Limitations include the 30 m resolution of Landsat, which produces mixed pixels in heterogeneous urban–agricultural mosaics; the sensitivity of absolute LST to acquisition date, humidity, and residual atmospheric effects, which the relative UHI threshold mitigates but does not eliminate; and the use of single annual dry-season scenes, which cannot resolve seasonal or diurnal variation. Future work should incorporate higher-resolution or thermally sharpened imagery, seasonal composites, and predictive models such as CA–Markov or machine learning to anticipate future UHI risk and evaluate greening scenarios.^{17–18,25}

Conclusion

Between 2017 and 2024, Payakumbuh City underwent marked urban intensification: built-up land rose from 38.77% to 50.36% of the city while agricultural land fell from 50.67% to 40.06%, mean NDVI declined from 0.62 to 0.53, and maximum LST increased from 31.85 °C to 34.03 °C. Land cover explained about 80% of LST variance (ANOVA $\eta^2 = 0.80$), with built-up areas 4.9 °C warmer than tree cover; NDVI related negatively and NDBI positively to LST (all $p < 0.001$). UHI-affected area expanded from 18.93 km² to 22.39 km² (+3.46 km², +4.59%), concentrating in the city centre and along road corridors and spreading southward. Urban expansion

and vegetation loss are therefore the key drivers of UHI intensification in Payakumbuh City. Strengthening urban greening toward the 30% green-open-space target, protecting agricultural and tree-covered land, and controlling built-up expansion are recommended, supported by continued multitemporal monitoring with higher-resolution and seasonal data for climate-sensitive spatial planning.

Declarations

Ethical Approval. This study used publicly available satellite imagery and open geospatial data and involved no human participants or animals.

Conflict of Interest.

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Data Availability. The Landsat 8 OLI/TIRS Collection-2 Level-1 imagery is openly available from the USGS EarthExplorer (<https://earthexplorer.usgs.gov>), and the city administrative boundary is from OpenStreetMap (© OpenStreetMap contributors, ODbL). The derived layers (LULC, NDVI, NDBI, LST, and UHI rasters) are available from the corresponding author upon reasonable request.

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