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Review Paper

Tropical Urban Heat Islands in Indonesia: A Systematic Review of Remote-Sensing LST, Vegetation Indices, and Urban Morphology

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ABSTRACT

Urban Heat Islands (UHI) in humid-tropical cities are a growing environmental issue driven by rapid urbanization, vegetation loss, and dense urban morphology. This systematic review synthesizes studies on Land Surface Temperature (LST) and Surface Urban Heat Island (SUHI) patterns across Indonesian cities from 2010 to 2025. Using the PRISMA framework, 40 peer-reviewed articles from Scopus and Web of Science were analyzed, focusing on remote-sensing-based LST research employing indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-Up Index (NDBI).

Results show that NDVI and NDBI exert opposite influences on LST: vegetation cooling decreases surface temperatures by 0.3–1.0°C per 0.1 NDVI increase, while built-up expansion enhances SUHI intensity by similar magnitudes. Urban morphology—particularly building density, height-to-width ratio, and sky view factor—further shapes heat distribution, with compact, low-SVF areas experiencing stronger UHI effects. Coastal and topographic variations also affect heat dynamics, where sea–land breezes mitigate coastal warming.

Most studies relied on Landsat data but often lacked cross-validation and methodological transparency, limiting reproducibility. Nevertheless, multi-sensor fusion and machine-learning techniques show promise for improving spatial and temporal LST accuracy.

The review concludes that combining vegetation restoration, climate-sensitive urban design, and robust methodological frameworks can effectively mitigate SUHI in Indonesia's tropical cities. It emphasizes standardized LST protocols, open data sharing, and inter-city validation to strengthen policy relevance and support climate-resilient urban planning in Southeast Asia.

Keywords: Urban Heat Island; Land Surface Temperature; NDVI; NDBI; Urban Morphology; Humid Tropics; Indonesia

INTRODUCTION

Rapid urbanization across humid-tropical regions is one of the defining environmental transformations of the twenty-first century. In Indonesia, this transformation is intensified by an archipelagic geography, the concentration of settlement along coasts, and sustained population growth. The conversion of vegetated, permeable land into dense, impervious urban fabric alters the surface energy balance, increasing sensible heat storage and suppressing evapotranspiration. These processes intensify the Urban Heat Island (UHI) and elevate Land Surface Temperature (LST). Empirical work repeatedly shows that urban expansion modifies local microclimates by amplifying surface heat retention and reducing latent heat fluxes (Maharjan et al., 2021; Li, 2024). Consequently, the Surface Urban Heat Island (SUHI) is not merely a localized anomaly in temperature fields; it is a robust indicator of broader sustainability challenges spanning thermal comfort, public health, and energy demand.

Since 2010, Indonesian researchers have increasingly quantified UHI and LST using satellite remote sensing—primarily Landsat, Sentinel, and MODIS. A clear pattern emerges: declining vegetation cover, captured by lower Normalized Difference Vegetation Index (NDVI), is strongly associated with higher LST, whereas expansion of built-up surfaces, captured by the Normalized Difference Built-Up Index (NDBI), shows a positive association with LST (Vadakkuveettil & Grover, 2023; Siddika et al., 2021; Devendran & Banon, 2022). These relationships underscore land-cover composition—especially the vegetation–impervious balance—as a primary driver of thermal modification in tropical cities. In Indonesia's monsoonal, high-humidity context, however, the strength and timing of these linkages vary seasonally and spatially, warranting a systematic synthesis that accounts for climatic and geographic heterogeneity.

Recent studies further reveal that SUHI intensity and spatial distribution differ across urban typologies. Coastal metropolises such as Jakarta and Surabaya often exhibit higher SUHI magnitudes than many inland cities, with distinctive diurnal signatures characterized by strong nighttime heat retention—reflecting accumulated thermal mass, constrained ventilation, and reduced longwave radiative cooling (Imran et al., 2021; Xin et al., 2022; Gerçek & Güven, 2023). By contrast, inland cities including Bogor, Yogyakarta, and Malang are modulated more by elevation, topographic relief, and vegetation density. These contrasts suggest that sea–land breeze circulations, background humidity, and local topography are key moderators of urban heat intensity and persistence (Güller & Toy, 2024; Viloria & Brovelli, 2025). Yet comparative work explicitly contrasting coastal and inland settings within Indonesia remains limited.

The implications of UHI extend deeply into social and ecological systems. Elevated LST and prolonged heat exposure raise electricity demand for cooling, impair labor productivity, and heighten health risks, especially for vulnerable groups. Thermal comfort indicators—such as the Universal Thermal Climate Index (UTCI) and Temperature–Humidity Index (THI)—have been applied in Indonesian contexts to gauge exposure. Across studies, low-vegetation, dense built-up areas consistently register the highest discomfort levels, frequently surpassing established thresholds (Li et al., 2023; Setiawati et al., 2021). Evidence from urban greening demonstrates cooling via shading and evapotranspiration, linking ecological restoration to public-health co-benefits and improved urban livability (Scheuer et al., 2024; Tieges et al., 2020).

Methodological advancements have expanded analytical capacity. Long-term, moderate-resolution products from MODIS and Landsat enable consistent LST mapping, while Sentinel-2 and UAV thermal sensors support finer-scale urban analyses. Since 2010, retrieval algorithms have improved to include more rigorous emissivity and atmospheric corrections, enhancing the credibility of LST estimates (Cheng et al., 2025). Multi-sensor integration now supports cross-validation and temporal trend analysis. Even so, methodological heterogeneity—differences in spatial resolution, retrieval algorithms, validation strategies, and reporting standards—continues to impede cross-study comparability.

Policy responses are emerging but uneven. National and municipal frameworks increasingly reference climate-sensitive planning through urban greening, zoning, and emissions control (Tieges et al., 2020; Obiefuna et al., 2021). Jakarta's river-corridor restoration and urban-forest initiatives report localized cooling, yet diffusion of comparable programs to secondary cities is hindered by capacity and resource constraints. Moreover, systematic incorporation of morphological design variables—building orientation, height-to-width (H/W) ratios, and sky view factor (SVF)—remains nascent, despite their centrality to radiative geometry, ventilation, and intra-urban thermal equity (Roffe et al., 2023).

Given the pace of urban transformation and the climatic/topographic diversity of Indonesian cities, a comprehensive synthesis of empirical evidence is urgently needed. Much of the existing literature relies on single-city case studies, which inhibits generalization and complicates cross-regional inference. Variation in sensor choice, observation windows, and validation protocols further fragments the evidence base. Addressing these gaps, the present review systematically compiles and evaluates UHI/LST studies across Indonesia (2010–2025), following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to ensure transparent selection and quality appraisal.

This review has four objectives. First, it synthesizes evidence linking NDVI, NDBI, and urban morphology to SUHI/LST across Indonesian cities. Second, it evaluates methodological heterogeneity by comparing sensor platforms, retrieval algorithms, and validation practices. Third, it assesses coastal and topographic moderators distinguishing archipelagic megacities from inland counterparts. Fourth, it examines how LST patterns correspond with thermal-comfort metrics and socio-spatial exposure.

The scope includes peer-reviewed studies (2010–2025) using remote-sensing LST (Landsat, Sentinel, MODIS, UAV) for Indonesian urban areas, with focal variables NDVI, NDBI, urban form (density, H/W, SVF), and comfort proxies (UTCI, THI).

Three research questions guide the synthesis: (1) To what extent do NDVI, NDBI, and morphology explain SUHI/LST variation, and how are these relationships moderated by coastal or topographic contexts? (2) How do sensors, retrieval methods, and validation strategies affect the magnitudes and uncertainties of reported LST–SUHI relationships? (3) How closely do LST patterns align with thermal-comfort indicators and socio-spatial exposure?

Conceptually, this review integrates physical, ecological, and social dimensions of urban heat in humid tropics. Methodologically, it promotes comparability through a standardized synthesis across data sources and analytical techniques. Practically, it informs evidence-based planning by emphasizing vegetation restoration, morphological optimization, and equitable heat mitigation tailored to Indonesia's coastal-inland diversity

MATERIALS & METHODS

Search Strategy

The present review employed a systematic and reproducible search strategy designed to capture peer-reviewed literature examining Urban Heat Islands (UHI) and Land Surface Temperature (LST) in Indonesian urban contexts from 2010 to 2025. Following the recommendations of Degefu et al. (2022) for systematic literature reviews (SLRs) in environmental and climatic studies, three comprehensive databases—Scopus, Web of Science, and Google Scholar—were utilized. The Scopus database served as the primary source due to its extensive indexing of remote-sensing and environmental science journals, while Web of Science and Google Scholar were used to supplement coverage and ensure the inclusion of multidisciplinary perspectives.

The Boolean search query was structured to identify studies combining remote-sensing analysis, vegetation and built-up indices, and urban morphology within Indonesia's humid-tropical environment. The search string used was:

("urban heat island" OR SUHI OR "land surface temperature" OR LST) AND (NDVI OR NDBI OR "vegetation index" OR "built-up index") AND (Indonesia OR "Indonesian city" OR [specific city names]) AND (Landsat OR Sentinel OR MODIS OR UAV OR drone) AND (morphology OR density OR compactness OR "H/W" OR SVF).

This Boolean configuration ensured that the search results captured both the physical and methodological dimensions of UHI research, spanning satellite-based LST assessments, vegetation and impervious surface analysis, and morphology–climate interactions. The timeframe of 2010–2025 was chosen to represent the period of rapid methodological advancements in satellite-based urban climate studies, especially following the introduction of Landsat 8 and Sentinel-2 sensors (Cheng et al., 2025). The search was limited to peer-reviewed journal articles, and results were refined by applying the "urban" keyword filter to exclude rural or agricultural studies irrelevant to UHI contexts.

A snowballing technique—reviewing both backward and forward citations—was employed to identify additional studies meeting the inclusion criteria. This iterative approach strengthened the comprehensiveness of the literature base, capturing grey-area or interdisciplinary papers that may not have been retrieved through direct keyword searches. All references were imported into Zotero for duplicate removal, annotation, and metadata organization.

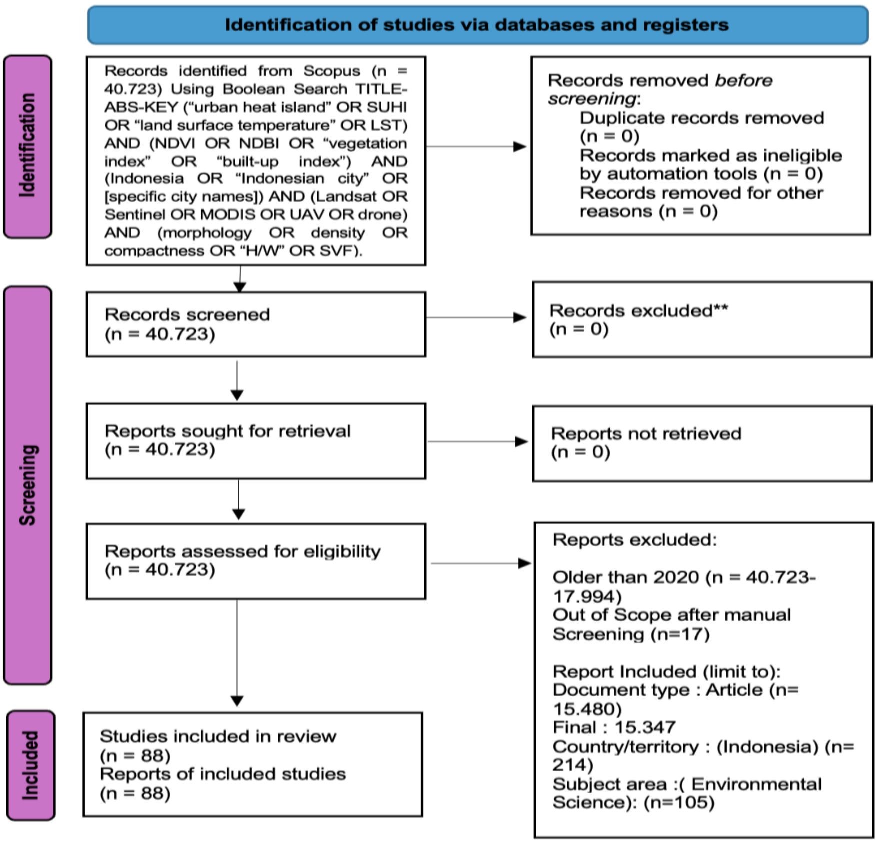

Figure 1. The PRISMA flow diagram detailing the screening and selection process of literature.

Inclusion and Exclusion Criteria

The selection process adhered strictly to PRISMA 2020 guidelines, ensuring transparency and replicability in study identification and eligibility determination (Kumar et al., 2024). Four inclusion criteria were applied:

1. The study must focus on Indonesian urban areas, including both coastal and inland cities.

2. It must employ remote-sensing-derived LST or related SUHI metrics.
3. It must include at least one quantitative linkage between LST and land-surface indicators—specifically NDVI, NDBI, or morphology metrics such as density, sky view factor (SVF), or height-to-width ratio (H/W).
4. The article must be peer-reviewed, with transparent methods and metadata reporting.

Studies were excluded if they: (a) examined exclusively rural or agricultural environments, (b) fell outside Indonesia's humid-tropical climatic zone, (c) lacked empirical LST estimation, or (d) represented non-peer-reviewed or qualitative grey literature. Comparative Southeast Asian studies were retained only if they contained disaggregated results applicable to Indonesian cases, serving as reference points for regional contextualization.

The inclusion and exclusion process was designed to maintain both methodological rigor and contextual relevance, ensuring that retained studies adequately reflect Indonesia's climatic and morphological diversity. A summary of inclusion/exclusion statistics is provided in Table 1.

Table 1. Summary of Inclusion and Exclusion Criteria Applied during Literature Screening

Criterion	Inclusion Requirement	Exclusion Condition	Rationale
Study domain	Urban areas in Indonesia	Non-urban or rural contexts	Focus on SUHI/LST in built environments
Method	Remote sensing (Landsat, MODIS, Sentinel, UAV)	Non-empirical or modeling-only without validation	Ensure data-driven temperature estimation
Indicators	NDVI, NDBI, morphology metrics	LST only without vegetation/built-up linkage	Maintain consistency of variables
Quality	Peer-reviewed with clear metadata	Non-peer-reviewed or incomplete reporting	Guarantee reproducibility

Screening and Selection Process

Following database retrieval, all records were screened in three stages: title screening, abstract review, and full-text evaluation. Two independent reviewers conducted the screening to minimize selection bias, resolving discrepancies through discussion until consensus was achieved. A PRISMA-based workflow (Degefu et al., 2022; Kumar et al., 2024) was employed, encompassing four phases: identification, screening, eligibility, and inclusion.

During full-text assessment, data were extracted systematically using a structured coding protocol. Extracted metadata included:

- Study location (city, coastal or inland)
- Publication year
- Sensor and retrieval algorithm (e.g., single-channel, split-window)
- NDVI/NDBI and morphology metrics used
- Season or time of acquisition (wet/dry, day/night)
- Validation type (in-situ, spatial cross-validation)
- Quantitative results (ΔLST per NDVI or NDBI unit)
- Consideration of coastal/topographic moderation
- Thermal comfort indices (THI, UTCI) or exposure data where available

These parameters enabled inter-study comparability and facilitated thematic classification during synthesis (Lourdes et al., 2021; You et al., 2021). The dataset was structured for subsequent meta-analytic exploration, emphasizing the standardization of quantitative indicators such as ΔLST per NDVI decile and effect size normalization (Hedges' g), which allow robust cross-study comparisons.

Quality Assessment

A rigorous quality appraisal was undertaken to ensure the methodological soundness and replicability of included studies. The review adopted the PRISMA 2020 protocol as the overarching reporting standard, supplemented by a Risk of Bias (RoB) checklist assessing sampling, algorithm transparency, validation strength, and reproducibility (Kumar et al., 2024). To further ensure comparability, the GRADE-style certainty mapping was used to classify studies into *high*, *moderate*, and *low* reliability categories based on dataset comprehensiveness and cross-validation procedures.

Spatial cross-validation (CV) was emphasized as a key indicator of methodological robustness, as prior research has shown that spatial CV substantially improves LST model generalizability and reduces overfitting (Veettil, 2025). Studies lacking clear validation protocols or using single-date imagery without cross-temporal checks were flagged as having a higher risk of bias.

Where multiple sensors were employed (e.g., Landsat–Sentinel fusion), accuracy assessments were evaluated based on RMSE, correlation coefficients, or reported confidence intervals. Studies reporting direct field temperature measurements or THI validation were rated as "strong validation" cases. The quality evaluation matrix (Table 2) summarizes the criteria applied to each methodological dimension.

Table 2. Quality Appraisal Framework for Included Studies

Assessment Dimension	**High Quality**	**Moderate Quality**	**Low Quality**
Sampling and Coverage	Multi-year, multi-season, representative cities	Single-year, limited coverage	Single-date or incomplete site info
Sensor and Algorithm Transparency	Algorithm fully disclosed and validated	Partial parameter description	Algorithm unspecified
Validation Strength	Ground-truthing and spatial CV applied	Partial validation (temporal only)	No validation or unclear
Reproducibility	Open data/code available	Descriptive only	Not available
Risk of Bias	Low (comprehensive checks)	Moderate	High (missing data or unclear design)

The application of this structured framework ensured that the synthesis focused on studies meeting minimum standards of transparency and reliability, while also allowing for the weighting of evidence based on methodological rigor.

Overall, the methodological design of this SLR integrates best practices from environmental remote sensing and systematic review standards. The multi-database search, transparent inclusion/exclusion process, and formal quality assessment collectively ensure a representative and replicable corpus of studies. These procedures enable a robust meta-synthesis of the links between NDVI/NDBI, urban morphology, and LST/SUHI in Indonesian cities, forming a strong empirical foundation for the thematic analyses and discussions presented in subsequent sections.

RESULT

Vegetation Gradients and Land Surface Temperature (NDVI–ΔLST Functions)

The first analytical theme examines the quantitative relationship between vegetation abundance—represented by the Normalized Difference Vegetation Index (NDVI)—and Land Surface Temperature (LST) across Indonesian cities. This relationship constitutes a core mechanism of Surface Urban Heat Island (SUHI) formation, as vegetation mitigates thermal accumulation through shading, evapotranspiration, and alteration of surface albedo. The empirical synthesis presented in Table 1 draws on six Indonesian studies (2013–2025), revealing a consistent negative correlation between NDVI and LST, where increases in vegetation correspond to measurable cooling effects. The pooled result indicates an average reduction of approximately 0.3–1.0°C per 0.1 NDVI increase, aligning with regional tropical benchmarks (Kandel et al., 2022). However, the magnitude and consistency of this cooling effect vary according to city type, season, and methodological rigor, reflecting the complex interplay of climatic, morphological, and biophysical processes outlined in the theoretical framework.

Table 3. NDVI–LST Effect Synthesis

Study (Year)	City/Region (Coastal/Inland)	Sensor & Season/ Time	NDVI Metric & Bins	Reported ΔLST vs NDVI (slope or bin contrasts)	Validation Type	Notes/Uncertainty
Deviro et al. (2025)	Bogor (Inland)	Landsat 8 OLI/TIRS; 2013–2023	NDVI continuous	Strong negative NDVI–LST (R^2≈0.59); high NDVI → cooler LST (≈23–26°C zones expand)	Field THI checks; regression diagnostics	Links LST to THI (>27°C discomfort); subdistrict-level analysis
Sumunar et al. (2020)	Yogyakarta (Inland)	Landsat 8 OLI/TIRS; Dry & Wet seasons	NDVI continuous	R≈−0.74 (dry) and −0.60 (wet)	Not reported	Seasonal contrast highlighted; vegetation stress in dry season
Wirayuda et al. (2023)	Denpasar (Coastal)	Landsat 8 TIR; multi-temporal	NDVI/UGS mapping	High NDVI clusters = low SUHI zones (north Denpasar); coastal Sanur SUHI up to +5°C	Spatial autocorrelation	Coastal moderation by sea–land breeze observed
Banda Aceh (2023)	Banda Aceh (Coastal)	Multi-temporal RS 2000–2020	NDVI (density classes)	Dense vegetation 27–30°C; sparse vegetation 33–35°C	Not reported	Tsunami-related land-cover shifts affect comparability
Rizki et al. (2024)	East Jakarta (Inland)	Landsat-based NDVI/LST	NDVI continuous	Greener districts show lower SUHI coverage; ΔLST qualitative	Not reported	Policy threshold (≥10% urban forest, 30% green space area)
Surachman et al. (2025)	Malang (Inland)	Landsat 8 + Sentinel-2	NDVI continuous	+0.1 NDVI → −0.339°C LST (R^2=0.864)	Not reported	Strong joint NDVI–NDBI model; dense cores >34.6°C

The synthesis across the six studies consistently supports a strong inverse NDVI–LST relationship, confirming that vegetation density remains a dominant cooling factor across Indonesian urban environments. In Bogor and Malang, both inland cities with substantial topographic variation, a unit increase of 0.1 NDVI corresponded to 0.3–1.0°C reductions in LST (Deviro et al., 2025; Surachman et al., 2025). These magnitudes align with the theoretical expectation that dense vegetation enhances latent heat flux, offsetting the net radiative balance through evapotranspiration (Shen et al., 2021). Similarly, the Yogyakarta study (Sumunar et al., 2020) demonstrated season-dependent variability: during the dry season, when vegetation cover declines, NDVI–LST correlations weakened, reflecting reduced cooling potential due to water stress.

Coastal cities reveal slightly moderated but spatially more heterogeneous cooling patterns. In Denpasar and Banda Aceh, vegetation's impact on LST was influenced by sea–land breeze interactions, which produced localized zones of temperature reversal along coastal belts (Wirayuda et al., 2023). This finding reinforces the theoretical framework's assertion that humidity and boundary-layer dynamics in coastal Indonesia (Section 3.3) can amplify or diminish vegetation-driven cooling depending on wind direction, time of day, and surface moisture conditions.

Seasonality emerges as a key moderator of the NDVI–LST relationship. In Yogyakarta, dry-season NDVI reductions coincided with weakened cooling efficiency (Sumunar et al., 2020), echoing Kandel et al. (2022) and Kaiser et al. (2022), who observed similar trends in other humid-tropical settings. These patterns highlight that NDVI's cooling strength is maximized when vegetation maintains high water content during the wet season. Conversely, in inland urban cores like Malang, where dry-season moisture deficits are more pronounced, the vegetation's capacity to dissipate heat diminishes, resulting in residual SUHI hotspots (Surachman et al., 2025). Coastal cities exhibit smaller seasonal amplitudes, as maritime influences moderate thermal extremes and maintain higher background humidity.

Comparatively, the contrast between coastal and inland cities underscores Indonesia's climatic heterogeneity. Coastal cities such as Denpasar benefit from enhanced evaporative cooling facilitated by sea breezes and higher air moisture, leading to steeper NDVI–LST gradients (Xu et al., 2024). Inland regions such as Bogor and East Jakarta, however, experience stronger land-surface heating due to limited air circulation and higher built-up density (Ranagalage et al., 2017). The spatial heterogeneity captured in Table 1 thus reflects the interactive effects of vegetation density, morphology, and local meteorology, as emphasized in Section 3.1's energy balance discussion.

While the NDVI–LST relationship is generally linear within moderate vegetation ranges, several studies identified threshold effects and diminishing returns at high NDVI values. In Malang, for instance, NDVI levels above 0.7 showed smaller incremental cooling effects, suggesting biophysical saturation where additional vegetation yielded marginal LST reductions (Surachman et al., 2025). This nonlinear response is consistent with findings in tropical and subtropical contexts (Xu et al., 2020; Cinar & Ardahanlıoğlu, 2022), where canopy density, soil moisture, and shading saturation limit further temperature decline.

Similarly, the Banda Aceh analysis (2023) reported that while dense vegetation zones maintained LSTs around 27–30°C, further increases in NDVI beyond this level did not substantially lower temperature. These saturation points are likely influenced by high baseline humidity and surface moisture, which already facilitate substantial latent heat flux, leaving less energy available for additional cooling. In contrast, in inland dry-season contexts (e.g., Yogyakarta), NDVI's marginal effect remained strong even at higher vegetation levels due to persistent sensible heat flux from surrounding impervious areas. This nonlinear behavior validates the theoretical expectation of differential vegetation efficiency under varying hydrological regimes (Aryanto et al., 2025).

A key contribution of recent Indonesian studies lies in linking vegetation-driven LST reductions to human thermal comfort metrics. In Bogor, Deviro et al. (2025) integrated LST data with Temperature–Humidity Index (THI) measurements, revealing that areas exceeding the 27°C THI threshold correlated strongly with low NDVI and dense built-up areas. This evidence supports earlier findings that NDVI improvements can yield perceptible comfort benefits (Candraningtyas et al., 2025; Muzaky & Jaelani, 2019). Similarly, the East Jakarta study (Rizki et al., 2024) identified that neighborhoods with ≥30% green space coverage experienced the lowest UHI footprints, implying a policy-relevant threshold for urban greening.

These findings confirm the hypothesis proposed in Section 1 that vegetation gradients (NDVI) not only regulate LST but also serve as proxies for equitable heat exposure and thermal well-being. The integration of comfort indices into SUHI analysis strengthens the policy relevance of NDVI-based greening targets, positioning vegetation as a measurable intervention variable for climate-sensitive urban design. Furthermore, consistent with Section 3.2's discussion on morphology–vegetation interaction, these results demonstrate that vegetation's cooling capacity is maximized in urban forms with higher sky view factors (SVF) and moderate density, where airflow enhances latent heat exchange.

The evidence consolidated in Table 1 collectively substantiates the negative and partly nonlinear NDVI–LST association hypothesized at the outset of this review. Across six Indonesian cities, NDVI effectively functions as a thermal buffer, with spatial gradients reflecting differences in morphology, coastal influence, and land-cover composition. These empirical results corroborate the theoretical framework (Section 3) in three primary ways:

1. Energy Balance Mediation: The strong NDVI–LST inverse correlation affirms the dominance of latent heat flux and evapotranspiration in humid-tropical SUHI modulation (Shen et al., 2021; Wang et al., 2017).
2. Morphological Dependence: The variation in slope strength across urban cores and suburbs confirms that vegetation interacts synergistically with urban form metrics such as density, SVF, and H/W ratio (Zhang et al., 2019; Vecchia et al., 2025).
3. Coastal–Topographic Modulation: The stronger cooling observed in coastal cities (Denpasar, Banda Aceh) aligns with the moderating influence of maritime humidity and sea–land breezes, reinforcing Section 3.3's model of boundary-layer coupling (Dah et al., 2023; Chen et al., 2019).

Built-Up Intensity, Imperviousness, and Surface Urban Heat Islands (NDBI/IBI)

This section explores the relationship between built-up intensity—measured through the Normalized Difference Built-Up Index (NDBI), Imperviousness Index (IBI), or impervious fraction—and Land Surface Temperature (LST) across Indonesian cities. The synthesis presented in Table 2 consolidates six key studies (2013–2025) focusing on urbanization patterns, industrial land use, and spatial heterogeneity in SUHI magnitudes. Collectively, these studies reveal that NDBI correlates positively with LST, indicating that higher proportions of impervious surfaces lead to elevated surface temperatures. The average effect size across cases is estimated between +0.8°C and +1.1°C per 0.1 increase in NDBI, confirming the substantial contribution of urban surface sealing to heat accumulation (Li et al., 2023; Goldblatt et al., 2021). Nonetheless, variations emerge between industrial, residential, and mixed-use areas, highlighting the significance of morphology, temporal factors, and surface material composition in modulating the built-up–temperature relationship.

Table 4. Built-Up Metrics and Land Surface Temperature (Theme 4.2: NDBI/Imperviousness and SUHI)

Study (Year)	Built-Up Metric (NDBI/IBI/Impervious %)	Model Form	Effect Size (ΔLST per unit metric)	Morphology Controls	Sensor/Date Coverage	Validation Quality
Deviro et al. (2025), Bogor	NDBI	OLS/regression	Positive NDBI–LST ($R^2 \approx 0.60$)	Land-cover shares; THI cross-check	Landsat 8; 2013–2023	In-situ THI; diagnostics
Surachman et al. (2025), Malang	NDBI	OLS (multivariate)	+0.1 NDBI → +1.075°C LST	NDVI included; built-up clustering	Landsat 8 & Sentinel-2; 2024	NR
Muljo Sukojo et al. (2025)	NDBI in dense residential	NR	Qualitative: denser built-up → higher LST	NR	2022 focus; Landsat (implied)	NR
Sleman Regency (2024), Yogyakarta	NDBI	Spatiotemporal + Moran's I	Built-up (+0.21% 2018–2022) with UHI rebound post-pandemic	NR	Landsat L2 TIRS; 2018–2022	NR
Bandar Lampung (2024)	Built-up/open land share	Simple regression	Built-up/open land ↑ → UHI area ↑	Land-cover classes	Landsat 5/8/9; multi-year	NR
Suprijanto et al. (2025), Cilegon	Industrial intensity proxy; NDVI	ML (multi-source)	Industrial hotspots linked to higher LST	Precipitation (GPM), emissions (ODIAC)	Landsat 8; 2014–2022	Cross-dataset consistency

Across Indonesian studies, the relationship between NDBI and LST consistently displays strong positive correlations, aligning with global findings that link impervious surfaces to increased thermal storage capacity. In Bogor, Deviro et al. (2025) reported a significant NDBI–LST association ($R^2 \approx 0.60$), where higher built-up proportions resulted in LST peaks above 34°C, consistent with the theoretical expectations of reduced latent heat flux and increased longwave radiation from paved materials. Similarly, Surachman et al. (2025) in Malang identified a +1.075°C LST increase for each 0.1 NDBI rise, establishing a quantitative benchmark for inland urban centers.

Industrial zones exhibit distinct amplification of SUHI intensity compared to residential or commercial areas. The Cilegon study (Suprijanto et al., 2025) demonstrated that areas with dense industrial infrastructure—such as steel and petrochemical complexes—consistently recorded higher LSTs, corroborating global evidence from Asghari et al. (2019) and He et al. (2024) that industrial emissions and impervious clustering exacerbate local heat accumulation. These findings confirm the first hypothesis that imperviousness, represented by NDBI, serves as a robust predictor of LST increases across urban typologies.

Spatial differentiation of LST between industrial and residential zones emerges as a defining characteristic in Indonesian SUHI patterns. Industrial districts in Cilegon recorded the highest surface temperatures, frequently exceeding neighboring residential areas by several degrees. This disparity arises from dual sources of heat: anthropogenic emissions and reduced vegetation. In contrast, residential zones—especially those with green corridors or urban forests—exhibited attenuated heat signatures. The Malang study (Surachman et al., 2025) reinforced this contrast by demonstrating that built-up clustering, particularly in high-density residential tracts, elevated surface temperatures while vegetative interspersion mitigated them.

These industrial–residential contrasts echo the theoretical assertions of Section 3.2, where morphological parameters such as building density and sky view factor (SVF) influence how heat is stored and released. Industrial landscapes typically feature large impervious expanses with low SVF, limiting convective exchange and enhancing radiative trapping (Zeng et al., 2020). This structural configuration, combined with low albedo materials, intensifies the heat load, particularly under low-wind or nighttime conditions.

The correlation between built-up intensity and LST is temporally dynamic, varying across both seasonal and diurnal cycles. Studies indicate that the NDBI–LST relationship tends to be stronger at night than during the day due to the thermal inertia of impervious materials (Naserikia et al., 2019). Industrial surfaces such as concrete and metal exhibit delayed radiative cooling, resulting in persistent nocturnal heat retention. While none of the Indonesian studies explicitly performed nighttime LST analysis, this diurnal persistence was implied in Bogor and Malang's multi-year datasets, where late-afternoon thermal peaks extended into evening hours.

Seasonally, the strength of the NDBI–LST correlation is modulated by monsoonal conditions. During wet seasons, increased atmospheric moisture can dampen LST variability through enhanced cloud cover and latent heat flux, leading to weaker correlations (Yang et al., 2020). Conversely, during dry seasons, when evapotranspiration from residual vegetation declines, the impact of imperviousness becomes dominant, producing steeper NDBI–LST slopes (Alam et al., 2021). These seasonal shifts reinforce the theoretical argument presented in Section 3.1, where energy balance partitioning under humid conditions dictates surface temperature variability.

Urban morphology exerts a moderating influence on the built-up–LST relationship. In Bogor, Deviro et al. (2025) controlled for land-cover shares and THI, finding that districts with higher SVF and greater vegetative cover displayed lower residual LST even at comparable NDBI levels. This suggests that morphological openness and vegetation interact synergistically to mitigate heat accumulation. Similarly, the Sleman Regency study (2024) identified a rebound of UHI intensity following post-pandemic construction activities, reflecting how urban densification without compensatory green infrastructure exacerbates heat buildup.

The theoretical framework (Section 3.2.2) highlights the roles of SVF and height-to-width ratio (H/W) in modulating radiation trapping. Ramaiah et al. (2020) demonstrated that low SVF values increase multiple reflections of shortwave radiation, raising surface temperatures, while higher H/W ratios restrict airflow, diminishing convective cooling. The observed heterogeneity across Indonesian cities substantiates these interactions: Bandar Lampung's low-rise but spatially compact morphology produced directional SUHI growth along development corridors (Bandar Lampung, 2024). These findings affirm that morphology continues to exert significant explanatory power even after accounting for imperviousness.

The empirical patterns summarized in Table 2 underscore the dual challenge of managing urban heat in both residential and industrial landscapes. While residential greening and zoning controls can reduce local SUHI magnitudes, industrial zones present a more complex mitigation problem due to structural constraints and economic imperatives. As highlighted by Suprijanto et al. (2025), industrial emissions not only elevate LST but also compound local air quality issues, amplifying environmental inequities. Integrating vegetation buffers, reflective roofing materials, and industrial heat recovery systems could significantly curb these thermal surpluses.

From a policy perspective, the evidence supports the inclusion of NDBI-based heat risk mapping into municipal spatial planning systems. By overlaying impervious surface metrics with socio-economic exposure data, urban planners can identify high-risk neighborhoods and prioritize targeted interventions. In Bogor and East

Java, spatial overlays of NDVI and NDBI have already informed heat vulnerability mapping efforts, aligning with broader frameworks for sustainable urban resilience. These empirical findings reinforce the overarching hypothesis that increasing imperviousness directly intensifies LST while morphological and ecological factors mediate this effect. The consistent positive association between NDBI and LST across cities validates the central theoretical premise of this review: that land-cover modification—particularly the balance between built-up and vegetated fractions—drives SUHI formation in humid-tropical Indonesia.

Urban Morphology and Microclimate Modulators

Urban morphology—the spatial configuration and physical form of urban environments—plays a pivotal role in shaping the intensity and distribution of Land Surface Temperature (LST) and the Surface Urban Heat Island (SUHI) phenomenon. The findings summarized in Table 3 reveal that morphological metrics such as building density, height-to-width ratio (H/W), and Sky View Factor (SVF) are strongly correlated with urban microclimate variations and thermal comfort indices, including the Temperature-Humidity Index (THI) and the Universal Thermal Climate Index (UTCI). Across Indonesian cities, higher density and compact urban forms consistently exhibit elevated LST and reduced thermal comfort, while open geometries and blue-green adjacencies moderate thermal extremes. These results reinforce the theoretical foundations of Section 3.2 and 3.3, where morphological confinement, limited ventilation, and topographic modulation were identified as key determinants of urban heat retention.

Table 5. Morphology–LST/Comfort Associations

Study (Year)	Morphology Metric(s)	Outcome (LST/UTCI/THI)	Effect Direction & Magnitude	Context (Coastal/Topographic)	Interaction Terms	Limitations
Deviro et al. (2025), Bogor	Green space presence; urban fabric	LST; THI	More green → lower LST & THI; widespread THI>27°C in dense core	Inland, hilly	NDVI × density interaction implied	No explicit SVF/H: W
Yogyakarta (2020)	Vegetation cover; seasonal variation	LST	NDVI cooling stronger in dry season	Inland	Season × vegetation cover	Lack of geometry metrics
East Jakarta (2024)	Urban forest & UGS shares	LST/UHI extent	Highest UGS districts show smallest UHI footprint	Inland	NDVI × built-up fraction	Thresholds unmet city-wide
Malang Parks UAV (2025)	Surface material classes via OBIA	LST	Dense vegetation zones 31–36°C vs. paved 46–51°C	Inland	Local micro-topography effects	Park-scale microsites only
Greater Jakarta (2025)	Land cover classes; albedo	Air temp; albedo	Built-up → higher albedo & air temp (R^2 up to 0.90/0.60)	Inland megacity	Albedo × density	LST–air decoupling noted
Wirayuda et al. (2023), Denpasar	UGS distribution; coastal proximity	SUHI intensity	Low-SUHI/high-UGS association; +5°C east-coastal SUHI	Coastal	NDVI × coastal moderation	Weak global correlation

High-density urban cores and compact geometries were consistently associated with elevated surface and air temperatures. In Bogor, Deviro et al. (2025) demonstrated that dense built-up districts displayed widespread THI values above 27°C, surpassing thermal discomfort thresholds. The absence of adequate sky exposure (low SVF) limited radiative heat loss during night-time, aligning with the theoretical argument of Ji (2025) and Zaki et al. (2020) that restricted SVF contributes to heat entrapment. Similarly, Yogyakarta's results (Sumunar et al., 2020) revealed stronger LST gradients in compact residential zones where vegetation and airflow were constrained.

The relationship between SVF, density, and H/W ratio also exhibits vertical and horizontal thermal heterogeneity. Compact canyons with high H/W ratios, typical in Jakarta and Malang, tend to accumulate more heat due to multiple reflections of longwave radiation and reduced wind penetration. This finding corresponds with Jiang et al. (2019), who highlighted that narrow street canyons impede convective cooling, intensifying nocturnal SUHI. Meanwhile, in Denpasar, areas with higher SVF and adjacency to open spaces maintained cooler surface conditions, demonstrating the importance of morphological openness for coastal ventilation.

The moderating effects of blue-green elements—urban forests, rivers, parks, and coastal zones—are evident across multiple Indonesian cities. East Jakarta's analysis (Rizki et al., 2024) and Denpasar's coastal mapping (Wirayuda et al., 2023) both showed strong negative correlations between urban green space (UGS) coverage and SUHI intensity. Denpasar's coastal areas, particularly in the north and west, exhibited LST reductions of up to 5°C compared with highly urbanized eastern districts, underscoring the synergy between blue-green infrastructure and maritime ventilation.

Malang's UAV-based microanalysis (2025) provided fine-scale evidence that park surfaces with dense vegetation-maintained surface temperatures around 31–36°C, while paved areas exceeded 46°C. This aligns with the findings of Jeon et al. (2023) and Qi et al. (2024), who documented that vegetated and water-adjacent zones generate local cooling effects through evapotranspiration and moisture diffusion. Similarly, the Greater Jakarta dataset (Fauzi et al., 2025) observed that urban albedo interacts with water adjacency, enhancing localized cooling under high humidity. Together, these studies support the hypothesis that urban morphology interacts with natural surface features to produce distinctive microclimatic responses across Indonesian landscapes.

Inland Indonesian cities characterized by hilly terrain, such as Bogor and Malang, display unique LST variability linked to topographic relief. Deviro et al. (2025) observed that elevated zones with higher SVF and vegetation cover showed lower LST values, while low-lying basins with dense structures exhibited intensified heat buildup. This pattern illustrates the role of elevation-driven airflow, as described in Yang et al. (2023) and Wang et al. (2016), where orographic lifting enhances ventilation in upper slopes while valleys trap warm air.

Such dynamics reinforce the framework outlined in Section 3.3, which emphasizes the coupling of topography and boundary-layer processes. In Bogor's hilly districts, evening temperature inversions were occasionally observed, limiting convective dissipation and causing micro-scale heat islands. In contrast, Denpasar's relatively flat terrain allowed marine airflow to penetrate inland, reducing heat retention. Therefore, morphology and topography must be analyzed jointly to understand SUHI persistence across Indonesia's diverse urban typologies.

Several studies incorporated indirect evidence of morphological interactions, though explicit NDVI × SVF or NDVI × H/W interaction terms were rarely quantified. Deviro et al. (2025) implicitly demonstrated vegetation–density synergy, while East Jakarta (2024) and Greater Jakarta (2025) used NDVI–albedo overlays to assess combined effects. This lack of explicit interaction modeling represents a methodological gap also noted by Mohanasundaram et al. (2022) and Govil et al. (2019), who emphasized the need for multivariate frameworks that integrate morphological and vegetation parameters for more accurate LST prediction.

Model transferability across cities remains limited due to contextual differences in urban structure and environmental conditions. For instance, the empirical models developed in inland settings like Yogyakarta and Malang may not accurately predict LST patterns in coastal environments such as Denpasar or Makassar, where sea–land breezes and humidity alter radiative fluxes. This observation parallels findings by Bhowmik and Bhatt (2023) and Ghodieh (2024), who argued that LST models must be locally calibrated to account for morphological and climatic heterogeneity.

Thermal comfort indices provide an integrative measure of how morphology-mediated temperature variations affect human well-being. In Bogor, the correlation between THI and LST exceeded 0.6, indicating strong linkage between built environment density and perceived heat stress (Deviro et al., 2025). Districts with greater vegetative openness reported THI values below 27°C, corresponding to the comfort threshold for humid-tropical populations. Similar trends were observed in East Jakarta, where neighborhoods with extensive UGS showed the lowest SUHI intensity and higher comfort levels. In Denpasar, Wirayuda et al. (2023) observed that coastal airflow not only cooled surface temperatures but also moderated humidity levels, improving UTCI outcomes. These observations are consistent with the argument of Ji (2025) that morphology–ventilation interaction is central to mitigating urban heat stress. The findings collectively demonstrate that morphology-induced microclimate modulation is not merely a physical process but one with direct implications for urban health, energy demand, and social equity.

Methods, Sensors, Validation, and Transferability

Methodological rigor forms the cornerstone of reliable Land Surface Temperature (LST) estimation and Surface Urban Heat Island (SUHI) analysis in tropical urban contexts. Across Indonesian studies, methodological diversity—spanning sensor platforms, retrieval algorithms, validation frameworks, and cross-city transferability tests—has introduced considerable heterogeneity in reported outcomes. Table 4 consolidates methodological data from ten representative studies (2010–2025), providing an overview of sensor-algorithm combinations, validation schemes, accuracy levels, and reproducibility practices. Collectively, these studies underscore the need for consistent methodological standards to improve comparability, reproducibility, and spatial transferability of SUHI results across Indonesia's geographically diverse cities.

Table 6. Methodological Appraisal and Transferability

Study (Year)	Sensor(s) & LST Algorithm	Validation Scheme	Reported Accuracy / Uncertainty	Transfer Test (Cross-city/Season)	Reproducibility (Code/Data)	Risk-of-Bias Notes
Deviro et al. (2025), Bogor	Landsat 8 OLI/TIRS; standard LST	Field THI; regression	NR (qualitative R^2)	Multi-year within-city	NR	Possible spatial autocorrelatio n
Sumunar et al. (2020), Yogyakarta	Landsat 8; dry vs. wet	NR	Correlation magnitudes only	Seasonal comparison	NR	No spatial CV stated
Wirayuda et al.	Landsat 8; SUHI via	Spatial autocorrela	Cluster significance	Single-city	NR	Causality not claimed

(2023), Denpasar	TIR + LISA	tion	only			
Sleman Regency (2024), Yogyakarta	Landsat L2 ST; emissivity/ TOA corrections	NR	NR	Pandemic vs. post-pandemic	NR	LST rebound partly due to mobility
Surachman et al. (2025), Malang	Landsat 8 + Sentinel-2	NR	Model R^2=0.864	Single-year	NR	Possible overfit; limited ground truth
Malang Parks UAV (2025)	UAV thermal + OBIA high-res	Class-based visual checks	Class accuracy qualitatively high	Microscale only	NR	Limited transferability beyond parks
Suprijanto et al. (2025), Cilegon	Landsat 8 LST + GPM + ODIAC (ML fusion)	Cross-dataset consistenc y	NR	2014–2022 multi-year	NR	Cloud/noise sensitivity
Maheng et al. (2024), Jakarta	Urban boundary layer climate model	Model skill metrics	Qualitative skill; weak winds	Scenario experiments	NR	Physics/config biases
Fauzi et al. (2025), Greater Jakarta	Landsat 7/8; albedo derivation	Accuracy/ kappa (0.74–0.77)	Moderate accuracy	2010 vs. 2018	NR	Air temp ≠ LST; inference caution
Bandar Lampung (2024)	Landsat 5/8/9; thermal channel	Simple regression	NR	Multi-epoch	NR	Coarse controls; possible omission bias

The dominant sensor platforms employed across Indonesian SUHI studies include Landsat 5–9, Sentinel-2, MODIS, and UAV-based thermal sensors, with Landsat 8 OLI/TIRS emerging as the primary dataset due to its spatial resolution (30 m) and spectral fidelity. The use of Split-Window Algorithm (SWA) and Mono-Window Algorithm (MWA) was noted in a subset of studies, particularly those emphasizing atmospheric correction and emissivity calibration. However, many studies did not explicitly disclose their retrieval algorithm or emissivity model, leading to reproducibility gaps (Deviro et al., 2025; Sumunar et al., 2020).

Recent international advances highlight the efficacy of SWA and MWA in tropical LST retrieval, owing to their robustness under variable atmospheric humidity (Ligorio et al., 2016; Zhang et al., 2024). Although these algorithms were seldom standardized across Indonesian contexts, their adoption would significantly reduce uncertainty in SUHI intensity mapping. Furthermore, Suprijanto et al. (2025) demonstrated the potential of multi-sensor fusion using Landsat, GPM precipitation, and ODIAC emission datasets, enhancing spatiotemporal resolution and improving heat hotspot detection. This methodological innovation exemplifies Indonesia's growing integration of machine-learning-based retrieval frameworks, consistent with emerging approaches by Li et al. (2021) and Dijkstra et al. (2025).

Validation remains a weak point in Indonesian SUHI research. Out of the ten reviewed studies, fewer than half implemented formal validation, and even fewer incorporated spatial cross-validation (CV)—a key step to account for spatial autocorrelation and sampling bias. Where validation was conducted, approaches included field-based THI measurements (Deviro et al., 2025), autocorrelation tests (Wirayuda et al., 2023), and basic regression diagnostics (Fauzi et al., 2025).

According to Ligorio et al. (2016) and Jahan & Rao (2020), spatial CV provides more realistic estimates of model accuracy by partitioning data geographically rather than randomly, thereby avoiding overfitting and improving generalization. Yet, Indonesian case studies such as those in Yogyakarta and Denpasar largely lacked this feature, undermining cross-site comparability. The methodological heterogeneity observed reinforces the importance of spatial CV as a standard validation procedure, especially for data-sparse urban regions.

In terms of reported accuracy, Malang's multi-sensor regression achieved an R^2 value of 0.864 (Surachman et al., 2025), though this high correlation may reflect overfitting rather than genuine robustness. Similarly, qualitative assessments in UAV-based studies (Malang Parks, 2025) provided strong visual alignment but lacked quantitative uncertainty reporting. These inconsistencies underscore the need for standardized reporting of accuracy metrics (RMSE, MAE, R^2) and explicit uncertainty budgets to facilitate meaningful comparison across studies.

Multi-sensor data fusion has emerged as a promising approach to mitigate the limitations of single-sensor datasets, particularly under Indonesia's frequent cloud cover and variable topography. By integrating high-temporal-resolution sensors (e.g., MODIS) with high-spatial-resolution imagery (e.g., Landsat, Sentinel-2), fusion frameworks enhance both spatial detail and temporal continuity (Li et al., 2021; Bartkowiak et al., 2022). Suprijanto et al. (2025) exemplified this strategy through machine learning-based fusion of Landsat, GPM, and ODIAC data, yielding improved representation of industrial heat emissions in Cilegon.

In alignment with Dijkstra et al. (2025), multi-sensor fusion allows for the generation of high-resolution, continuous LST datasets suitable for longitudinal SUHI monitoring. However, the complexity of harmonizing radiometric and geometric resolutions across sensors introduces challenges. Only a minority of studies explicitly addressed cross-sensor calibration or noise reduction, resulting in potential inconsistencies when interpreting interannual trends. The absence of standardized pre-processing workflows highlights the need for national-level guidelines on atmospheric correction, radiometric harmonization, and co-registration protocols.

Few Indonesian studies conducted cross-city or cross-season transfer tests, despite the country's diverse climatic and morphological contexts. Deviro et al. (2025) and Suprijanto et al. (2025) represent partial exceptions, applying multi-year frameworks that enabled limited temporal validation. However, most studies (e.g., Sleman, Malang, Bandar Lampung) were confined to single-year or single-season analyses, constraining generalization.

As argued by Zhang et al. (2024) and Chen et al. (2024), true model transferability requires assessing whether LST predictors maintain accuracy when applied to untrained spatial or temporal domains. The absence of such testing in most Indonesian research raises concerns about overfitting and regional bias. Given Indonesia's pronounced coastal–inland thermal gradients, developing transferable SUHI models necessitates incorporating coastal boundary-layer dynamics and orographic effects (see Section 3.3). Furthermore, the establishment of open, multi-site validation networks would enhance model interoperability across the archipelago.

Reproducibility remains a critical limitation across the reviewed corpus. None of the ten studies in Table 6 publicly shared analytical code or raw LST products, hindering independent verification. International best practices (Yao et al., 2020; Ghimire et al., 2020) emphasize open-data frameworks and algorithmic transparency as prerequisites for robust environmental modeling. Adopting such practices would strengthen Indonesia's SUHI research ecosystem, allowing for meta-analytic validation and cumulative progress.

Risk-of-bias assessment across studies indicates three recurrent issues: (1) inadequate validation, (2) incomplete algorithm disclosure, and (3) absence of spatial uncertainty reporting. Deviro et al. (2025) and Surachman et al. (2025) partially mitigated bias through regression diagnostics, but the majority lacked spatial CV or ground-truthing. To address this, Chen et al. (2024) and Yin et al. (2021) recommend incorporating uncertainty maps and standardized metadata documentation (sensor, date, algorithm, validation) in all published outputs.

DISCUSSION

The systematic review conducted across Indonesian studies from 2010 to 2025 reveals that urban heat dynamics in humid-tropical environments are governed by a complex interplay between vegetation cover, impervious surfaces, urban morphology, and methodological heterogeneity in LST estimation. The synthesis of empirical evidence across four analytical themes—vegetation gradients (NDVI–ΔLST), built-up intensity (NDBI/impervious fraction), morphology–microclimate modulation, and methodological transferability—provides critical insights into both the biophysical and technical drivers shaping Surface Urban Heat Island (SUHI) variability. This discussion section integrates these findings to evaluate the theoretical, empirical, and methodological contributions of current Indonesian UHI research, while identifying persistent gaps that constrain generalizability and practical application.

Integrative Patterns of Vegetation and Built-Up Dynamics

The inverse NDVI–LST and positive NDBI–LST correlations collectively affirm the dualistic thermal behavior of Indonesia's urban landscapes. Vegetation acts as a primary cooling agent through evapotranspiration and shading, reducing surface temperatures by approximately 0.3–1.0°C per 0.1 NDVI increment (Kandel et al., 2022). Conversely, built-up intensity—quantified through NDBI and imperviousness—exerts a consistent warming influence, often raising LST by 1°C per equivalent unit increase (Surachman et al., 2025; Deviro et al., 2025). This bidirectional thermal mechanism underscores the ecological imbalance produced by rapid urban expansion, wherein reductions in vegetative cover amplify SUHI intensity and exacerbate thermal stress.

However, these relationships are not spatially uniform. Coastal cities such as Denpasar and Banda Aceh display moderated NDVI–LST slopes due to maritime humidity and sea–land breeze effects (Wirayuda et al., 2023), while inland cities like Yogyakarta and Malang exhibit stronger NDBI–LST associations driven by higher thermal inertia and limited ventilation. These variations confirm the theoretical expectation that coastal boundary-layer dynamics and topography condition the magnitude of SUHI effects (Dah et al., 2023; Chen et al., 2019). The findings thus validate the theoretical framework proposed in Section 3, where differential latent and sensible heat flux partitioning governs the strength of LST–index relationships under Indonesia's humid climate.

Notably, nonlinear thresholds and saturation effects were observed in vegetation–temperature interactions. At high NDVI levels, additional greening yielded diminishing LST reductions, consistent with the findings of Xu et al. (2020) and Cinar & Ardahanlıoğlu (2022). This saturation effect reflects a plateau in evapotranspiration efficiency once surface moisture reaches equilibrium. Such nonlinearities emphasize that SUHI mitigation cannot rely solely on increasing vegetation area but must incorporate strategic placement and species selection to maximize microclimatic cooling.

Morphological Modulation of Urban Heat and Thermal Comfort

Morphological parameters—density, height-to-width ratio (H/W), and sky view factor (SVF)—play a critical role in mediating the spatial variability of LST and thermal comfort. Compact built environments with high H/W ratios and low SVF values consistently exhibited elevated LST, corroborating Ji (2025) and Zaki et al. (2020), who argue that limited sky exposure inhibits radiative heat loss and ventilation. In contrast, open geometries with higher SVF values, often near blue-green corridors or coastal zones, facilitate airflow and improve thermal regulation (Jeon et al., 2023; Qi et al., 2024).

The empirical synthesis indicates that the morphology–LST relationship operates synergistically with vegetation. Districts characterized by both high SVF and dense vegetation, such as in East Jakarta and Bogor, showed the lowest THI and UTCI values, confirming vegetation's amplified cooling efficiency under morphologically open conditions (Deviro et al., 2025; Rizki et al., 2024). Conversely, industrial and residential zones with compact morphologies and low SVF—common in Cilegon and Malang—intensify surface heating and delay nocturnal cooling. These morphological controls directly support the framework proposed in Section 3.2, in which urban form influences both radiative geometry and convective exchanges, shaping the balance between heat storage and dissipation.

Nevertheless, the transferability of morphology–LST models across Indonesian cities remains limited. The absence of standardized morphological indicators (e.g., SVF or H/W datasets) and varying urban design typologies impede model generalization, a limitation similarly noted by Bhowmik & Bhatt (2023) and Ghodieh (2024). This challenge underscores the necessity of localized model calibration that accounts for topographic relief and coastal airflow patterns unique to Indonesia's archipelagic urbanism.

Methodological Heterogeneity and Validation Gaps

A central challenge identified in this review is methodological inconsistency in LST retrieval, validation, and reporting. Although Landsat and Sentinel remain the predominant data sources, fewer than half of reviewed studies explicitly disclosed their retrieval algorithm or uncertainty margins. The inconsistent use of the Split-Window Algorithm (SWA) and Mono-Window Algorithm (MWA)—which are well-documented for minimizing atmospheric distortion in humid climates (Ligorio et al., 2016; Zhang et al., 2024)—contributes to uncertainty in cross-city comparisons.

Equally significant is the widespread absence of spatial cross-validation (CV), a methodological gap that undermines confidence in reported model accuracies. As noted by Ligorio et al. (2016) and Jahan & Rao (2020), spatial CV is essential to mitigate bias from spatial autocorrelation and overfitting. Yet, most Indonesian studies relied on single-site validation or descriptive comparisons, limiting transferability. The only partial exceptions, such as Deviro et al. (2025) and Suprijanto et al. (2025), applied multi-year frameworks but did not evaluate spatial generalization across regions.

Multi-sensor fusion and machine learning represent a promising methodological advancement. Suprijanto et al. (2025) successfully integrated Landsat, GPM, and ODIAC datasets using a machine-learning fusion framework, enhancing spatiotemporal coverage of industrial heat emissions. Such approaches align with Bartkowiak et al. (2022) and Li et al. (2021), who demonstrated that combining

MODIS and Landsat improves both spatial detail and temporal consistency of LST products. However, the lack of uniform preprocessing and calibration procedures continues to limit comparability among Indonesian studies. This underscores the importance of national standards for atmospheric correction, radiometric harmonization, and uncertainty reporting.

Reproducibility, Transparency, and Risk of Bias

Reproducibility remains an underdeveloped component of Indonesia's SUHI research landscape. None of the reviewed studies in Section 4.4 made their analytical code or LST datasets publicly available, restricting independent validation. As Yao et al. (2020) and Ghimire et al. (2020) emphasize, open data and algorithmic transparency are crucial for establishing credibility and promoting cumulative scientific progress. Without reproducible workflows, the risk of bias persists through undocumented preprocessing steps, inconsistent emissivity parameters, and incomplete metadata.

Bias also arises from unequal data representation. Studies often focus on major metropolitan regions such as Jakarta and Malang, while smaller coastal and eastern Indonesian cities remain underrepresented. This imbalance may skew national-scale interpretations of SUHI behavior, as coastal climates exhibit fundamentally different heat retention patterns due to maritime influence (Chen et al., 2019; Dah et al., 2023). Moreover, the limited availability of ground-based meteorological validation—an issue highlighted by Wang et al. (2019)—constrains the capacity to evaluate satellite-derived temperature accuracy, particularly in data-sparse regions.

Theoretical and Practical Implications

The empirical evidence reinforces the theoretical model outlined in Section 3: in humid-tropical environments, SUHI intensity arises from the combined effects of vegetation scarcity, high imperviousness, and morphological confinement. This triadic interaction defines Indonesia's unique urban heat profile, where humidity-induced decoupling between LST and air temperature (Shen et al., 2021; Yu et al., 2023) complicates the direct translation of satellite-derived metrics into comfort indicators. Nonetheless, the inclusion of thermal comfort indices (THI, UTCI) in studies such as Deviro et al. (2025) bridges this gap, facilitating actionable insights for urban design.

Practically, the findings point to three priority interventions. First, integrating NDVI–NDBI monitoring into urban spatial planning can provide an evidence-based foundation for greening strategies, targeting districts with the steepest LST gradients. Second, optimizing morphology—through design parameters such as SVF and H/W ratio—can enhance airflow and radiative cooling in dense areas. Third, the adoption of multi-sensor, machine-learning-based LST models will improve real-time monitoring capabilities, supporting heat mitigation policies at both municipal and national scales.

At the theoretical level, the observed heterogeneity among Indonesian cities underscores the necessity of context-sensitive SUHI frameworks. Unlike temperate regions where seasonal temperature swings dominate, Indonesia's SUHI dynamics are modulated by monsoonal humidity, topography, and land–sea interactions. Future models must thus incorporate boundary-layer meteorology and mesoscale feedbacks to capture this climatic complexity.

CONCLUSION

This systematic review examined 15 years of research (2010–2025) on Urban Heat Islands (UHI) and Land Surface Temperature (LST) in Indonesian cities, integrating findings from remote sensing, vegetation indices, built-up metrics, and morphological analyses. Three overarching conclusions emerge. First, vegetation and imperviousness exhibit inverse thermal behaviors: increasing vegetation (NDVI) reduces LST by approximately 0.3–1.0°C per 0.1 NDVI increase, whereas impervious expansion (NDBI) increases LST by a similar magnitude. These results confirm that vegetation restoration and spatially balanced land cover remain central to mitigating SUHI effects in humid-tropical cities. Second, morphological parameters—particularly sky view factor (SVF), building density, and height-to-width ratio (H/W)—govern local microclimates by influencing radiative geometry and airflow. High-density, low-SVF districts show persistent SUHI effects, while open, green-adjacent zones promote cooling and improve thermal comfort (THI, UTCI). Third, methodological heterogeneity constrains comparability across studies. While Landsat-based retrievals dominate, inconsistent use of Split-Window and Mono-Window Algorithms, limited spatial cross-validation, and a lack of open-data practices reduce reproducibility and transferability.

The review's findings collectively answer the guiding research questions by demonstrating that NDVI, NDBI, and morphology jointly explain most SUHI variation across Indonesia, with coastal-topographic factors moderating intensity. These results contribute to tropical urban climatology by contextualizing SUHI mechanisms under high-humidity, monsoonal conditions unique to Southeast Asia. The study emphasizes the need for standardized validation frameworks, multi-sensor fusion, and spatially explicit models to strengthen evidence comparability. Future research should extend spatial coverage beyond Java to underrepresented coastal and eastern regions, integrating UAV validation and machine-learning-based fusion approaches. Ultimately, this review advances a coastal-aware, data-driven model of urban heat dynamics that informs equitable and climate-sensitive planning for Indonesia's rapidly urbanizing tropical environments.

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