INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

URBAN HEAT ISLAND ASSESSMENT USING THERMAL REMOTE SENSING AND GEOSPATIAL TECHNIQUES

Dr. Reetu
Assistant Professor
Department of Geography
GCW, Gohana
Email: rituraman125@gmail.com

Dr. Sharmila Badhwar
Associate Professor
Department of Geography
GCW, Sonipat
Email: sharmilasangwan1@gmail.com

Abstract
Urban heat islands are spatially uneven expressions of altered surface energy balance, urban form, land cover, and human activity. Thermal remote sensing has become central to their assessment because it provides repeatable observations of land-surface temperature (LST) across entire metropolitan regions. Yet the apparent simplicity of a heat map can conceal substantial analytical uncertainty: LST is not equivalent to near-surface air temperature or human thermal stress; satellite overpass time captures only a narrow portion of the diurnal cycle; emissivity and atmospheric correction affect retrieval accuracy; and the measured surface urban heat-island intensity depends strongly on the definition of urban and rural reference areas. This paper presents an analytical review and a reproducible methodological framework for assessing surface urban heat islands using thermal imagery and geospatial techniques. It compares major data sources, including Landsat, MODIS, ECOSTRESS, ASTER, and Sentinel-3; describes pre-processing and LST-retrieval choices; and integrates land-cover indices, local climate zones, terrain, urban morphology, and socioeconomic exposure. The framework emphasizes multi-date sampling, explicit quality control, spatial autocorrelation diagnostics, spatial regression, hotspot analysis, scale sensitivity, and validation. The evidence synthesis indicates that vegetation and water generally suppress daytime surface heating, while imperviousness and low moisture availability raise LST, but the strength and even direction of associations vary with season, background climate, urban form, and observation time. The paper concludes that defensible UHI assessment requires moving beyond single-scene mapping toward uncertainty-aware, multi-scale analysis linked to exposure and vulnerability. Such an approach can support targeted tree planting, cool materials, ventilation corridors, blue-green infrastructure, and post-intervention monitoring without treating satellite LST as a direct substitute for experienced heat.

Keywords: surface urban heat island; thermal infrared remote sensing; land-surface temperature; GIS; spatial regression; local climate zones; heat vulnerability

1. Introduction

Urbanization modifies the exchange of radiation, heat, moisture, and momentum between the land surface and the atmosphere. Buildings and paved materials commonly replace vegetated or moist surfaces, increasing heat storage and reducing evapotranspiration; street canyons alter shading and long-wave radiation; and anthropogenic heat from transport, buildings, and industry adds to the urban energy budget. These changes produce urban heat islands (UHIs), commonly understood as temperature differences between urban and less urbanized surroundings. The phenomenon is not singular. Canopy-layer UHI refers to air-temperature differences within the space occupied by people and buildings, boundary-layer UHI concerns the urban atmospheric plume above roof level, and surface UHI (SUHI) describes differences in radiometric land-surface temperature. Thermal satellite imagery primarily observes the last of these (Voogt & Oke, 2003; Oke et al., 2017). The distinction is fundamental. Satellite-derived

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

LST represents the effective radiometric temperature of the visible surface within a pixel at the instant of observation. It is shaped by roof, road, soil, vegetation, water, and shadow fractions, as well as by viewing geometry, emissivity, and atmospheric conditions. A hot roof can dominate a daytime pixel even when shaded pedestrian air temperature is lower; conversely, a tree canopy may appear cool because of evapotranspiration while humid, low-wind conditions still impose substantial physiological heat stress. Therefore, SUHI maps are best interpreted as surface-energy and land-cover diagnostics rather than direct maps of health risk. Their value increases when combined with weather stations, mobile transects, urban morphology, population, and vulnerability indicators (Weng, 2009; Zhou et al., 2019).

Thermal remote sensing nevertheless offers major advantages. Landsat provides a multi-decadal record at neighborhood-relevant spatial detail; MODIS and Sentinel-3 provide frequent observations suited to seasonal and regional analysis; ECOSTRESS adds finer thermal detail and variable overpass times; and ASTER offers high-quality historical multispectral thermal observations. Cloud platforms and open geospatial software now allow large image collections to be processed consistently, making it feasible to examine long-term trends rather than isolated hot days (Gorelick et al., 2017; Shi et al., 2021). At the same time, increased computational capacity does not automatically produce valid inference. A visually persuasive temperature surface can still be biased by cloud-edge contamination, unrepresentative rural references, resampling, spatial dependence, or uncontrolled differences in weather between dates.

2. Conceptual and Analytical Foundations

2.1 Surface energy balance and the origin of urban thermal contrasts

At the surface, available energy can be summarized as the balance among net radiation, sensible heat, latent heat, heat storage, and anthropogenic heat. Urbanization changes each term. Dark or low-albedo materials may absorb more short-wave radiation, although the net effect depends on roof reflectance and canyon shading. Dense materials store energy during the day and release it after sunset. Limited vegetation and sealed soils reduce latent heat flux, transferring a larger fraction of available energy into sensible heat and storage. Urban geometry can suppress or redirect long-wave radiative loss, while roughness modifies turbulent exchange. Background climate matters because the same intervention does not perform identically in humid, arid, coastal, or high-elevation settings. Zhao et al. (2014) demonstrated that local background climate strongly influences UHI processes, reinforcing the need for climate-specific interpretation.

$$R_n + QF = H + LE + \Delta QS + \Delta QA \quad (1)$$

R_n = net radiation; QF = anthropogenic heat; H = sensible heat; LE = latent heat; ΔQS = storage; ΔQA = advection and other residual terms.

Thermal imagery does not measure each flux directly; it observes the integrated surface-temperature response. Consequently, identical LST values can arise from different combinations of radiation, moisture, material properties, and aerodynamic exchange. This equifinality is one reason that bivariate correlations between LST and a single index such as NDVI or NDBI are descriptive rather than causal. A stronger design combines multiple predictors, controls for terrain and meteorology, tests spatial dependence, and evaluates whether relationships are stable across seasons and spatial scales.

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

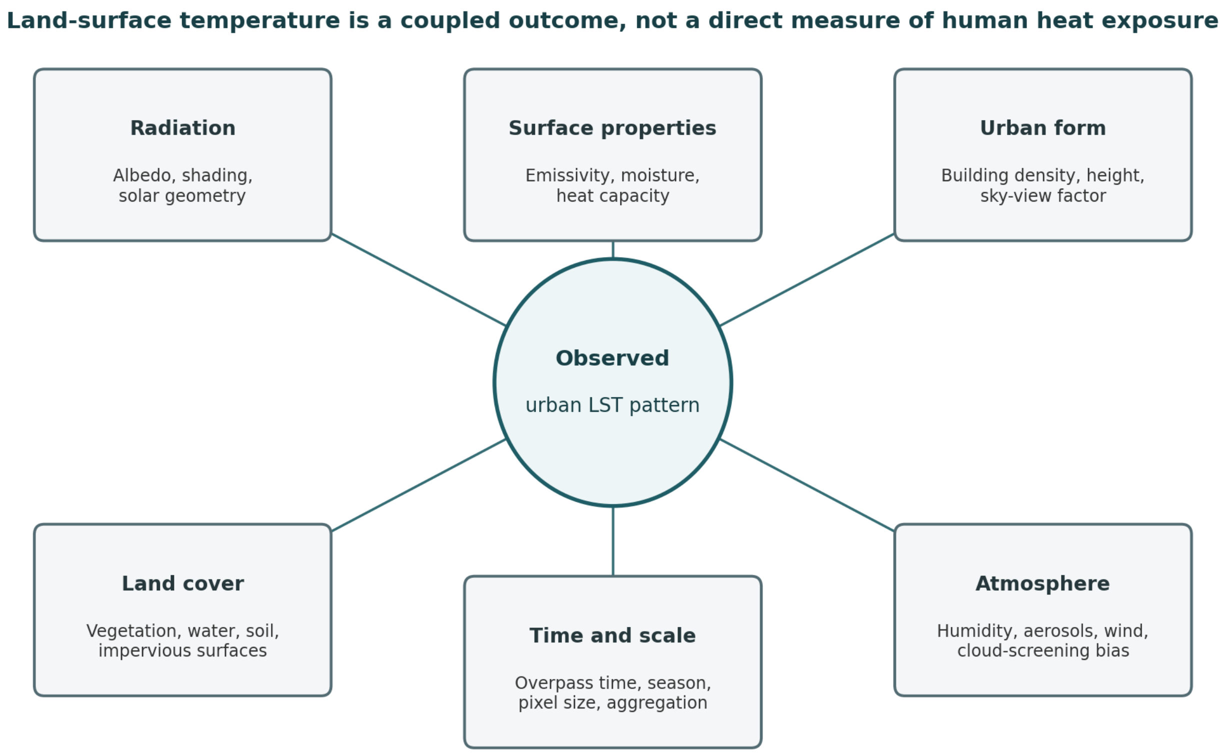


Figure 1. Coupled controls on observed urban land-surface temperature. The diagram highlights why LST must be interpreted jointly with land cover, urban form, atmospheric conditions, time, and scale.

2.2 From UHI to SUHI: definition and reference sensitivity

SUHI intensity is usually expressed as an LST difference between urban and non-urban surfaces. This apparently straightforward metric is highly sensitive to the definition of both classes. An administrative boundary may include extensive farmland, forest, or peri-urban development, while a fixed rural ring may cross different elevations, biomes, or water bodies. A rural reference that is irrigated can exaggerate urban warming; a dry bare-soil reference can produce an apparent urban cool island. Objective comparison therefore requires ecological and topographic matching, exclusion of water where appropriate, and transparent reporting of the reference geometry (Imhoff et al., 2010; Peng et al., 2012).

$$SUHII = mean(LSTurban) - mean(LSTreference) \quad (2)$$

The reference should be climate- and land-cover-matched, not merely outside an administrative boundary.

Local Climate Zones (LCZs) offer a stronger alternative to a binary urban-rural split. The LCZ system classifies urban and natural landscapes according to built form, surface cover, materials, and thermal-relevant structure. It improves comparability by allowing, for example, compact high-rise, open low-rise, dense trees, low plants, and bare soil to be evaluated as distinct thermal environments rather than being collapsed into broad classes (Stewart & Oke, 2012; Bechtel et al., 2015). Recent reviews show growing adoption of LCZ-based SUHI assessment, but also reveal inconsistent reporting of SUHI calculation methods, a problem that should be corrected through explicit equations, masks, and reference definitions (Fernandes et al., 2023).

2.3 Analytical review approach

The paper uses a structured analytical synthesis of foundational urban-climate studies, peer-reviewed remote-sensing research, and current agency documentation for operational thermal products. The emphasis is methodological rather than bibliometric: studies were selected to represent core concepts, global and multi-city evidence, LST retrieval and validation, LCZ classification, landscape-pattern analysis, spatial statistics, and recent

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

developments in cloud computing and data fusion. Agency sources from the U.S. Geological Survey, NASA, and the European Space Agency were used for product specifications and processing caveats. Findings are organized around a complete workflow from problem definition to planning application, with attention to reproducibility and uncertainty.

3. Thermal Data Sources and Sensor Selection

Sensor choice determines the spatial, temporal, spectral, and diurnal dimensions of the analysis. No single system simultaneously provides fine spatial detail, frequent repeat observations, all-weather capability, and full diurnal coverage. The study question must therefore precede data selection. Neighborhood-scale hotspot mapping often favors Landsat or ECOSTRESS; seasonal and day-night comparisons favor MODIS or Sentinel-3; long-term historical analysis favors the Landsat archive; and emissivity-focused or multispectral thermal research may use ASTER. Combining sensors can reduce individual limitations, but cross-sensor differences in overpass time, pixel size, retrieval algorithm, and quality flags must be harmonized rather than ignored.

Table 1. Major thermal remote-sensing sources for urban heat-island assessment.

Platform / product	Typical thermal detail	Temporal strength	Best use in UHI studies	Important cautions
Landsat 4-9 Level-2 ST	Delivered on 30 m grid; native TIR is coarser	16-day single-satellite cycle; multi-decadal archive	Neighborhood pattern, land-cover change, long-term summer composites	Daytime only for standard ST; clouds, emissivity gaps, mixed pixels, revisit limitations
MODIS MOD11/MOD21	1 km standard LST	Daily and day/night products	Regional comparison, seasonal climatology, diurnal contrast	Coarse urban mixing; clear-sky bias; product-specific emissivity assumptions
ECOSTRESS L2 LST&E	70 m	Variable ISS overpass times	Fine-scale thermal heterogeneity and different times of day	Irregular temporal sampling; swath coverage; quality-mask requirements
ASTER L2 / GED	90 m LST; 100 m emissivity database	Targeted historical acquisitions	Multispectral TIR, emissivity support, validation and historical studies	Sparse acquisitions; archival mission context; coverage gaps
Sentinel-3 SLSTR LST	1 km TIR	Frequent global coverage	Regional monitoring and cross-sensor comparison	Coarse for intra-urban detail; cloud and emissivity uncertainty

3.1 Landsat surface-temperature products

For most city-scale studies, Landsat is the practical starting point because its spatial detail resolves major neighborhoods, industrial zones, parks, and peri-urban transitions. The current Collection 2 Level-2 surface-temperature product uses calibrated thermal radiance, atmospheric profiles, ASTER emissivity information, and quality layers to deliver analysis-ready ST. The official scale conversion is ST = (DN × 0.00341802) + 149.0 K. Using this product is generally preferable to reconstructing LST from Level-1 data unless the research specifically evaluates retrieval algorithms or requires a custom atmospheric treatment. Analysts must retain quality-assurance bands, exclude clouds and shadows, document missing ASTER GED areas, and recognize that the 30 m grid does not create 30 m independent thermal information from a coarser native detector (U.S. Geological Survey, 2026; Malakar et al., 2018).

When Level-1 processing is necessary, the typical sequence is conversion from digital number to spectral radiance, radiance to brightness temperature, estimation of land-surface emissivity, and emissivity correction to LST. Single-

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

channel and split-window algorithms differ in atmospheric inputs and use of thermal bands. For Landsat 8/9, operational products and well-validated algorithms should be favored over ad hoc equations copied without scene-specific constants. Jiménez-Muñoz et al. (2014) provide a widely cited treatment of single-channel and split-window retrieval, while Hulley et al. (2012) and Malakar et al. (2018) demonstrate the importance of uncertainty characterization and validation.

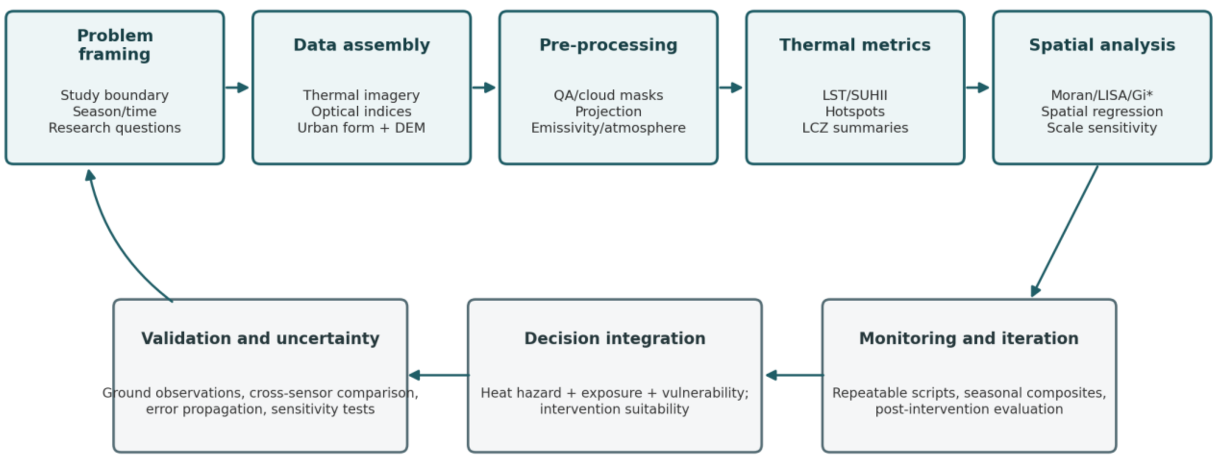
3.2 Moderate- and high-temporal-resolution products

MODIS provides daily LST at approximately 1 km, including day and night observations and quality information. MOD11 uses a heritage split-window approach, whereas MOD21 retrieves temperature and emissivity more dynamically and can reduce biases over arid surfaces. MODIS is particularly valuable for seasonal climatologies, heat-wave context, and comparison among cities, but urban pixels often mix built-up, vegetation, water, and rural land. The correct analytical scale is therefore district-to-regional rather than individual streets. Sentinel-3 SLSTR provides thermal observations at about 1 km with a dual-view design that supports atmospheric correction and regular global monitoring. Validation studies indicate that product choice and explicit emissivity treatment remain important even at this coarser scale (NASA MODIS Land Team, 2025; Pérez-Planells et al., 2021).

ECOSTRESS, mounted on the International Space Station, provides LST and emissivity at 70 m with variable acquisition times. This irregular timing is a scientific advantage for examining how thermal patterns change outside the fixed morning overpasses of Landsat, but it complicates compositing and direct comparison. Versioned products must be identified explicitly because earlier products have been retired and processing has evolved. ECOSTRESS is especially useful for park-cooling gradients, industrial heat, and intra-urban heterogeneity when clear observations align with the study period (Hook & Hulley, 2026). ASTER offers 90 m multispectral thermal data and underpins the global emissivity database used by Landsat processing. Its acquisition record is less systematic, making it most suitable for targeted historical scenes, emissivity analysis, and cross-validation rather than routine monitoring.

4. Integrated Methodology for UHI Assessment

A defensible UHI study is a sequence of linked design decisions rather than a single raster calculation. Figure 2 presents the recommended workflow. Each stage should preserve metadata, masks, parameter choices, and intermediate diagnostics so that results can be reproduced. The unit of analysis should be stated at the beginning: individual thermal pixels, regular grids, census units, LCZ polygons, neighborhoods, or administrative wards. Pixel-level analysis retains detail but increases spatial dependence and noise; aggregated units aid interpretation but can conceal within-zone extremes and introduce the modifiable areal unit problem. A multi-scale design that compares at least two spatial units is therefore preferable.



INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

Figure 2. Reproducible workflow for thermal remote-sensing and geospatial assessment of the surface urban heat island.

4.1 Study boundary, time window, and scene selection

The study boundary should include the full urbanized area and a sufficiently broad reference landscape, but it should not be defined solely by an administrative polygon. Recommended alternatives include a morphological urban extent derived from built-up data, a functional urban area, or an LCZ map with a surrounding buffer. Elevation, coastlines, irrigated agriculture, large water bodies, and biome transitions should be inspected before selecting rural reference zones. When topography is important, reference pixels can be matched to urban pixels by elevation band, slope, and background land cover. This reduces the risk of attributing natural temperature gradients to urbanization. Single-date studies are vulnerable to weather and phenology. A stronger design uses a seasonal collection with consistent overpass timing and filters for cloud cover, precipitation history, unusual wind, and synoptic conditions. Median or robust-mean composites reduce residual cloud and outlier effects, while percentile composites can target extreme surface heat. Separate daytime and nighttime analyses are essential where sensors permit, because daytime SUHI is strongly influenced by radiation and evapotranspiration whereas nighttime patterns reflect heat storage, release, geometry, and turbulent mixing. Multi-year analysis should compare equivalent seasonal windows and report the number of valid observations per pixel.

4.2 Pre-processing and quality assurance

Pre-processing should include geometric consistency, projection to an appropriate local coordinate system, radiometric scaling, cloud and shadow masking, removal of saturated or low-quality pixels, and harmonization of spatial resolution. Resampling must match the variable: nearest neighbor for categorical land cover, bilinear or cubic methods for continuous surfaces only when justified, and area-weighted aggregation when moving to coarser grids. Thermal data should not be sharpened to optical resolution and then interpreted as newly observed fine-scale temperature unless a validated downscaling model and uncertainty analysis are provided. Cloud edges require particular attention because thin cloud, haze, and shadows can produce physically implausible cool or warm artifacts.

Quality assurance is more than a mask. Analysts should map observation count, retrieval uncertainty or QA class, distance to cloud, and missing-data frequency. Clear-sky thermal products systematically omit cloudy conditions, creating clear-sky sampling bias. In humid or monsoon climates, the available scenes may represent unusually dry days rather than the full warm season. Gap filling and data fusion can improve continuity, but they transform the research question from observation to model-based estimation. Such outputs should be validated with withheld scenes or ground data and labeled as reconstructed rather than directly observed (Wu et al., 2021).

4.3 LST retrieval and emissivity correction

For Level-1 Landsat workflows, the general radiometric sequence is shown below. Coefficients are sensor- and scene-specific and must be read from metadata. Emissivity can be estimated using land-cover classes, NDVI threshold methods, or external spectral databases. Urban surfaces are heterogeneous, so a single emissivity value for all built-up land is rarely adequate. Roof membranes, concrete, asphalt, dry soil, metal, vegetation, and water have different emissivities; mixed pixels add further uncertainty. Operational Level-2 products incorporate a more complete treatment and should be used whenever their assumptions fit the study.

$$L\lambda = ML \times Qcal + AL \quad (3)$$

Conversion of calibrated digital number to top-of-atmosphere spectral radiance.

$$TB = K2 / \ln(K1 / L\lambda + 1) \quad (4)$$

At-sensor brightness temperature in Kelvin.

$$Pv = [(NDVI - NDVImin) / (NDVImax - NDVImin)]^2 \quad (5)$$

Fractional vegetation approximation used in one common NDVI-threshold emissivity approach.

$$LST = TB / [1 + (\lambda TB / \rho) \ln(\varepsilon)] - 273.15 \quad (6)$$

Simplified emissivity correction; λ is effective wavelength, ε is emissivity, and ρ combines physical constants.

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

Equation (6) is useful for teaching the logic of emissivity correction but should not be treated as universally sufficient. Atmospheric transmittance, upwelling and downwelling radiance, sensor response, surface anisotropy, and uncertainty in ε all affect retrieved temperature. A methodological paper should report the product level, algorithm, thermal band, calibration constants, emissivity source, atmospheric data, output units, and quality thresholds. Validation should use radiometric surface-temperature measurements where available. Near-surface air temperature can support contextual comparison but is not a direct ground truth for LST.

4.4 Explanatory variables and geospatial indicators

The explanatory dataset should represent surface cover, moisture, urban form, terrain, and human activity. Optical indices provide efficient proxies but should not substitute for physically interpretable variables when better data exist. NDVI captures vegetation greenness; NDBI contrasts short-wave infrared and near-infrared reflectance and often tracks built-up or dry surfaces; NDWI or MNDWI highlights water or moisture; albedo describes reflected short-wave energy; impervious-surface fraction quantifies sealing; and fractional vegetation cover supports energy-balance interpretation. Terrain variables include elevation, slope, aspect, and topographic position. Urban morphology can be represented by building coverage, floor-area ratio, height, sky-view factor, road density, canyon orientation, and LCZ class. Distance to water, park size, vegetation patch configuration, and connectivity help evaluate cooling footprints.

Table 2. Common variables for explaining urban LST and SUHI patterns.

Variable	Example expression / source	Expected analytical role	Interpretive cautions
NDVI	(NIR − Red)/(NIR + Red)	Vegetation amount and vigor; evapotranspirative cooling proxy	Saturates in dense vegetation; seasonal and soil-background effects
NDBI	(SWIR − NIR)/(SWIR + NIR)	Built-up/dry-surface proxy	Can confuse bare soil and built materials
NDWI/MNDWI	Band ratios emphasizing water or moisture	Water presence and surface-moisture contrast	Index definition varies; shadows may be confused
Impervious fraction	Classification or global built-up products	Direct measure of sealed urban surface	Classification accuracy and temporal mismatch matter
Albedo	Weighted broadband reflectance	Short-wave absorption and cool-material assessment	High albedo may increase pedestrian radiant load in some geometries
LCZ	WUDAPT or local morphology classification	Comparable urban-form strata	Classification accuracy and within-class heterogeneity
Urban morphology	Buildings, LiDAR, DSM, street network	Shading, storage, ventilation, sky-view effects	Often unavailable or temporally inconsistent
Socioeconomic exposure	Population, age, housing, outdoor work, energy access	Links heat hazard to people and adaptive capacity	Must not be inferred from LST alone; privacy and scale concerns

5. Analytical Synthesis of Evidence

5.1 Vegetation, water, and impervious surfaces

Across climates, vegetation is one of the most consistent correlates of lower daytime LST, principally through shading and evapotranspiration. The relationship is usually nonlinear: sparse vegetation may provide limited cooling, while connected tree canopy can generate stronger effects than the same area fragmented into small patches. Park size, edge-to-area ratio, tree height, soil moisture, and surrounding urban density influence both

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

internal coolness and the distance of cooling beyond a park boundary. Water bodies can create strong local surface-temperature contrasts, but their effect depends on depth, season, wind, humidity, and shoreline geometry. In some climates, humidification may reduce thermal comfort even when surface temperature falls, illustrating again that LST and physiological heat stress are related but distinct.

Impervious-surface fraction is generally associated with higher daytime LST because sealed surfaces reduce moisture availability and often absorb and store substantial energy. However, built-up indices can conflate exposed soil with urban materials, and dense urban cores are not always the hottest daytime surfaces. Tall buildings may shade streets and roofs; highly reflective roofs can remain cooler; industrial or low-rise peripheral zones with large exposed roofs and parking lots may exceed compact centers. At night, dense built form can remain warmer because stored heat is released and radiative cooling is restricted. These contrasts support LCZ- and morphology-based analysis rather than the assumption that temperature increases monotonically with urban density (Estoque et al., 2017; Stewart & Oke, 2012).

5.2 Climate, season, and observation time

Multi-city studies show that SUHI magnitude and direction vary with ecological setting and time of day. Peng et al. (2012) documented broad global differences between daytime and nighttime SUHI across hundreds of cities, while Imhoff et al. (2010) demonstrated relationships among development intensity, ecological setting, vegetation, and surface temperature across U.S. biomes. In humid climates, conversion of vegetated land to impervious surfaces often produces strong daytime warming through reduced evapotranspiration. In dry climates, irrigated urban vegetation can create daytime cool islands relative to surrounding bare land. Seasonal phenology, soil moisture, monsoon timing, snow, and crop cycles can reverse apparent urban-rural contrasts.

Satellite overpass time therefore acts as a sampling filter. A late-morning Landsat scene is not representative of late-afternoon maximum heat or pre-dawn minimum temperature. Fixed overpasses are valuable for consistency, but they cannot describe the full diurnal cycle. MODIS day-night observations, geostationary products, ECOSTRESS variable timing, and ground sensors can provide complementary temporal information. A robust paper should avoid unqualified phrases such as 'the city temperature' and instead state the sensor, local acquisition time, season, and weather context.

5.3 Urban form, landscape configuration, and scale

Landscape composition describes how much vegetation, water, impervious surface, or bare soil exists; configuration describes how those components are arranged. Studies of large Southeast Asian cities show that both composition and pattern influence LST (Estoque et al., 2017). A continuous tree corridor may cool more effectively than isolated patches of equal total area because it provides shade continuity and supports airflow and moisture. Conversely, large uninterrupted impervious patches create extensive thermal reservoirs. Configuration metrics such as patch density, edge density, aggregation, and connectivity can add explanatory value, but many metrics are correlated and scale-dependent. A small, theory-driven subset is preferable to indiscriminate metric selection.

Scale affects both measurement and inference. At 1 km, a MODIS pixel averages multiple neighborhoods and may obscure park cooling; at 70-100 m, thermal heterogeneity is clearer but individual streets remain mixed; at very fine modeled resolution, apparent detail may exceed observational support. Relationships also change with aggregation: NDVI may strongly explain pixel-level daytime LST, while building height and socioeconomic variables become more important at neighborhood scale. This scale dependence is not a nuisance to remove but a property to analyze. Results should be tested at multiple grid sizes or units, and interventions should be recommended only at a scale supported by the data.

6. Uncertainty, Limitations, and Validation

Uncertainty enters at every stage: instrument calibration, atmospheric correction, emissivity, cloud detection, spatial resolution, temporal sampling, classification, reference selection, model specification, and interpretation. Reporting only a final LST map implies a level of certainty that the data do not support. A practical uncertainty framework separates measurement uncertainty, sampling uncertainty, model uncertainty, and decision uncertainty. Measurement uncertainty concerns the thermal retrieval itself; sampling uncertainty concerns the dates and clear-sky conditions observed; model uncertainty concerns variables, spatial weights, algorithms, and validation; and

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

decision uncertainty concerns whether an observed surface hotspot corresponds to population exposure and whether a proposed intervention will work in that urban context.

Table 3. Major sources of uncertainty and recommended controls.

Uncertainty source	Potential effect	Recommended control / reporting
Cloud, haze, and cloud-edge contamination	False cool/warm pixels; biased composites	Use QA bits, cloud-distance buffers, visual checks, robust compositing, and valid-observation counts.
Clear-sky sampling bias	Warm-season sample may exclude humid/cloudy days	Describe meteorological representativeness; compare with station records and scene availability.
Emissivity error	Systematic LST bias over heterogeneous urban materials	Use operational products or validated emissivity sources; perform sensitivity analysis by surface type.
Atmospheric correction	Bias under high water vapor or aerosol load	Use product QA/uncertainty, validated algorithms, and scene-specific atmospheric inputs.
Mixed pixels and resampling	Apparent fine detail or diluted hotspots	Report native thermal resolution; avoid treating resampled pixels as independent observations.
Urban/rural reference choice	Large changes in estimated SUHII	Use matched references, LCZ contrasts, and sensitivity tests with alternative buffers/classes.
Spatial autocorrelation	Inflated significance and unstable coefficients	Test Moran's I; use spatial models or robust spatial inference.
Temporal mismatch among predictors	Spurious relationships when land cover and LST dates differ	Use contemporaneous or carefully harmonized datasets and document temporal offsets.
Validation mismatch	Air-temperature stations do not directly validate radiometric LST	Use radiometers for LST validation; use air temperature as a separate contextual variable.
Exposure interpretation	Surface hotspots may not identify highest health risk	Integrate population, housing, work patterns, shade, humidity, and adaptive capacity.

6.1 Validation strategy

Ideal validation uses calibrated ground or tower radiometers with a footprint that can be matched to the satellite pixel and observation time. Because urban surfaces are heterogeneous, a point measurement over grass or asphalt may not represent a mixed satellite pixel. Validation sites should cover key surface types, and representativeness should be assessed using high-resolution imagery. Cross-sensor comparison can provide additional evidence but is not independent validation when products share emissivity databases or atmospheric inputs. If only weather stations are available, the analysis should examine association between LST and air temperature without calling the station value ground truth for LST.

A complete validation report should include bias, MAE, RMSE, sample size, surface type, temporal tolerance, spatial matching method, and uncertainty of the ground instrument. For statistical models, spatially blocked validation and transfer tests across dates or districts are more informative than random splits. Sensitivity analysis

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

should alter cloud buffers, rural references, grid sizes, emissivity assumptions, and spatial weights. A conclusion is robust when its direction and planning implication remain stable across reasonable alternatives, not merely when one model produces a high R^2.

7. From Heat Maps to Urban Planning Decisions

7.1 Integrating hazard, exposure, and vulnerability

A surface heat map represents hazard, not risk. Risk emerges where high thermal conditions intersect with people, sensitive activities, and limited adaptive capacity. A planning GIS should therefore overlay persistent LST hotspots with population density, age structure, health sensitivity, informal housing, roof material, outdoor work, school and hospital locations, electricity access, tree-canopy inequity, and cooling-center accessibility. Variables should be normalized transparently, and weighting should be justified through policy priorities, expert elicitation, or sensitivity analysis rather than selected solely for visual effect. The output should distinguish three questions: Where is the surface hottest? Where are the most people exposed? Where are the consequences likely to be greatest? Equity analysis is particularly important because lower-income or marginalized communities may experience hotter materials, less canopy, smaller dwellings, limited cooling access, and greater outdoor labor. Yet neighborhood socioeconomic data are often aggregated, while thermal pixels are fine. Analysts must avoid ecological fallacy and protect privacy. Results are best used to identify priority areas for field verification and engagement rather than to label individuals. Participatory mapping can reveal shaded routes, water access, indoor overheating, work schedules, and informal coping strategies that satellites cannot observe.

7.2 Matching interventions to thermal mechanisms

Interventions should target the mechanisms identified in the analysis. Tree canopy is most effective where soil volume, water, species selection, and maintenance support healthy growth and where shade benefits pedestrians or buildings. Cool roofs directly reduce roof-surface heating and can lower building cooling demand, but highly reflective ground materials may increase short-wave radiant exposure at pedestrian level in some urban canyons. Permeable and moisture-retaining surfaces can enhance evaporative cooling where water is available and drainage conditions are suitable. Blue infrastructure can cool locally but requires attention to humidity, safety, and water quality. Ventilation corridors depend on regional winds and building geometry and should be evaluated with morphology and, where possible, urban climate modeling.

The geospatial framework can support intervention suitability mapping. For example, persistent high-LST, low-canopy residential zones with adequate planting space may be assigned high tree-planting suitability; large hot industrial roofs may be assigned high cool-roof suitability; overheated paved schoolyards may require combined shade, reflective or permeable materials, and schedule changes. Scenario analysis can estimate the thermal effect of increasing canopy or albedo, but model assumptions should be explicit and results validated after implementation. Remote sensing is particularly useful for before-after-control-impact monitoring when equivalent seasons, weather conditions, and observation times are compared.

8. Recommended Research Protocol

The following protocol synthesizes the methodological recommendations into an implementable design. First, define the urban extent using morphology or LCZs and create two or more ecologically matched reference alternatives. Second, assemble a warm-season image collection spanning multiple years, retain acquisition time and meteorological context, and generate robust daytime and, where possible, nighttime composites. Third, use official Level-2 LST products with QA masks unless custom retrieval is a research objective. Fourth, map observation count and retrieval quality before interpreting temperature. Fifth, derive a parsimonious set of vegetation, moisture, imperviousness, albedo, terrain, and morphology variables aligned to the thermal support. Sixth, summarize LST by LCZ and planning unit, calculate SUHII under alternative reference definitions, and identify persistent hotspots using local spatial statistics. Seventh, model drivers with spatial diagnostics and blocked validation. Eighth, validate with radiometric observations or carefully framed cross-sensor and station comparisons. Ninth, integrate hazard with exposure and vulnerability. Tenth, translate mechanisms into intervention-suitability maps and establish a repeat-monitoring schedule.

For an empirical city application, the paper's analytical framework can be converted into testable hypotheses. H1:

INTERNATIONAL JOURNAL OF EXPLORING EMERGING TRENDS IN ENGINEERING
Peer-Reviewed, Refereed, Indexed and International Journal, https://ijoeete.com/
(Peer Review Journal as per UGC 2025 Standard Guidelines)
|ISSN No. 2394-0573 |Volume: 13, Issue: 2 | April – June 2026

warm-season daytime LST decreases nonlinearly with tree-canopy and moisture availability after controlling for elevation and urban form. H2: nighttime LST is more strongly associated with building density, heat-storage proxies, and low sky-view factor than daytime LST. H3: LCZ-based contrasts explain more thermal variance and provide more stable inter-date comparisons than a binary administrative urban-rural classification. H4: spatial models and blocked validation yield lower but more realistic predictive performance than ordinary regression with random train-test splits. H5: priority heat-risk areas differ from surface-temperature hotspots after population and vulnerability are incorporated.

9. Conclusion

Thermal remote sensing and geospatial techniques provide a powerful basis for assessing the surface urban heat island, but the analytical value of the output depends on choices made before and after LST is mapped. The strongest studies distinguish surface temperature from air temperature and human heat stress; use multi-date and, where possible, day-night observations; preserve QA and uncertainty; define urban and reference surfaces transparently; classify urban form with LCZs or morphology; and account for spatial dependence and scale. Evidence consistently links vegetation, moisture, and water to daytime cooling and imperviousness to surface warming, yet these relationships are conditioned by climate, season, geometry, and observation time. The central implication is that UHI assessment should move from descriptive single-scene heat maps toward reproducible, uncertainty-aware decision systems. Such systems combine thermal hazard with exposure and vulnerability, identify persistent rather than transient hotspots, and match interventions to the mechanisms producing heat. Landsat, MODIS, ECOSTRESS, ASTER, and Sentinel-3 are complementary rather than interchangeable; sensor selection should be driven by the spatial and temporal question. When implemented with validation, spatial statistics, and community context, the proposed framework can support equitable urban greening, cool materials, blue-green infrastructure, ventilation planning, heat-action plans, and rigorous post-intervention evaluation.

References

1. Avdan, U., & Jovanovska, G. (2016). Algorithm for automated mapping of land surface temperature using Landsat 8 satellite data. Journal of Sensors, 2016, 1480307. https://doi.org/10.1155/2016/1480307
2. Bechtel, B., Alexander, P. J., Böhner, J., Ching, J., Conrad, O., Feddema, J., Mills, G., See, L., & Stewart, I. (2015). Mapping local climate zones for a worldwide database of the form and function of cities. ISPRS International Journal of Geo-Information, 4(1), 199–219. https://doi.org/10.3390/ijgi4010199
3. Estoque, R. C., Murayama, Y., & Myint, S. W. (2017). Effects of landscape composition and pattern on land surface temperature: An urban heat island study in the megacities of Southeast Asia. Science of the Total Environment, 577, 349–359. https://doi.org/10.1016/j.scitotenv.2016.10.195
4. Fernandes, R., Nascimento, V., Freitas, M., & Ometto, J. (2023). Local climate zones to identify surface urban heat islands: A systematic review. Remote Sensing, 15(4), 884. https://doi.org/10.3390/rs15040884
5. Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). Geographically weighted regression: The analysis of spatially varying relationships. Wiley.
6. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031
7. Hook, S., & Hulley, G. (2026). ECOSTRESS tiled land surface temperature and emissivity instantaneous L2 global 70 m v003 [Data set]. NASA Land Processes Distributed Active Archive Center. https://doi.org/10.5067/ECOSTRESS/ECO_L2T_LSTE.003
8. Hulley, G. C., Hughes, C. G., & Hook, S. J. (2012). Quantifying uncertainties in land surface temperature and emissivity retrievals from ASTER and MODIS thermal infrared data. Journal of Geophysical Research: Atmospheres, 117(D23), D23113. https://doi.org/10.1029/2012JD018506

9. Hulley, G. C., Hook, S. J., Abbott, E., Malakar, N., Islam, T., & Abrams, M. (2015). The ASTER Global Emissivity Dataset (ASTER GED): Mapping Earth's emissivity at 100 meter spatial scale. Geophysical Research Letters, 42(19), 7966–7976. https://doi.org/10.1002/2015GL065564
10. Imhoff, M. L., Zhang, P., Wolfe, R. E., & Bounoua, L. (2010). Remote sensing of the urban heat island effect across biomes in the continental USA. Remote Sensing of Environment, 114(3), 504–513. https://doi.org/10.1016/j.rse.2009.10.008
11. Jiménez-Muñoz, J. C., Sobrino, J. A., Skoković, D., Mattar, C., & Cristóbal, J. (2014). Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data. IEEE Geoscience and Remote Sensing Letters, 11(10), 1840–1843. https://doi.org/10.1109/LGRS.2014.2312032
12. Malakar, N. K., Hulley, G. C., Hook, S. J., Laraby, K., Cook, M., & Schott, J. R. (2018). An operational land surface temperature product for Landsat thermal data: Methodology and validation. IEEE Transactions on Geoscience and Remote Sensing, 56(10), 5717–5735. https://doi.org/10.1109/TGRS.2018.2824828
13. NASA MODIS Land Team. (2025). Land surface temperature and emissivity products (MOD11 and MOD21). https://modis-land.gsfc.nasa.gov/temp.html
14. Oke, T. R., Mills, G., Christen, A., & Voogt, J. A. (2017). Urban climates. Cambridge University Press.
15. Peng, S., Piao, S., Ciais, P., Friedlingstein, P., Ottlé, C., Bréon, F.-M., Nan, H., Zhou, L., & Myneni, R. B. (2012). Surface urban heat island across 419 global big cities. Environmental Science & Technology, 46(2), 696–703. https://doi.org/10.1021/es2030438
16. Pérez-Planells, L., Niclòs, R., Puchades, J., Coll, C., Göttsche, F.-M., Valiente, J. A., Valor, E., & Galve, J. M. (2021). Validation of Sentinel-3 SLSTR land surface temperature retrieved by the operational product and comparison with explicitly emissivity-dependent algorithms. Remote Sensing, 13(11), 2228. https://doi.org/10.3390/rs13112228
17. Shi, H., Xian, G. Z., Auch, R. F., Gallo, K., & Zhou, Q. (2021). Urban heat island and its regional impacts using remotely sensed thermal data—A review of recent developments and methodology. Land, 10(8), 867. https://doi.org/10.3390/land10080867
18. Stewart, I. D., & Oke, T. R. (2012). Local climate zones for urban temperature studies. Bulletin of the American Meteorological Society, 93(12), 1879–1900. https://doi.org/10.1175/BAMS-D-11-00019.1
19. U.S. Geological Survey. (2026). Landsat Collection 2 surface temperature. https://www.usgs.gov/landsat-missions/landsat-collection-2-surface-temperature
20. U.S. Geological Survey Earth Resources Observation and Science Center. (2020). Landsat 8–9 Operational Land Imager/Thermal Infrared Sensor Level-2, Collection 2 [Data set]. https://doi.org/10.5066/P9OGBGM6
21. Voogt, J. A., & Oke, T. R. (2003). Thermal remote sensing of urban climates. Remote Sensing of Environment, 86(3), 370–384. https://doi.org/10.1016/S0034-4257(03)00079-8
22. Weng, Q. (2009). Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. ISPRS Journal of Photogrammetry and Remote Sensing, 64(4), 335–344. https://doi.org/10.1016/j.isprsjprs.2009.03.007
23. Wu, P., Yin, Z., Zeng, C., Duan, S.-B., Göttsche, F.-M., Ma, X., Li, X., Yang, H., & Shen, H. (2021). Spatially continuous and high-resolution land surface temperature product generation: A review of reconstruction and spatiotemporal fusion techniques. IEEE Geoscience and Remote Sensing Magazine, 9(3), 112–137. https://doi.org/10.1109/MGRS.2021.3050782
24. Zhao, L., Lee, X., Smith, R. B., & Oleson, K. (2014). Strong contributions of local background climate to urban heat islands. Nature, 511(7508), 216–219. https://doi.org/10.1038/nature13462

25. Zhou, D., Xiao, J., Bonafoni, S., Berger, C., Deilami, K., Zhou, Y., Frolking, S., Yao, R., Qiao, Z., & Sobrino, J. A. (2019). Satellite remote sensing of surface urban heat islands: Progress, challenges, and perspectives. Remote Sensing, 11(1), 48. https://doi.org/10.3390/rs11010048