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Nikita Mahajani, Nandini Halder and Deepak Kumar

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Review Article

Local Climate Zones for Urban Thermal and Heat Assessment: A Systematic Review and Bibliometric Analysis (2015–2026)

Nikita Mahajani[1†], Nandini Halder[2] and Deepak Kumar[2]

[1] Indian Institute of Technology, Hyderabad 502284, Telangana, India
[2]School of Architecture and Planning, Vishwakarma University, Pune 411048, Maharashtra, India
[†]Corresponding author: Nikita Mahajani; nikita.designbuilder@gmail.com
ORCID IDs: 0000-0001-7828-8233 (N. Mahajani); 0009-0007-0667-5112 (N. Halder);
0000-0001-5846-5255 (D. Kumar)

Abstract

Local Climate Zones (LCZs) provide a standardised classification of urban form that has become central to intra-urban thermal research, yet the literature remains methodologically fragmented. This study couples bibliometric mapping with a thematic and methodological synthesis of LCZ applications to urban heat. The review followed PRISMA 2020. We searched Scopus and Web of Science on 24 September 2026 using an outcome-focused string that did not require policy-related vocabulary. Of 528 records, 427 remained after de-duplication; record-level screening produced 313 full-text candidates, from which 95 studies were included. The field is young and expanding. A total of 80% of studies date from 2023 onward and the partial-year 2026 count exceeds every complete preceding year. The corpus is geographically concentrated, China contributes 67 of 95 studies, and Web of Science contributed 13 studies that a Scopus-only search would have missed. Thematic indicators show land surface temperature or heat-island analysis in 83% of studies, classification in 56%, machine learning in 32%, thermal comfort in 21%, and heat risk in 14%; surface-temperature and classification themes co-occur in 43 studies. LCZ classes consistently differentiate surface thermal behaviour, with compact and industrial classes warmest and vegetated and water classes coolest. This consistency rests on a narrow geographic and methodological range. Classification accuracy is reported inconsistently, and studies use different heat-island reference conventions. The data-to-decision framework is therefore presented as an organising synthesis of the reviewed literature, not as a validated model. Cross-city validation, standardised reporting, and evidence from under-represented heat-vulnerable regions are priorities.

Keywords

Local climate zone; Urban heat island; Land surface temperature; Thermal comfort; Remote sensing; Machine learning; Bibliometric analysis; PRISMA 2020

1. INTRODUCTION

Cities concentrate population, infrastructure, and economic activity, and in doing so generate distinctive thermal environments that intensify the risks of a warming climate. The urban heat island (UHI) effect elevates heat exposure, raises cooling-energy demand, and increases heat-related morbidity and mortality (Manoli et al. 2019; Tuholske et al. 2021). These pressures are projected to worsen as urbanisation and climate change interact (IPCC 2021), placing intra-urban thermal differentiation at the centre of sustainable-cities research.

Progress was long constrained by the absence of a standardised way to describe urban form for climatic purposes. The Local Climate Zone scheme (Stewart and Oke 2012) resolved this by classifying the urban landscape into seventeen classes defined by structure, land cover, and thermal properties, replacing the ad hoc urban–rural dichotomy with a transferable typology (Stewart et al. 2014; Oke et al. 2017). Community mapping infrastructure such as WUDAPT and the LCZ Generator (Ching et al. 2018; Demuzere et al. 2021), global LCZ products (Demuzere et al. 2022), and benchmark datasets (Zhu et al. 2020) subsequently lowered the barrier to LCZ-based analysis.

The framework has since expanded well beyond mapping, underpinning land surface temperature (LST) and UHI analysis, outdoor thermal-comfort assessment, and heat-risk mapping (Bechtel et al. 2019; Kotharkar et al. 2021). Existing reviews have documented mapping methods and classification accuracy (Huang et al. 2023; Quan and Bansal 2021) or European monitoring practice (Lehnert et al. 2021), but treat the field largely from a mapping standpoint. No review has coupled the bibliometric structure of LCZ-thermal research with a systematic thematic and methodological synthesis of its findings.

This gap has practical consequences. The LCZ scheme is now used to justify interventions as well as to describe thermal patterns: where to plant, where to restrict density, which neighbourhoods to prioritise in heat-action

planning. The reliability and transferability of its findings therefore bear directly on exposed populations. Yet the literature has grown quickly and unevenly across urban climatology, remote sensing, building science, and planning, each with its own conventions for classification, thermal measurement, and validation. Without a consolidated account of how these communities define and measure the same phenomena, agreement between studies may reflect shared methodological habits instead of independent replication, and disagreement may reflect instrument choice instead of real inter-city difference. Methodology must therefore be treated as evidence in its own right, not as background detail, before the field's accumulated results can responsibly inform practice. That requirement shaped the design of this review: the search was framed around thermal outcomes instead of policy vocabulary, both databases were interrogated, and the methodological attributes of every included study were coded alongside its findings, so that each synthesis claim can be weighed against the evidence behind it.

We conducted a PRISMA 2020-based review of 95 studies (2015–2026) retrieved from Scopus and Web of Science using an outcome-focused search string that did not require policy vocabulary. Four questions guide the work: how the field has evolved thematically, temporally, and geographically (RQ1); which classification methods and data sources dominate and with what trade-offs (RQ2); how the framework is applied across LST/UHI, comfort, and heat-risk assessment (RQ3); and what role modelling and machine learning play, and where the principal gaps lie (RQ4).

2. MATERIALS AND METHODS

2.1 Research design

The review followed the PRISMA 2020 statement (Page et al. 2021), integrated with bibliometric mapping and structured thematic synthesis. The protocol was not prospectively registered; the full search string, eligibility criteria, screening registers, and coding dictionary are reported here and in the Supplementary Material.

2.2 Data sources and search strategy

Two databases were searched: Scopus and Web of Science (Core Collection). The search string was revised to remove the requirement for policy-related vocabulary because that requirement could exclude technically oriented LCZ studies focused on urban temperature or heat-island behaviour. The revised string pairs LCZ terms directly with thermal outcomes:

2.3 Eligibility criteria

Peer-reviewed, English-language journal articles and reviews applying or analysing the LCZ framework with a stated urban heat, LST, thermal-comfort, or heat-risk outcome were eligible (Table 1).

Table 1: Eligibility criteria applied at each review stage.

Stage	Criterion	Rule
Identification	Databases	Scopus and Web of Science (Core Collection)
Identification	Search fields	Title, abstract, keywords (LCZ terms AND thermal-outcome terms)
Screening	Publication years	2015 – 24 September 2026
Screening	Document type	Peer-reviewed journal article or review
Screening	Language	English
Eligibility	Topical relevance	LCZ applied or analysed with a stated thermal outcome
Eligibility	Evidence type	Primary research and reviews recorded separately; reviews excluded from empirical counts
Eligibility	Accessibility	No open-access restriction applied

Accessibility did not form an eligibility criterion; inclusion depended on topical and methodological relevance. Restricting the review to openly available full texts could bias the corpus toward particular publishers and better-resourced research groups and distort the reported publication trends and geographical distribution.

2.4 Screening and selection

Screening followed the PRISMA sequence: titles, abstracts, and keywords were screened in full before any record proceeded to full-text assessment (Fig. 1). No record was excluded at abstract screening after full-text assessment had begun.

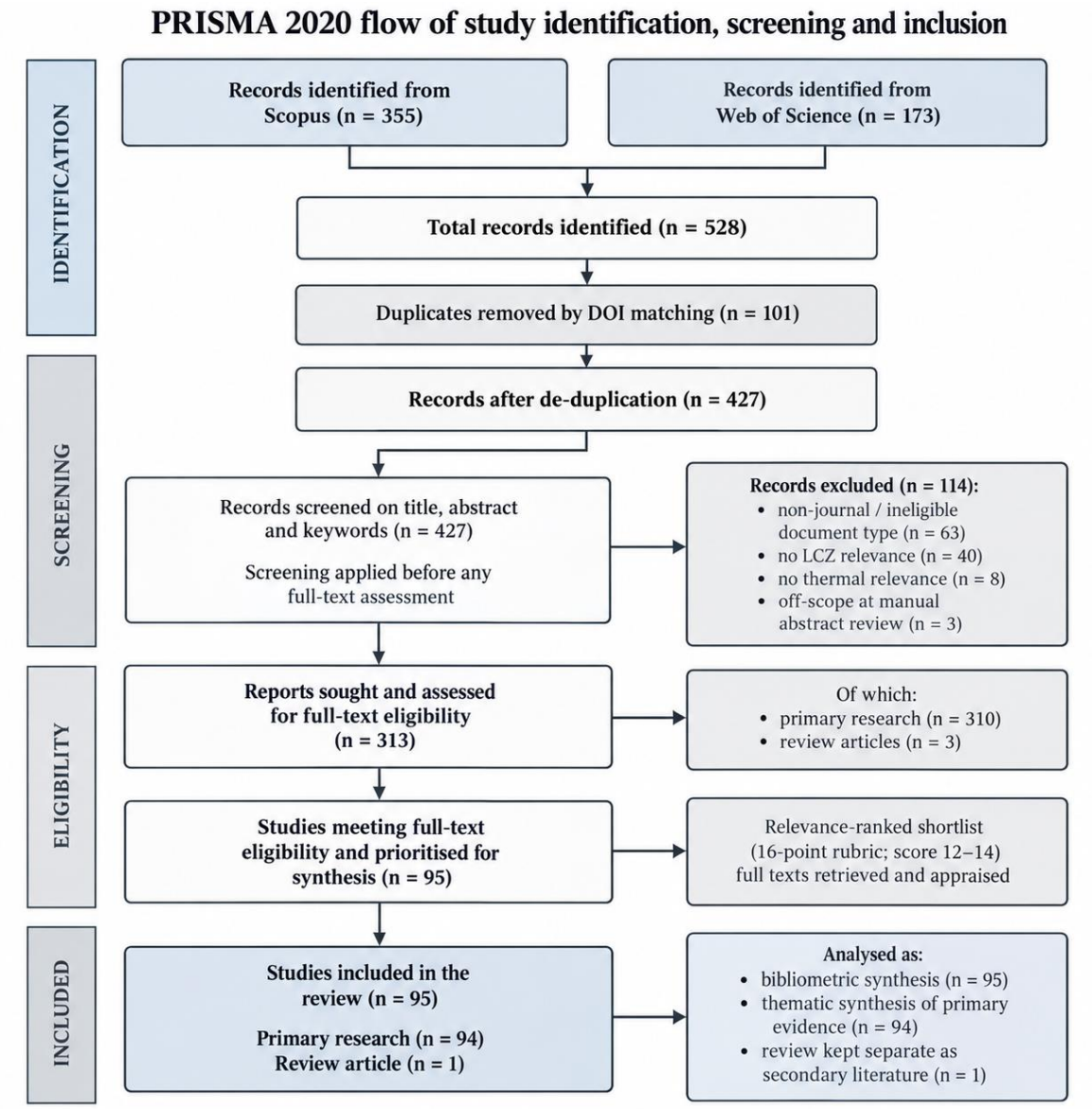


Fig. 1: PRISMA 2020 flow of identification, screening, and inclusion for the two-database search.

The searches returned 528 records; removal of 101 DOI duplicates left 427. Record-level screening excluded 114 records (63 ineligible document type, 40 without LCZ relevance, 8 without a thermal outcome, 3 off-scope at manual abstract review), leaving 313 full-text candidates comprising 310 primary-research records and 3 reviews. Full texts were assessed against a 16-point relevance rubric covering direct LCZ presence in the title, a thermal outcome in the title, and an explicit LCZ–outcome linkage in the abstract. Ninety-five studies (score 12–14) met the eligibility criteria: 94 primary-research articles and 1 review.

2.5 Data extraction, coding, and quality appraisal

A structured schema captured bibliographic metadata, objective, methodology, tools, data sources, spatial scale, findings, and author-identified gaps. The coding protocol included two additional measures. The first was a dictionary specifying the exact term groups matched across title, abstract, and author keywords; the resulting indicators are descriptive and overlapping and record topical presence rather than assign a single adjudicated theme. The second was an independent check of thematic coding: a second coder re-coded a random subsample using the same dictionary, and discrepancies were resolved against the full text. Because the corpus is methodologically heterogeneous and contains no comparable effect estimates, a meta-analytic risk-of-bias instrument was not appropriate. Each study was instead appraised for reporting adequacy across four dimensions: whether the classification basis is stated, whether classification accuracy is reported, whether the thermal data source and resolution are specified, and whether validation against independent observations is described. These dimensions were used to weight confidence in synthesis claims, not to rank studies. Reviews were recorded as secondary literature and excluded from empirical counts.

2.6 Bibliometric analysis

Metadata were exported from both databases and de-duplicated by DOI. Author-keyword co-occurrence was analysed with full counting after thesaurus normalisation of synonymous terms. Sixteen keywords met a minimum occurrence of three. Annual counts, country distributions (full counting of affiliations), source distributions, and database provenance were also recorded; citation counts from the two databases are reported separately because their coverage differs.

2.7 Thematic synthesis

Included primary studies were characterised against five indicators derived from the coding dictionary: LST/UHI analysis, LCZ classification and mapping, machine learning and prediction, thermal comfort and stress, and heat risk and health. The five themes overlap. A study addressing both surface temperature and heat risk is counted under both themes, so the prevalence figures are non-exclusive.

3. RESULTS

3.1 Bibliometric analysis

3.1.1 Database contribution and coverage

The databases differed in coverage (Fig. 2). Of the 95 included studies, 47 (49%) were indexed in Scopus alone, 35 (37%) in both databases, and 13 (14%) in Web of Science alone. A single-database search would therefore have missed 14% to 49% of the eligible literature, depending on the database. The difference reflects the distribution of LCZ-thermal research across urban-climate, remote-sensing, and building-science venues with different indexing coverage. Both databases were therefore retained in the search.

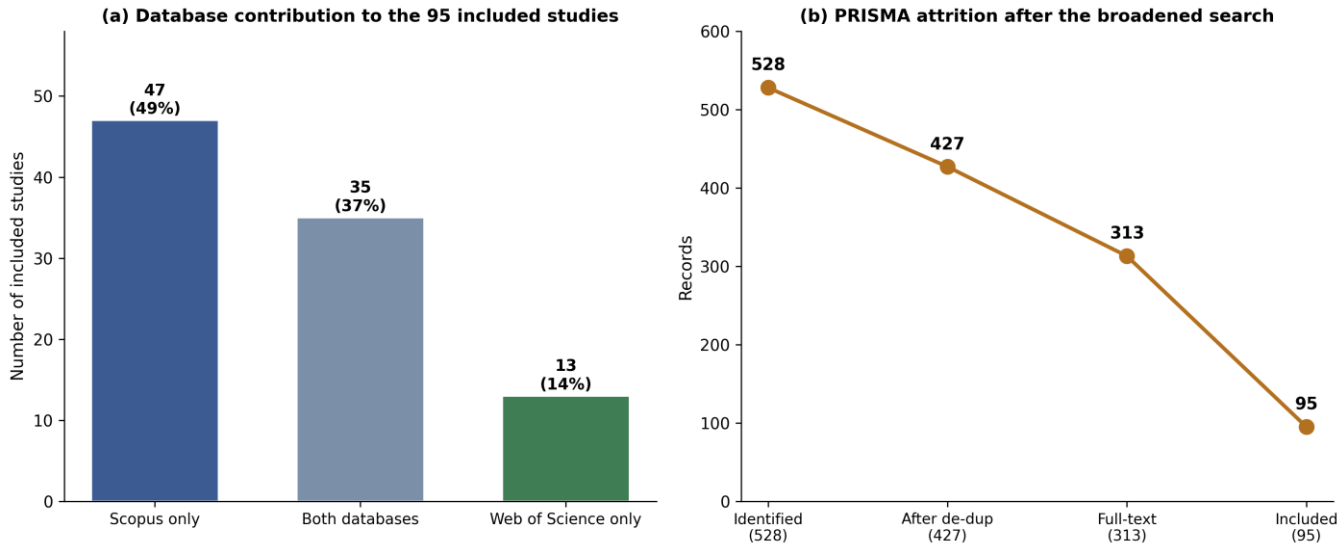


Fig. 2: (a) Contribution of Scopus and Web of Science to the 95 included studies, including the 13 studies retrieved from Web of Science alone; (b) record attrition across PRISMA stages after the broadened search.

3.1.2 Temporal evolution

Publication counts increased after 2021 (Fig. 3): 6 studies in 2022, 10 in 2023, 14 in 2024, 24 in 2025, and 28 in the partial year 2026. Seventy-six of the 95 studies (80%) were published from 2023 onward. The 2026 count already exceeds every complete preceding year, although the year is incomplete.

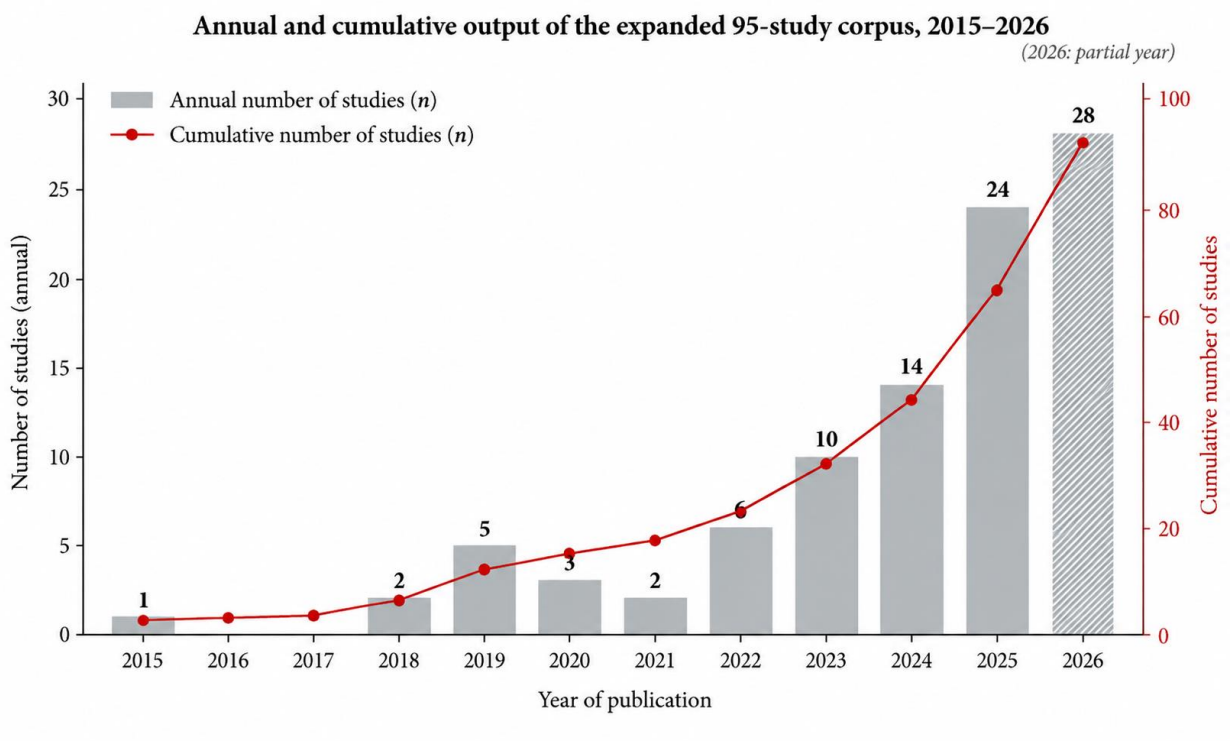


Fig. 3: Annual and cumulative output of the 95-study corpus, 2015–2026 (2026 partial; search closed 24 September 2026).

3.1.3 Geographic distribution

Most contributions came from East Asia (Fig. 4). China contributes 67 of the 95 studies, followed by Hong Kong (12), Australia (9), South Korea, the United Kingdom, and the United States (7 each), Japan (6), and Canada (4). European contributions are dispersed across several countries, with few studies from each. Africa, South America, and most of South and Southeast Asia are sparsely represented in the corpus.

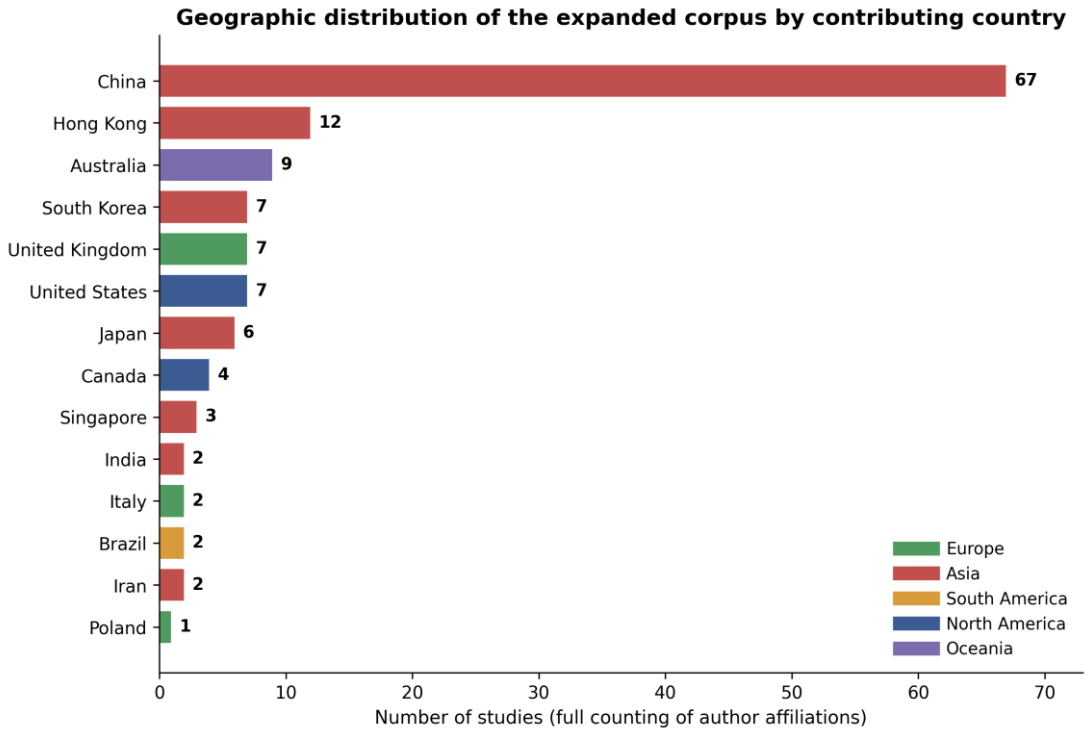


Fig. 4: Geographic distribution of the corpus by contributing country.

3.1.4 Leading sources and thematic structure

The leading outlets were (Fig. 5a): *Building and Environment* (32 studies), *Sustainable Cities and Society* (31), and *IEEE JSTARS* (10), with *Korean Journal of Remote Sensing* and *Buildings* (3 each). These outlets place LCZ-thermal research mainly in building-science and remote-sensing venues. Cumulative growth (Fig. 5b) shows a marked increase after 2022.

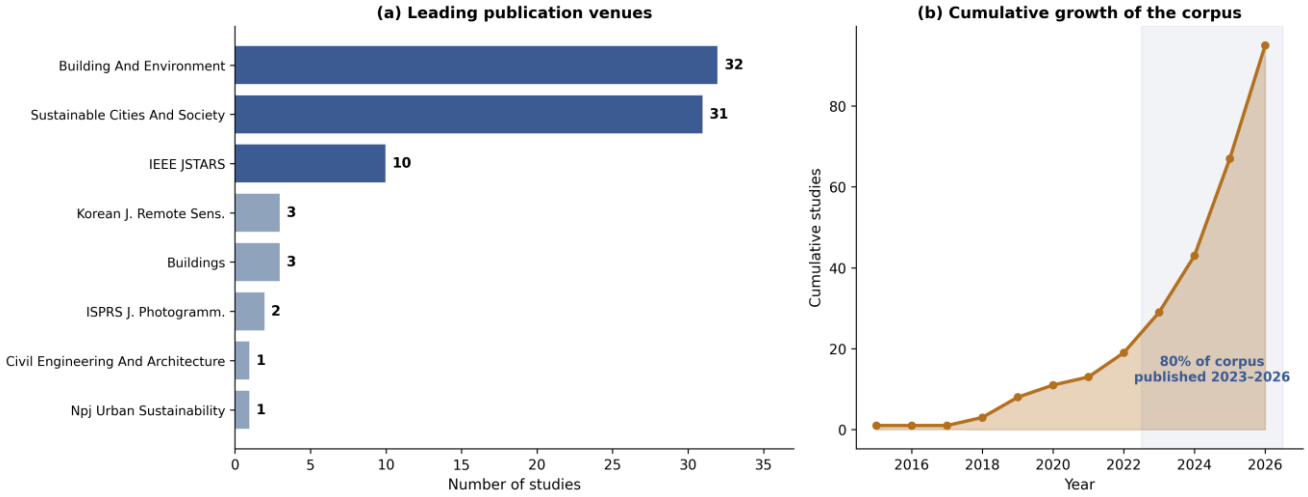


Fig. 5: (a) Leading publication venues of the corpus; (b) cumulative growth, with the concentration of output in 2023–2026.

The author-keyword co-occurrence network contains 16 keywords meeting the minimum occurrence of three. "Local climate zone" has 80 occurrences, followed by "urban heat island" (44) and "land surface temperature" (29). Four groupings are visible: the LCZ framework; a heat-island and air-temperature grouping; a surface-temperature grouping including Landsat; and a methods-and-outcomes grouping covering urban morphology, outdoor thermal comfort, heat risk, and machine learning. The presence of interpretable machine-learning terms, including SHAP-based attribution and extreme gradient boosting, at the occurrence threshold indicates that data-driven attribution is established in this literature.

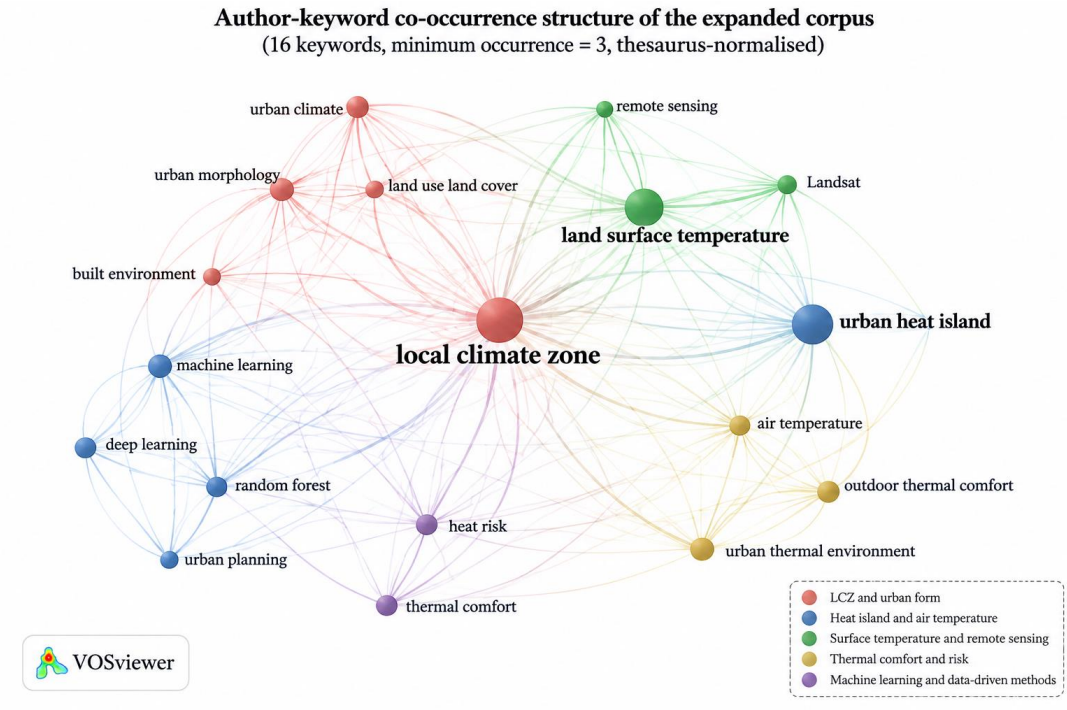


Fig. 6: Author-keyword co-occurrence structure of the corpus (16 keywords, minimum occurrence three, thesaurus-normalised). Node size denotes occurrence frequency; colour denotes thematic grouping.

3.2 Thematic synthesis

The five thematic indicators were applied to all 95 studies (Fig. 7a). Land surface temperature or heat-island analysis occurs in 79 studies (83%), LCZ classification in 53 (56%), machine learning or prediction in 30 (32%), thermal comfort or stress in 20 (21%), and heat risk or health in 13 (14%). The co-occurrence matrix (Fig. 7b) shows 43 studies addressing both surface temperature and classification and 27 combining surface temperature with machine learning; comfort and heat-risk themes co-occur in one study. The distribution places remote-sensing analysis at the centre of the corpus, while human-centred outcomes occur in smaller and more separate groups.

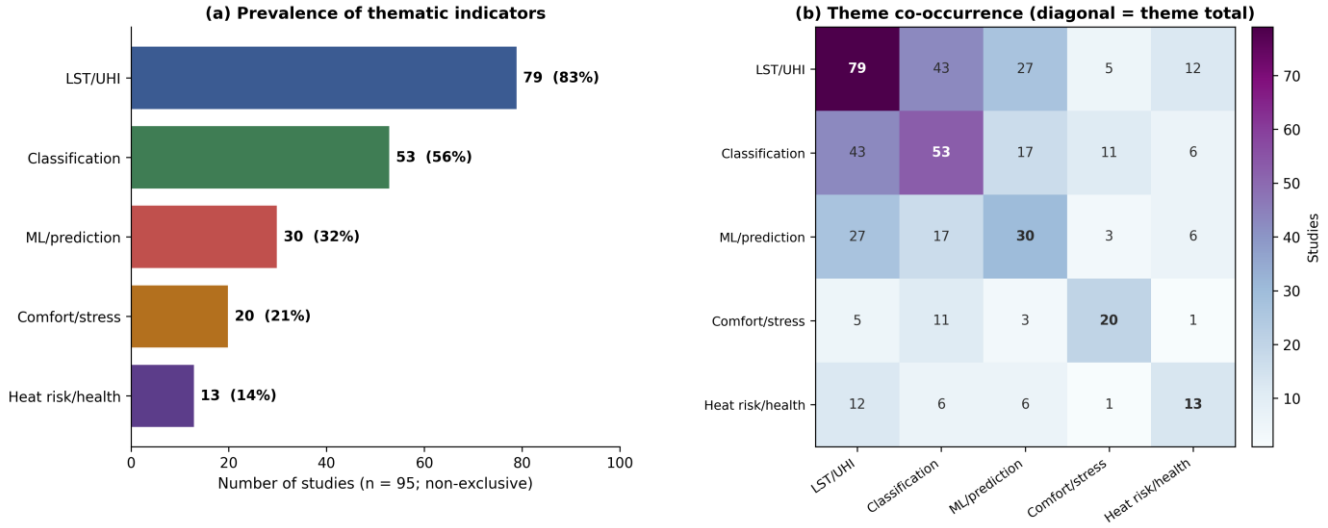


Fig. 7: (a) Prevalence of thematic indicators across the 95 included studies (non-exclusive); (b) theme co-occurrence matrix, with diagonal values giving the total for each theme.

Three aspects of this distribution warrant comment. Surface-temperature analysis accounts for 79 of 95 studies, placing satellite thermal remote sensing at the centre of the empirical literature; canopy-level measurements are less common. Classification appears in 53 studies, so LCZ-map derivation remains an active research task thirteen years after the scheme was formalised. Machine-learning studies account for 30 papers, compared with 33 papers for thermal comfort and heat-risk indicators combined. Methodological development therefore has a similar volume to these two human-centred outcomes considered together.

Thematic composition changed over time (Fig. 8). Surface-temperature and classification themes occur throughout the period, whereas machine-learning and heat-risk themes appear predominantly from 2023 onward. This pattern is consistent with the recent increase in these terms in the keyword network.

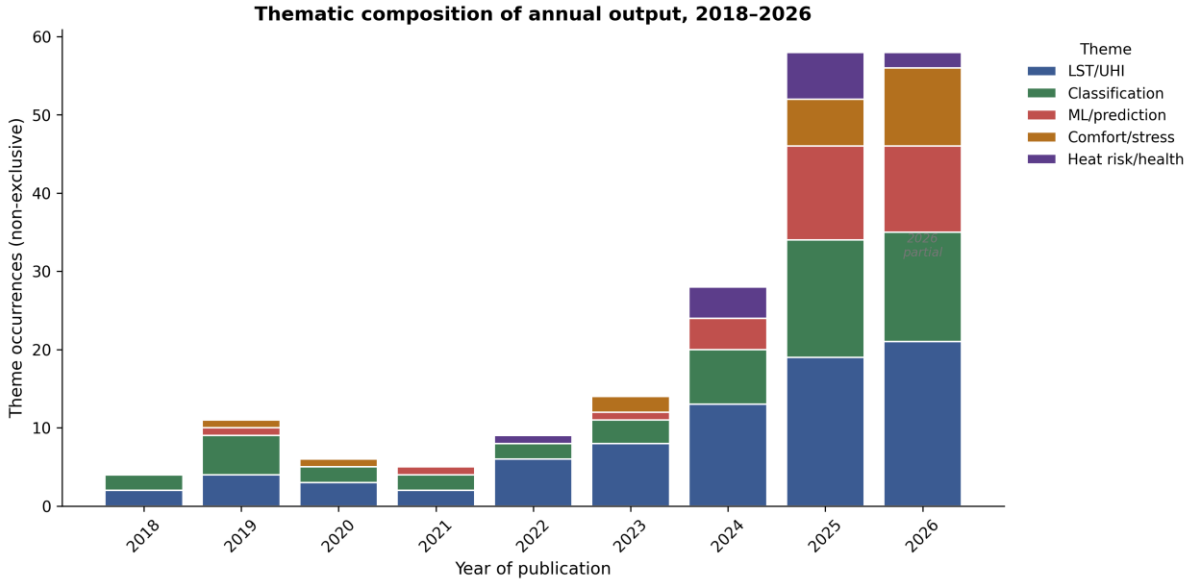


Fig. 8: Thematic composition of annual output, 2018–2026 (non-exclusive theme occurrences; 2026 partial).

Classification and surface temperature co-occur in 43 studies. This pairing corresponds to a common workflow in which an LCZ map is produced and then compared with a thermal raster. Comfort and heat-risk studies overlap in only one study; these two human-centred literatures appear to have developed largely in parallel despite shared population-level concerns. Machine learning co-occurs with surface temperature in 27 studies but with comfort in only three, so its use remains concentrated on physical thermal outcomes.

3.2.1 Land surface temperature and urban heat island analysis

LST and UHI analysis is the dominant empirical concern (79 studies). Across diverse climates and classification routes, studies consistently report that compact and industrial built classes exhibit the highest surface temperatures and that vegetated and water classes are coolest. This ordering recurs across the study period. It appears in early applications of the scheme (Leconte et al. 2015; Yang et al. 2018; Hu et al. 2019) and in recent work (Kim et al. 2026). Representative studies spanning 2015–2026 are summarised in Table 2.

Table 2: Representative studies addressing land surface temperature and urban heat island analysis.

Study	Study setting	Year	Key focus and inference
Leconte et al. 2015	Multi-city / not specified	2015	Using the LCZ scheme with mobile air-temperature measurements in Nancy. Thirteen LCZs were mapped; nighttime temperature differences between contrasting LCZs exceeded 4 °C, while heterogeneous LCZs contained recurrent microscale hotspots and coldspots.
Yang et al. 2018	Nanjing	2018	Assessed thermal behaviour across 14 LCZs in Nanjing using 401 days of fixed-point air-temperature observations. LCZ classes showed distinguishable thermal behaviour across hourly to annual scales, linked to structural and land-cover properties.
Hu et al. 2019	Nanjing	2019	Combined remote-sensing/GIS LCZ classification with Landsat LST and CFD simulation in Nanjing. Classification reached 92% accuracy (κ = 0.911); seasonal and diurnal LST differed systematically among LCZs and were related to building height, density, layout and green ratio.
Anjos et al. 2020	Multi-city / not specified	2020	Examined LCZ-specific UHI under different synoptic conditions using in-situ air-temperature observations. Mean maximum UHII reached 6.0 °C, with 11.0 °C under anticyclonic conditions and values near 0 °C under overcast or rainy conditions; LCZ subclasses improved spatial interpretation.
Yeonsu et al. 2021	Suwon	2021	Used CNN-based LCZ classification and Landsat LST in Suwon and Daegu. Classification accuracies were 87.9% and 81.7%; LST generally increased with building density at relatively low building height, and SUHI was strongest in summer but often weak or negative in winter.
O'Malley and Kikumoto 2022b	Tokyo	2022	Examined relative heat storage using LCZs and MODIS LST in Tokyo. Lower ΔUHI values occurred in higher-rise and compact LCZs, indicating greater relative heat-storage effects than in lower-rise and open forms.
Xiang et al. 2023	Multi-city / not specified	2023	Used source–sink theory and LCZs to construct an SUHI mitigation network. Open high-rise and open mid-rise zones dominated heat-source landscapes, while low vegetation and water were important heat sinks; source/sink surfaces, corridors and barrier points were mapped for mitigation planning.
Liu et al. 2024	Guangzhou	2024	Combined LCZ classification with InVEST and CA-Markov scenarios in Guangzhou. Compact low-rise and heavy-industry zones had higher UHI intensity, while water and dense-tree zones had stronger cooling; the Environmental Protection scenario increased heat-mitigation and energy-saving indicators relative to baseline.
Maleki et al. 2025	Multi-city / not specified	2025	Linked LCZ, LST and urban water consumption in Tehran. LCZ2 and LCZG had the highest per-capita water consumption, while LCZ7 had the lowest; population density, LST and water use showed measurable relationships.
Kim et al. 2026	Suwon	2026	Used 70-m ECOSTRESS observations to quantify seasonal and diurnal SUHII in Suwon. SUHII was stronger and more heterogeneous in summer

			and daytime; dense built LCZs consistently warmed, natural LCZs generally cooled, and the warming effects of low- and high-rise forms varied between day and night.

The corpus also increasingly examines the temporal structure of the thermal signal, including diurnal and seasonal variation, daytime–night-time contrasts, sensitivity of intensity estimates to the non-urban reference, and spill-over between adjacent zones (Shu et al. 2026) and neighbouring-environment effects (Zhou et al. 2026a).

3.2.2 Thermal comfort, heat stress, and heat-risk assessment

Human-centred outcomes are addressed in a smaller share of the corpus: thermal comfort or stress in 20 studies and heat risk or health in 13 (Table 3). Studies apply established indices, including the Universal Thermal Climate Index and physiologically equivalent temperature, and increasingly couple LCZ classification to exposure and vulnerability frameworks to identify populations at risk (Ren et al. 2025; Lan et al. 2025).

Table 3: Representative studies addressing thermal comfort, heat stress, and heat-risk outcomes, sampled across the study period.

Study	Study setting	Outcome domain	Key focus and inference
Lau et al. 2019	Hong Kong	Thermal comfort / stress	Combined field measurements and questionnaire surveys across eight Hong Kong LCZs. Microclimatic conditions differed among LCZs, with LCZ1 reaching 38.9 °C; compact/high-rise settings were associated with less favourable outdoor thermal comfort.
Anjos et al. 2020	Multi-city / not specified	Thermal comfort / stress	Examined LCZ-specific UHI under contrasting synoptic conditions using in-situ air-temperature observations. UHII varied from near 0 °C under cloudy/rainy conditions to 11.0 °C under anticyclonic conditions, showing strong weather dependence of thermal exposure.
O'Malley and Kikumoto 2022a	Tokyo	Heat risk / health	Investigated urban heat mitigation in Tokyo using LCZ and daytime LST. Lower-rise and open LCZs recorded higher LSTs than several compact/high-rise classes, and predominantly compact low-rise municipalities were identified as priority areas for heat mitigation.
Jo et al. 2023	Suwon	Thermal comfort / stress	Compared PET and UTCI across five LCZs in Suwon during summer. Daytime PET differences reached 6.7 °C and UTCI differences 3.7 °C; thermal comfort varied substantially among LCZs and between daytime and nighttime.
Lee et al. 2024	Multi-city / not specified	Heat risk / health	Compared two planned South Korean new towns using deep-learning LCZ classification and Landsat 9 thermal data. Differences in urban planning produced different LCZ compositions, SUHI magnitudes and heat vulnerability patterns.
Sheng et al. 2025	Multi-city / not specified	Thermal comfort / stress	Combined machine-learning-refined LCZ mapping with field measurements and UTCI/PET in a cold coastal city. High-density/high-rise LCZs had poorer winter comfort; UTCI was more sensitive to wind speed, whereas PET responded more strongly to solar radiation.
Ren et al. 2025	Jinan	Heat risk / health	Integrated LCZ with the HEVA model to map multi-temporal heat risk in Jinan. High-risk areas concentrated in the dense urban core, risk peaked around noon to early afternoon, and LCZ6 showed unexpectedly high hazard, exposure and vulnerability.

Wang et al. 2026	Zhengzhou	Thermal comfort / stress	Used WRF coupled with BEP+BEM to simulate multi-summer UHI and heat stress across LCZs in Zhengzhou. Building density and height were important morphological factors; LCZ1 had the strongest nocturnal canopy UHI, and heat stress increased across LCZs during heatwaves.
Tesfaldet et al. 2026	Multi-city / not specified	Heat risk / health	Combined multi-source remote sensing with LCZ-based risk stratification and Random Forest analysis during extreme heat in Dubai. Daytime cooling coexisted with persistent nighttime heat retention; LCZs 5, 6 and 8 showed episodic heat spikes, while albedo was the dominant UHI predictor.

Earlier studies found systematic differences in outdoor comfort between LCZ settings (Lau et al. 2019; Anjos et al. 2020). Later studies examined seasonal and adaptive dimensions (Jo et al. 2023; Sheng et al. 2025). Across these studies, compact, low-vegetation zones produce the least comfortable conditions, while the relative effectiveness of vegetation and built-geometry interventions varies with urban form and background climate (Codemo et al. 2026). The comparatively low prevalence of heat-risk and health indicators relative to surface-temperature indicators shows that the chain from surface temperature through human exposure to health outcome remains less studied than surface temperature itself.

3.2.3 Modelling and machine-learning approaches

Machine-learning indicators are present in 30 studies (Table 4), and the keyword network confirms a distinct methodological cluster. Machine learning has two roles: instrumentally, classifiers derive LCZ maps from imagery; substantively, tree-based models and neural networks are combined with interpretability methods such as SHapley Additive exPlanations to attribute thermal outcomes to morphological and land-cover drivers and to predict temperatures at block or city scale (Zhang et al. 2026c; Gao et al. 2026; Yu and Pan 2026). The methodological trajectory spans statistical and early learning-based analyses from 2019 (Hu et al. 2019; Yeonsu et al. 2021), contribution-analysis approaches in the mid-2020s (Peng et al. 2024; Qiao et al. 2024), and recent interpretable attribution of two- and three-dimensional morphology (Li et al. 2025b; Zhang et al. 2026d). The substantive stream has established that urban thermal responses are nonlinear and interaction-rich, relationships that linear methods obscure. Models are overwhelmingly trained and validated within a single city, so transferability remains largely untested.

Table 4: Representative studies employing modelling and machine-learning approaches, sampled across the study period.

Study	Study setting	Analytical role	Key focus and inference
Hu et al. 2019	Nanjing	Prediction / classification	Combined Random Forest LCZ classification with Landsat LST and CFD simulation in Nanjing. Classification reached 92% accuracy (κ = 0.911); seasonal and diurnal LST patterns varied systematically among LCZs and were related to building height, density, layout and green ratio.
Yeonsu et al. 2021	Suwon	Prediction / classification	Applied CNN deep learning to LCZ classification in Suwon and Daegu and then analysed SUHI and LST by LCZ. Classification accuracy reached 87.9% and 81.7%, respectively, and the resulting LCZ maps resolved distinct thermal patterns.
Lin et al. 2023	Multi-city / not specified	Driver attribution	Used Random Forest regression to quantify the importance and marginal effects of urban thermal-environment factors on seasonal LST in Fuzhou. Building morphology was the dominant factor within built LCZs, with standard deviation of building height having about 34% relative importance.
Qiao et al. 2024	Multi-city / not specified	Driver attribution	Combined stepwise regression with SHAP-explained XGBoost to attribute UHII to 15 drivers across 17 LCZs in 369 Chinese cities. Daytime UHI was strongly associated

			with urban 3-D structure, whereas natural environmental factors had greater influence at night.
Lin et al. 2025	Fuzhou	Driver attribution	Used NSGA-II to optimise LCZ configurations for heat-risk reduction and FLUS to test practical urban-renewal transformations in Guangzhou. The theoretical optimisation reduced total heat risk by 33.14 units, but practical transformation achieved only 48.52% of the theoretical optimum.
Qin et al. 2026	Multi-city / not specified	Driver attribution	Combined CNN-based LCZ mapping with a comprehensive thermal comfort score, Random Forest and GWR across the Yangtze River Delta. Summer heat stress increased over time; dense trees generally provided the most consistent cooling, while LCZ effects varied spatially and by urban form.

Thematic patterns show a field concentrated on remote-sensing applications, with smaller literatures on human-centred outcomes. The distribution matches the venue profile in Section 3.1.4 and the keyword structure in Fig. 6, where surface-temperature and LCZ terms have the highest occurrence counts. The geographic concentration in Section 3.1.3 also matters: research systems with access to high-resolution satellite archives and computational infrastructure are well placed to study surface temperature and machine-learning applications. The thematic, geographic, and methodological concentrations therefore describe related aspects of the same corpus.

3.3 Methodological synthesis

Reporting of methods and data sources is uneven across the corpus (Fig. 9). Landsat is the most frequently named thermal source (15 studies), followed by in-situ or mobile measurement (9), MODIS (4), ECOSTRESS and Sentinel (3 each). Simulation tools appear in a small number of studies (ENVI-met and WRF, 4 each). Within machine learning, SHapley Additive exPlanations is the most frequently named method (13), followed by Random Forest (11), XGBoost (6), and convolutional or deep-learning architectures (5). These counts are based on explicit mentions in titles, abstracts, or keywords and therefore understate actual use. The need to infer method use from limited reporting also points to inconsistent methodological reporting.

Three axes structure the field: the basis on which LCZ maps are derived, the source of thermal evidence, and the analytical approach linking them (Table 5). Satellite surface temperature gives broad coverage and long archives at the cost of resolution and overpass-timing bias, and measures a surface rather than an air temperature. Canopy air temperature measures the human-relevant variable directly, but its coverage is sparse.

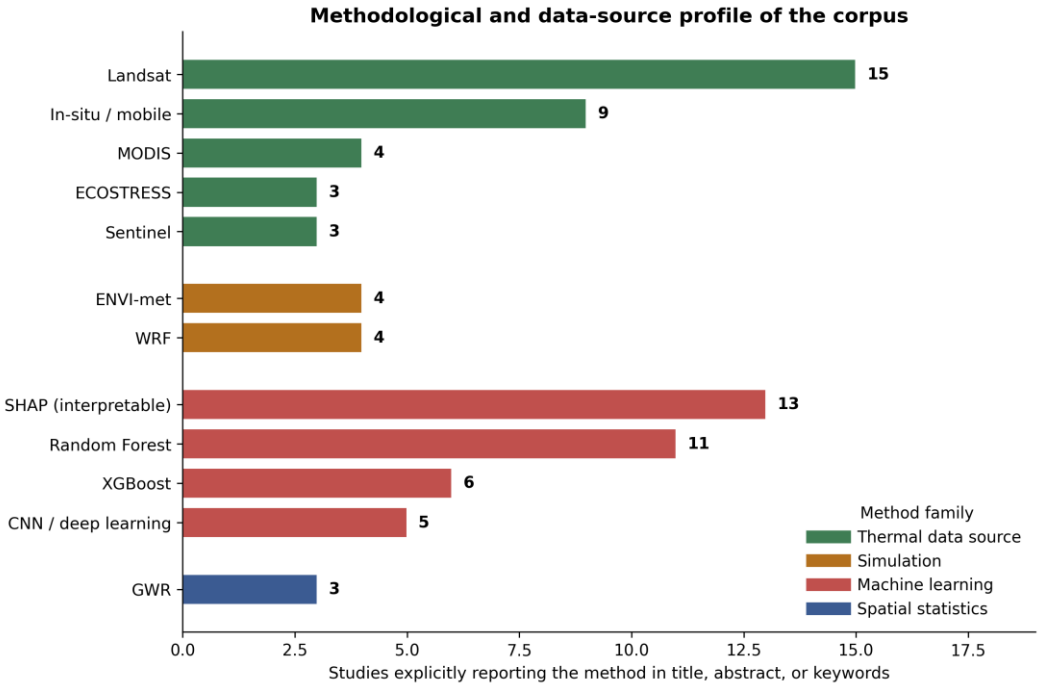


Fig. 9: Methodological and data-source profile of the corpus, by method family. Counts reflect explicit reporting in title, abstract, or keywords and are non-exclusive.

Process-based simulation supplies complete three-dimensional fields at high computational cost. Synthesised across these axes, one tension organises the field: spatial and thermal fidelity trade against transferability and scalability, and predictive performance trades against interpretability and validation. Inconsistent reporting of classification basis, evidence source, resolution, observation timing, and reference-area conventions limits the extent to which apparent disagreements can be separated from methodological artefacts.

Table 5: Methodological synthesis of the corpus: recurrent strategies, evidence sources, strengths, and trade-offs, with representative studies.

Strategy	Thermal evidence	Representative studies	Strength	Key trade-off
Satellite surface-LST mapping	Landsat (~100 m); MODIS (~1 km)	Kim et al. 2026; Palanisamy et al. 2024	Reproducible; long archive	Coarse; timing bias; surface ≠ air
High-resolution diurnal sensing	ECOSTRESS (~70 m)	Xu et al. 2025	Diurnal, including night	Short archive; sparse revisit
In-situ / mobile / citizen networks	Canopy air temperature	Wang et al. 2026	Human-relevant	Sparse coverage
Process-based simulation	ENVI-met; WRF output	Codemo et al. 2026; Wang et al. 2026	Mechanism; scenario testing	Costly; validation-dependent
ML attribution and prediction	Any of the above as predictors	Zhang et al. 2026c; Gao et al. 2026	Nonlinear attribution	Single-city training
GIS-based / supervised classification	Pairs with any thermal source	Zhou et al. 2026b; Xi et al. 2026a	Accurate; planning-compatible	Data-intensive; low transferability

4. DISCUSSION

4.1 A rapidly expanding and geographically concentrated field

The corpus describes a field that is young, expanding, and concentrated. Eighty percent of studies date from 2023 onward (Fig. 3), and the partial 2026 count already exceeds every complete preceding year. China contributes to roughly seven in ten included studies (Fig. 4). This concentration limits external validity. Findings generated mainly within one national research system and its characteristic urban morphologies and climates cannot be assumed to transfer to tropical, informal, and rapidly urbanising contexts that are sparsely represented in the corpus.

4.2 What the evidence supports, and how firmly

The best-supported claim in the corpus is that LCZ classes differentiate intra-urban surface thermal behaviour, with compact and industrial classes warmest and vegetated and water classes coolest. This ordering recurs across climates, methods, and both databases, and is the field's principal consolidated result (Table 2). The strength of this finding is limited by the composition of the corpus. It is dominated by satellite-derived surface temperature from a small number of countries, while classification accuracy and heat-island reference areas are reported inconsistently (Fig. 9). The consistency across studies may therefore partly reflect shared methodological choices rather than independent confirmation across diverse designs. Transferability to unstudied regions and urban forms remains provisional.

The corpus contains few studies linking LCZ classes to measured health outcomes and almost none from tropical or informal settlements. Populations with high exposure to urban heat are therefore under-represented in the evidence base used to inform heat policy. The concentration of satellite-based studies in well-instrumented cities also shapes the questions addressed: spatial pattern, seasonal variation, and morphological attribution are easier to study than sustained field measurement, longitudinal health records, or informal urban form. This helps explain why the transferability gap persists despite rapid growth in the literature.

4.3 Methodological choices as determinants of apparent findings

A substantial share of variation between studies is traceable to methodological choice rather than real inter-city difference. The thermal signal a study reports is conditioned by sensor and resolution, by whether surface or canopy temperature is measured, by overpass timing, by classification route, and by how the non-urban reference is delineated (Table 5). Because these choices covary with the phenomena measured, they can manufacture apparent contradictions that are artefacts. Cross-study synthesis will remain fragile until these parameters are reported consistently and, ideally, standardised.

4.4 The interpretable-modelling frontier and the validation gap

Machine learning has bifurcated into an instrumental role, classifying LCZ maps, and a substantive role, attributing drivers and predicting outcomes (Table 4, Fig. 8). The substantive stream has exposed the nonlinearity and interaction structure of urban thermal drivers. Yet models are almost universally trained and validated within a single city, so transferability remains untested; this is the same constraint identified for the classification scheme, recurring at the modelling layer. The data-driven and process-based streams also remain largely separate, although hybridising them is the clearest route to combining physical interpretability with computational tractability.

4.5 A framework derived from the reviewed literature

The framework can be read as a data-to-decision pipeline (Fig. 10). Data sources feed an LCZ classification layer, which supports thermal applications and planning outcomes. Modelling and machine learning cut across these layers. Two constraints frame the pipeline: a transferability-and-validation gate, through which single-city assumptions currently pass largely unchecked, and a feedback loop from outcomes back to classification that is rarely closed.

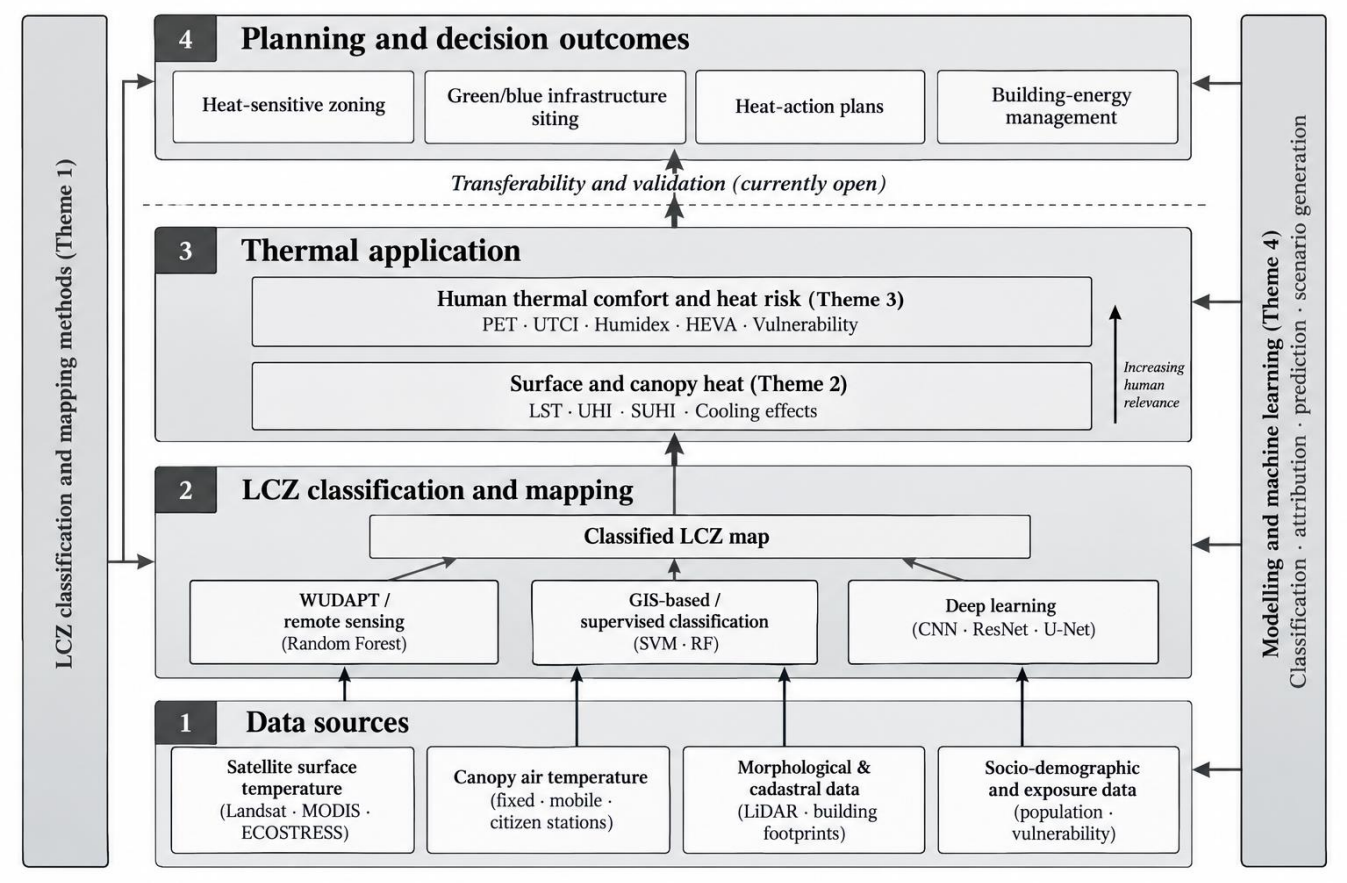


Fig. 10: Data-to-decision framework derived inductively from the reviewed literature. The framework contains four strata: data sources, LCZ classification, thermal application, and planning outcomes. Modelling and machine learning form the vertical analytical spine, while a transferability-and-validation gate and an outcomes-to-classification feedback loop frame the system.

We present this framework as an organising synthesis derived from the reviewed literature, not as a validated model. It has not been tested against independent data. Its strata were identified from the thematic structure of the corpus rather than derived from theory, and its applicability beyond the represented evidence base is untested. Empirical evaluation is therefore required.

4.6 Policy and planning implications, limitations and future research directions

The reproducible thermal ordering of LCZ classes gives planners a standardised vocabulary for classifying urban form by thermal behaviour, supporting pre-screening of heat-priority areas and the incorporation of thermal criteria into zoning and development control. Because the cooling effectiveness of vegetation is contingent on morphology and climate, green- and blue-infrastructure siting should be LCZ-specific rather than uniform. Coupling LCZ classification to exposure and vulnerability frameworks is an operational route for directing heat-action resources where exposure and sensitivity coincide (Ren et al. 2025). These implications should be applied cautiously. The evidence base is concentrated in a small number of countries and urban forms, so practitioners in under-represented contexts should treat LCZ-derived generalisations as hypotheses requiring local validation, not as transferable design rules.

This review has several concrete limitations. Records indexed only elsewhere or in the grey literature may have been missed, and the English-language restriction remains. The search string no longer requires policy vocabulary, but it still depends on explicit LCZ and thermal-outcome terms. The 95 included studies were selected from 310 primary-research candidates using a relevance rubric, so the corpus favours studies with explicit LCZ–thermal framing rather than providing an exhaustive census. Quality appraisal addressed reporting adequacy, not internal validity, because methodological heterogeneity prevented use of a formal risk-of-bias instrument. Thematic indicators are

text-presence measures rather than fully adjudicated codes; independent re-coding of a subsample reduced but did not remove interpretive subjectivity. Method counts in Fig. 9 also understate actual use because they depend on explicit reporting. Finally, 2026 is a partial year, and citation counts from the two databases are reported separately.

Five priorities follow. First and most important, systematic cross-city and cross-climate external validation of both classification schemes and predictive models is required to convert within-city results into transferable knowledge. Second, standardised reporting of classification basis, accuracy, thermal-evidence source, resolution, observation timing, and reference-area convention would enable cross-study synthesis. Third, the chain from surface temperature through canopy air temperature to human exposure and health outcomes needs to be closed and validated, given the low prevalence of health-linked studies (Fig. 7a). Fourth, evidence must be extended to tropical, informal, and Global-South urban contexts. Fifth, coupling interpretable machine learning to process-based simulation within a single study design would test whether data-driven attribution reproduces physically modelled thermal fields, and at what computational cost.

5. CONCLUSIONS

This review provided an integrated account of Local Climate Zone research in urban thermal and heat assessment, coupling bibliometric mapping with thematic and methodological synthesis. The review included 95 studies published between 2015 and 2026, of which 94 are primary research and one is a review retained separately as secondary literature. The search used both Scopus and Web of Science and applied an outcome-focused strategy without accessibility restrictions.

Three conclusions emerge. First, the field is young, rapidly expanding, and geographically concentrated: 80% of studies date from 2023 onward, and China contributes to roughly seven in ten. Second, the corpus supports the founding premise that LCZ classes differentiate intra-urban surface thermal behaviour, but this consistency rests largely on shared methodological choices within a narrow geographic range. Claims of general transferability therefore remain provisional. Third, interpretable machine learning has become a substantive analytical stream rather than only a classification tool, yet its models are almost universally validated within a single city.

The review consolidates the bibliometric, thematic, and methodological dimensions of the literature and proposes a data-to-decision framework derived from the reviewed studies. The framework identifies a transferability-and-validation gate and is presented as an empirical hypothesis rather than a validated model. The next step is cross-city testing of the framework, standardised reporting of classification and thermal measurements, and expansion of evidence from under-represented heat-vulnerable regions.

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DESCRIPTION OF ABBREVIATIONS

LCZ – Local Climate Zone; UHI – Urban Heat Island; SUHI – Surface Urban Heat Island; LST – Land Surface Temperature; WUDAPT – World Urban Database and Access Portal Tools; ML – Machine Learning; PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

SUPPLEMENTARY MATERIAL

Record-level screening register (427 records), full-text candidate register (313), full-text screening decisions (95), coding dictionary, summary statistics, and citation metadata are provided as separate supplementary files.

Author Contributions: N. Mahajani: conceptualisation, methodology, formal analysis, writing (original draft). N. Halder: methodology, visualisation, writing (review and editing). D. Kumar: data curation, visualisation, writing (review and editing).

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability: All screening registers and coded data are provided in the Supplementary Material.

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