ReGeo ISSN: 2177-3246

MACHINE LEARNING AND REMOTE SENSING APPLICATIONS IN URBAN HEAT ISLAND RESEARCH: A BIBLIOMETRIC ANALYSIS

APLICAÇÕES DE APRENDIZADO DE MÁQUINA E SENSORIAMENTO REMOTO NA PESQUISA DE ILHAS DE CALOR URBANO: UMA ANÁLISE BIBLIOMÉTRICA

APLICACIONES DE APRENDIZAJE AUTOMÁTICO Y TELEDETECCIÓN EN LA INVESTIGACIÓN DE ISLAS DE CALOR

10.56238/revgeov17n2-098

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ABSTRACT
Urban heat islands pose critical climate adaptation challenges as global urbanization accelerates. While artificial intelligence and remote sensing have emerged as powerful tools for urban thermal analysis, the rapidly growing research at this intersec- tion lacks comprehensive synthesis. This bibliometric study examines 381 publications (2004-2026) from Web of Science Core Collection to map field structure, evolution, and knowledge foundations. Using bibliometrix in R, we conducted performance analysis (pro- ductivity, citations) and science mapping (co-authorship, co-word, bibliographic coupling, co-citation networks). Results reveal exponential recent growth-publications increased from 11 (2019) to 135 (2025), with 95% of research produced in seven years (2019- 2025). Geographic concentration is pronounced: China (33,6%), India (9,45%), and USA (7,61%) dominate, while Sub-Saharan Africa and Latin America remain underrepresented despite high heat vulnerability. Research converges on machine learning-enhanced ther- mal remote sensing, with Random Forest (7.87% of papers) as the dominant algorithm and land surface temperature (28,87%) as the primary variable. Citation metrics indicate field maturity (h-index = 47, g-index = 75, mean citations = 20,93), building on foundations spanning urban climatology, remote sensing methodology, and machine learning. Howe- ver, thematic analysis reveals critical gaps: research emphasizes detection over health impacts, mitigation validation, and policy integration.

Keywords: Urban Heat Islands. Machine Learning. Artificial Intelligence. Remote Sensing. Bibliometric Analysis.

RESUMO
As ilhas de calor urbanas (ICU) representam desafios críticos para a adaptação climática

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conforme a urbanização global se acelera. Embora a inteligência artificial e o sensoriamento remoto tenham surgido como ferramentas poderosas para análise térmica urbana, o crescimento acelerado da pesquisa nesta interseção carece de síntese abrangente. Este estudo bibliométrico examinou 381 publicações (2004–2026) da Web of Science Core Collection para mapear a estrutura, evolução e bases de conhecimento da área. Utilizando o pacote bibliometrix em R, realizamos análise de desempenho (produtividade, citações) e mapeamento científico (coautoria, co-palavras, acoplamento bibliográfico e redes de cocitação). Os resultados revelaram crescimento recente exponencial: as publicações aumentaram de 11 (2019) para 135 (2025), com 95% da pesquisa produzida em sete anos (2019–2025). A concentração geográfica é acentuada: China (33,6%), Índia (9,45%) e EUA (7,61%) dominam a produção, enquanto África Subsaariana e América Latina permanecem sub-representadas, apesar da alta vulnerabilidade ao calor. A pesquisa converge para o sensoriamento remoto térmico aprimorado por aprendizado de máquina, com o Random Forest (7,87% dos artigos) como algoritmo dominante e a temperatura da superfície terrestre (28,87%) como variável principal. As métricas de citação indicam maturidade do campo (índice h = 47, índice g = 75, média de citações = 20,93), consolidando-se sobre fundamentos que abrangem climatologia urbana, metodologia de sensoriamento remoto e aprendizado de máquina. No entanto, a análise temática revelou lacunas críticas: a pesquisa enfatizou a detecção em detrimento dos impactos na saúde, validação de mitigação e integração de políticas públicas.

Palavras-chave: Ilhas de Calor Urbanas. Aprendizado de Máquina. Inteligência Artificial. Sensoriamento Remoto. Análise Bibliométrica.

RESUMEN
Las islas de calor urbanas (ICU) plantean desafíos críticos de adaptación climática conforme se acelera la urbanización global. Si bien la inteligencia artificial y la teledetección han surgido como herramientas poderosas para el análisis térmico urbano, el crecimiento acelerado de la investigación en esta intersección carece de una síntesis exhaustiva. Este estudio bibliométrico examinó 381 publicaciones (2004–2026) de la Web of Science Core Collection para mapear la estructura, evolución y bases de conocimiento del área. Utilizando el paquete bibliometrix en R, realizamos un análisis de rendimiento (productividad, citas) y un mapeo científico (coautoría, co-palabras, acoplamiento bibliográfico y redes de cocitación). Los resultados revelaron un crecimiento reciente exponencial: las publicaciones aumentaron de 11 (2019) a 135 (2025), concentrando el 95% de la producción en siete años (2019–2025). La concentración geográfica es acentuada: China (33,6%), India (9,45%) y EE. UU. (7,61%) dominan la producción, mientras que el África Subsahariana y América Latina permanecen subrepresentadas, pese a su alta vulnerabilidad térmica. La investigación converge en la teledetección térmica mejorada por aprendizaje automático, con Random Forest (7,87% de los artículos) como algoritmo dominante y la temperatura de la superficie terrestre (28,87%) como variable principal. Las métricas de citas indican madurez del campo (índice h = 47, índice g = 75, promedio de citas = 20,93), consolidándose sobre fundamentos de climatología urbana, metodología de teledetección y aprendizaje automático. No obstante, el análisis temático reveló brechas críticas: la investigación prioriza la detección en detrimento de los impactos en la salud, la validación de mitigación e integración de políticas públicas.

Palabras clave: Islas de Calor Urbanas. Aprendizaje Automático. Inteligencia Artificial. Teledetección. Análisis Bibliométrico.

1 INTRODUCTION

Urban heat islands (UHI), defined as elevated urban temperatures relative to surrounding rural areas, represent a major climate-adaptation challenge (Ahmed *et al*., 2013; Deilami *et al*., 2018; Stewart; Oke, 2012). Urban temperature differentials can reach 3–12ºC (Ahmed *et al*., 2013; Yang *et al*., 2023), increasing heat-related mortality risk (Ahmed *et al*., 2013; Deilami *et al*., 2018), electricity demand for cooling (Deilami *et al*., 2018; Kafy *et al*., 2020), and thermal discomfort (Kafy *et al*., 2021). At the same time, climate change amplifies baseline temperatures, intensifying urban heat exposure (Jiang *et al*., 2024).

Remote sensing has become the main data source for large-scale UHI analysis (Ahmed *et al*., 2013; Deilami *et al*., 2018; Zhou *et al*., 2019), while machine learning methods have improved the modeling of complex, non-linear thermal patterns (Deilami *et al*., 2018; Jiang *et al*., 2024; Logan *et al*., 2020). The convergence of UHI phenomena, Earth observation systems, and AI-based analytics has created a fast-growing research frontier, especially after 2019 (Jiang *et al*., 2024; Zhou *et al*., 2019). However, this rapid expansion has outpaced systematic synthesis of who produces the research, which methods dominate, how impact is distributed, and where critical knowledge gaps remain.

Despite important domain-specific reviews (UHI mitigation (Deilami *et al*., 2018), thermal remote sensing (Voogt; Oke, 2003; Li *et al*., 2013; Zhou *et al*., 2019), environmental AI (Jiang *et al.*, 2024)), no prior study has provided a comprehensive bibliometric synthesis focused specifically on the UHI, AI, and remote sensing intersection as an integrated field. This gap motivates the present study, which applies performance analysis and science mapping (Zupic; Čater, 2015) to characterize temporal evolution, productivity structures, thematic convergence, citation impact, collaboration patterns, and knowledge foundations.

This study pursues five objectives: (1) map temporal evolution and growth phases (Jiang *et al*., 2024); (2) characterize geographic and institutional productivity; (3) identify dominant and emerging themes through keyword structures (Jiang *et al*., 2024); (4) assess influence through citation-based indicators and highly cited works (Donthu *et al*., 2021); and (5) examine collaboration and intellectual structure through co-authorship, bibliographic coupling, and co-citation networks (Donthu *et al*., 2021). The paper is structured as follows: Section 2 describes the methodology; Section 3 presents the results; Section 4 discusses findings, limitations, and future research; and Section 5 concludes.

2 METHODOLOGY

This study employed bibliometric analysis to systematically examine the scholarly landscape of AI and machine learning applications in UHI research using remote sensing. Bibliometric methods enable quantitative assessment of large volumes of literature, revealing patterns in productivity, impact, collaboration, and knowledge structure (Donthu *et al*., 2021). The analysis integrated performance analysis (measuring output and impact) and science mapping (visualizing structure and relationships) (Cobo *et al*., 2011; Zupic; Čater, 2015).

Data were retrieved from Web of Science (WoS) Core Collection, chosen for comprehensive coverage, rigorous indexing, and complete citation metadata essential for bibliometric analysis (Mongeon; Paul-Hus, 2016). The search was conducted in January 2026, covering publications through December 2025. The following search query was executed:

- TS = ("urban heat island" OR "surface urban heat island" OR "SUHI" OR "UHI")
- AND TS = ("remote sensing" OR "satellite" OR "Landsat" OR "MODIS"OR "Sentinel")
- AND TS = ("machine learning" OR "deep learning" OR "neural network" OR "artificial intelligence").

The query combined three thematic domains: (1) UHI phenomena, (2) remote sensing technologies and (3) artificial intelligence and machine learning methods. The topic field (TS=) searches titles, abstracts, author keywords, and Keywords Plus simul- taneously.

Inclusion: Articles and review articles; all languages; all years available (resulting range: 2004-2026); published and early access articles.

Exclusion: Conference proceedings, book chapters, editorial materials, meeting abstracts; duplicate records; incomplete metadata (missing title, author or year) (Deilami *et al*., 2018; Donthu *et al*., 2021).

The initial search yielded 397 records. After removing duplicates and incomplete metadata, the final dataset comprised 381 publications spanning 23 years (2004-2026).

Bibliographic data were downloaded in plain text tagged format on February 3, 2026, including: bibliographic details (title, abstract, keywords), authorship (names, order), publication information (journal, year, volume, DOI), institutional affiliations (addresses with country information), citation data (times cited from WoS), and cited references (Aria; Cuccurullo, 2017).

The analysis followed a two-dimensional framework (Donthu *et al*., 2021; Zupic; Čater, 2015): (1) Performance Analysis examining productivity and citation impact, and (2) Science Mapping revealing intellectual structure through network analysis (Cobo *et al*., 2011; Zupic; Čater, 2015).

Author, institution, and country productivity measured by total publications (TP).

ISSN: 2177-3246

Institution names were normalized to resolve variations in naming conventions. Temporal trends analyzed through annual publication counts, cumulative growth, and growth rate calculations. Source productivity ranked by publication count; Bradford's Law distribution examined to identify core journals (Alabi, 1979; Winters *et al.,* 2018).

Citation impact assessed at document level (total citations, mean, median, distribution, most cited papers), field level (h-index, g-index, i10-index), and source level (Bradford's Law). The h-index measures both productivity and impact: h papers with ≥ h citations each (Hirsch, 2005). The g-index gives more weight to highly cited papers: top g papers with ≥ g2 citations total (Egghe, 2006). The i10-index counts papers with ≥ 10 citations (Jiang et al., 2024).

Author keywords extracted from DE field, normalized (lowercase, trimmed), filtered (length >2), and counted by frequency. Co-occurrence networks constructed with keywords as nodes and co-appearance as edges. High-frequency keywords indicate core themes; co-occurrence patterns reveal thematic clusters (Aria; Cuccurullo, 2017; Zupic; Čater, 2015).

Networks with authors as nodes and co-authorship as edges (edge weight = joint papers). Authors with ≥ 2 publications included. Metrics calculated: authors per document, single vs. multi-authored papers, international collaboration percentage, collaboration index (Newman, 2001; Nascimento *et al*., 2024).

Publications sharing cited references are bibliographically coupled, revealing current thematic clusters. Networks with publications as nodes, shared references as edges, and overlap strength as edge weights (Donthu *et al*., 2021; Zupic; Čater, 2015).

References cited together in later publications are co-cited, revealing foundational works. Networks with cited references as nodes, co-citation relationships as edges, and co-citation frequency as edge weights (Donthu *et al*., 2021; Aria; Cuccurullo, 2017).

For all networks, node-level centrality calculated: degree centrality (direct connections), betweenness centrality (bridge nodes connecting clusters) and PageRank (iterative importance based on connections to influential nodes) (Donthu *et al*., 2021).

All analyses conducted using bibliometrix (version 5.2.1) in R (Aria; Cuccurullo, 2017), a comprehensive package implementing established bibliometric methods for performance analysis and science mapping. Bibliometrix provides functions for productivity metrics, citation analysis, impact indices, network construction and centrality calculations. Visualizations produced at 300 DPI resolution.

3 RESULTS

The final dataset comprised 381 publications spanning 23 years (2004–2026) from

137 sources, authored by 1.515 researchers across 1.809 appearances (mean 4,75 authors per document). The dataset accumulated 7.974 total citations (mean: 20,93; median: 7 citations per document). Document types were predominantly articles (86,1%), followed by proceedings papers (6%) and reviews (4,5%). The dataset contained 1.042 author keywords and 17.487 cited references.

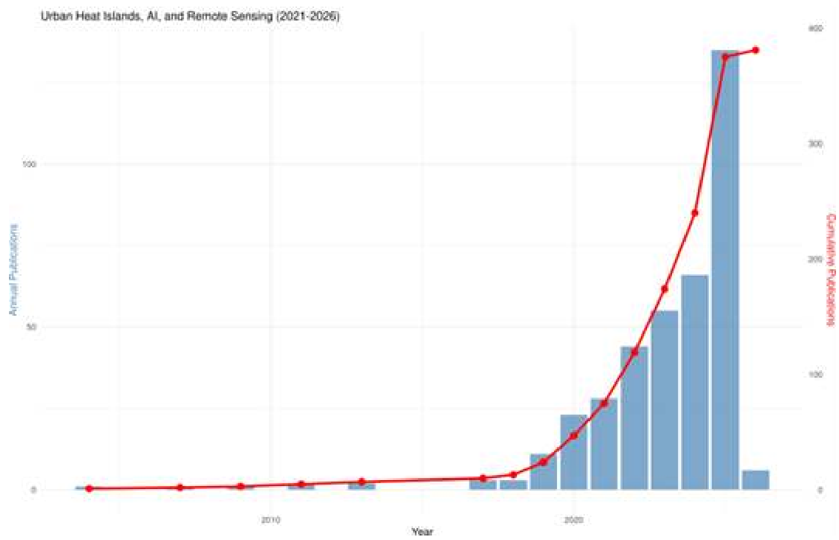
Temporal analysis revealed three phases. The field emerged slowly from 2004–2018 with only 13 publications across 15 years, transitioned in 2019–2021 (11 to 28 publications per year) and entered exponential growth from 2022 onward: 44 (2022); 55 (2023); 66 (2024) and 135 in 2025 (35,4% of all papers).

Cumulative production reached 75 publications (19,7%) by 2021; 174 (45,7%) by 2023 and 240 (63%) by 2024, indicating strong recency and a steep post-2019 acceleration visible in the annual and cumulative trend curves (

Figure 1).

Figure 1

Annual and cumulative publication trends



Source: Prepared by the authors from WoS data (2004–2026).

China led with 128 publications (33,6%), followed by India (9,45%) and USA (7,61%). The top five countries represented 58,5% of publications (

Table 1), indicating moderate concentration in national output. International collaboration occurred in 36% of papers.

Table 1

Top countries by publication count

COUNTRY	PUBLICATIONS	PERCENTAGE	RANK
China	128	33,6	1
India	36	9,45	2
USA	29	7,61	3
Germany	15	3,94	4
Korea	15	3,94	5
Iran	14	3,67	6
Bangladesh	10	2,62	7
Italy	10	2,62	8
United Kingdom	8	2,1	9
Australia	7	1,84	10

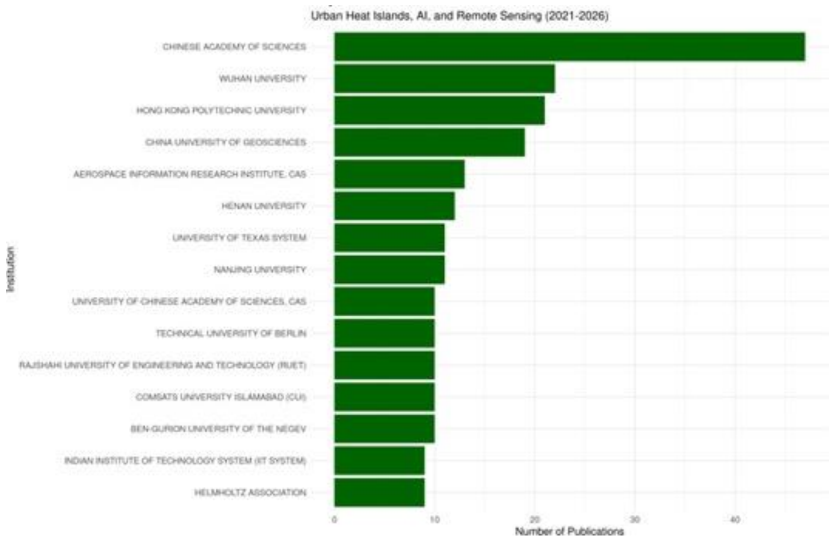
Source: Prepared by the authors from WoS data.

Chinese Academy of Sciences led with 47 publications, followed by Wuhan University (22) and Hong Kong Polytechnic University (21). The top ten institutions contributed 176 publications (46,2% of total), indicating substantial concentration in a limited institutional core. The gap between the leading institution and the second-ranked one (47 vs. 22 publications) further highlights a strongly asymmetric productivity structure, as shown in

Figure 2.

Figure 2

Top institutions by productivity

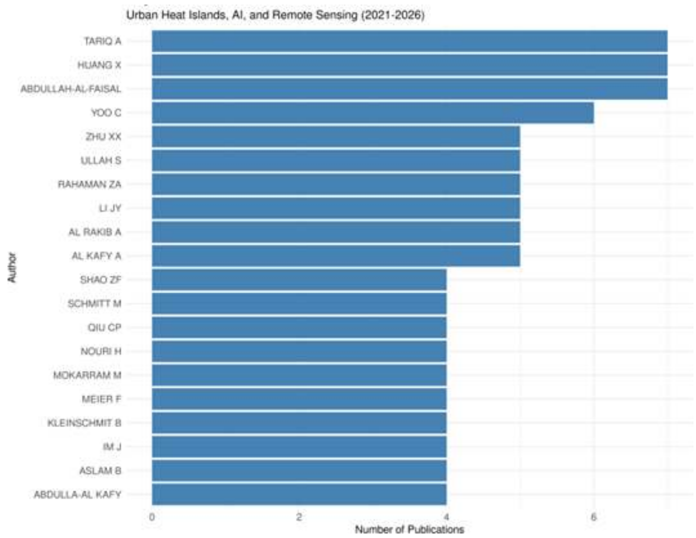


Source: Prepared by the authors from normalized institutional affiliations.

Three authors tied at 7 publications: Abdullah-Al-Faisal, Huang, X. and Tariq, A. Additionally, Yoo, C. contributed six publications. The top ten authors produced 57 publications (15% of the dataset). Single-authored papers were rare (3.7%). This pattern indicates a long-tail authorship structure, with a small leading group and broad participation from many lower-output authors (Figure 3).

Figure 3

Top authors by publication count



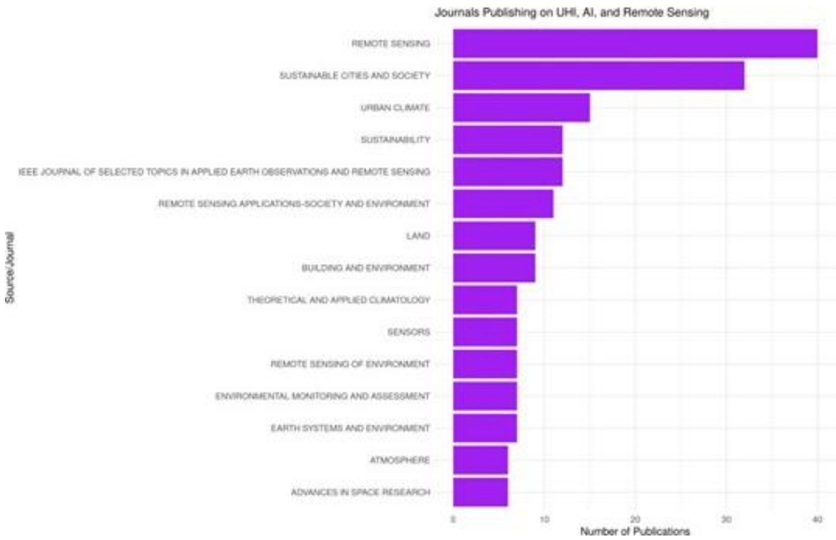
Source: Prepared by the authors from WoS data.

Remote Sensing (40 publications) was the leading source, followed by Sustainable Cities and Society (32) and Urban Climate (15). The top ten sources accounted for 40,4% of publications, while the top twenty reached 55,4%, indicating concentration in a core set of outlets with continued multidisciplinary dispersion beyond the leading journals (

Figure 4).

Figure 4

Top publication sources



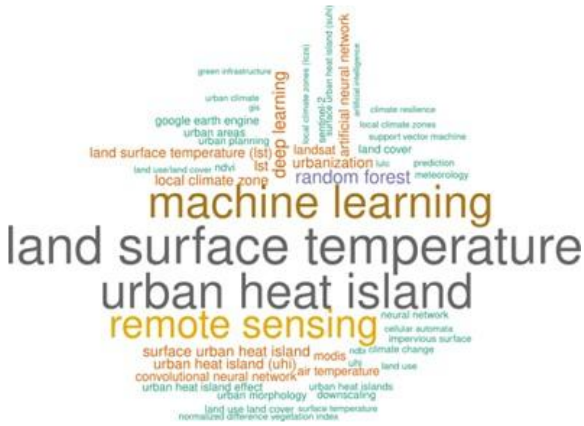
Source: Prepared by the authors from WoS data.

The top 30 author keywords accounted for 772 occurrences. The four dominant terms were land surface temperature (110), urban heat island (102), machine learning (94) and remote sensing (80). Methodological terms remained highly visible, including random forest (30), deep learning (27) and artificial neural network (18), while data source terms such as Landsat (16), MODIS (14) and Google Earth Engine (13) reinforced the strong coupling between machine-learning workflows and satellite-derived thermal indicators. As shown in

Figure 5, the thematic profile is centered on temperature mapping and predictive modeling, with secondary emphasis on urban form and planning-related descriptors.

Figure 5

Keyword word cloud



Source: Prepared by the authors from DE keywords.

The citation impact profile was assessed using standard bibliometric indices. The h-index of 47 indicates that 47 publications have each received at least 47 citations, reflecting a solid core of influential studies (Hirsch, 2005). The higher g-index of 75 gives more weight to the highly cited tail of the distribution, while the i10-index of 170 shows that 44,6% of the dataset has reached at least 10 citations (Egghe, 2006; Donthu *et al*., 2021).

Citation counts were strongly right-skewed (Q1 = 1, median = 7, Q3 = 25), with many low-cited documents and a smaller group of highly influential papers (Nascimento *et al*., 2024). A complete summary is provided in

Table 2 and the distribution shape is shown in Source: Prepared by the authors from WoS data.

Figure 6.

Table 2

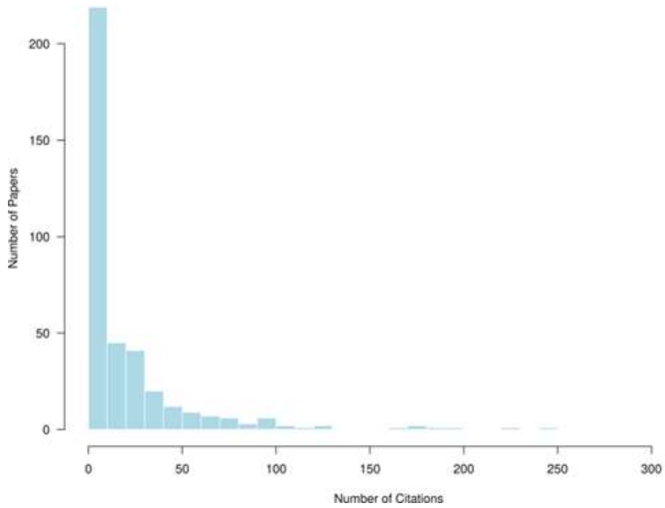
Citation metrics summary

METRIC	VALUE
Total Citations	7974
Mean Citations per Document	20,93
Median Citations	7
Max Citations	311
Min Citations	0
H-Index	47
G-Index	75
i10-Index	170
i10-Percentage	44,62

Source: Prepared by the authors from WoS data.

Figure 6

Citation distribution



Source: Prepared by the authors from WoS citation counts.

Zhan *et al.* (2013) was the most cited paper (311 citations), followed by Ahmed *et al.* (2013) (243) and Hu and Weng (2009) (223). The top ten papers accounted for 1.921 citations (24,1% of total citations). In this section, "top cited papers" refers to documents inside the study corpus (the 381 selected records).

This differs from "top cited references", which are foundational works cited by the corpus. The full top-cited ranking is presented in Table 3, and the top-cited profile is

ISSN: 2177-3246

visualized in

Figure 7.

Table 3

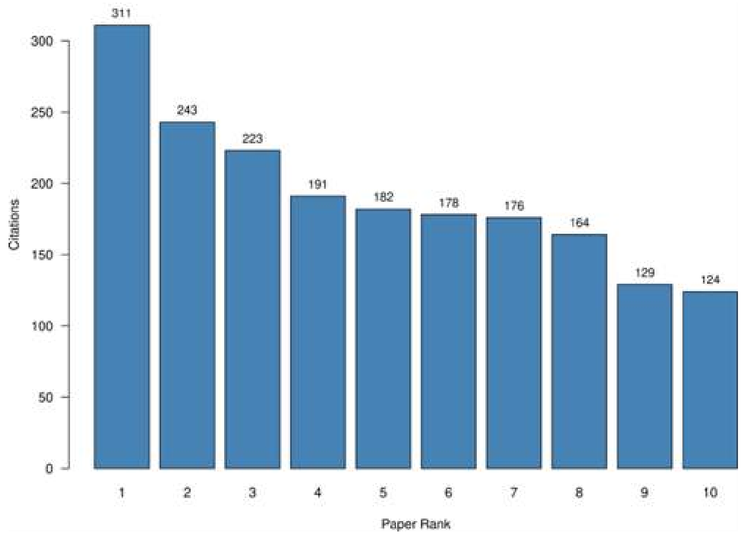
Top cited papers

FIRST AUTHOR	YEAR	TITLE (SHORTENED)	SOURCE	CIT.
Zhan *et al.*	2013	Disaggregation of remotely sensed land surface temperature: survey, taxonomy, issues, and caveats	Remote Sensing of Environment	311
Ahmed *et al.*	2013	Simulating land-cover changes and impacts on land surface temperature in Dhaka, Bangladesh	Remote Sensing	243
Hu and Weng	2009	Estimating impervious surfaces using self-organizing map and multilayer perceptron neural networks	Remote Sensing of Environment	223
Logan *et al.*	2020	Influence of urban characteristics on remotely sensed land surface temperature	Remote Sensing of Environment	191
Kafy *et al.*	2021	Prediction of seasonal urban thermal field variance index with machine learning in Cumilla, Bangladesh	Sustainable Cities and Society	182

Source: Prepared by the authors from WoS data.

Figure 7

Top cited publications

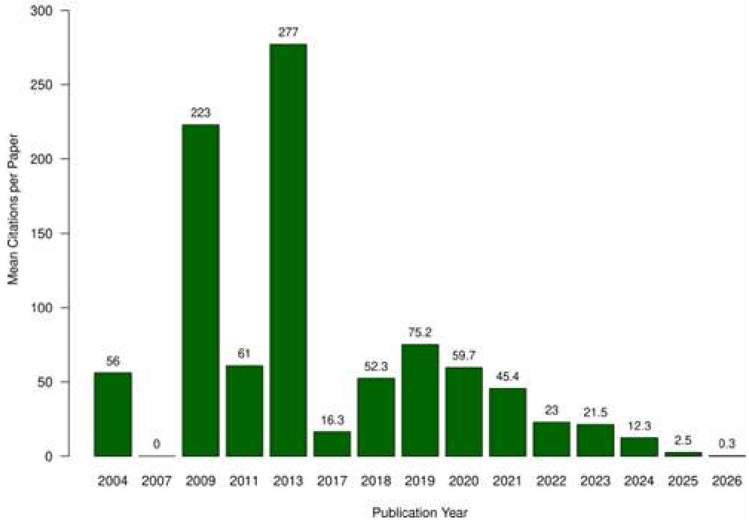


Source: Prepared by the authors from WoS citation counts.

Mean citations varied strongly by period: 2004–2011 (80,2), 2019 (75,2), 2020–2021 (51,9), 2022–2024 (18,2) and 2025–2026 (2,4), reflecting the citation-window effect (Figure 8).

Figure 8

Mean citations by publication year



Source: Prepared by the authors from WoS citation counts.

Collaboration intensity was high (4,75 authors per document) (Newman, 2001), with 36% international collaboration (Nascimento *et al*., 2024). The co-authorship network indicates a structured collaboration core: Rahaman, Z.A., Al-Kafy, A. and Al-Rakib, A. appear as central hub authors with many direct partnerships, consistent with high degree centrality (Donthu *et al*., 2021), while Rahman, M.M. and Lee, S. occupy bridge positions that connect otherwise separate collaboration groups. Tariq, A. appears as a high-influence connector linked to other well-connected researchers.

This structure is important because it suggests that knowledge diffusion in the field depends on a limited set of core and bridge authors; strengthening links beyond this core could improve cross-group integration and methodological exchange (Zupic; Čater, 2015; Newman, 2001; Nascimento et al., 2024). Team-size distribution and network topology are shown in Figures 9 and 10 (Figure 9; Figure 10), respectively.

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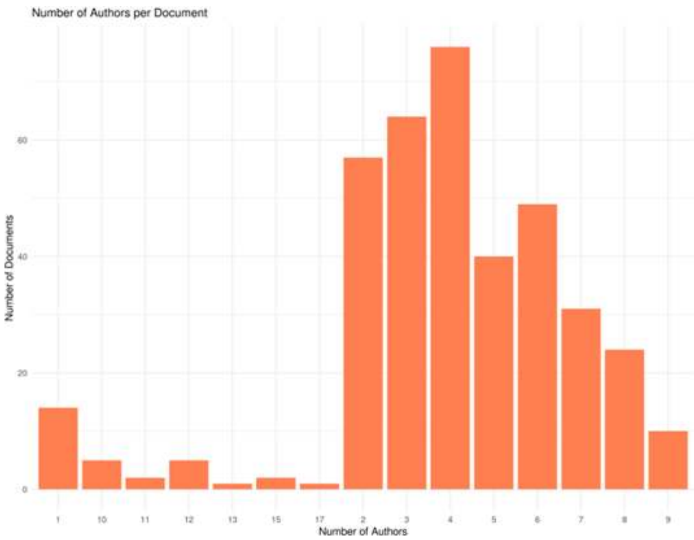
ISSN: 2177-3246

Figure 9

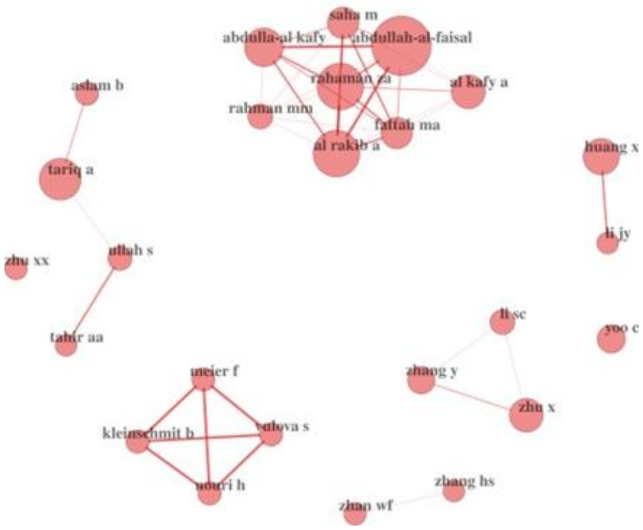
Team-size distribution



Source: Prepared by the authors from authorship data.

Figure 10

Co-authorship network



Source: Prepared by the authors using bibliometrix network outputs.

Foundational references show a clear cross-disciplinary base. Stewart and Oke (2012) was the most locally cited work (66 citations), followed by Oke (1982), Weng *et al*. (2004) and Breiman (2001). Together, these references represent the integration of urban climate theory, thermal remote sensing methodology and machine-learning analytics that underpins the field.

The top cited references span 1982–2021 (median around 2010–2011), indicating that recent growth relies on both classic conceptual foun- dations and modern computational methods.

4 DISCUSSION

The temporal evolution reveals rapid emergence rather than steady maturation. Exponential growth - from 11 publications (2019) to 135 (2025), with 95% produced in seven years - indicates a field in acceleration phase, differing from gradual decades-long development typical of established disciplines (Jiang *et al*., 2024; Zhou *et al*., 2019).

Three concurrent developments explain post-2019 surge. Google Earth Engine adoption (2015-2017), deep learning frameworks production-ready (2018-2019) and Sentinel-2 high-resolution imagery (2015) created "readiness threshold" around 2018-2019 (Gorelick *et al*., 2017; Yoo *et al*., 2019).

Top-cited papers (Yoo *et al*., 2019; Logan *et al*., 2020) demonstrated ML outperformed traditional approaches. Post-2018 IPCC assessments (Intergovernmental Panel on Climate Change (IPCC), 2022; Intergovernmental Panel On Climate Change (IPCC), 2023; Shukla *et al*., 2022; Calvin *et al*., 2023) emphasized urban heat risk reduction as a near-term adaptation and mitigation priority, creating monitoring demand (Jiang *et al*., 2024).

Strong citation impact (h- index=47 typical of established domains within 23-year window), established foundational references spanning four decades and three disciplines, journal infrastructure emergence (Remote Sensing, 40 papers; Sustainable Cities and Society, 32; Urban Climate, 15; top-10 publishing, 40,4%) and methodological standardization around Random Forest (7,87%) and LST (28,87%) (Oke, 1982; Logan *et al*., 2020; Zhou *et al*., 2019).

However, early maturity characteristics persist: lack of prolific authors (maximum 7 papers, only three authors; ~96% with 1-2 papers vs. mature fields with highly prolific researchers at 20 to 50 or more publications), geographic concentration (China's 33,6% unusually high for global problem) (Jiang *et al*., 2024) and limited theoretical development (methodological keywords dominate over application keywords) (Jiang *et al*., 2024; Zhou *et al*., 2019).

Three plausible scenarios emerge for the 2026–2030 period. First, publication rates may stabilize between 100 and 150 papers annually as core methodologies reach maturity. Second, the field could transition from a focus on methodology toward practical applications, such as public health and mitigation strategies, thereby opening new research frontiers (Jiang *et al*., 2024). Alternatively, the field may be absorbed into broader urban climate science, as Urban Heat Island (UHI) detection evolves from a primary research topic into a standardized analytical tool (Zhou *et al*., 2019). Ultimately, distinguishing among these trajectories will require empirical data extending beyond 2026.

China's leading contribution (33,6%, 128 papers - far exceeding India and USA) reflects four factors: (1) Intense urban heat burden from compressed urbanization (657 million urban residents added 1980-2020, creating 8-12°C differentials) (Peng *et al*., 2012; Zhou *et al*., 2019). (2) National satellite infrastructure (GaoFen constellation providing free domestic access) (Zhou *et al*., 2019). (3) AI development prioritization (2017 plan with NSFC funding increasing 300% for AI and environment) (Liu; Shi, 2020). (4) Institutional publication mandates (environmental remote sensing and AI as a low-risk research domain) (Jiang *et al*., 2024).

Concentration creates methodological concentration risk: if 1 in 3 studies focuses on Chinese cities (humid subtropical, high-density), models may not generalize to arid cities, tropical informal settlements, or temperate contexts (Liu; Shi, 2020; Zhou *et al*., 2019).

Nations with significant representation, notably India (9,45%), Iran (3,67%) and Bangladesh (2,62%), exhibit common structural drivers, including established remote sensing (RS) infrastructure, proficiency in English-language academic norms, substantial graduate student populations, and exposure to severe urban heat.

Conversely, the critical underrepresentation of Sub-Saharan Africa (<1%), Latin America (excluding Brazil) and Southeast Asia (excluding India) signals a concerning geographic imbalance (Menezes; Macadar, 2025; Zhou *et al.*, 2019). This disparity fosters a threefold inequity: research inequity, characterized by a lack of agency among local scientists; methodological inequity, where models may fail to generalize to underrepresented environmental settings; and resource inequity, which renders these vulnerable regions invisible to global climate finance mechanisms (Maria, 2019).

At 36%, the rate of international collaboration in Urban Heat Island (UHI) research remains modest when compared to other global environmental challenges, such as climate change (45–50%) and biodiversity (40–45%). This discrepancy signifies a loss of potential for cross-climate validation and the enrichment of methodological diversity (Jiang *et al*., 2024).

Several systemic barriers underpin this fragmentation, including concerns over data sovereignty, complexities in publication credit, funding mismatches, and linguistic hurdles (Cunha-Melo *et al*., 2006). To mitigate these challenges, the establishment of a "Global Urban Heat Intelligence Network", featuring shared repositories and standardized validation datasets, could serve as a crucial catalyst for fostering international cooperation and scientific synergy.

Thematic concentration around LST, machine learning, and remote sensing within this corpus: Four keywords - land surface temperature (28,87%), urban heat island

(26,77%), machine learning (24,67%), remote sensing (21%) - define the conceptual core of the retrieved literature (Jiang *et al*., 2024).

This pattern should be interpreted in light of the search strategy, which required UHI, remote sensing, and artifi- cial intelligence or machine learning terms. Therefore, the results indicate concentration within this corpus, not that all UHI research is equivalent to ML applied to satellite- derived LST. Even so, the observed emphasis on surface UHI (satellite LST) may still contribute to blind spots regarding air temperature UHI (only 3,67% mention air temperature explicitly), although air temperature is often more directly linked to human thermal comfort and health outcomes (Voogt; Oke, 2003; Zhou *et al*., 2019).

The predominance of Random Forest (7,87%) in the literature reflects its significant methodological fit, specifically its ability to handle non-linearity, provide robust feature importance metrics, and maintain data efficiency. This trend is further sustained by precedent effects, rooted in the seminal status of Breiman (2001), and the algorithm's accessibility, as its simple APIs offer a lower barrier to entry compared to deep learning frameworks that necessitate GPUs and extensive hyperparameter tuning (Logan *et al*., 2020).

However, the relative underutilization of Convolutional Neural Networks (CNNs) (3,94%) and physics-informed networks suggests a missed opportunity for performance gains, likely due to path dependency. This is particularly notable given that deep learning approaches have demonstrated superior performance over Random Forest in complex urban scene classification tasks (Liu; Shi, 2020; Yoo *et al*., 2019).

Current research predominantly emphasizes the detection and mapping of Urban Heat Islands (UHI), yet significantly underrepresents critical areas such as health impacts, mitigation strategies, and policy implementation. Keywords related to health, mortality, and heat stress constitute less than 1% of the literature (Ahmed *et al*., 2013; Zhou *et al*., 2019), a figure mirrored by research on mitigation interventions (Deilami *et al*., 2018).

Although "urban planning" is mentioned in 2,62% of papers, terms associated with policy governance and implementation remain nearly absent (<0,5%). This disparity suggests that academic incentives prioritize technical novelty over applied utility. Consequently, while cities increasingly possess sophisticated UHI mapping, they lack evidence-based guidance on cost-effective mitigation, a widening "knowledge-practice gap" where technical capability outpaces application science (Deilami *et al*., 2018).

The most frequently cited references converge into three primary knowledge domains: (1) Urban climate theory (Oke, 1982; Stewart; Oke, 2012), which establishes the fundamental physical mechanisms and classification schemes; (2) Remote sensing methodology (Weng *et al*., 2004; Zhan *et al*., 2013), providing the essential toolkit for data acquisition and processing; and (3) Machine learning algorithms (Breiman, 2001), supplying the necessary analytical frameworks.

While this three-pillar foundation offers significant advantages, notably bypassing the need to develop new theory or infrastructure from Scratch, it also fosters a degree of fragmentation. This results in "identity ambiguity," where the field fluctuates between being an urban climatology subfield, a remote sensing application, or a machine learning test case.

Consequently, disparate disciplinary priorities lead to communication barriers and methodological tensions. In practice, researchers must often navigate the trade-off between achieving high statistical performance and maintaining physical plausibility, ensuring that models preserve established ecological links between vegetation, impervious surfaces and land surface temperature.

Zhan *et al*. (2013) as a highly cited paper (311 citations, 2,3 times second- ranked) exemplifies methodological infrastructure rather than empirical contribution. Timing as catalyst: published 2013 when MODIS had 13-year archive, Landsat-8 launched, Sentinel-2 imminent, exactly when disaggregation demand surged.

Review papers accumulate citations differently than empirical studies; Zhan *et al*. (2013) is cited by hundreds of applications regardless of specific algorithm or context. By synthesizing scattered approaches into coherent taxonomy, it reduced barriers for new researchers, lowering knowledge threshold and accelerating field growth.

Median publication year of top-20 cited references (~2010-2011) vs. dataset median (2024) = approximately 13-14 year gap between foundations and current applications. This reveals maturation process:

- Phase 1 (1980s-2000s): theory establishment.
- Phase 2 (2000s-2010s): method development (RS matured, thermal sensors improved, ML algorithms emerged).
- Phase 3 (2010s): technology readiness (Google Earth Engine, deep learning frameworks, Sentinel-2).
- Phase 4 (2019-present): rapid application growth with readiness convergence.

This 13-14 year lag is intermediate between rapid-adoption AI (1-2 years) and slow-adoption fundamental science (30 or more years), reflecting Earth observation's unique requirements.

Network centrality identifies authors occupying strategically important positions (Donthu *et al*., 2021). Authors with the highest betweenness centrality, notably Rahman, M.M. and Lee, S. (Figure 10), bridge otherwise disconnected clusters, facilitating knowledge transfer across methodological or geographic boundaries (Zupic; Čater, 2015).

However, reliance on few bridge authors creates vulnerability if these individuals shift focus, retire or face mobility constraints. Deliberately cultivating additional bridges through postdoc exchanges, collaborative grants requiring multi-country teams, and rotating research network leadership could reduce fragmentation (Nascimento *et al*., 2024).

Network fragmentation likely exhibits multiple disconnected components (clusters without inter-connections), common in interdisciplinary fields (Newman, 2001; Aria; Cuccurullo, 2017). This creates inefficiencies, especially limited cross-validation and knowledge silos (regional papers remaining less visible across clusters) (Nascimento *et al*., 2024). Breaking down silos requires infrastructure: multilingual databases, transla- tion funding, international conferences, shared code repositories, and validation datasets enabling asynchronous cooperation (Maria, 2019).

PageRank divergence from degree centrality reveals influence propagates through quality of connections (collaborating with influen- tial authors) rather than quantity (Donthu *et al*., 2021). Strategic collaboration with few high-impact researchers may yield greater field influence than numerous peripheral collaborations. However, this can exacerbate inequities through preferential attachment (cumulative advantage) (Lotka, 1926).

To mitigate these systemic imbalances, it is essential to implement interventions that incentivize cross-status collaboration, such as mentorship programs, seed grants for international teams including underrepresented regions, journal policies recognizing collaborative capacity-building, wich could shift patterns toward more integrative structures (Nascimento *et al*., 2024).

Exclusive reliance on WoS Core Collection covers high-impact journals but exhibits systematic bias, predominantly indexing English-language publications (Mongeon; Paul-Hus, 2016). Chinese, Spanish, Portuguese literature likely underrepresented (Maria, 2019; Cunha-Melo *et al*., 2006). Scopus would expand corpus 30-40%; Google Scholar would capture grey literature but introduce quality challenges (Mongeon; Paul-Hus, 2016). Our WoS choice prioritizes quality over comprehensiveness, accepting ~60-70% global output coverage.

Older papers accumulate more citations from longer exposure. Papers from 2024-2025 (37% of dataset) had <2 years, suppressing apparent impact (Zupic; Čater, 2015). This affects identification of "most influential" papers (favors pre-2020 work), h-index (dominated by five or more year windows) (Hirsch, 2005) and assessment of emerging methods (deep learning, PINNs may appear minor due to recency). Alternative metrics less sensitive to publication date (field-weighted impact, citations per year) and future reassessment can mitigate this.

Thematic analysis relies on author-supplied keywords, which reflect authors' framing rather than objective classification. Strategic keyword selection may emphasize trendy terms ("machine learning") even when use is minor (Menezes; Macadar, 2025). Editorial constraints (5-8 keyword limit) force prioritization, potentially omitting secondary themes. Vocabulary evolution means dif- ferent terminology for similar concepts across time periods. We chose precision (author keywords know their content) accepting reduced recall (not all themes keyworded) (Zupic; Čater, 2015).

Co-authorship metrics depend on assumptions that may not hold. Name disambiguation errors remain possible despite matching algo- rithms (Newman, 2001). Authorship order insensitivity treats all co-authors equally, ignoring contribution levels. Network boundary artifacts (only UHI, AI, and RS authors included) truncate true collaboration patterns. Metrics should be interpreted as relative rankings within corpus rather than absolute measures.

This bibliometric analysis is fundamentally descriptive, documenting patterns but not definitively establishing causal explanations (Donthu *et al*., 2021). Our interpretations (Google Earth Engine enabling growth) are plausible hypotheses consistent with observed patterns, but alternative explanations exist. Disentangling factors requires counterfactual analysis impossible with observational bibliometric data. Confirming causal mechanisms requires experimental evidence (author surveys on method choice factors) beyond bibliometric scope (Zupic; Čater, 2015).

5 CONCLUSION

This bibliometric analysis of 381 publications (2004-2026) at the UHI, AI and remote sensing intersection reveals a rapidly emerging field achieving methodological maturity in UHI detection within a compressed timeframe. Using performance analysis and science mapping on Web of Science data, this study provides the first comprehensive synthesis of field structure, knowledge foundations, and research trajectories (Donthu *et al*., 2021).

Six principal findings characterize this interdisciplinary field. First, the field has experienced exponential growth from 11 papers in 2019 to 135 in 2025, with 95% published since 2019, indicating critical technology convergence around 2018–2019 (Deilami *et al*., 2018; Zhou *et al*., 2019).

Second, geographic concentration (with China producing 33,6%, India 9,45%, and the USA 7,61%) creates methodological risks through limited transferability of models optimized for Chinese megacities, while also creating equity gaps through severe underrepresentation of Sub-Saharan Africa and Latin America (Jiang *et al*., 2024; Zhou *et al*., 2019).

Third, methodological convergence around Random Forest (7,87%) and land surface temperature (28,87%) enables rapid progress in detection but marginalizes air-temperature-based analyses that are more directly linked to human heat exposure (Voogt; Oke, 2003; Zhou *et al*., 2019).

Fourth, the field demonstrates premature maturity despite its recency, with an h-index of 47, g-index of 75 and mean citations of 20,93, supported by integration of urban climatology, remote sensing, and machine-learning foundations over a 13–14 year citation lag (Donthu *et al*., 2021).

Fifth, collaboration remains moderately fragmented, averaging 4,75 authors per paper and 36% international collaboration, though network structures still limit cross-regional and cross-methodological knowledge exchange (Jiang *et al*., 2024; Newman, 2001).

Sixth, a persistent application gap exists, with strong capacity for UHI detection but limited emphasis on health outcomes (less than one%), mitigation effectiveness (less than one%) and policy integration (governance less than 0.5%) (Deilami *et al*., 2018; Zhou *et al*., 2019).

This study contributes by establishing a 2026 baseline for the UHI-AI-remote sensing literature, applying a replicable performance-analysis and science-mapping framework (Donthu *et al*., 2021) and identifying actionable gaps in geography, theme, and collaboration structure (Menezes; Macadar, 2025; Newman, 2001).

Five strategic priorities emerge for the field's evolution. A thematic shift is needed to move from asking “can we map UHI accurately?” to “which interventions reduce UHI cost-effectively in different contexts?” through longitudinal quasi-experimental designs (Deilami *et al*., 2018; Zhou *et al*., 2019).

Geographic expansion should prioritize understudied regions including Sub-Saharan Africa and Latin America, as well as small-to-medium cities, using transfer learning pipelines (Liu; Shi, 2020; Menezes; Macadar, 2025). Health integration must connect satellite-derived thermal indicators with mortality and morbidity datasets to support operational early-warning systems (Ahmed *et al*., 2013; Zhou *et al*., 2019). Explainable AI approaches should advance from pure prediction to interpretable evidence on which urban features drive thermal outcomes across climates (Jiang *et al*., 2024; Logan *et al*., 2020).

Finally, operationalization requires building real-time monitoring and short-term forecasting systems that directly support heat emergency response and urban management

(Jiang *et al*., 2024; Zhou *et al*., 2019). The field of urban heat island research supported by artificial intelligence and remote sensing has emerged as dynamic and methodologically mature. It has achieved rapid growth through technology convergence, established core detection paradigms, and produced a body of influential foundational work (Jiang *et al*., 2024; Zhou *et al*., 2019).

However, concerning patterns persist: geographic concentration can leave vulnerable populations without validated tools, thematic convergence sidelines health, mitigation, policy questions and network fragmentation constrains knowledge exchange (Deilami *et al*., 2018; Jiang *et al*., 2024). The field therefore risks plateauing as a sequence of technical demonstrations rather than evolving into a solution-oriented climate-adaptation discipline.

The next decade will determine whether this field fulfills its transformative potential. Transitioning from exponential growth to sustained societal impact requires deliberate action: expanding into underrepresented geographies, shifting from detection to intervention and validation, integrating health outcomes, and strengthening international collaborative networks (Jiang *et al*., 2024; Zhou *et al*., 2019). Funders, researchers, and policymakers each have distinct roles in enabling this transition through targeted funding, strategic research agendas, and regulatory integration (Menezes; Macadar, 2025).

This analysis serves both as recognition of a significant interdisciplinary advance and as a basis for strategic action. The technical capability to monitor UHI at unprecedented scale and resolution now exists. The central challenge is to convert that capability into adaptation outcomes, reducing heat exposure, protecting vulnerable populations, and supporting evidence-based urban planning (Logan *et al*., 2020; Zhou *et al*., 2019). Ultimately, success will be judged not only by what the field can detect, but by whom it protects and which actions it enables.

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