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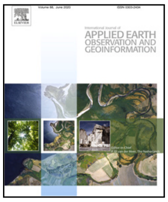

UAV-based built environment perception: Progress, challenges, prospects, and regulatory contexts

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ABSTRACT

Uncrewed Aerial Vehicles (UAVs) have proven to be a transformative technology for the fine-scale perception of the built environment. The recent proliferation of new platforms, sensors, and algorithms creates unprecedented opportunities to understand a complex environment. However, effectively harnessing these opportunities requires a systematic assessment of the emerging methodological practices to address challenges concerning the comparability, reproducibility, and generalizability of the knowledge being produced. Therefore, this study aims to systematically map the dominant methodological workflows in UAV-based built environment perception and critically assess their implications for scientific knowledge production. We conducted a systematic review of 201 peer-reviewed articles in the last decade (2015–2025), complemented by the construction of a novel global dataset of UAV flight policies across 80 countries, to deconstruct the dominant research workflows and to synthesize the progress and challenges across key application domains. Our analysis, leveraging a novel method that integrates PRISMA, machine learning, and Large Language Models, reveals a pronounced convergence in research practices, which stands in contrast to the apparent diversity of available technologies. We determine that the state of the art is characterized by: (i) a geographical concentration of studies in the Global North, correlated with permissive regulatory environments; (ii) a technological path dependency on a 'standardized toolkit' of multirotor UAVs and RGB sensors; and (iii) a methodological reliance on self-collected data (91%) that often remains non-public, fostering a research ecosystem of quantitative, computer vision-based analysis. By diagnosing these dominant patterns and their associated challenges, we propose a forward-looking agenda centered on fostering open science, diversifying technologies, and expanding methodological horizons to build a more integrated, robust, and equitable research future.

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1. Introduction

Uncrewed Aerial Vehicles (UAVs), commonly known as drones, have emerged as a transformative technology for investigating the built environment, providing unparalleled capabilities for high-resolution, multi-dimensional, and on-demand mapping for urban research (Zhang et al., 2023; Zhou, 2025). Over the past decade, the proliferation of UAV platforms outfitted with a variety of sensors (such as visible light cameras, thermal imagers, and LiDAR) has enabled the fine-grained perception of critical urban elements, including 3D spatial morphology, vegetation volume, and micro-scale thermal environment, achieving stable centimeter-level precision, and even sub-centimeter spatial resolution under optimal flight conditions (Wei and Li, 2025; Tepanosyan et al., 2021; Ivošević et al., 2025). This technological progress has catalyzed a wave of innovation across numerous application domains (Luo et al., 2022b).

However, this rapid and diverse development is accompanied by a new set of challenges. As the field of UAV-based built environment perception evolves steadily, a critical need arises to look beyond individual applications and to systematically examine the overall research landscape that is taking shape (Gohari et al., 2024; Luo et al., 2025c). The sheer heterogeneity in technologies, data acquisition practices, and analytical methods — compounded by a complex and uneven global landscape of geographical disparities and divergent regulatory environments — raises questions about the comparability, reproducibility, and generalizability of the knowledge being produced (Cheng et al., 2024; Patial et al., 2025; Cheng et al., 2024). Without a clear understanding of the dominant trends and their potential limitations, the field risks evolving into a collection of fragmented, non-cumulative studies. This fragmentation makes it difficult to synthesize findings across different studies, increasing the methodological risk of creating unexamined biases, such as algorithms optimized for a specific urban context failing to generalize elsewhere, and hindering the establishment of a robust, evidence-based foundation for urban science and practice (Buters et al., 2019; Doornbos et al., 2024).

While existing literature reviews have provided valuable summaries within specific thematic areas such as air quality or 3D modeling (Table 1), their domain-specific focus, by its very nature, cannot address these overarching, cross-cutting challenges. To move beyond this fragmentation and enhance the collective scientific value of the field, it is necessary to undertake a review with a distinct, methodology-centric focus. Such an analysis is crucial not just for cataloging what has been done, but for understanding how it has been done. This requires a shift in perspective: from viewing the diversity of methods as a simple collection of tools, to deconstructing the underlying methodological choices that define the field’s common practices (Ito et al., 2024). This involves treating the convergence of technologies and methods, a core finding of this paper, not as a given, but as a central phenomenon to be investigated and understood.

Therefore, this study provides the first foundational analysis of the field’s methodological structure by pursuing two primary objectives: (i) to map the dominant research workflows, by systematically tracing the flow from technological platform and sensor selection to common data acquisition and analytical techniques, while considering the influence of key contextual factors such as regulatory environments; and (ii) to assess the implications of these workflows, by critically examining how they influence crucial aspects of scientific knowledge production, such as research reproducibility, comparability, and the breadth of scientific questions addressed. To guide this endeavor, we address the following three research questions:

- What are the dominant patterns characterizing the current state of UAV-based built environment perception research, considering the interplay of technology, methodology, and regulation?
- How do these dominant patterns shape the methodological practices and challenges of the field?
- Based on the synthesis of progress and challenges, what are the key prospects and a forward-looking agenda for a more integrated, robust, and equitable research field?

2. Contextualizing UAV-based built environment perception

The perception of the built environment relies on a multi-scale, ‘space–air–ground’ data ecosystem (Fig. 1). Space-borne platforms provide macroscopic coverage but lack the fine-grained detail necessary to capture the human-scale city (Hu et al., 2024; J. Zhang et al., 2025; Y.

Table 1
Positioning this review in relation to representative prior reviews.

Review study	Primary focus	Contribution and perspective
This study	Cross-thematic analysis of methodological pathways in UAV-based built environment perception	Provides the first synthesis of the entire field's methodological landscape. Quantitatively assesses 11 indicators to map dominant patterns in technology, data, geography, and methods.
Lambey and Prasad (2021)	UAV applications in air quality monitoring	Domain-specific technical review. Focuses on measurement techniques and sensor performance for pollutant monitoring.
Smith et al. (2021)	UAV use in urban thermal environment studies	Domain-specific application review. Emphasizes sensor types and data use for thermal analysis.
Xu et al. (2023b)	Diverse UAV applications in smart city management	Application-oriented technical review. Centers on the workflows and technological integration for smart city management.
Hu and Minner (2023)	Role of UAVs and 3D urban modeling in planning and heritage conservation	Case-study-driven synthesis. Reviews the application of 3D modeling for planning and conservation purposes.
Mishra et al. (2023)	Uncrewed aerial system applications in water resource mapping and management (WRMM)	Domain-specific application review. Provides a comprehensive overview of sensors, software, challenges, and applications across various water resource sub-domains.
Cheng et al. (2024)	Semantic segmentation techniques and datasets for UAV remote sensing images	Method-specific technical review. Focuses on a single, mainstream analytical technique (semantic segmentation) and its associated datasets.

Zheng et al., 2023), and are further constrained temporally by fixed revisit intervals and cloud cover. Similarly, crewed (piloted) aircraft offer extensive coverage with high resolution and wide spectral capabilities. While primary data acquisition can be costly, it remains more cost-effective and flexible than high-resolution satellite tasking (Almohsen, 2024; Dash et al., 2017). Crucially, freely available aerial orthoimagery from governments and commercial entities (e.g., Google, Esri) can be processed via accessible photogrammetry to generate 3D virtual environments (reality capture) (Biljecki et al., 2015). This capability provides continuous spatial coverage highly advantageous for extensive inter- and intra-neighborhood urban perception studies, a scale often challenging to achieve with UAVs alone (Pöppl et al., 2025). In contrast, ground-based platforms offer microscopic, immersive views but suffer from limited, fragmented spatial coverage and time-consuming data collection processes (Biljecki et al., 2023). UAVs have emerged to occupy a critical meso-scale niche, bridging both the spatial and temporal gaps of traditional platforms (Dadrass Javan et al., 2024; Coops et al., 2025; Li and Chang, 2019). By offering operator-controlled, on-demand flight schedules and agile maneuverability, UAVs bypass satellite revisit limitations, the deployment and navigational constraints of crewed platforms, and the labor-intensive nature of ground surveys (Mishra et al., 2023; Q. Zheng et al., 2023; Huang et al., 2018). Their unique ability to combine a synoptic aerial view with high-detail proximate sensing, coupled with centimeter-level resolution and flexible deployment, allows for unprecedented multi-dimensional mapping of urban environments, including vertical surfaces like building facades and intricate urban canyons (Luo et al., 2025c).

Crucially, the scientific value of this UAV-based 'perception' must be contextualized as a multi-sensory theoretical construct. While the term 'perception' in UAV applications typically evokes the capture of imaging-based geometric and spectral features, human experience of the built environment is inherently multi-sensory. It extends beyond the visual to include environmental factors such as urban soundscapes and air quality. Consequently, UAV-based perception encompasses a broader range of non-imaging remote sensing techniques, such as audio signal recording and air constituent sampling, to quantify these multi-dimensional environmental inputs. Although the UAV's perspective is inherently non-human, its importance lies not in merely replicating the human vision or hearing, but in its ability to precisely quantify the comprehensive physical and environmental context in which human experience occurs. Human perception, though unfolding at street level, is profoundly shaped by meso-scale characteristics such as building density, green space accessibility, and the dispersion of air pollutants. UAVs provide an essential, objective baseline of this physical reality. The primary purpose of this research field, therefore, is to forge a stronger analytical link between the objectively measured, multi-sensory city 'as sensed from above,' and the subjectively perceived city 'as experienced from below.'

In this context, 'perceptions of the built environment' represent a broad domain that encompasses both the objective quantification of physical elements (e.g., urban microclimate, green infrastructure) and their translation into subjective human-centric sub-elements. Specifically, these sub-elements include assessments of nature quality, aesthetic beauty, psychological relaxation, perceived safety, spatial efficiency, and the provisioning of ecosystem services. However, as our subsequent analysis will reveal, the current UAV-based literature predominantly focuses on measuring the physical proxies of the environment, often falling short of directly assessing these richer subjective sub-elements.

2.1. Core technological components: platforms and sensors

The core technological components of a UAV system are its platform and sensor payload, which together define its data acquisition capabilities. UAV platforms are primarily categorized by their aerodynamic characteristics. Multirotor platforms, prized for their hovering capability and agility, are ideal for detailed, close-range inspection in complex spaces (Garg, 2022; Luo et al., 2022a). In contrast, fixed-wing platforms leverage aerodynamic lift to achieve extended endurance and elevated speeds, rendering them effective for extensive area mapping (Tang et al., 2023). Hybrid systems combining vertical take-off and landing (VTOL) with efficient forward flight represent a promising but still maturing technology, currently limited by higher costs and complexity (Sutariya et al., 2024).

The choice of sensor determines the type of environmental information that can be captured. RGB cameras are the most prevalent because of their affordability and high-resolution, intuitive imagery, though they are limited to the visible spectrum (Liu et al., 2022; Kapil et al., 2023). To capture information beyond human vision, advanced sensors are employed. Multispectral cameras analyze specific narrow bands of light for applications like vegetation health assessment (e.g., NDVI). Thermal infrared sensors detect emitted radiation to map surface temperatures and analyze energy efficiency. LiDAR, as an active sensor, generates precise 3D point clouds independent of lighting conditions, making it invaluable for accurate morphological reconstruction (Grasso et al., 2023; Lee and Lee, 2022). Beyond these primary modalities, a variety of other sensors serve diverse and highly specialized functions. For example, ultraviolet (UV) imaging sensors are specifically deployed to detect anomalous electrical discharges in high-voltage electric utility assets (Moore et al., 2018). The selection of any sensor thus involves a critical trade-off between its scientific capability, financial cost, and the demands of its data processing workflow (Suslu et al., 2023). While financial budgets determine hardware accessibility and scientific objectives dictate the required data type, the processing workflow acts as an independent technical barrier (Aasen et al., 2018). Even when

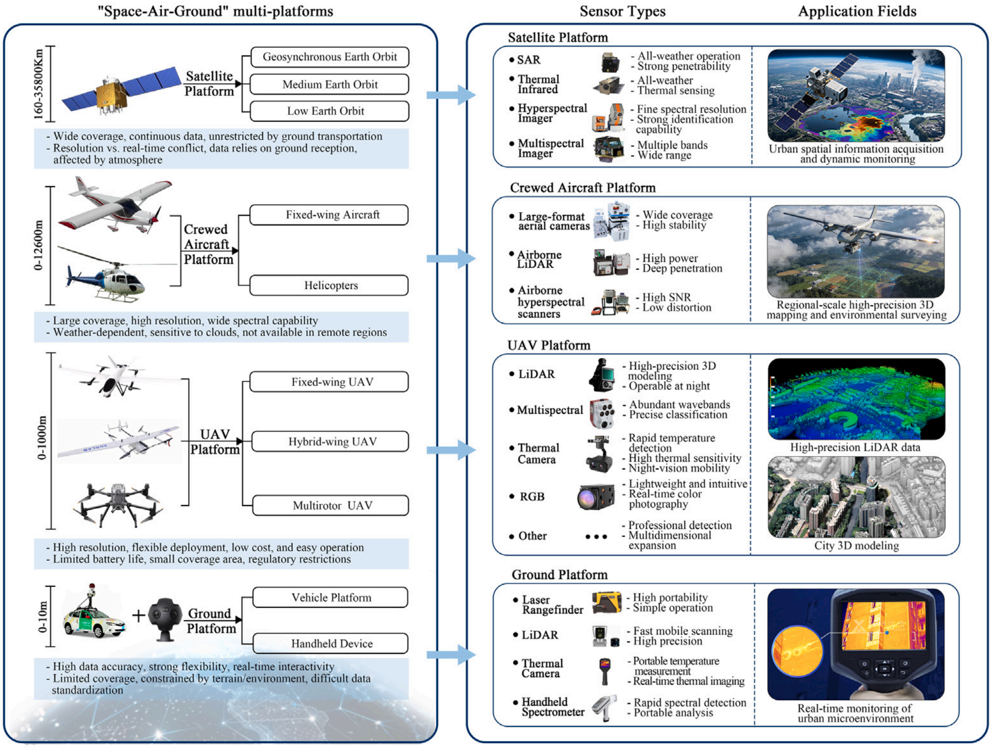


Fig. 1. Comparison of 'Space–Air–Ground' multi-platform sensing system, detailing the platforms, associated sensor types, and typical application fields.

advanced sensors are affordable and scientifically necessary, their steep operational bottlenecks often deter adoption. For instance, generating 3D models or orthomosaics from RGB imagery relies on highly automated and user-friendly Structure-from-Motion (SfM) pipelines (Iglhaut et al., 2019; Finn et al., 2023), whereas extracting absolute surface temperatures from thermal data demands rigorous radiometric calibration and complex atmospheric correction (Vanhellemont, 2020). Similarly, leveraging LiDAR requires specialized computational expertise in point cloud registration and algorithmic noise filtering (Gao et al., 2021; Zheng et al., 2022). Consequently, these workflow-induced barriers frequently compel researchers to default to standard RGB sensors, directly driving the technological convergence observed in this field.

2.2. Key contextual factors: geography and regulation

The deployment of the UAV technology is largely shaped by two non-technological, contextual factors: geographical context and regulatory environment (Bauranov and Rakas, 2021). First, geographically, high-density urban cores, with their tall buildings and narrow 'urban canyons,' create challenges such as turbulent wind gusts, GPS signal loss, and visual line-of-sight obstruction. These conditions demand high maneuverability and advanced collision avoidance capabilities (Shah et al., 2024; Hentzen et al., 2019). In contrast, low-density suburbs or open parklands offer a more permissive environment for a wider range of platforms, including fixed-wing UAVs. Second, strict aviation regulations act as a decisive gatekeeper, enforcing flight altitude ceilings (typically 120 m or 400 ft), restrictions on flying over people, and designated no-fly zones around critical infrastructure, such as airports and government buildings (Bauranov and Rakas, 2021). While procedures for obtaining waivers or special permissions for research purposes may exist, navigating these bureaucratic and time-consuming procedures adds significant administrative overhead to research projects (Luo et al., 2022b).

Together, this intricate interplay of technological capabilities, sensor-specific trade-offs, and powerful contextual constraints forms the decision-making landscape for researchers. It is this landscape that shapes the patterns, trends, and biases in UAV-based urban research that we deconstruct in the subsequent sections.

3. Methodology

3.1. Literature search and screening

This study integrates conventional systematic review techniques with advanced machine learning and Large Language Models (LLMs) to improve the reproducibility and efficiency of identifying pertinent publications in this domain (Ito et al., 2024). In this study, the LLM is used solely as an auxiliary tool, rather than serving as the sole basis for drawing conclusions. The paper processing workflow was divided into two main phases: (i) a traditional processing phase and (ii) an innovative processing phase. In the first phase, we gathered and evaluated the literature, and in the second phase, we extracted essential information from the selected papers to compose the review. The first phase of the process employed a conventional systematic review methodology, similar to the 'Preferred Reporting Items for Systematic Reviews and Meta-Analyses' (PRISMA) guidelines, to guarantee the study's reproducibility and rigor (Moher et al., 2009; H. Zhang et al., 2025).

We conducted a systematic search in the Scopus and Web of Science databases, chosen for their extensive disciplinary coverage. The selection of keywords is critical for controlling the domain of the retrieved literature. To comprehensively and accurately capture relevant studies, we systematically selected key terms across three core conceptual dimensions. The 'Platform' terms (e.g., UAV, drone) were selected to encompass all standard nomenclatures for uncrewed aerial systems. The 'Context' terms (e.g., urban, built environment) were chosen to strictly anchor the spatial scope to the built environment. Finally, the 'Task' terms (e.g., urban monitoring, digital twin) were included to capture the specific applications, analytical paradigms, and target environmental phenomena associated with built environment perception. The core keywords and the rationale for their selection are summarized in Table 2. The complete and detailed Boolean search string used in the

Table 2
Rationales and keywords used in the literature search across three conceptual dimensions.

Conceptual dimension	Core keywords	Rationale
Platform	‘Uncrewed Aerial Vehicle’, ‘Unmanned Aerial Vehicle’, ‘UAV’, ‘Drone’	To encompass all standard and alternative nomenclatures for uncrewed aerial systems.
Context	‘city’, ‘urban’, ‘built environment’	To strictly anchor the spatial scope to human-centric settlements, excluding purely natural or agricultural lands.
Task	‘Urban Environmental Perception’, ‘Urban Monitoring’, ‘Digital Twin’, ‘Smart Cities’, etc.	To capture the specific applications, spatial analysis paradigms, and target environmental phenomena.

databases is provided in Supplementary Material C. This initial search yielded 2331 potentially relevant publications.

The screening process was conducted in two stages, assisted by the AI-powered tool ASReview (Van De Schoot et al., 2021). In this step, we reviewed 502 articles and identified 272 as relevant. We excluded studies that did not utilize UAV data (e.g., those employing only ground-based infrared remote sensing instead of UAVs), as well as those not focused on a built environment context (e.g., concentrating solely on natural ecosystems or agricultural monitoring) or perception (e.g., focusing only on the development of UAV traffic management systems). Furthermore, studies strictly focused on localized structural infrastructure inspection (e.g., bridge crack detection or building material fatigue) were systematically excluded. While technically significant, these applications pertain primarily to structural engineering and defect monitoring, diverging from the holistic, human-centric environmental perception that this review targets. Upon completion of the initial labeling, ASReview generated a list of papers ranked by relevance from high to low, based on the inference of its trained Natural Language Processing (NLP) model. In step 3, we began at the top of this ranked list and manually screened the remaining unlabeled papers, adhering to the aforementioned threshold of stopping after 10 consecutive irrelevant articles. This step added 2 more papers, resulting in a total of 274 publications.

In the next phase, we utilized the state-of-the-art multimodal LLM (GPT-4o) for information extraction. To address the time-consuming nature of manual extraction, we adopted the approach based on LLMs to achieve semi-automation of the process (Ito et al., 2024). In step 4 of information extraction, we used the Scopus and Web of Science databases, iteratively refining the search query through their advanced search functions, and manually downloaded the filtered papers. Among the 274 publications, we successfully located the full text for 201 and used them for subsequent steps. Beginning with step 5, we utilized Python to extract text from the documents and subsequently formulated and transmitted prompts (steps 6 and 7).

The results from step 7 were initially retrieved and tabulated in step 8. These results were then consolidated into a single text document in step 9 to facilitate subsequent analysis and discussion. Only an initial pool of papers, a minimal amount of manual labeling, manual document downloading, and user-defined queries are needed for the approach outlined. The remaining processes can be automated to generate review content for different categories in a natural language format, thus achieving semi-automation from screening to reporting (Fig. 2).

We manually verified the precision of the GPT-4o model on a random sample of 20 papers (approximately 10% of the whole corpus) and proved its accuracy to be as high as 97.7%, commensurate with those reported in previous studies. Out of a total of 220 questions (11 questions per paper), the GPT-4o model provided 215 correct answers. The incorrect answers primarily stemmed from ambiguous expressions in the source texts. To ensure the reliability of the responses, we instructed the model to respond with ‘Not mentioned’ when pertinent information was absent, thereby preventing factual hallucination (Xia et al., 2025). Furthermore, we conducted additional cross-validation for some of the key low-frequency categories.

3.2. Indicators for literature comparison and statistical analysis

The data extraction process followed a standardized protocol to ensure that the information extracted from each publication was consistent and comparable. For the 201 studies included in the analysis, we designed a standardized analytical framework for data extraction. This framework is structured around four core thematic dimensions that systematically deconstruct each study (Fig. 3). Each dimension acts as a macro-level category that is further operationalized into specific, quantifiable indicators.

First, the dimension of perceived objects: This dimension focuses on the specific elements of the built environment being perceived and the spatial scope of the study. For example, it includes indicators for the built environment elements involved (e.g., greenery, water bodies, streets, and buildings), as well as broader elements like urban public spaces, community landscapes, and the city as a whole (e.g., the overall urban thermal environment). Additionally, the research scale (e.g., region, city, neighborhood, and building) is a key aspect considered in this study.

Second, the dimension of technical equipment: This dimension covers the hardware configuration of the UAV and the types of sensors used. It includes indicators for sensor types (e.g., RGB, LiDAR, multispectral, thermal infrared), UAV categories (e.g., multirotor, fixed-wing), and brands (e.g., DJI, Parrot).

Third, the dimension of data and analysis: This dimension pertains to the methods of data acquisition, analytical techniques, data availability, and multi-source data fusion. It covers indicators for analytical methods (e.g., image classification, semantic segmentation), data acquisition sources (e.g., self-collected, public data), data availability (unavailable, accessible via URL, available upon request), and data source types (single UAV data or multi-source fusion).

Fourth, the dimension of research types: This dimension defines the nature, type, and theoretical framework of the research. It includes indicators for the overall research type (qualitative, quantitative, mixed) and the detailed research type (e.g., exploratory analysis, model development).

All 11 indicators, including their detailed definitions and examples, are documented in Supplementary Material A. During the data extraction process, we employed this indicator framework to collect the data for each study, enabling a comprehensive coding and systematic comparison of the research. In the analysis phase, we conducted descriptive statistics and comparative assessments on the extracted data. First, we calculated the frequency distributions for all 11 indicators to delineate the dominant patterns, such as the most commonly used sensor types, the preferred research scales, and typical data sources. Subsequently, we performed cross-tabulation and contextual analysis to explore the relationships between different dimensions. For instance, we examined how sensor selection (e.g., LiDAR vs. thermal infrared) varies in countries. We also analyzed the relationship between data availability and analytical methods to identify bottlenecks concerning reproducibility. By identifying the co-occurrence patterns among the indicators, we pinpointed key research gaps.

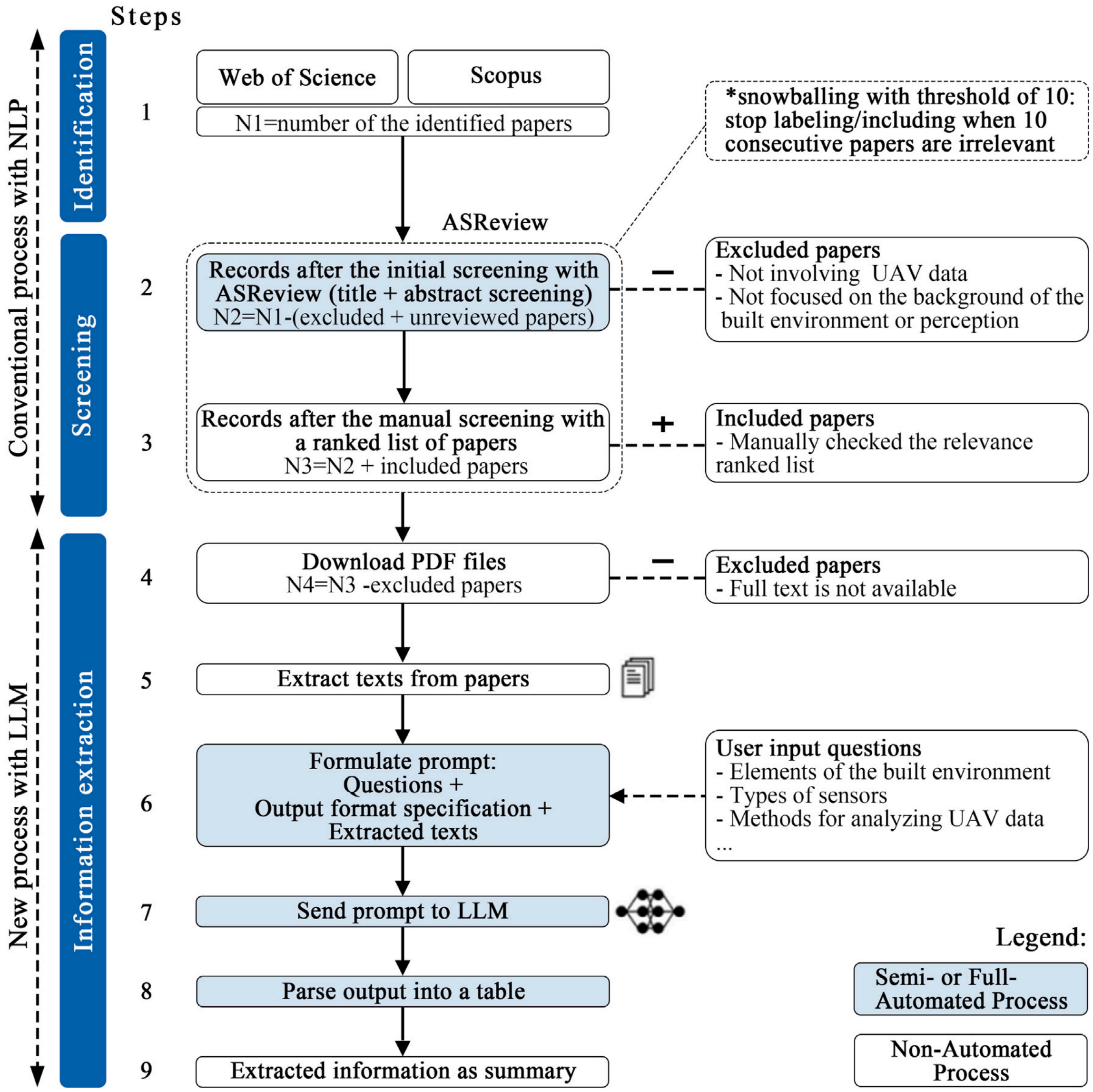


Fig. 2. Database retrieval and literature screening process.

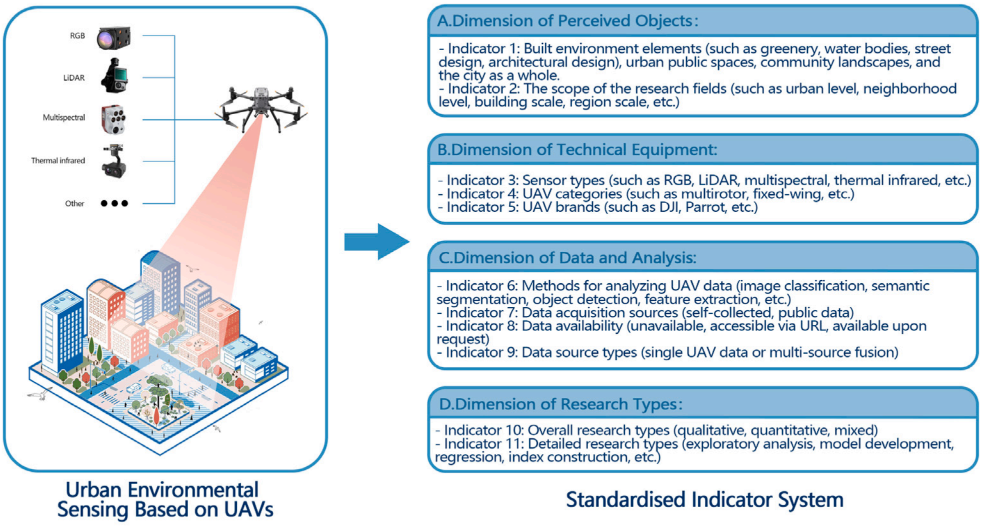


Fig. 3. Standardized index system for UAV-based urban environmental perception review.

3.3. UAV flight restriction policy extraction

In terms of policy review, we compared and analyzed the restrictive conditions for UAV flights imposed by the laws and regulations of multiple countries. The specific methodology for constructing our Global UAV Flight Altitude Restriction Dataset (detailed contents can be found in Supplementary Material B) involved three main steps:

(i) Data acquisition: We acquired official flight regulations published by national civil aviation authorities, such as the Federal Aviation Administration (FAA) in the United States, the European Union Aviation Safety Agency (EASA), and the Civil Aviation Administration of China (CAAC). (ii) Data extraction and integration: We combined these official regulations with flight restriction map layers downloaded from the DJI FlySafe platform (which currently covers around 20 countries) to obtain rules on UAV no-fly zones and altitude limits. Our research expanded upon this base dataset. (iii) Systematic compilation and georeferencing: We systematically compiled the maximum permissible flight altitudes, registration/licensing requirements, and flight zone restrictions for UAVs across 80 countries and regions. Crucially, we standardized this information and linked it to the corresponding national administrative boundaries, creating a georeferenced database of UAV flight policies.

This dataset provides the crucial empirical foundation for our subsequent analysis. As introduced in Section 1, understanding the role of these regulatory environments is central to our goal of deconstructing the factors that shape the landscape of UAV-based research. This dataset, therefore, lays a foundational basis for interpreting the spatial distribution disparities and geographical biases in built environment perception research under different regulatory environments.

4. Results

4.1. Geography, themes and spatial scales

Our systematic review reveals that the progress in UAV-based built environment perception research is characterized by distinct patterns in its geographical distribution, thematic focus, and scale selection.

First, geographically, research activities are highly concentrated (Fig. 4A). A significant portion of studies originates from East Asia (n = 98) and Southern Europe (n = 22), forming the core knowledge production zones (Shou et al., 2024; Xu et al., 2020; Cappellazzo et al., 2023). In contrast, vast regions such as South America (n = 3), Africa (n = 2), and Oceania (n = 1) have received considerably less attention (Henn and Peduzzi, 2024; Benmhahe et al., 2024; Wagner and Egerer, 2022). Furthermore, analysis of author affiliations and study locations (Fig. 5A) reveals a strong tendency for researchers to focus on their own national contexts. This is particularly evident for scholars from China (77 publications) (Xin et al., 2021; Xiao et al., 2022; Luo et al., 2025c) and South Korea (16 publications) (Jo and Park, 2025; Kim et al., 2021), where research is almost exclusively conducted domestically.

Second, the research agenda demonstrates a strong thematic focus on a few key elements (Fig. 4C). Our analysis shows that greenery and water bodies are the most studied category (n = 89) (Yang et al., 2022; Wei et al., 2019; Tepanosyan et al., 2021), followed by building design (n = 46) (Kushwaha et al., 2019; Treccani and Adami, 2023), the city as a whole (n = 37) (Chen et al., 2022; Hernández-Vega et al., 2018), and street design (n = 29) (Kushwaha et al., 2022). The prominence of these themes is driven by multiple factors. First, they hold recognized importance in issues such as urban ecology, sustainable development, and public health, making them more likely to receive policy and financial support (Bungau et al., 2022; Addas, 2023; Zhang and Qian, 2024). Second, and more critically, these elements possess a high degree of quantifiability. Metrics such as the coverage rate of vegetation, the volume of buildings, and the geometric forms of streets align well with the data types provided by mainstream sensors like RGB cameras, alongside important advanced sensors such as LiDAR (Luo et al., 2024; Gupta et al., 2024). This coupling of thematic importance and technical feasibility has created a strong reinforcing effect, concentrating research interest in these areas. Concurrently, there is a clear lack of research on elements of the built environment that embody complex social and experiential values. The categories of landscape (n = 7) and public space (n = 2) occupy a minuscule proportion of the literature (Elsadek et al., 2024; Vollmer et al., 2023).

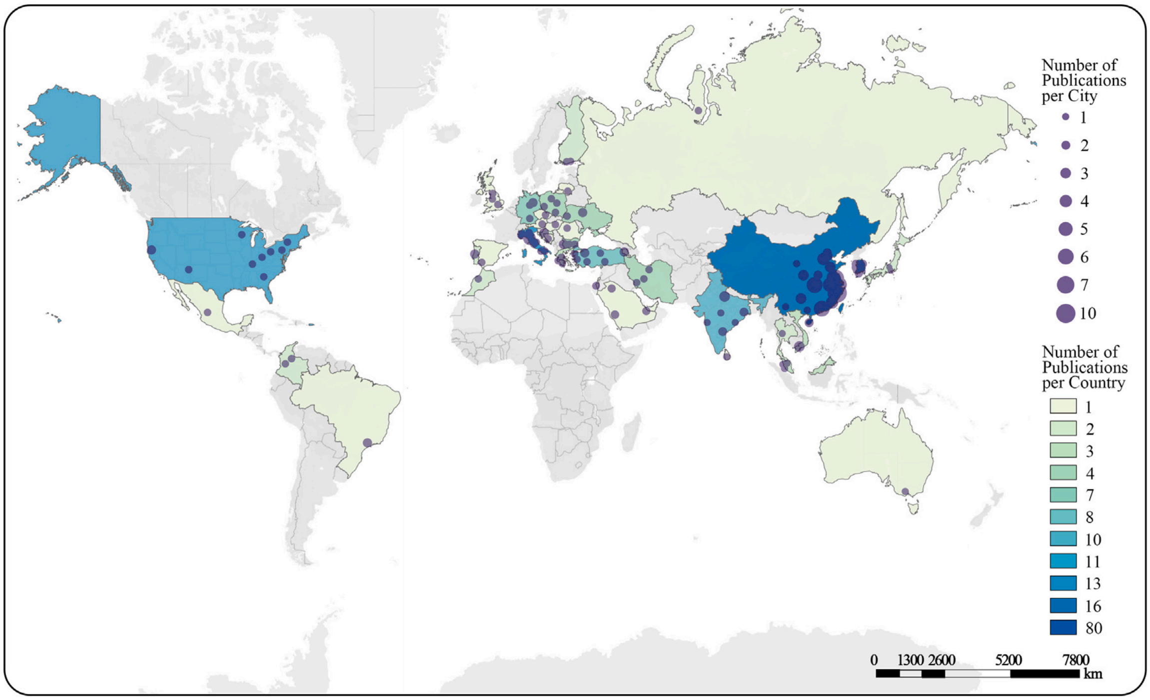
As shown in Fig. 4B, the number of publications in this area has grown exponentially since 2020. However, an analysis combined with Fig. 5B (the thematic evolution heat map) reveals that this growth is primarily driven by research on dominant themes such as ‘greenery and water’ (Y. Li et al., 2025; H. Li et al., 2025) and ‘building design’ (Li and Wu, 2024; Nagy et al., 2024). Emerging research on ‘landscape’ and ‘public space’ (Elsadek et al., 2024; Vollmer et al., 2023), which represent the cognitive frontiers of the field, has not experienced corresponding growth alongside the field’s expansion.

Finally, in terms of the spatial scale, approximately 62% of the research focuses on the city level (Guo et al., 2024; Chen et al., 2022; Zeng et al., 2024), followed by the neighborhood level at about 30% (Kaya and Erener, 2024; Järvi et al., 2023). While this meso-scale focus has direct practical value for urban planning, it also relatively neglects the synergistic effects at the more macro regional scale (3%) (H. Li et al., 2025) and the human-centric experience at the more micro building scale (5%) (Kushwaha et al., 2019).

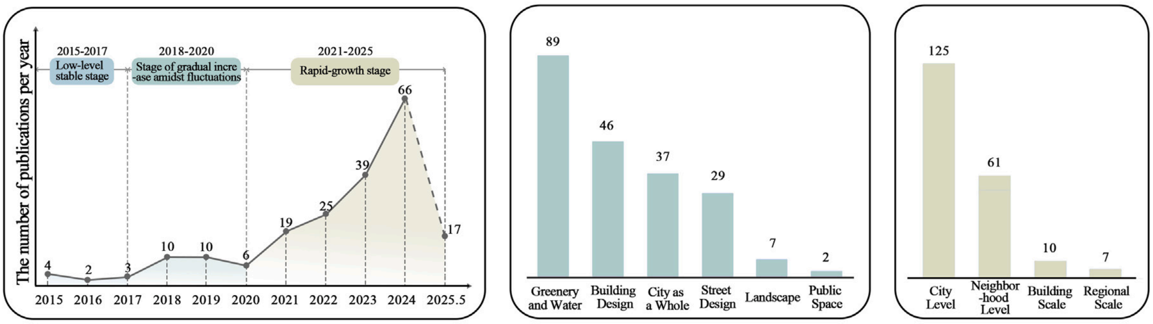
4.2. UAV and sensor selection

The progress in UAV-based built environment perception is clearly demonstrated by the widespread adoption of specific hardware, resulting in a landscape dominated by a few key platforms and sensors. At the UAV platform level, multirotor UAVs (n = 181) hold an absolutely dominant position (Fig. 6A), primarily attributable to their operational flexibility, hovering capabilities, and their capacity to perform high-precision data acquisition tasks in complex environments (Jarzabek-Rychard and Karpina, 2016; Chen et al., 2023; Lin et al., 2023). Furthermore, compared to fixed-wing UAVs, multirotor platforms have lower requirements for take-off and landing space and possess greater environmental adaptability, thus securing their leading role in built environment perception research (Zhang and Zhu, 2023). In contrast, fixed-wing UAVs appeared in only 13 studies (Dimitrov et al., 2024; Shao et al., 2021). Research by Lim et al. (2024) indicates that this type of UAV is limited in its application scenarios due to higher take-off and landing space requirements and relatively insufficient maneuverability in low-altitude, fine-grained monitoring scenarios. Additionally, 8 papers did not specify the type of UAV used (Suleymanoglu et al., 2023; Daranagama and Witayangkurn, 2021), and 2 studies employed a ‘fixed-wing + multirotor’ hybrid platform (Zhou et al., 2021). Through this combined platform, they achieved a synergistic operation of rapid coverage by fixed-wing and flexible supplementary surveying by multirotor in large-area, high-climatic-complexity scenarios, ultimately satisfying the practical requirements for the topographical attributes and mathematical precision of the 3D models (Avena et al., 2021).

The choice of UAV brand is also noteworthy. Among the many brands, products from DJI (n = 122) are widely used (Fig. 6B), mainly owing to their mature technology, stable performance, diverse product range, and user-friendly operation (B. Zhao et al., 2024; Y. Zhao et al., 2024; Adami et al., 2023). Moreover, DJI’s high cost-effectiveness and market share in fields such as aerial photography, surveying, and environmental monitoring have made it the preferred choice for researchers. In comparison, the usage frequency of UAVs from brands like SenseFly, Parrot, Tarot, and AgEagle is lower (Dimitrov et al., 2021; Kaya and Erener, 2024; Dimitrov et al., 2024) . This dominant pattern of ‘multirotor platform + DJI brand’ reveals that the vast majority of research is conducted within a highly standardized hardware ecosystem.



A.Geographic areas covered in the 201 publications

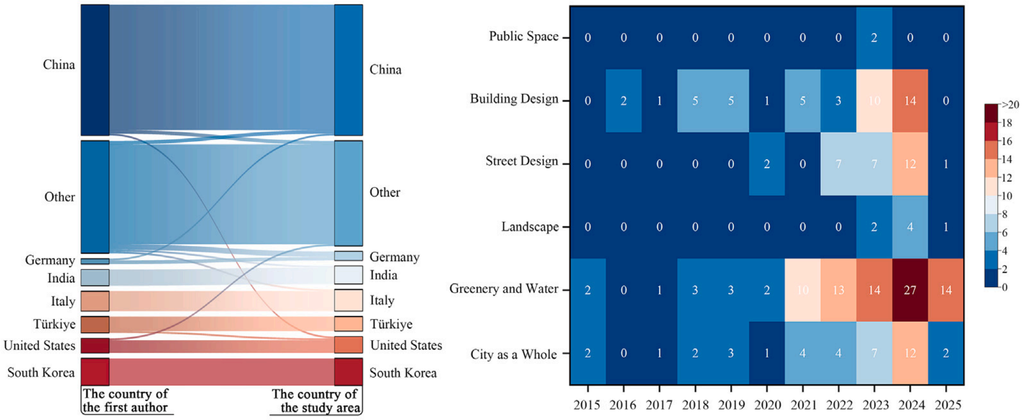


B.Publication years

C.Elements of the built environment

D.Scope of research fields

Fig. 4. Overview of the selected studies. (A) Geographic regions covered by the selected studies, (B) publication years of these papers, (C) elements of the built environment, and (D) scope of research fields.



	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Public Space	0	0	0	0	0	0	0	0	2	0	0
Building Design	0	2	1	5	5	1	5	3	10	14	0
Street Design	0	0	0	0	0	2	0	7	7	12	1
Landscape	0	0	0	0	0	0	0	0	2	4	1
Greenery and Water	2	0	1	3	3	2	10	13	14	27	14
City as a Whole	2	0	1	2	3	1	4	4	7	12	2

(A) (B)

Fig. 5. Analysis of geographical distribution and thematic focus of studies. (A) Relationship between the first author's country affiliation and the geographical location of the study area, (B) temporal evolution and thematic trends in UAV-based built environment research publications.

It is important to note that 57 papers did not specify the UAV brand used (Candan and Kaçar, 2023; Hollósi et al., 2024). This reflects that some research focuses more on data acquisition methods and analytical techniques rather than the equipment itself; it also suggests that the standardization of data sharing and experimental reporting still has room for improvement, as the lack of detailed brand information poses a challenge to research reproducibility.

The type of sensor is crucial for UAV data acquisition, as it directly influences the data's precision, resolution, and suitability for various application scenarios. Various sensors, such as RGB cameras, multispectral sensors, thermal infrared sensors, and LiDAR, can capture information in different dimensions, hence expanding the applicability of UAVs in built environment analysis (Zhang and Zhu, 2023). Among these, the usage frequency of RGB sensors (n = 109) far exceeds that of other types (Fig. 6C). Their low cost, high spatial resolution, and the intuitive nature of the data they produce have made them the preferred tool for entry into this field (Xia et al., 2023; Shao et al., 2021). However, this over-reliance on RGB sensors has profoundly shaped the way researchers 'see' the city, prioritizing the definition of perception problems as issues within the visible light spectrum, such as morphological recognition, color analysis, and texture extraction (Luo et al., 2022b). In contrast, the usage frequency of sensors capable of capturing non-visible light information, such as multispectral (n = 44), thermal infrared (n = 43), and LiDAR (n = 40), is lower. This is primarily because these sensors have higher costs and greater data processing complexity, and they are often used for specific scenarios like thermal environment monitoring, 3D modeling, and vegetation health assessment (Xiao et al., 2022; Feng et al., 2022). Additionally, 28 studies mentioned other types of sensors, such as the TSI SIDEPAK AM510 particulate matter monitor, the ENEA MONICA sensor, and the OPC-N3 sensor, which are mainly used for air quality monitoring, further expanding the scope of UAV applications in built environment perception (C. Li et al., 2022; Dubey et al., 2022).

In conclusion, the 'standardized toolkit' composed of multirotor platforms, DJI-branded products, and RGB sensors, has become a cornerstone of research practice. The emergence of this toolkit signifies a clear technological convergence within the field. The following section will further explore how this convergence manifests in the specific application pathways chosen by researchers.

4.3. The coupling relationship between technology selection and application domains

The convergence of technological paths is further manifested in the strong coupling relationship formed between UAV types, sensor selections, and specific application domains (Fig. 7). This has led to the formation of several well-established and efficient application pathways, which represent a key aspect of the field's progress. Our analysis reveals several dominant patterns.

First, RGB sensors are widely used across multiple functions. As general-purpose sensors, RGB cameras are frequently coupled with multirotor UAVs, becoming a core tool, especially in the ecological monitoring of vegetation and green–blue spaces and in urban 3D modeling (Li et al., 2023). This reinforces the aforementioned 'visible spectrum preference,' causing the understanding of green spaces to be largely focused on visual presentation, and the analysis of urban morphology to be centered on its geometry and texture.

Second, thermal infrared sensors show a high degree of specialization. These sensors almost exclusively serve the monitoring of 3D urban thermal environments and general UHI effects (Xu et al., 2021; Song and Park, 2020). This high degree of specialization makes them a key technology in this subfield, but it also results in their infrequent use for exploring the cross-cutting impacts between the thermal environment and other built environment elements, such as social activities or building energy consumption.

Third, LiDAR sensors are primarily coupled with structural and geometric analysis. UAV LiDAR technology is highly bound to urban 3D modeling and spatial information extraction (Grasso et al., 2023; Koszyk et al., 2024). Its advantage lies in precisely capturing the geometric structure of urban space, making it indispensable for research on street canyon morphology, building volume analysis, and similar topics.

Fourth, multispectral sensors are strongly associated with ecological applications. These sensors are primarily associated with vegetation ecological monitoring and LULC classification (R. Li et al., 2025; Gupta et al., 2024). Their application paradigm largely draws from agricultural and ecological remote sensing, excelling at assessing vegetation health through vegetation indices (e.g., NDVI).

In summary, these stable coupling relationships provide an efficient 'technical toolchain' for solving specific problems, reflecting a high degree of technological standardization in current research practices. At the same time, this high degree of specialization presents a challenge for fostering innovative, cross-sensor fusion research aimed at investigating the complex interactions between different elements of the built environment (Nagy et al., 2024; H. Wang et al., 2023).

4.4. Data acquisition and availability

Our analysis of the reviewed literature reveals distinct patterns in how data is acquired and shared within the field of UAV-based built environment perception. These practices can be characterized by three key findings regarding data sources, availability, and integration.

First, concerning the origin of data sources, our results show a strong prevalence of project-specific data collection. A staggering 91% of the analyzed studies (n = 182) relied on self-collected datasets, which were typically gathered for the specific purposes of the research project. In contrast, only a small fraction of studies (9%, n = 19) utilized publicly available datasets that were sourced from external repositories (Majidizadeh et al., 2024; Feng and Yi, 2022). This indicates that the predominant portion of research in this field is conducted using privately curated data.

Second, we assessed the data availability status as reported in the publications. This analysis serves as a direct measure of the accessibility of research data to the wider scientific community. We found that for more than two-thirds of the studies (n = 145), the data was not made accessible. Only a minority of papers provided a direct download link via a URL (n = 30) or stated that the data was available upon reasonable request (n = 26) (Maiti et al., 2023; Wagner and Egerer, 2022).

Third, in terms of data source integration, we examined whether studies relied solely on UAV-derived data or fused it with other data types. Our findings indicate that 70% of the papers employed a single UAV data source, primarily using information acquired directly by sensors onboard the UAV (e.g., RGB or thermal cameras). The remaining 30% adopted a multi-source data fusion strategy. The most common approaches involved integrating UAV data with satellite remote sensing imagery (e.g., Landsat, Sentinel-2), street-level imagery (e.g., Google Street View), or ground-based monitoring data from fixed or mobile sensors (Zhao et al., 2022; Luo et al., 2022b; Xu et al., 2023a; Li and Chang, 2019).

4.5. Dominant analytical techniques and methodological convergence

At the data analysis level, the field exhibits a highly concentrated methodological framework centered on computer vision. Its primary objective is to transform UAV-acquired visual data into structured, quantitative information through automated or semi-automated workflows.

Feature extraction is the most fundamental and widely used method among the employed analytical methods. It refers to the computational process of isolating and quantifying specific visual, spectral, or geometric attributes — such as image color, texture, structural volume, and morphology — from high-resolution raw UAV data, including

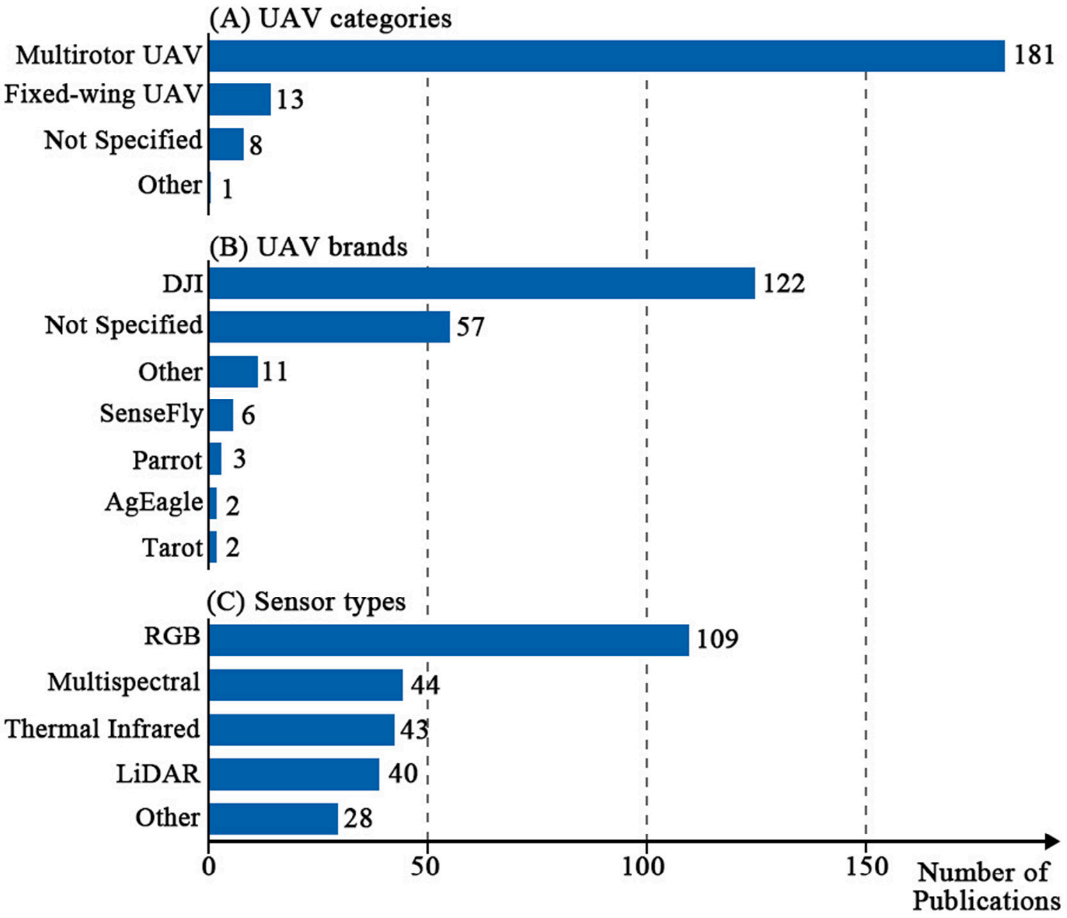


Fig. 6. Frequency distribution of dominant hardware selections in the reviewed literature. The figure shows the number of publications for (A) UAV categories, (B) UAV brands, and (C) sensor types.

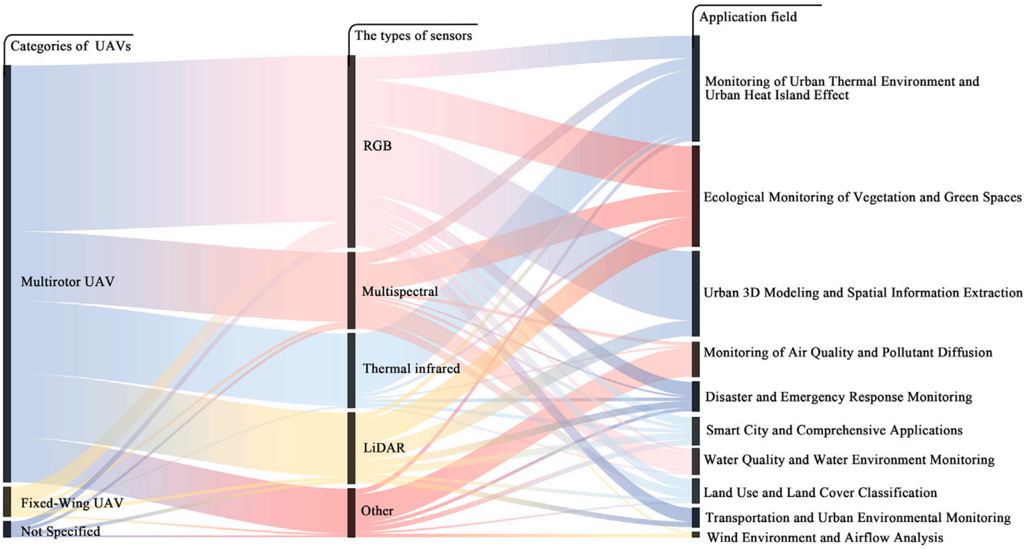


Fig. 7. The relationship between UAV platform types, onboard sensors, and application domains.

imagery and 3D point clouds. The high usage rate of this method (approximately 72.6%) stems from its efficiency in processing complex, high-dimensional UAV data and its effectiveness in capturing key environmental information (La Salandra et al., 2023). For example, Xia et al. (2023) utilized feature extraction algorithms to obtain information such as green volume, image color, and structural features. The study by Li and Wu (2024) employed color feature extraction and statistical analysis to examine building facades and roof colors.

Image feature extraction algorithms also serve as the foundation for subsequent tasks like image classification and semantic segmentation.

Machine learning techniques, particularly deep learning, such as image classification and semantic segmentation, represent more advanced analytical capabilities within this method. According to our analysis, 33 papers (16.4%) used image classification techniques (Sailaja et al., 2024), and 22 papers (10.9%) employed semantic segmentation (Shou et al., 2024; Han et al., 2023). For instance, R. Li et al. (2025) used multispectral image classification to analyze the distribution and status of urban green space. Luo et al. (2022b) utilized computer vision techniques to perform semantic segmentation on UAV panoramic images for the identification and quantification of various landscape elements. However, the practical accuracy and robustness of these advanced deep learning algorithms are highly vulnerable to complex urban anomalies (e.g., severe optical reflections from glass facades, occlusions) and adverse weather conditions.

The cumulative effect of these technical preferences is the establishment of a highly dominant quantitative research orientation. A striking 89% of the reviewed publications employed purely quantitative methods (Cho et al., 2024; Xu et al., 2023a; Kim et al., 2021), while mixed-methods research integrating qualitative insights accounted for only 11% (Elsadek et al., 2024)(Fig. 8). This stark disparity clearly reveals the epistemological inclination of the field.

Within this dominant orientation, quantitative research is characterized by its reliance on a specific set of computational and statistical tools. It primarily employs statistical modeling, machine learning algorithms (e.g., Random Forest, Support Vector Machines, Convolutional Neural Networks) (Zhou et al., 2025; Modiri et al., 2015), and spatial data processing techniques (e.g., semantic segmentation, image feature extraction, multi-source data fusion) (Han et al., 2023; Chen et al., 2024b) to precisely analyze key elements of the built environment. For example, the study by Zhao et al. (2018) employed a Convolutional Neural Network on UAV-acquired ultra-high-resolution infrared and optical images, achieving active localization and recognition of environmental anomalies. Additionally, some studies combine UAV LiDAR point clouds with image classification algorithms to reconstruct 3D urban spatial structures, thereby quantifying indicators such as the street green view index and building morphology (Luo et al., 2025a; Zhang et al., 2024). The common characteristic of these methods is their emphasis on data-driven, high-precision quantification, relying on automated workflows for spatiotemporal modeling and scene-level analysis. Furthermore, 22 studies (11%) utilized a mixed-methods approach, integrating quantitative and qualitative research (Tepanosyan et al., 2021). In these cases, qualitative analysis primarily depended on policy and regulatory discussions and spatial semantic analysis. For instance, Shou et al. (2024) combined semantic segmentation with immersive VR subjective evaluations to quantify the correlation between the visual characteristics of urban rivers and the perceptions of young people. The research by Khalaim et al. (2021) focused on the constraints of urban green space planning policies under extreme high temperatures, revealing the compatibility between UAV thermal imaging data and the needs of urban microclimate governance.

A more detailed categorization based on research objectives further reveals how these quantitative techniques are applied. Our analysis shows that model development is the most common activity, found in 67% of all studies (n = 135) (Corzo Perez et al., 2024; Preethi Latha et al., 2019; Xiao et al., 2022). With its broad coverage and diverse technical pathways, it has become the core driving force for the field's advancement, with models frequently being used for tasks such as environmental assessment, spatial feature extraction, and prediction (Feng et al., 2022). Secondly, exploratory analysis (24%) also holds a significant position (B. Li et al., 2022; Son and Kim, 2025). As a preliminary analytical approach conducted without predefined hypotheses, it employs visualization and statistical techniques to identify underlying data structures and inter-variable relationships. In UAV-based studies, it is frequently utilized for pattern recognition and phenomenon exploration, with the objective of uncovering latent statistical patterns and correlations, thereby providing a theoretical foundation for subsequent modeling efforts. Meanwhile, index construction (8%) (Strashok et al., 2022) and regression analysis (9%) (Song and Park, 2020) further reinforce this method's tendency to simplify complex urban phenomena into operationalizable indicators and statistical relationships.

4.6. Institutional and regulatory constraints

Research on UAV-based built environment perception is profoundly shaped by a complex and imbalanced global regulatory framework (Bauranov and Rakas, 2021). These regulations are not neutral parameters but act as a significant external factor influencing research design and feasibility. Our analysis of flight policies across 80 countries/regions reveals two key characteristics: a convergent 'low-altitude consensus' and a pronounced regional differentiation.

A dominant feature of global UAV regulation is a widespread consensus on low-altitude flight limits. As shown in Fig. 9, a significant number of countries (40 out of 80), including major research producers like China, the United States, and key EU member states, restrict the maximum flight altitude for UAVs to 120 m (approximately 400 ft). This ceiling is generally rooted in aviation safety management rather than specific research needs. However, it has a direct consequence for scientific inquiry: it effectively confines the vast majority of UAV-based perception research to the urban canopy level. This systematically limits the potential for studies focusing on high-rise building facades, the vertical ecology of urban canyons, and other macroscopic 3D urban forms (Ali, 2019). While some jurisdictions permit applications for higher altitude flights, the approval process is often reported as cumbersome and time-consuming, thereby reducing research efficiency (Luo et al., 2022b).

Beyond this general consensus, significant policy differentiation across regions further creates an uneven landscape for research opportunities. On one hand, a few countries, such as South Korea, Japan, and Colombia, offer a more permissive airspace (150–152 m), providing greater flexibility for studies that require a broader vertical scope. On the other hand, highly restrictive regulations in certain regions create significant operational obstacles. For instance, the extremely low altitude limits in Iran and Singapore (30–60 m), alongside complete flight bans in countries like Morocco, severely hinder or entirely prevent UAV perception research. These disparities, often linked to national security concerns, airspace management priorities, or urban density, constitute a critical variable that impacts the geographical distribution and scope of research. A detailed compilation of the UAV flight policies can be found in Supplementary Material B.

5. Discussion

The preceding analysis in the Results section has systematically mapped the dominant patterns in UAV-based built environment perception. A central finding emerging from these results is a pronounced convergence across multiple facets of research practice. Rather than a field characterized by diverse and varied approaches, our synthesis reveals that a well-defined and highly concentrated set of methodological choices dominates.

Fig. 10 provides an integrated visualization of this landscape of convergence. The Sankey diagram illustrates the dominant research pathway, visually confirming the strong correlations between self-collected data, a focus on physical elements, the use of mainstream sensors, and a concentration in specific geographical regions.

However, we must critically reassess the nature of this observed convergence. While it might be tempting to view the overwhelming dominance of specific hardware (e.g., DJI multirotors and RGB sensors) as a sign of methodological maturity, it is fundamentally an artifact

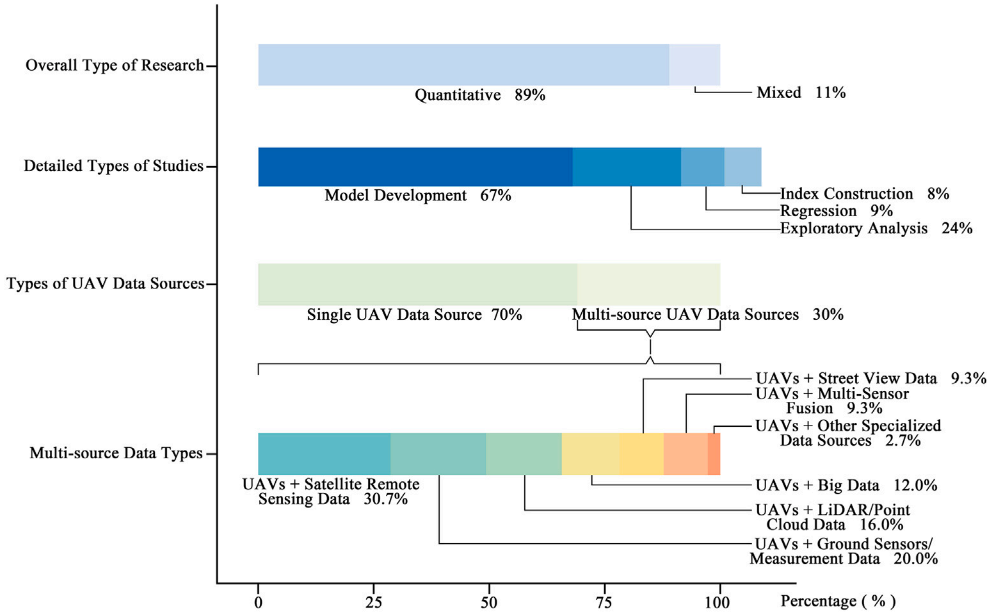


Fig. 8. Dominant analytical techniques and methodological convergence.

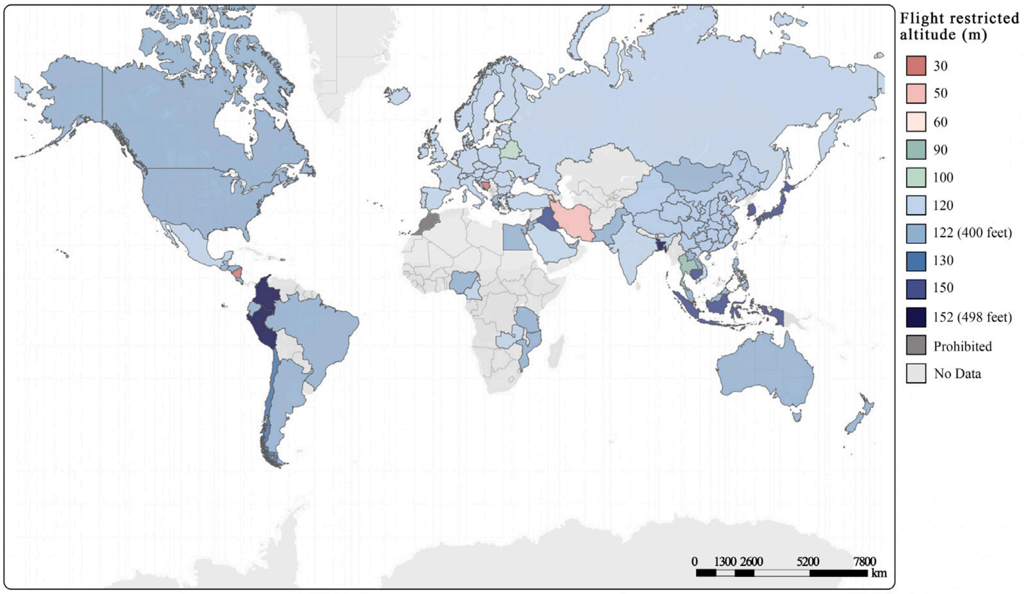


Fig. 9. Global map of UAV flight altitude limits across 80 countries/regions (Taking Mini and Micro UAVs as examples, the flight conditions of other types of UAVs may vary according to civil aviation regulations).

of external constraints. As our analysis suggests, this hardware convergence is heavily driven by limited research budgets, vendor lock-in by market leaders, and regional supply chain accessibility, rather than pure scientific optimization. Furthermore, we must reflexively acknowledge a parallel paradox within our own review methodology. Just as market forces drive hardware homogenization in primary research, the use of highly standardized protocols (PRISMA) and LLMs for literature synthesis carries the inherent risk of driving methodological homogenization at the meta-level. LLMs naturally favor structured, quantifiable data extraction, potentially filtering out nuanced qualitative insights or non-standard theories. Therefore, whether choosing a UAV sensor or a literature synthesis tool, the field must remain critically aware of how accessible and standardized tools implicitly shape and constrain the boundaries of scientific inquiry.

Consequently, while this standardized approach has undoubtedly contributed to the field's rapid progress and efficiency, this multi-layered convergence also gives rise to several significant methodological and theoretical challenges. These challenges have profound implications for the scientific rigor, validity, and overall trajectory of the field. The remainder of this section will synthesize these findings to diagnose and discuss three key challenges that stem directly from this observed convergence: a crisis in reproducibility, limitations on model generalizability, and a constrained scope of scientific inquiry.

5.1. Key challenges for the field

5.1.1. The reproducibility crisis: a challenge of the closed data ecosystem

The most immediate challenge stemming from the methodological convergence is a critical threat to scientific reproducibility, rooted in

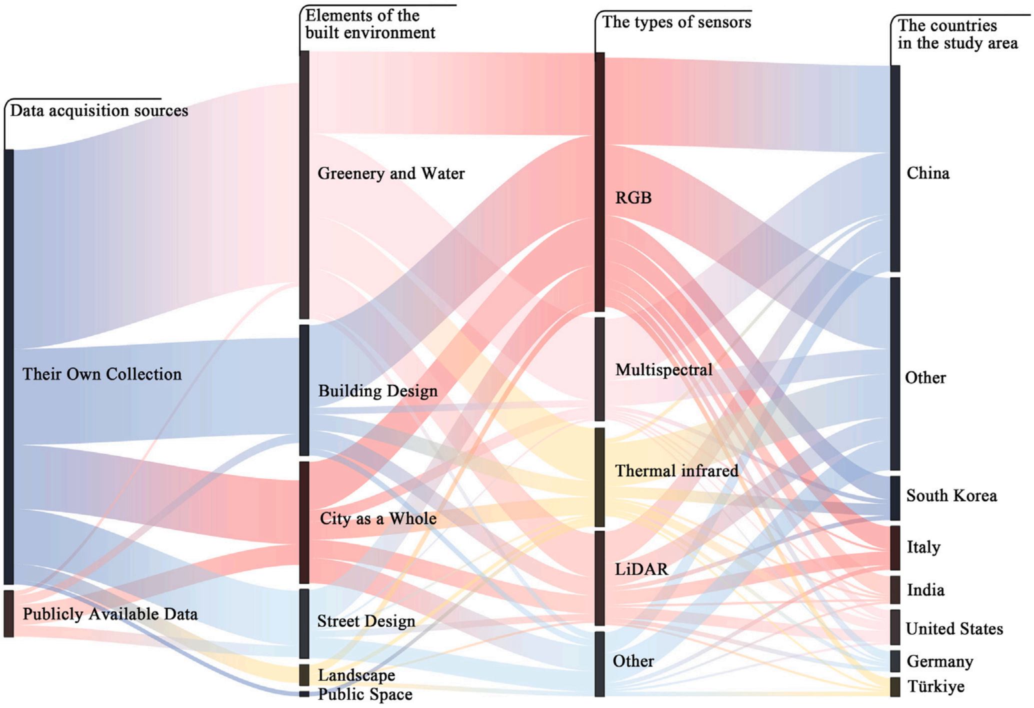


Fig. 10. Visualization of the convergence in geography, technology, and methodology in built environment perception. The diagram reveals the dominant research pathway, showing strong correlations between self-collected data, a focus on physical elements, the use of mainstream sensors, and geographical concentration.

what our findings reveal to be a closed data ecosystem. The overwhelming reliance on non-public datasets, as observed in 91% of the reviewed studies, profoundly undermines the transparency, comparability, and cumulative nature of knowledge in this domain. While collecting project-specific datasets is often a practical necessity for novel research, the value of these datasets to the broader scientific community is severely diminished when the resulting datasets remain inaccessible (Luo et al., 2022b; Cheng et al., 2024).

This lack of data sharing creates a cascade of negative consequences for the field. First, it erects significant barriers to entry. The high costs of specialized UAV equipment and the steep technical threshold for data collection can skew research opportunities toward well-resourced institutions and regions, a factor that likely contributes to the geographical imbalances identified in our results. Second, and more critically, the absence of widely adopted public benchmark datasets creates a severe bottleneck for methodological advancement. Unlike in the street-view research domain, where datasets like Cityscapes have catalyzed progress by providing a common ground for evaluation (Cordts et al., 2016), the UAV field lacks a similar standard. This makes it nearly impossible to conduct fair and rigorous comparisons of new algorithms and models, hindering the objective assessment of methodological merits across studies (Biljecki and Ito, 2021; Ito et al., 2024).

The pervasive inaccessibility of data, with over two-thirds of publications not providing access to their datasets, directly obstructs the core scientific principle of verification. This practice prevents the independent replication of findings, a cornerstone of scientific rigor. It also suppresses the potential for secondary analysis, where existing data could be re-purposed to answer new research questions at a fraction of the cost. Ultimately, this closed ecosystem fosters a culture of non-cumulative science, leading to a proliferation of isolated, 'one-off' studies that, while individually valuable, contribute little to building a shared, robust, and verifiable body of knowledge.

5.1.2. The generalizability challenge: a geographically and technologically biased knowledge base

Beyond reproducibility, the pronounced convergence on specific geographical contexts and a standardized technological toolkit poses a second fundamental challenge: it raises concerns about the generalizability of current models and fosters the creation of a potentially biased global knowledge base. This issue is not merely theoretical; it is a direct consequence of the structural patterns revealed in our analysis. The bivariate map in Fig. 11A provides a stark visualization of this pronounced spatial imbalance, illustrating the interplay between research intensity (quantified by the absolute count of study areas to identify global hubs of knowledge production) and regulatory environments across 80 countries/regions.

The map clearly reveals a distinct spatial pattern that concentrates research activities in the Global North. Regions characterized by high research intensity and permissive, standardized flight policies — represented by the deep purple hues covering China, the United States, and parts of Europe — form the de facto core production zones of knowledge in this field. Consequently, algorithms are developed, trained, and validated almost exclusively on data captured in these specific contexts, using a remarkably uniform set of hardware (i.e., multirotor UAVs with RGB sensors). Our global understanding of UAV-based perception is thus being constructed upon a narrow and geographically concentrated evidence base, shaped by a specific technological paradigm.

The scatter plot (Fig. 11B) further illuminates the complex, nonlinear nature of this relationship. While a simple linear correlation is not evident, the plot reveals a distinct 'permissive threshold' effect. Significant research activity is almost exclusively concentrated in countries where the flight altitude limit is 120 m or higher. Below this threshold, research is sparse to non-existent, suggesting that restrictive regulations act as a powerful gatekeeper, effectively filtering out opportunities for scientific inquiry. Furthermore, the plot highlights that permissive regulation is a necessary, but not sufficient, condition for a thriving research ecosystem. Importantly, this bivariate mapping does not imply direct regulatory causation. A large number of countries with permissive policies (120–150 m) still exhibit low research output, indicating that the observed 'permissive threshold' effect strongly coincides with other variables. Specifically, factors such as robust scientific funding, a strong tech industry presence, and the demands of rapid urbanization act as the underlying critical drivers.

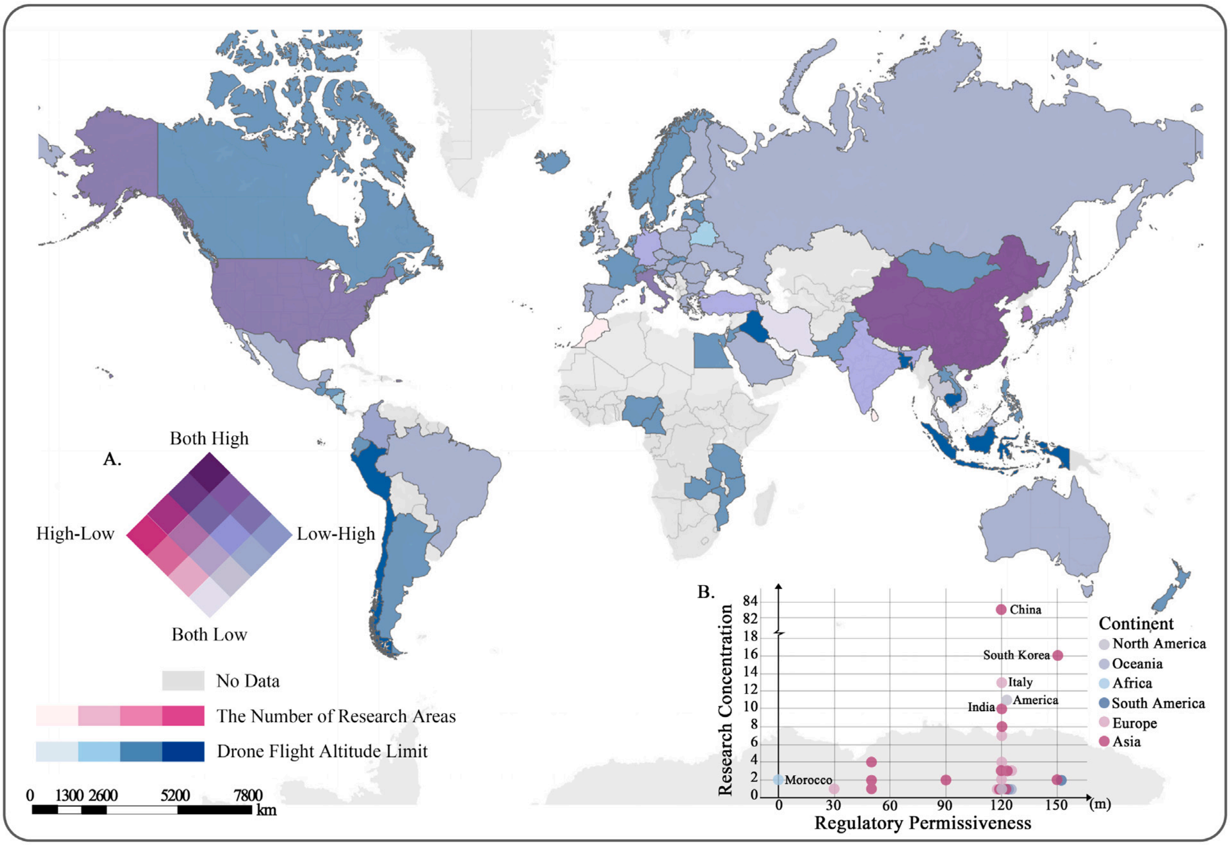


Fig. 11. The relationship between research concentration and regulatory environments, visualized through (A) a bivariate map and (B) a scatter plot. The map (A) reveals the spatial pattern of this relationship, highlighting a concentration of research (indicated by pink hues) and permissive policies (blue hues) in the Global North, resulting in purple clusters of high activity. The scatter plot (B) further clarifies the statistical nature of this relationship, showing a 'permissive threshold' effect where significant research concentration occurs almost exclusively in countries with flight altitude limits of 120 m or higher. Each point represents a country, colored by continent.

The confluence of these geographical, technological, and regulatory patterns creates a critical, unaddressed problem of generalizability. The ability of models trained in these 'core' research zones to perform reliably in unseen environments, particularly in the vastly different urban morphologies of the Global South, remains highly uncertain. As Fig. 11 highlights, vast regions of Africa, South America, and parts of Asia are characterized by a dual challenge: low research activity often compounded by more restrictive or less defined flight policies. Uncritically applying models developed in high-income, formally planned cities to the often informal, organically developed, and structurally different urban landscapes of these 'peripheral' regions is fraught with risk. It could not only lead to poor model performance and inaccurate environmental assessments but may also result in ineffective or even detrimental planning interventions based on flawed, biased assumptions.

5.1.3. The scope limitation: a constrained understanding of 'perception'

Finally, the methodological convergence on a quantitative, computer vision-centric framework presents a more subtle yet equally profound challenge: it constrains the scope of scientific inquiry and fosters a narrow, techno-centric understanding of 'perception' itself. Our findings indicate that the field is overwhelmingly dominated by quantitative approaches that prioritize problems readily solvable by existing computational techniques. This creates a powerful selection bias, where the research questions being asked are often shaped more by the available tools than by the multifaceted nature of the urban environment.

This technological path dependency leads to the systematic neglect of built environment dimensions that are crucial for a holistic understanding but are harder to quantify through automated visual analysis. Phenomena such as the experiential qualities of a public space, the nuances of social interaction, and the impact of non-visual sensory inputs — like the soundscape of a street or the olfactory environment of a park — remain largely outside the purview of current mainstream research. While the geometric and spectral properties of a city are undoubtedly important, a research paradigm that focuses almost exclusively on them risks equating what is technologically measurable with what is scientifically important.

By defining 'perception' primarily as a task of machine-based object detection, classification, and segmentation, the field inadvertently sidelines the rich body of knowledge from disciplines like urban sociology, environmental psychology, and human geography that study human perception. This limits the potential for truly interdisciplinary research and risks producing a partial, disembodied understanding of the built environment. Ultimately, this constrained scope poses a long-term challenge to the holistic advancement of urban science, as it hinders our ability to ask more complex questions about how people truly experience, interpret, and are affected by the cities they inhabit (Taherdoost, 2022).

5.2. Future research agenda

Based on the diagnosis of the key challenges facing the field, we propose a forward-looking research agenda structured around four interconnected priorities. This agenda aims to steer the field toward a more robust, reproducible, and equitable future by directly addressing the issues of openness, generalizability, and scope.

5.2.1. Fostering open science and enhancing reproducibility

A top priority must be to counteract the closed data ecosystem and enhance reproducibility. This requires a collective cultural shift toward open science, focused on two key actions. First is the development of large-scale, high-quality public benchmark datasets for various built environment perception tasks. Such datasets would not only enable the fair and rigorous comparison of algorithms, lowering the barrier to entry for researchers with limited resources, but would also serve as a common ground for methodological innovation (Elamin and El-Rabbany, 2022; Luo et al., 2022b). Second, a stronger commitment to promoting data and code sharing is essential. Journals, funders, and academic institutions should increasingly incentivize or mandate the sharing of data and analysis code alongside publications, thereby fostering a more transparent and verifiable research ecosystem (Alsamhi et al., 2021).

5.2.2. Diversifying technologies to enhance generalizability

To break the current path dependency on a ‘standardized toolkit’ and address the challenge of generalizability, future research should actively pursue technological diversification. This includes fostering collaboration to develop and validate low-cost, open-source sensor solutions (e.g., for multispectral or thermal imaging) and integrating them with open-source UAV platforms. Such efforts are a technical prerequisite for democratizing research opportunities, particularly in the understudied contexts of the Global South (Park et al., 2020; Zhang et al., 2024). Concurrently, there is a critical need to move beyond single-modality analysis and develop novel algorithms for effective multi-modal data fusion. Integrating UAV data with other sources, from satellite imagery and street-level views to ground-based IoT sensors, is essential for building a more holistic and robust understanding of complex urban systems (Mwangangi et al., 2022; L. Wang et al., 2023).

5.2.3. Expanding methodological horizons for a broader scope of inquiry

To overcome the constrained scope of scientific inquiry, the field must actively expand its methodological horizons beyond its current quantitative, vision-centric focus. A crucial step is the integration of qualitative and experiential data. This could involve innovative mixed-methods approaches, such as using UAV imagery as a visual prompt in photo-elicitation interviews to explore residents’ sense of place, or developing participatory sensing methods where communities are involved in the data collection and interpretation process (Luo et al., 2025b). Furthermore, research should move beyond the current visual dominance to explore multi-sensory perception. This frontier includes developing and deploying UAVs equipped with microphone arrays for 3D soundscape mapping or miniature chemical sensors for perceiving the urban smellscape, thereby constructing a more immersive and human-centered understanding of the built environment (Torija et al., 2020; Lotinga et al., 2025).

5.2.4. Engaging with emerging urban technologies and governance

Finally, to ensure its long-term relevance and impact, the field must proactively engage with emerging technological and economic trends that are reshaping the urban landscape. As the low-altitude economy (e.g., UAV logistics, eVTOLs) develops, it will generate unprecedented streams of urban data (Lammers et al., 2023; Wei et al., 2024). Future research should not only leverage this data but also critically study and participate in shaping the accompanying data governance and airspace management frameworks to ensure they align with public interests like equity and privacy (Chi et al., 2023; Comtet and Johannessen, 2022). The ultimate prospect lies in integrating real-time UAV data streams into digital twin platforms. This would transform UAVs from static data collection tools into the dynamic ‘neural endings’ of a city’s digital replica. Particularly, the advanced digital twin generation of built features allows researchers to simulate and evaluate complex urban sub-elements — such as ecosystem services, aesthetic quality, and environmental efficiency — before physical interventions occur. Ultimately, this capability enables a shift from merely describing the city to actively optimizing its operations through a complete ‘sensing–cognition–feedback’ loop (Chen et al., 2024a; Luo et al., 2025a).

6. Conclusion

This study has provided a comprehensive and critical analysis of the field of UAV-based built environment perception through a systematic review of 201 core publications. By employing an innovative methodology that integrates machine learning and LLMs, we have moved beyond a simple catalog of applications to deconstruct the field’s underlying methodological structure. Our central finding is the revelation of a pronounced methodological convergence — a standardized paradigm characterized by a concentration in geography, technology, and data practices — that defines the field’s current trajectory.

While this convergent paradigm has undoubtedly propelled rapid progress, our analysis demonstrates that it also casts long shadows over the future of the discipline. We have diagnosed three fundamental challenges that stem directly from this convergence: a crisis in reproducibility due to a closed data ecosystem; a constraint on generalizability arising from a geographically and technologically biased knowledge base; and a limitation in the scope of inquiry constrained by a techno-centric view of ‘perception’. The primary contribution of this research, therefore, is not merely to chart the field’s progress, but to provide a robust, evidence-based diagnosis of these systemic challenges and to offer a structured agenda for addressing them.

Ultimately, UAVs have equipped us with an unprecedented ability to ‘read’ the city at a fine scale. This review, however, argues that the critical future challenge lies not just in improving the technical accuracy of this reading, but in fundamentally rethinking what we choose to ‘read’ and how we ‘interpret’ it. Propelling the field toward a more open, globally representative, and human-centered future requires moving beyond the current standardized paradigm. Leveraging this transformative technology to foster a more just and sustainable urban future depends not on the tools themselves, but on our collective wisdom in deploying them.

CRediT authorship contribution statement

Xinya Kong: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Filip Biljecki:** Writing – review & editing, Supervision. **Jing Yao:** Writing – review & editing. **Fan Zhang:** Writing – review & editing. **Yan Zhang:** Writing – review & editing. **Shensheng Chen:** Writing – review & editing. **Yuzhen Tang:** Writing – review & editing. **Wenhui Xu:** Writing – review & editing. **Pengyuan Liu:** Writing – review & editing. **Zexin Lei:** Writing – review & editing. **Junjie Luo:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to check the grammar and improve readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data including literature search strings, analytical indicators, and UAV flight policy datasets.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jag.2026.105324.

Data availability

Data will be made available on request.

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