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Towards building-scale urban analytics and simulation

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Perspective

Abstract

Buildings serve as the basic cells of a city, forming a complex urban system that integrates physical and social characteristics. While urban analytics and simulation have traditionally been constrained by data availability and computational complexity, recent advancements in sensing, AI and high performance computing have made building-scale inquiry increasingly feasible. This perspective proposes and highlights Building-Scale Urban Analytics and Simulation through four key pillars. First, it calls for a unified modeling standard that aligns the semantic depth of building engineering with the geographic breadth of urban science. Second, it highlights the need for constructing comprehensive building datasets with full spatiotemporal coverage through AI-driven data foundations. Third, it advocates for the use of generative AI to diagnose building quality and efficacy. Fourth, it proposes a bottom-up simulation paradigm that integrates AI with generative rules to model complex morphological and behavioral transformations. This vision provides a critical bridge between building studies and urban studies.

Keywords

building studies
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1 Introduction

Global building data products are progressing rapidly across temporal coverage, spatial extent, and attribute richness (Liu et al. 2023). This advancement is driven by diverse data sources including aerial, satellite, and ground-based imagery, as well as multi-source geospatial and social media data through increasingly abundant sensors. Meanwhile, this data abundance necessitates a corresponding evolution in computing facilities and infrastructure, which are developing fast to provide the power required for large-scale and high-precision urban computing (Zhang et al. 2025). The shift toward distributed and cloud-based environments makes it technically feasible to analyze and simulate large-scale and complex urban systems at the individual building level, moving beyond the limitations of traditional coarse-grained models.

The building scale is of particular significance because it constitutes the fundamental operational unit for a wide range of urban practices, which rely on building-level feasibility assessments and land parcel analysis. Urban regeneration, the comprehensive process of improving the physical, social, and economic conditions of existing urban areas, demands precise diagnostics of individual building conditions, including structural integrity, functional obsolescence, and vacancy status. Urban governance and management require building-granularity data for regulatory compliance, energy auditing, and public safety inspections. In each of these domains, decisions that are ultimately enacted at the building scale have traditionally been informed by coarse, aggregated data, resulting in a critical mismatch between the resolution of available information and the granularity of required action.

The convergence of massive data and high computational power is currently being catalyzed by the transformative evolution of AI technology (Liu et al. 2026). The breakthrough in large models offers the potential for automating feature extraction and modeling complex urban dynamics that were previously inaccessible. This technological readiness, combined with the growing demand for building-scale insights, is driving both building studies and urban studies toward a common frontier: analytics and simulation at the individual building level.

On one hand, building studies are expanding outward:

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building-scale data foundations increasingly inform neighborhood and district-level assessments. On the other hand, urban studies are deepening inward: fine-grained building data enables analysis of the socio-physical composition of urban spaces at unprecedented detail. While geometric layout and material performance are critical for physical simulation, the diagnosis of building quality and efficacy is paramount for urban regeneration. Building-Scale Urban Analytics and Simulation serves as the critical nexus where these trajectories converge (Figure 1). The perspectives presented in this paper are grounded in our systematic review of 291 studies, distilled from 3,305 publications (see the Electronic Supplementary Material for details. The Electronic Supplementary Material (ESM) is available in the online version of this article.).

2 Towards unified building modeling standards

2.1 Data standards

In building studies, the Industry Foundation Classes (IFC) provides the primary standard for Building Information Modeling, offering high-fidelity semantic details for the lifecycle management of individual buildings (Li et al. 2024). Conversely, in urban studies, the City Geography Markup Language serves as the open data model for the storage and exchange of virtual 3D city objects, focusing on the geographic and topological relationships within the broader city landscape.

2.2 Current limitations of building modeling standard

The integration of urban and building studies is currently hindered by divergent modeling standards. Our systematic review of 291 studies reveals an ontological mismatch: CityGML treats buildings as spatial shells with limited semantic depth, while IFC focuses on internal components without a unified geographic coordinate system. This leads to data fragmentation where building function is defined through fundamentally different frameworks; urban studies rely on land-use classifications integrating Points of Interest, zoning codes, and socio-economic indicators to characterize function at the city scale, whereas building studies employ room-level functional typologies derived from spatial programming and occupancy schedules that capture internal organization in detail. Consequently, there is no standardized protocol for translating the high-fidelity details of a building model into the macroscopic data structures required for city-wide simulation.

2.3 Towards AI-driven semantic integration of building models

Achieving semantic interoperability between building and urban modeling frameworks represents the single most critical prerequisite for building-scale urban analytics. The fundamental barrier to cross-domain research is not the absence of data, but the lack of a shared ontological foundation. Integrating definitions of buildings from building engineering (e.g., IFC) and urban science (e.g., CityGML) demands more than a shared file format; it requires a common semantic ontology that maps concepts across disciplines. Future efforts should employ AI-driven ontology matching and automated semantic mapping to reconcile divergent attribute definitions, coordinate reference systems, and levels of detail. Such integration would enable, for

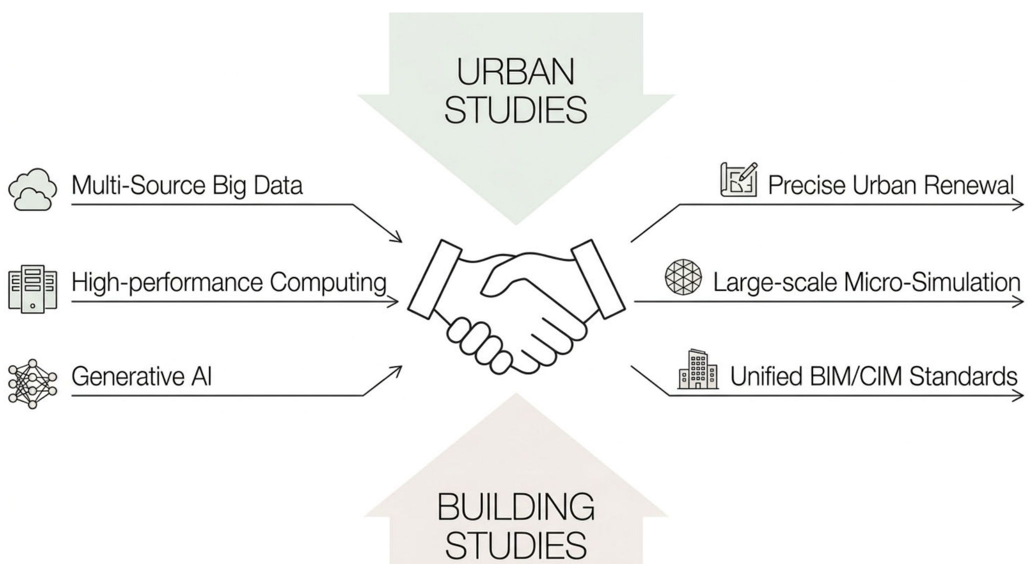

Fig. 1 Intersection of building and urban studies

example, the automatic translation of an IFC model's detailed room-level thermal properties into CityGML-compatible attributes suitable for district energy simulation. This semantic unification is the prerequisite upon which the data construction efforts discussed in Section 3 depend: without agreed-upon standards for what building attributes mean across scales, even the most comprehensive datasets remain siloed.

3 Construction of building datasets

3.1 Trends in building data construction

In building studies, data construction historically relies on high-fidelity, site-specific methodologies including engineering surveys, on-site measurements, and the aggregation of administrative records such as building permits, utility consumption data, census housing records, and local historical building codes. The field has increasingly transitioned toward digital twins through Terrestrial Laser Scanning and Scan-to-BIM workflows that transform physical structures into semantically rich digital assets, though these methods remain labor-intensive and difficult to scale across entire cities.

In contrast, urban studies focus on scalability through active and passive sensing. Aerial photogrammetry, drone-based LiDAR, and fused multi-source datasets such as optical imagery with radar backscatter enable machine learning and deep learning models to predict building footprints and heights over vast areas with increasing accuracy. In data-sparse regions, geostatistical methods like Kriging are employed to estimate missing attributes by analyzing the spatial continuity of the built environment.

3.2 Current limitations in data coverage and resolution

Significant imbalances in spatiotemporal resolution and coverage hinder both macro-scale regeneration and micro-scale transformation. For urban studies, the primary deficiency lies in the absence of vector-based longitudinal data and deep semantic attributes necessary for tracking city evolution. While global building footprints are expanding, essential indicators such as precise construction age, occupancy status, and renovation history remain scarce in large-scale datasets, preventing accurate capture of stock dynamics like demolition or retrofit rates.

For building physics studies, existing urban datasets often lack the geometric fidelity and physical parameters required for high-precision simulation. Performance models depend on detailed indoor structures and precise material properties that are typically absent from city-scale products. Most open-source building data provide only Level of Detail (LOD) 1 (extruded footprints with flat roofs) or LOD 2 (simplified roof structures) representations, while LOD 3 (detailed architectural features including windows and doors) and LOD 4 (full interior structures) remain largely unavailable at the urban scale. This results in data islands where engineering-grade information is too localized for city-wide application, while global datasets are too coarse for building performance evaluation.

3.3 Building an AI-driven foundation for global coverage

The most urgent research priority for building data construction is the development of an AI-driven data foundation that transcends the constraints of direct sensing. Next-generation models should utilize multi-modal generative intelligence to infer latent building attributes from environmental context. By evaluating spatial relationships between a building, its neighborhood morphology, and historical urban textures, machine learning and deep learning models can predict variables that are traditionally difficult to acquire, such as vacancy status, construction age, or specific socio-economic functions. Furthermore, generative modeling provides a robust methodology for spatiotemporal reconstruction, synthesizing missing historical information rather than relying on static snapshots. A particularly promising direction is the use of generative AI foundation models pre-trained on diverse urban imagery to enable zero-shot or few-shot inference of building attributes in data-sparse regions, dramatically reducing the cost of global-scale data construction. Such reasoning-based approaches enable a truly comprehensive digital foundation that reflects the complex rules of urban growth and decay, providing the essential input layer upon which all subsequent diagnostic and simulation efforts depend. With such a comprehensive data foundation in place, the critical next step is to develop diagnostic frameworks capable of interpreting these data, the subject of Section 4.

4 Diagnosing building quality and efficacy

While Section 3 addresses the construction of spatiotemporally complete building datasets, this section turns to how these data are interpreted and evaluated. Building quality and efficacy are higher-order diagnostic attributes that cannot be directly sensed but must be inferred through analytical frameworks combining physical, social, and functional indicators.

4.1 Scope of building quality and efficacy

Building quality is a multidimensional concept comprising physical quality (structural integrity and material maintenance), construction quality (workmanship standards), perceptual quality (user satisfaction), and functional quality (suitability for intended use) (Zhong et al. 2019). Building efficacy focuses on the dynamic utilization state of the built environment and encompasses three critical dimensions: vacancy, representing absolute idling where buildings remain entirely unoccupied; inefficiency, where actual usage intensity falls significantly below designed carrying capacity; and functional mismatch, denoting the misalignment between original design intent and current operational reality (Li and Long 2024). Diagnosing these attributes is essential for precise urban regeneration and evidence-based governance.

4.2 Limitations of current diagnostic approaches

Current assessment methodologies suffer from confused conceptual definitions and inconsistent metrics. Building quality is frequently conflated with narrow building design aesthetics or technical performance indicators, leading to a neglect of long term structural and management health. Distinguishing between building performance and building quality is fundamental to refined urban regeneration. Building performance involves quantifiable physical indicators such as thermal energy consumption, ventilation, and structural performance, which are typically treated as independent metrics. Furthermore, building efficacy lacks clear formal definitions and sufficient empirical research. This deficiency is often due to the difficulty of obtaining high resolution internal usage data, such as electricity or water consumption, at the individual building level to validate occupancy and functional utility.

4.3 Towards AI-driven diagnosis

The most critical frontier in building quality and efficacy diagnosis lies in the development of AI-driven, multi-modal assessment frameworks that fundamentally transform how buildings are evaluated. Future systems should integrate multi-modal data fusion to overcome the limitations of single-source observations. AI models can execute physical appearance assessments by identifying material aging or structural cracks from remote sensing and street-view imagery. These visual assessments should be synthesized with social sensing data, such as mobile signaling patterns and resident complaint texts processed by large language models (a form of generative AI), to monitor occupancy dynamics and social performance in real time. Critically, future diagnostic systems must move beyond per-building evaluation toward urban-scale comparative diagnosis, benchmarking individual buildings against neighborhood and city-wide baselines to identify relative underperformance. This multi-modal, multi-scale approach facilitates a paradigm shift from static physical checks to dynamic socio-technical evaluations, enabling continuous building health monitoring that supports proactive rather than reactive urban regeneration strategies. These diagnostic insights, in turn, provide the essential input for the next frontier: building-scale urban simulation that can project how interventions reshape urban form over time.

5 AI-driven bottom-up simulation

5.1 Evolution of urban simulation

Urban simulation is undergoing a significant transition from macroscopic spatial interaction models, such as gravity models, toward microscopic agent-based modeling. Traditional macroscopic approaches often overlook the granular dynamics of individual entities, whereas agent-based modeling provides a framework to capture the heterogeneous behaviors of urban actors. The rapid development of AI, spanning traditional machine learning, generative AI, and agentic AI, provides the necessary tools to enhance both the behavioral fidelity and computational efficiency of these simulations (Liu et al. 2025), allowing for the representation of complex urban systems at the individual building level. The emergence of urban building energy modeling (Yan et al. 2025) exemplifies this trend of scaling building-level analysis to the urban scale.

5.2 Limitations of current simulation approaches

Despite these advances, current building-scale urban simulations face several critical limitations. Most agent-based models rely on simplified behavioral rules and fixed utility functions that cannot represent the complex reasoning underlying real-world decisions about building development and adaptation. Geometric modeling through shape grammar and socio-economic simulation typically operates as separate, loosely coupled modules, preventing coherent representation of how physical form and human activity co-evolve. Furthermore, existing urban building energy models remain largely static, capturing performance at discrete time points without modeling the morphological and functional transitions that reshape demand patterns over decades. These fragmented approaches, while technically sophisticated in individual components, fail to capture the emergent dynamics arising from the continuous interaction between micro-scale building changes and macro-scale urban spatial restructuring.

5.3 Next generation of building-scale simulation

The most transformative prospect for building-scale simulation lies in the deep integration of geometric evolution logic with interdisciplinary semantic reasoning. This represents the central challenge and opportunity for the field. Shape grammar must transcend preset design rules in this paradigm, evolving into a dynamic generation engine that fuses multi-dimensional knowledge, including building evolution patterns, urban planning expertise, and human behavioral logic (Yin et al. 2024; Burke et al. 2025). When this geometric engine is combined with cognitive bottom-up agents, large language model-based agents (agentic AI) can perform complex logical reasoning by synthesizing environmental context, socio-economic incentives, and physical constraints. This enables agents to drive specific morphological transformations such as building expansion or functional adaptation through a reasoning-based process rather than fixed utility functions. Crucially, this closed-loop framework, where data-driven graph networks manage spatial interactions while agents make decisions based on integrated knowledge, provides a high-fidelity pathway for understanding how building transformations self-organize into macro-scale urban spatial patterns (Figure 2). Advancing this AI-driven, bottom-up simulation paradigm is essential for moving urban prognosis from extrapolation of historical trends toward genuine scenario reasoning under novel conditions.

6 Conclusions

This perspective calls for urban studies to embrace the building scale as its essential frontier for achieving fine-grained urban governance and sustainable management of existing building stocks. We identify four critical and interrelated actions that the research community should undertake. First, we call for a unified modeling standard to bridge the semantic gap between building engineering and urban science, enabling seamless data interoperability across scales and disciplines. Second, comprehensive building datasets with full spatiotemporal coverage should be constructed through AI-driven data foundations that transcend the constraints of direct sensing. Third, AI-driven assessment frameworks should be developed to diagnose building quality and efficacy through multi-modal data fusion, shifting from static physical examinations to dynamic, continuous socio-technical evaluations that directly inform urban regeneration strategies. Fourth, a new generation of bottom-up simulation should be advanced, integrating large language model agents with generative morphological rules to model complex building-level transformations and their emergent urban-scale consequences. Together, these four pillars provide a transformative framework for urban prognosis at building-level resolution, offering the high-fidelity insights necessary for creating resilient and sustainable human settlements.

Electronic Supplementary Material (ESM): The Electronic Supplementary Material contains the complete systematic literature review, including: review methodology and framework (Figure S1 in the ESM), research classification system (Table S1 in the ESM), temporal distribution analysis (Figure S3 in the ESM), building attribute definitions (Figure S4 in the ESM), data sources and datasets (Tables S2–S6 in

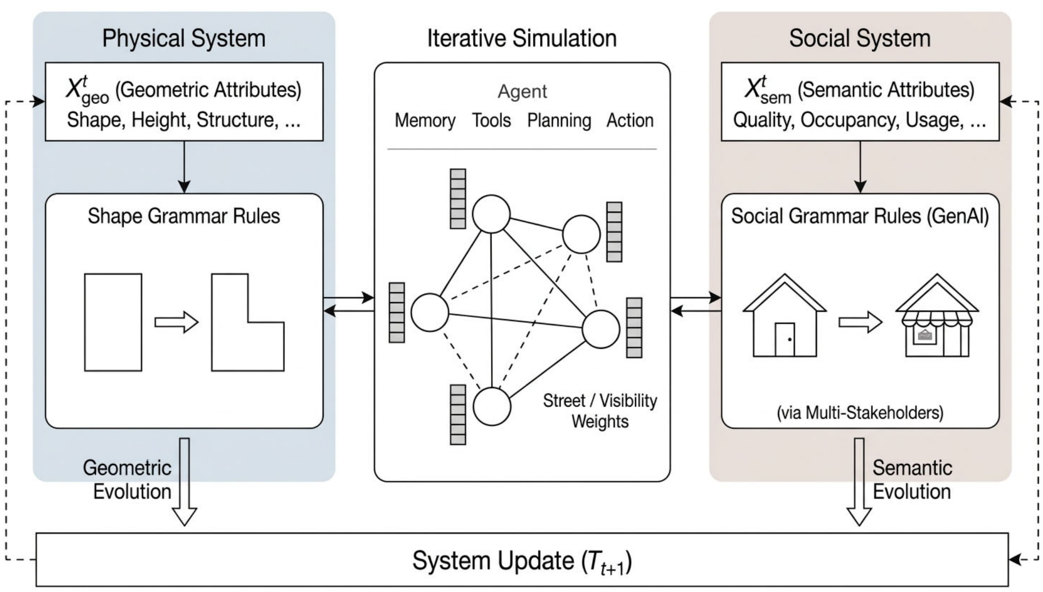

Fig. 2 AI-driven building-scale urban simulation based on agents and graphs

the ESM), and methodological landscape (Figure S5 in the ESM). The ESM is available in the online version of this article at 10.1007/s12273-026-1461-9.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval

This study does not contain any studies with human or animal subjects performed by any of the authors.

Author contribution statement

Yecheng Zhang: writing—original draft, visualization, investigation, formal analysis. Ying Long: funding acquisition, project administration, writing—review & editing

References

Burke R, Sengupta R, Ford A (2025). A 3D agent-based model for simulating urban densification in Toronto, Canada. *Environment and Planning B*: *Urban Analytics and City Science*: 52: 527–544.

Li Q, Mou L, Sun Y, et al. (2024). A review of building extraction from remote sensing imagery: Geometrical structures and semantic attributes. *IEEE Transactions on Geoscience and Remote Sensing*, 62: 4702315.

Li Y, Long Y (2024). Inferring storefront vacancy using mobile sensing images and computer vision approaches. *Computers*, *Environment and Urban Systems*, 108: 102071.

Liu Z, Tang H, Feng L, et al. (2023). China Building Rooftop Area: The first multi-annual (2016–2021) and high-resolution (2.5 m) building rooftop area dataset in China derived with super-resolution segmentation from Sentinel-2 imagery. *Earth System Science Data*, 15: 3547–3572.

Liu M, Zhang L, Chen J, et al. (2025). Large language models for building energy applications: Opportunities and challenges. *Building Simulation*, 18: 225–234.

Liu Z, Wu Y, Bu F, et al. (2026). Urban-scale radiative cooling potential and spatial heterogeneity: A study based on urban building energy modeling (UBEM). *Building Simulation*, 19: 219–233.

Yan D, Wu Y, Malik J, et al. (2025). Ten questions on future and extreme weather data for building simulation and analysis in a changing climate. *Building and Environment*, 269: 112461.

Yin L, Yin F, Silverman RM (2024). Rethinking demolition plans to fight neighborhood blight in shrinking cities: Applying agent-based policy simulations. *Cities*, 150: 105035.

Zhang Y, Zhao H, Long Y (2025). CMAB: A multi-attribute building dataset of China. *Scientific Data*, 12: 430.

Zhong B, Xing X, Love P, et al. (2019). Convolutional neural network: Deep learning-based classification of building quality problems. *Advanced Engineering Informatics*, 40: 46–57.