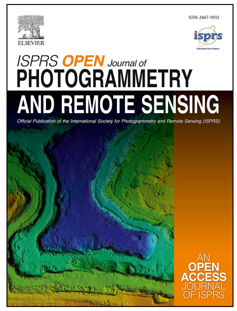

Leveraging multisource data in GeoAI frameworks for urban analysis. Challenges, opportunities, and future directions

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Leveraging multisource data in GeoAI frameworks for urban analysis. Challenges, opportunities, and future directions

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Abstract

Geospatial artificial intelligence (GeoAI) systems leverage multisource big data, including high-resolution spatiotemporal images, textual data, IoT and sensor data streams, social media, crowdsourced data, and geolocated metadata, to accurately capture urban contexts and dynamics. Consequently, the rich, multisource data enable GeoAI inference and support analysis of social patterns, urban form, traffic dynamics, and human activity, thereby enhancing the accuracy and granularity of urban analytics. However, processing heterogeneous data presents significant challenges in GeoAI systems, including data quality and compatibility issues, spatial and temporal alignment, data gaps, provenance management, and biases. Moreover, data from varied sources raises concerns about quality, privacy, ethics, and governance due to the risk of exposing sensitive socio-spatial details. Realizing the potential of multi-sourced data depends on principled, scalable, and ethically grounded research and practice. Practitioners require human-centric approaches that support interpretable and predictive modeling in a safe, transparent, and privacy-preserving manner. This review examines advancements in machine learning for urban geospatial analysis and the methods reshaping the GeoAI discipline. It highlights recent datasets for training GeoAI frameworks and discusses challenges with multi-sourced data. We also review advances in human-centric aspects of GeoAI, covering current trends and exploring future directions in geospatial urban intelligence.

Keywords: GeoAI, deep learning, urban analysis, human-centric, artificial general intelligence, and multimodal.

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1. Introduction

Urban environments are intricate ecosystems that inextricably connect people, infrastructure, and the environment. Urban contexts thus require a more holistic approach in their analysis and comprehension to promote sustainability, public safety, and infrastructure resilience. Accurate and reliable urban analysis and interpretation support decision-making in urban planning and management, therefore making it a worthy research undertaking. However, handling the complex urban contexts arising from intricate, interrelated systems and their constant interactions, resulting from economic, social, and environmental flux, poses significant challenges that traditional analytical techniques cannot address [1]. This situation is exacerbated by surging population growth, which is driving cities to sprawl outward and the emergence of new cities. The situation intensifies environmental pressures and challenges planners to develop strategies that support sustainable urban growth. [2].

Urban analysis is essential for capturing, interpreting, and visualizing urban complexities. The process enables planners to understand the interactions among land use, infrastructure, environment, and social dynamics across spatial and temporal scales. Traditional geospatial tools and methods, such as manual surveys, mapping, and conventional GIS modeling, often fail to address the rapid pace, multiscale, and increasing complexity of contemporary urban contexts. Moreover, these methods are often time-consuming and labor-intensive, and they require specialized skills that may not be widely available. Still, traditional modeling approaches rarely consider critical spatial information such as coordinates and Euclidean distances, topological and spatial relationships, and interactions between objects [3, 4]. As a result, these challenges motivated a shift from traditional analysis to data-driven geospatial reasoning, marking a noteworthy evolution in our ability to analyze and understand urban environments. It also enables responsive, adaptive, and sustainable urban planning approaches that better address the diverse needs of modern cities, including traffic planning and optimization, land use zoning, emergency response, and infrastructure management [5, 6].

The advent of artificial general intelligence (AGI) marks a promising era of data-driven approaches, demonstrating commendable potential for urban analysis and interpretation with unprecedented efficiency and accuracy [7-9]. To begin with, integrating AGI into urban analytics has redefined the field, enabling more efficient processes that can accurately and quickly handle the intricacies of urban environments. Then, the explosion of spaceborne sensor infrastructure and the rapid improvement in photogrammetry have amplified this technological leap, enabling acquisition and access to diverse high-resolution and temporal data. The resulting large-scale spatial data, combined with multisource big data derived from satellite imagery, photogrammetry infrastructure, social media, and the urban Internet of Things (IoT) networks, powered by high-performance computing (HPC), facilitates the scalable training of geospatial models, enabling intelligent analysis and inference of urban environments [10, 11].

GeoAI functions at the intersection of geospatial science, artificial intelligence, and machine learning to derive insights from features, contexts, trends, associations, and relationships within large urban datasets [12]. It's thus instrumental for urban applications such as land-use zoning, traffic optimization, infrastructure management, and urban sprawl analysis. Geospatial intelligence also enables proactive risk assessment and mitigation, supports vulnerability mapping, and enhances situational awareness in contexts such as urban traffic congestion, disaster response, urban healthcare investigations, and infrastructure failures. This cultivates a dynamic, responsive approach to urban planning and management [13-16]. Additionally, GeoAI plays a crucial role in climate action. GeoAI models can map urban flooding, infer carbon sequestration, and model urban heat island effects, underscoring the significance of GeoAI for climate mitigation and adaptation planning. For example, integrating physics-based and data-driven GeoAI models for flood risk assessment in coastal cities has demonstrated how hydrodynamic modeling and data analysis can quantify the impacts of urban flooding, underscoring GeoAI's ability to deliver actionable geospatial insights [13, 17].

Abundant literature sources highlight that recent GeoAI advances and the rapid adoption are significantly driven by the integration of diverse data modalities into GeoAI training models, enabling a more comprehensive understanding of urban form, interactions, and characteristics [18, 19]. For instance, by incorporating optical and SAR imagery, digital surface models, nighttime light data, mobility data, social perception indicators, and GIS layers in the GeoAI inferencing pipeline, researchers have improved accuracy in identifying urban functions, land use patterns, population distribution, and infrastructure mapping [9, 20, 21]. Still, integrating 3D geospatial data, point clouds, and digital twins has enhanced the robustness and situational awareness of urban GeoAI models [22, 23]. Owing to the potential of combining rich multisource data into GeoAI pipelines, research is rapidly advancing towards multimodal generative AI, building models capable of generating supplementary multimodal training data, including text, video, audio, images, robotic sensors, and 3D models [24]. This trend opens new possibilities for intelligent contextual reasoning, enabling a more nuanced analysis of complex urban processes and providing valuable insights for urban planning, resource management, and policymaking.

However, multimodal and multisource data pose significant challenges to the GeoAI processing landscape, including data compatibility issues, bias and skewness, domain shift, inequality, data quality, missing data, and structural complexity [25, 26]. Moreover, given that Geospatial data contains location information and metadata that can reveal user profiles, this raises critical concerns regarding data management, user privacy, and safety [27]. Thus, the literature converges on the need to address challenges arising from multi-sourced data, proposes developing privacy-preserving techniques, and recommendations for governance frameworks that support ethical- and safety-oriented deployment. Further, studies emphasize the importance of explainable GeoAI in addressing the opacity in the inferencing process [12, 25, 26]. Lastly, urban datasets need to be obtained from diverse geographic regions to ensure balanced geospatial intelligence and to promote spatially agnostic, spatially explicit, and generalizable models [28, 29].

As GeoAI's dominance in urban decision-making increases, it's necessary to conduct reviews that highlight recent advances, challenges, and opportunities, and to track scientific progress in the domain. Our review seeks to contribute to the ongoing discourse on advancing GeoAI frameworks and developing robust, trustworthy, and ethical human-centric GeoAI systems that address data incompleteness and skewness, mitigate bias, preserve privacy, and embed ethics and safety as core design [30-38].

1.1 Comparison with existing reviews

The potential of GeoAI in urban analysis and its role in guiding urban planning and development decisions have sparked considerable research interest, attracting reviews in the field. Recent scientific reviews have been conducted focusing on: the influence of foundation models on the evolution and enhancement of GeoAI [9, 39], applications of GeoAI in urban floods monitoring and mitigation [13, 17], urban security [40], spatially-explicit GeoAI in urban geography [41-45], urban topography and mapping [46-51], traffic management [52, 53], smart and sustainable cities [54-56].

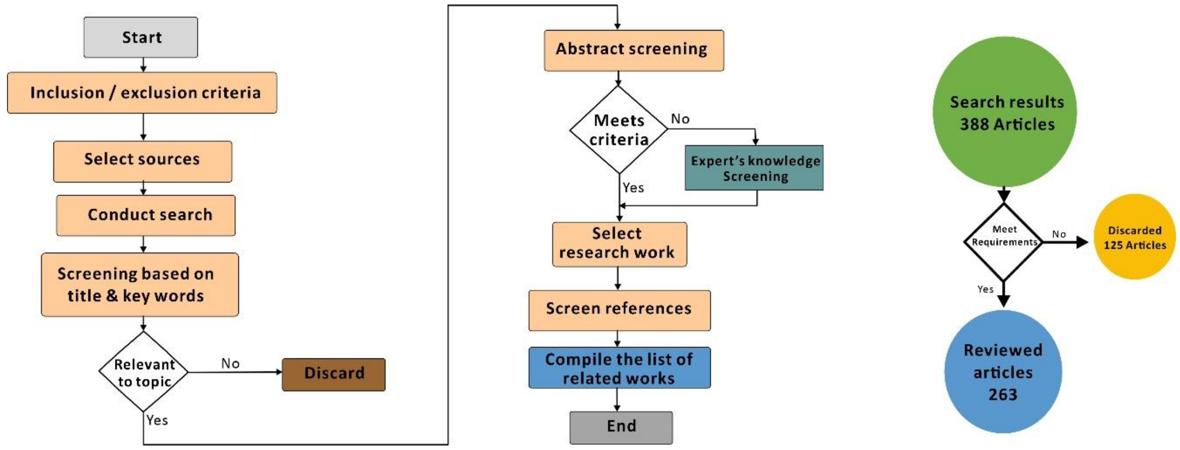
In addition, more reviews have been conducted on the use and application of multimodal data in urban GeoAI [5, 6, 11, 15], the transition from vision models to multimodal models [26, 54], and the progression towards generalist artificial systems [57, 58]. Further works have explored advances in human-centric GeoAI for community infrastructure and human dynamics [29, 58], as well as in explainable AI [15, 32, 59].

These studies highlight a significant rise in GeoAI research and its applications in various urban applications. However, there are few works exploring the influence of multisource data in the advancements in GeoAI, particularly the constraints it introduces and possible solutions. Moreover, relatively few reviews address the uneven conditions of GeoAI deployment, such as data inequality, algorithmic and data bias, missing data, and ethical governance. As the field evolves rapidly, periodic reviews are essential to keep the research community informed about gaps and progress, and to stimulate further research. This non-exhaustive review acquaints beginners with recent advances in leveraging multisource data and related technical challenges. It also shares the evolution of data-driven geospatial models and highlights emerging challenges and limitations in ethical governance and institutional capacity. The article also presents notable GeoAI applications in urban contexts.

1.2 Eligibility criteria

This review aims to cover broadly, but non-exhaustively, publications relevant to advances in methods, challenges in using data from multiple sources, and governance issues related to GeoAI. This approach aligns with our study's focus on GeoAI, an interdisciplinary field spanning many fields and applications. We systematically gather, review, and filter relevant literature, primarily using the Web of Science (WOS) platform and Scopus. Our qualitative analysis of recent research follows these steps: scope identification and manual refinement. In line with the systematic review methodology outlined in [44, 60], we adopted a two-tiered approach to define the scope using keywords and expressions. At the first level, we used the following search terms: "GeoAI," "Machine learning," "Deep Learning," "AI," and "Geospatial AI."

Since the search syntax covers a broad range, we adopted a second-level search to refine the scope. We used the search terms indicated in **Fig. 1(b)** to extract publications related to our research interest. We restricted the search to papers written in "English" published between 2020 and 2025 to obtain recent, state-of-the-art publications. Notably, our second-level search criteria focused on GeoAI methods, relevant applications, datasets, data-governance constraints, and human-centered approaches. After the second-level search, 388 articles were identified as relevant to the topic of interest. However, after further screening, 125 articles were discarded for failing to meet the relevance criteria.



(a) Article selection workflow

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TITLE-ABS-KEY(GeoAI) AND ( LIMIT-TO ( SUBJAREA,"ENGI" ) OR LIMIT-TO ( SUBJAREA,"ENVI" ) OR LIMIT-TO ( SUBJAREA,"COMP" ) OR LIMIT-TO ( SUBJAREA,"EART" ) OR LIMIT-TO ( SUBJAREA,"SOCI" ) ) AND ( LIMIT-TO ( EXACTKEYWORD,"Geoai" ) OR LIMIT-TO ( EXACTKEYWORD,"Artificial Intelligence" ) OR LIMIT-TO ( EXACTKEYWORD,"Machine Learning" ) OR LIMIT-TO ( EXACTKEYWORD,"Deep Learning" ) OR LIMIT-TO ( EXACTKEYWORD,"Geo-spatial" ) OR LIMIT-TO ( EXACTKEYWORD,"Remote Sensing" ) OR LIMIT-TO ( EXACTKEYWORD,"Geospatial Artificial Intelligence" ) OR LIMIT-TO ( EXACTKEYWORD,"Spatial Analysis" ) OR LIMIT-TO ( EXACTKEYWORD,"Spatial Data" ) OR LIMIT-TO ( EXACTKEYWORD,"Learning Systems" ) OR LIMIT-TO ( EXACTKEYWORD,"Machine-learning" ) OR LIMIT-TO ( EXACTKEYWORD,"Mapping" ) OR LIMIT-TO ( EXACTKEYWORD,"Remote-sensing" ) OR LIMIT-TO ( EXACTKEYWORD,"Urban Planning" ) OR LIMIT-TO ( EXACTKEYWORD,"Urban Area" ) OR LIMIT-TO ( EXACTKEYWORD,"Geospatial Artificial Intelligence (geoai)" ) OR LIMIT-TO ( EXACTKEYWORD,"Foundation Models" ) OR LIMIT-TO ( EXACTKEYWORD,"Sustainable Development" ) OR LIMIT-TO ( EXACTKEYWORD,"Deep Neural Networks" ) OR LIMIT-TO ( EXACTKEYWORD,"Environmental Monitoring" ) OR LIMIT-TO ( EXACTKEYWORD,"Disaster Management" ) OR LIMIT-TO ( EXACTKEYWORD,"Data Handling" ) OR LIMIT-TO ( EXACTKEYWORD,"Large Language Model" ) OR LIMIT-TO ( EXACTKEYWORD,"Language Model" ) OR LIMIT-TO ( EXACTKEYWORD,"Graph Neural Networks" ) OR LIMIT-TO ( EXACTKEYWORD,"Urban Development" ) OR LIMIT-TO ( EXACTKEYWORD,"Knowledge Graph" ) OR LIMIT-TO ( EXACTKEYWORD,"Geo-spatial Data" ) OR LIMIT-TO ( EXACTKEYWORD,"Urban Growth" ) OR LIMIT-TO ( EXACTKEYWORD,"Spatially Explicit" ) OR LIMIT-TO ( EXACTKEYWORD,"Multi-modal" ) OR LIMIT-TO ( EXACTKEYWORD,"Knowledge Graphs" ) OR LIMIT-TO ( EXACTKEYWORD,"Geographic Information System" ) OR LIMIT-TO ( EXACTKEYWORD,"Floods" ) OR LIMIT-TO ( EXACTKEYWORD,"Smart City" ) OR LIMIT-TO ( EXACTKEYWORD,"Large Language Models" ) OR LIMIT-TO ( EXACTKEYWORD,"Land Cover" ) OR LIMIT-TO ( EXACTKEYWORD,"Human Geography" ) OR LIMIT-TO ( EXACTKEYWORD,"Explainable Ai" ) OR LIMIT-TO ( EXACTKEYWORD,"Data Quality" ) OR LIMIT-TO ( EXACTKEYWORD,"Data Fusion" ) OR LIMIT-TO ( EXACTKEYWORD,"Urban Transportation" ) OR LIMIT-TO ( EXACTKEYWORD,"Urban Design" ) OR LIMIT-TO ( EXACTKEYWORD,"Geospatial" ) OR LIMIT-TO ( EXACTKEYWORD,"Intelligence Models" ) OR LIMIT-TO ( EXACTKEYWORD,"Built Environment" ) OR LIMIT-TO ( EXACTKEYWORD,"Geospatial Data" ) )
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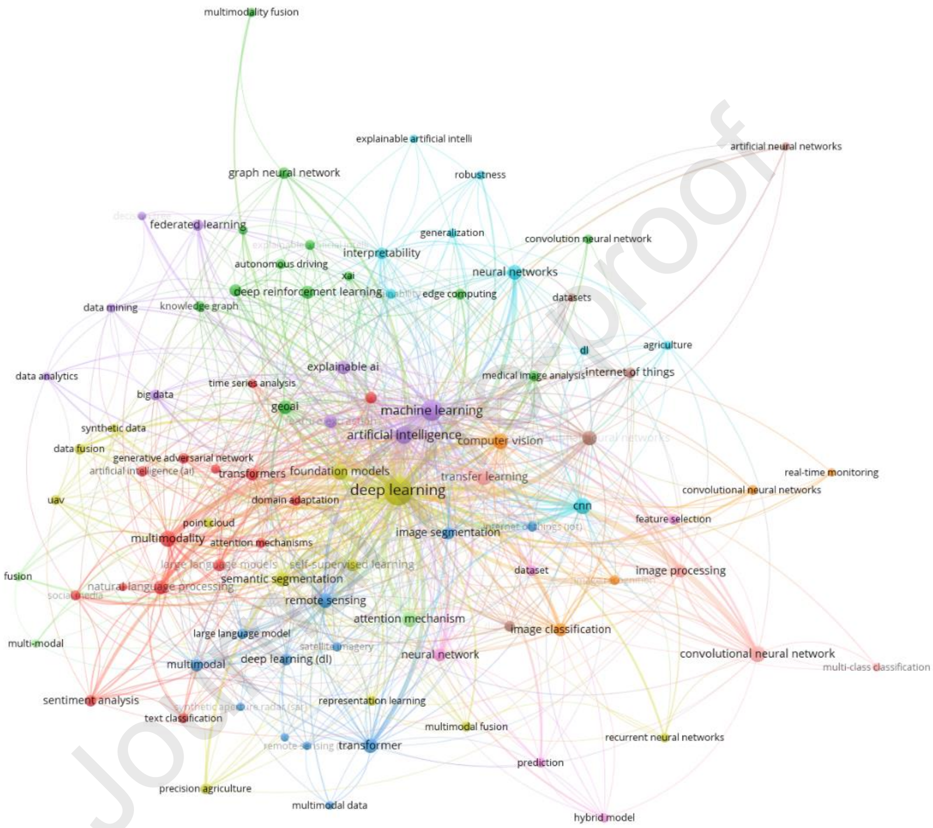
(b) Search terms used in our review

Fig. 1 The literature selection workflow.

Later, we manually refined the resultant pool. thorough examination of retrieved articles to ensure their alignment with the review's focus and the study's scope. We screened titles, keywords, abstracts, methodologies, and scope to assess their relevance, as visually represented in the workflow diagram (Fig. 1). This step is crucial to maintaining the relevance and quality of the literature review. When the initial assessment did not clearly indicate an article's relevance, we delved deeper into the article's abstract as guided by expert knowledge.

The co-occurrence network analysis presented in **Fig. 2** illustrates the interlinkages among various fields under study and their semantic relationships to GeoAI, while **Fig. 3** presents our research taxonomy to help the reader understand the interlinkages among the various sections of the review. The selected articles converged on three major areas: (I) Multisource data: Influence of multisource data on the development of urban geospatial analysis methods. (II) Data acquisition, data quality, ownership, access, diversity, processing, and institutional mechanisms for fair access that address bias, incompleteness, skewness, and generalization. (III) Data handling and alignment to human-centric principles relating to safety, ethics, and security. Contextualizing the progression of multisource data and its impact on the evolving GeoAI paradigm shows that emerging data challenges place GeoAI within broader institutional, ethical, and systemic frameworks. The findings of this review indicate that GeoAI's ultimate success depends on equitable urban research and development, human-centric urban planning, governance structures, and social-spatial involvement by urban planners, researchers, practitioners, and other stakeholders.

Although the synthesis consolidates findings from the reviewed studies, offering a cohesive overview of progress, current trends, and prospects for both future researchers and practitioners, this review paper has several intrinsic limitations. First, although the adopted search strategy captures the latest articles in the field from 2020 to 2025, some recent and relevant preprints and emerging methods may have been omitted. Second, the review focuses exclusively on English-language articles, potentially excluding impactful studies published in other languages. Additionally, interpretative judgments regarding the validity and consideration of certain articles may vary across different knowledge contexts. Finally, the review does not delve into the analytical aspects of model performance or the metrics used



across studies, which may compromise the balance between breadth and depth.

Fig. 2. Co-occurrence network analysis

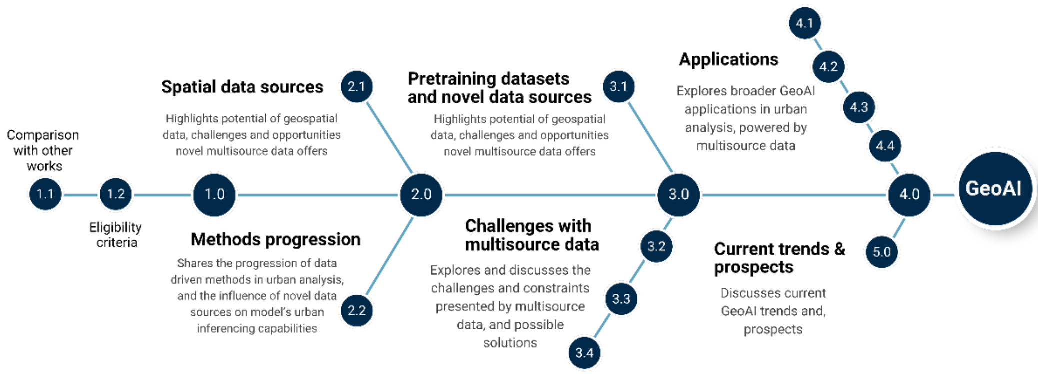


Fig. 3. Taxonomy of our research work

The review article is structured to provide an exploration of leveraging multisource data in GeoAI frameworks for urban analysis as follows. **Chapter 1** introduces the topic, distinguishing the current review from previous studies, and highlighting the literature selection criteria and limitations. This introductory chapter provides context for the importance of geospatial analysis and its evolving role across fields, and outlines the scope of the studies explored. **Chapter 2** shares the latest developments in geospatial analysis, covering advances in multisource data and the evolution of machine learning techniques. This chapter discusses how integrating multisource data has enhanced geospatial analysis capabilities and examines the transformative impact of machine learning algorithms on geospatial analysis and interpretation. **Chapters 3** and **4** focus on current pre-training datasets for GeoAI models, their challenges, limitations, and the opportunities they present. Later, the chapter discusses human-centric perspectives within GeoAI frameworks and explores practical applications of GeoAI in urban contexts. The review concludes with a discussion of current trends and future research directions in **Chapter 5,** followed by a concluding chapter.

2. Advances in urban geospatial analysis

This section reviews recent advances in geospatial analysis, focusing on how multi-sourced data has shaped the urban geospatial models from classical machine learning to deep learning and GeoAI. We highlight key techniques in data diversity and their impact on urban analysis and interpretation.

2.1 Advances towards multisource data in geospatial analysis

RS technologies collect extensive geospatial data (both static and dynamic) from the ground surface using sensors and photogrammetric infrastructure, leading to spatial big data (SBD). The SBD, when analyzed accurately, helps uncover social, environmental, and economic interactions across the urban space, supporting research in topographical mapping, urban planning, emergency response, environmental monitoring, and land cover analysis [18, 61]. Early RS relied on traditional photogrammetry infrastructure and low-flying aircraft, yielding images with low spatial and temporal resolution that could not meet evolving scientific and practical demands [62]. Owing to technological advances, massive Earth observation missions, and enhanced photogrammetry infrastructure, sub-meter spatial resolution and high temporal frequency have been achieved from spaceborne platforms [5, 63]. In turn, this progress has expanded access to high-quality SBD, supporting geospatial intelligence, planetary research, and urban studies, thereby delivering insights that inform policymaking for sustainable urban development [64, 65].

Further, RS infrastructure generates multimodal data, including optical, synthetic aperture radar (SAR), thermal, hyperspectral, and LiDAR imagery. Multispectral optical and LiDAR sensors mounted on terrestrial vehicles and low-altitude aircraft capture broader spectral and 3D data, offering detailed insights into land cover phenomena based on land-surface materials. These data are essential and support urban tasks such as land-use and land-cover analysis, ecological investigation, and urban forest inventory and mapping [66, 67]. Data captured across different platforms and technologies can provide a robust perspective and dynamic view of an urban phenomenon. For instance, thermal sensors capture thermal infrared radiation emitted and reflected from the Earth's surface, producing thermal infrared images (TIR) [68]. The TIR supports research on the impacts of climate change, urban heat emissions, wildfires, and volcanic activity. On the other hand, digital surface models (DSMs) generated from aerial, satellite, or LiDAR images provide elevation data for three-dimensional analysis of urban morphology, such as terrain analysis of environmental modeling [69]. These multimodal data exhibit broader spectral, structural, and temporal heterogeneity, which is necessary for cross-modal inference.

Although RS data reveals essential urban characteristics and details, some aspects of urban contexts and interactions, such as human activity patterns, complex spatial contexts, and urban mobility and social perception, may not be sufficiently inferred from unimodal RS images. Several studies have attempted to explain the influence of multimodal and multisource data in advancing the analysis and understanding of urban contexts. For instance, Xia et al. observe that relying solely on unimodal data in urban analysis proves inadequate for fully grasping the complexities of urban environments. Besides, analyzing unimodal data obtained from a single source, such as satellite imagery, census data, or traffic patterns, tends to yield insights from a narrow spectrum of the multifaceted context [70]. This limited perspective tends to yield incomplete or misleading conclusions about urban phenomena, as it overlooks the intricate interactions among elements and contexts, especially in interrelated urban contexts. Hu et al., in support of this observation, propose combining multi-sourced data to gain a more comprehensive view and significantly enhance understanding of broader urban contexts and urban morphology [71]. Further, Linden et al. observe that fusing LiDAR data with DSM can provide rich spectral and structural cues, enhancing detailed topographic and urban modeling, such as canopy mapping, detection of vertical structures, detection of infrastructure changes, and building extraction [72]. Besides, some RS data acquisition technologies, such as SAR, use microwave signals and thus are rarely affected by environmental conditions such as extreme weather, clouds, and vegetation cover. Being weather-independent makes SAR suitable for reliable year-round observations across seasons and weather variability [73]. When applied in urban contexts, SAR can be fused with hyperspectral data to provide a rich scattering signature for surface and texture discrimination, thus supporting investigations into vegetation health, monitoring built-up areas, and assessing surface roughness [74]. Other supplementary data include nighttime light data and ancillary urban sensing streams, which can be combined with optical imagery and GIS layers to gain insights into economic activities and urban intensity [75].

Recent studies have explored integrating 3D geospatial data, point clouds, and digital twin concepts to enhance accuracy and situational awareness in urban environments. For instance, Cai et al. applied machine learning to 3D point clouds and digital twins to derive insights from high-dimensional geospatial data, thereby expanding the potential for urban analysis [76]. Rahman et al. proposed integrating orthophotos, point clouds, and digital surface models to improve urban geospatial representations and to achieve more accurate 3D modeling [77].

These studies highlight the potential of incorporating multi-sourced data, spurring an upsurge in research on multimodal data in urban analysis. Recent trends indicate that an increasing number of studies are leveraging novel data sources, including supplementary data such as street-view images, trajectory data, knowledge graphs, geospatial vector data, and OpenStreetMap map layers, to create a more comprehensive representation of urban spaces [78, 79]. In addition, insights from urban studies indicate that diverse sources enrich spatial-temporal data and complement the geometric and semantic information critical for understanding and interpreting geospatial contexts. The integration also enables cross-validation of findings, fills gaps where unimodal data fails, thereby revealing complex relationships and representations that may not be evident from unimodal data. This multifaceted approach reinforces static mapping and spatiotemporal reasoning, reducing ambiguities and error accumulation that are typical in multi-stage unimodal pipelines. This, in turn, enhances the analysis and robustness of modeling dynamic urban systems [57, 75].

In the current SBD era, driven by GPS-enabled devices, mobile technologies, widespread Internet access, and social media, urban environments generate substantial volume and variety of georeferenced data related to social interactions. These data sources offer unprecedented insights into urban contexts that are not discernible from other forms of RS imagery [80, 81]. Addressing these new data streams requires innovative methods for handling, processing, analyzing, and interpreting information to infer the interdependencies that characterize contemporary urban society. Analyzing such data can provide critical insights into urban sprawl, traffic patterns, crime trends, and other socio-economic dynamics [82].

Moreover, the multiple data sources have surged the volume (size as perceived in storage space), the variety (diversity ranging from geo-tagged maps, raster and vector data, meta-data from social media, and GPS devices), and the velocity (the frequency at which data is generated and streamed) of the urban spatial big data [83]. Further, the unique nature of geospatial data, which includes location details embedded in spatial data from acquisition devices such as GPS scanners, mobile mapping tools, and apps with location-tracking capabilities, as well as volunteered Geographic information (VGI), makes the veracity parameter in spatial big data crucial. Veracity (verifiable quality) pertains to quality issues arising from data collected from diverse sources without a standardized quality assessment protocol for the source data [84]. While these new data sources complement the authoritative datasets that have long dominated the field of urban analysis, they are often less certain, asynchronous, and occasionally incomplete [84, 85]. Besides, when data is highly repetitive and collected in an ad hoc manner, it may also introduce "dirty and irrelevant" information. Researchers argue that, despite the availability of data-checking and alignment mechanisms to detect "out of range" distributions, harmonizing multisource urban geospatial data remains a significant challenge. Additional concerns tied to the veracity parameter, including privacy, confidentiality, and security, are addressed in later sections.

The shift from single-modality to multimodal and multisource data has rapidly transformed urban analysis, necessitating practical methods and techniques to exploit the opportunities presented by these data while addressing critical concerns raised by the new paradigm regarding data quality, integrity, privacy, safety, and ethical practices [86].

2.2 Progression of data-driven geospatial models

To understand the progression of data-driven geospatial models in urban analysis, we take a panoramic view of how advancements in RS big data have transformed machine learning models, transitioning from purely image-based to multimodal models and, ultimately, to GeoAI models.

Geospatial image analysis has advanced through significant technological milestones, with emerging waves of innovations stimulating new data analysis paradigms [87]. Early methods relied on manual feature descriptors to interpret urban phenomena. This undertaking was labor-intensive and prone to errors. At the time, simple classifiers categorized features for tasks such as image classification and semantic segmentation, achieving moderate success due to low image resolution. However, manual feature engineering proved inadequate for complex data and high-resolution images, prompting the development of object-based image classification (OBIA) methods [88]. OBIA performed a detailed, precise delineation of objects by classifying them based on their texture, shape, contrast, size, spatial, and spectral properties. It improved upon pixel-based methods by analyzing images at the object level, enabling enhanced interpretation of image objects and their relationships. The potential of OBIA makes the technique applicable to urban applications, such as urban vegetation investigation, cartography, and land cover mapping [89]. Nonetheless, OBIA faced challenges in developing scale-independent segmentation schemes for diverse tasks, leading to computational overhead from repeated iterations while probing optimal scales. The method also struggled to handle hierarchical relationships across high-resolution images, limiting its scalability and generalizability [90, 91].

Later, disruptive techniques, particularly machine learning (ML), evolved, accelerating advances in image analysis through a data-driven paradigm. The availability of training data, the accessibility of computational infrastructure, and the practice of code sharing have accelerated the rapid advancement in ML. This data-driven technique possesses remarkable analytical power to learn representations, patterns, and relationships in data, enabling predictions without explicit programming and thereby replacing manual feature engineering in OBIA [92, 93]. While ML excels in classification, recognition, detection, and segmentation, which are fundamental techniques in computer vision, conventional ML models face difficulties when applied to urban RS tasks. Specifically, these models struggle to accurately handle the complex relationships and hierarchical dependencies found in high-dimensional urban data. The intricate, non-linear features in heterogeneous RS images, along with the complexity of urban scenes, limit the effectiveness of ML models designed for standard computer vision applications [94].

Deep Learning (DL), a subfield of ML, differs from traditional ML in the way it processes data and learns patterns. While ML algorithms often rely on relatively shallow feature learning and perform well with structured datasets, DL, particularly convolutional neural networks (CNNs), use multiple layers to analyze more complex, unstructured data [95]. CNNs have excelled at geospatial analytics tasks, such as automatic building footprint extraction, detection of informal settlements, urban mapping, and road network segmentation, thanks to their ability to analyze complex representations [96]. Other DL algorithms include recurrent neural networks (RNNs), which exploit hierarchical relationships and representations, making them suitable for spatial-temporal predictions and change studies such as urban sprawl and traffic patterns [97].

Key machine learning technologies that have reshaped urban analysis include Transformers, large language models, vision-based models, and foundation models (FMs). Specifically, LLMs and multimodal language models (MLLs) have been widely adopted for their ability to exploit and integrate text, images, and other unstructured multimodal data that previous methods could not handle. While LLMs and MLLs demonstrate significant potential for feature extraction from multimodal and multisource data, they do not fully replace conventional machine learning approaches such as convolutional neural networks (CNNs), graph-based methods, or ensemble techniques. For detailed content on these subjects, we refer readers to reviews on Transformers [98], LLMs in remote sensing [96-98], and multimodal LLM applications in urban geospatial tasks [99-101].

Multimodal data led to the application of multimodal learning to a range of urban analysis tasks. Multimodal convolutional neural networks (CNNs) leverage both RGB images and depth data to infer urban characteristics, such as building height estimation, that is challenging to achieve with optical images alone. [102]. DVL-Suite is a multimodal LLM framework designed for change detection. It captures diverse urban dynamics, including expansion and transformation patterns, disaster assessment, and environmental challenges. For instance, the DVL-Suite framework incorporates an embedded chat model for image-level question answering, thereby facilitating a comprehensive understanding of city dynamics through language-based interactions. [103]. StreetviewLLM employs a retrieval-augmented generation technique to extract urban perception from multimodal data sources, including street view imagery and textual data. The model demonstrates the ability to accurately infer urban indicators, including population density, proximity to healthcare, access to urban green spaces, building height, and impervious surfaces. [104]. Other multimodal LLM frameworks have recently been proposed for urban tasks, including walkability and road safety assessment [105, 106], dumpsite monitoring [107], urban traffic flow optimization [108], and cross-modal tasks [109].

These technological advances have accelerated the development of artificial intelligence (AI), broadly defined as information technologies that replicate, enhance, or extend human intelligence, including perception, reasoning, learning, and decision-making. AI relies on large datasets and analytical methods to identify patterns, generate predictions or recommendations, and improve performance through continuous learning [9, 58, 96]. Over time, AI has become integral to geospatial analytics. Through machine learning and pattern recognition, AI enables advanced spatial modeling and data interpretation within the urban geospatial domain, leading to the development of GeoAI systems. Consequently, GeoAI has become a critical tool for analyzing complex spatial patterns, interpreting urban networks, and monitoring transformations, thereby establishing its central role within contemporary geospatial ecosystems [110]

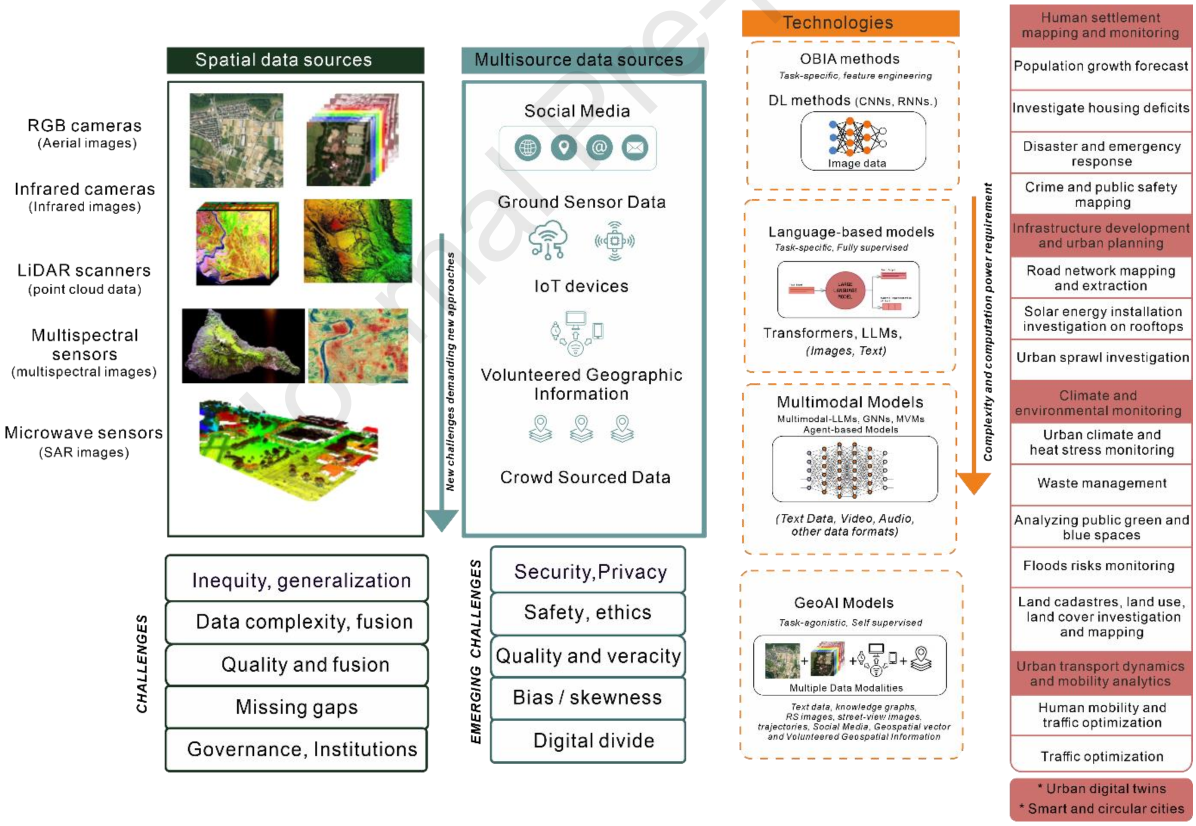


Fig. 4. GeoAI multisource data, progression, and urban analysis application.

The existing literature indicates that integrating GeoAI in urban studies, including urban geography, city analysis, mapping, and related fields, does not replace traditional spatial methods, concepts, or theories. Instead, GeoAI extends and reinforces these approaches. Traditional techniques such as Geographic Information Systems (GIS), empirical surveys, cartographic analysis, and morphological analysis provide grounded theoretical frameworks and rigorous interpretive mechanisms but struggle to capture the nonlinear and complex dimensions of images. [111, 112]. Conversely, GeoAI demonstrates strong capabilities for automated processing of high-dimensional, multimodal, and multisource data and has proven to be an adaptable, scalable, and data-driven technique [113]. However, some researchers contend that GeoAI is still underdeveloped and is yet to achieve the analytical depth and the interpretive clarity that characterize traditional spatial analysis methods [114, 115].

Fig. 4 illustrates the progression of novel data sources that extend urban analysis beyond conventional RS data. These sources provide critical information that deepens geographic understanding of urban environments and their dynamics. However, they present challenges, including complexities in data fusion, biases and skewness, data gaps and incompleteness, and security and privacy issues associated with location and user information. Additionally, data quality may be undermined by inconsistent standards applied during data collection and transmission. [116]. Emerging challenges involve the lack of standardized data governance, data islands, and fragmented data silos. These factors hinder the application of methods developed using heterogeneous datasets. Furthermore, economic disparities and limited access to expertise and computational resources contribute to digital inequalities in the training of GeoAI frameworks.

Further, the figure highlights advancements in data-driven technologies, tracing the transition from the OBIA era to the current GeoAI era. It also shares some urban GeoAI applications, indicating a significant increase in downstream applications enabled by new data sources. Earlier urban analysis applications that relied solely on RS imagery faced limitations in inferring certain urban dynamics, such as mobility and transportation. These developments indicate growing adoption of multisource data and suggest wider uptake of GeoAI for automated analysis of urban challenges. By overcoming challenges from new data sources and leveraging spatial intelligence, the GeoAI paradigm promises to deliver enhanced capabilities, efficiency, and precision for comprehensive interpretation, perception, understanding, and prediction of urban space.

3. Emerging issues with data, constraints, and human-centric perspectives

This section outlines the most recent and readily accessible datasets used to train GeoAI systems for urban geospatial tasks. The outlined datasets include unconventional datasets such as vector, trajectory, LiDAR, and address datasets. Later, we share the challenges arising from data complexity, incompatibility, bias, and incompleteness. We also highlight issues related to inference, explainability, transparency, and generalizability. Finally, we discuss privacy, ethics, safety, and data management, aligning with the scope of this review.

3.1 Pre-training datasets for GeoAI models

Pre-training datasets for machine learning models are central to the performance and capabilities of the inferencing engine. Training datasets serve as the foundational infrastructure, akin to a root system that supports and nurtures the pre-training, testing, and evaluation of machine learning models. Usually, models pretrained on natural images struggle with geospatial downstream tasks. This is due to the domain variance between natural images and geospatial scenes. As a result, GeoAI models are increasingly trained on geospatial datasets aligned with diverse geospatial tasks to achieve optimal performance. Therefore, studying these datasets and identifying emerging trends constitutes a relevant research inquiry.

To comprehensively understand the utility of pretraining datasets, it is essential to recognize the fundamental technologies that underpin urban analysis tasks. Conventional vision-based models are developed for specific tasks, such as scene classification and perception. However, recent advancements in machine learning have led to the development of multitask models. In urban contexts, image scenes are categorized into classes such as built-up areas, roads, waterways, and plantations through semantic segmentation and image classification. In semantic segmentation (also known as dense prediction), models assign each pixel in an image to a specific class, producing segmentation maps. The generated thematic maps play a crucial role in interpreting essential tasks, including the extraction of urban building footprints, roads, and powerlines. Other applications of semantic segmentation include snow extraction, land cover distribution, urban mapping, building damage assessment, and agricultural area identification, making it a fundamental technique in urban analysis [117, 118]. In object detection, although the task is intricately linked to semantic segmentation, it extends beyond merely identifying "what" is present in an image to also delineating "where" [119]. This capability is critical for supporting tasks in urban planning, disaster response, and environmental investigation. Other fundamental tasks include change detection, which helps identify variations in the land surface state. [120, 121]. Collectively, these tasks play a critical role in urban analysis and are considered in urban pre-training datasets.

Another technological leap that has recently emerged is visual question-answering (VQA), which has become a standard in multitask applications, particularly in urban contexts. Under VQA, questions are formulated in natural language, and the inferencing engine interacts with the system to extract the necessary information from the target urban scenes or images. Consequently, VQA datasets are developed to train models for visual-language understanding. These datasets integrate text corpora as question-and-answer pairs with images to facilitate information retrieval and visual question-answering tasks. [122, 123]. Other datasets that enhance the training of urban analysis models include LiDAR (Light Detection and Ranging) data, which provide a comprehensive three-dimensional representation of objects and surfaces from various angles, using thousands of points per square meter, referred to as point clouds [124]. Geospatial models enhance the understanding of urban environments by integrating 3D geospatial data, point clouds, and digital twin technology. This integration provides precise, detailed representations of urban areas, enabling the simulation, monitoring, and prediction of urban phenomena such as traffic patterns, infrastructure conditions, and environmental changes [26, 125, 126].

Further, geographic vector data serves as a digital representation of geographic reality, utilizing three-dimensional geometric forms, points, lines, and polygons, to create a comprehensive repository of information. This data can be sourced from multiple sources, including images and maps, and is notably memory efficient [127]. The compatibility of vector data with a wide range of applications has made vector geographic datasets popular for training geospatial models in urban analysis. Trajectory data derived from GNSS and INS technologies supports precise object localization, facilitating the study of movement patterns and resource distribution across both temporal and spatial dimensions. When combined with other data sources, the augmented training data significantly enhances the representation of critical geographical features across applications [128]. Further, address datasets offer a comprehensive catalog of geographical areas, enabling precise placement and detailed descriptions, which are essential for location analysis. This dataset supports vital applications, such as route mapping for emergency responses, resource allocation, and location mapping, making it indispensable in urban settings.

Novel data sources include crowdsourced social media and volunteered geographic information (VGI). Powered by Internet penetration and wide use of mobile devices, social media data have been used in urban studies to infer park visitation and perception in twin cities [129], mapping riverscapes and cultural ecosystems [130], infer livability of urban regions [131], mapping urban crime hotspots and risky regions [132], predict urban traffic congestion

[133], among other urban applications. In addition, street-view imagery has been used in urban analysis to map green spaces, assess walkability, and examine other urban dynamics [134, 135].

While current pretraining datasets have expanded considerably to encompass multimodal and multisource data, this review presents the datasets reported for pretraining models in urban analysis. **Table 1** presents recent datasets for urban analysis, classified by application domain, annotations, modalities, spatial resolution, year of development, and references. Although the listed datasets are not exhaustive and do not delve into the analytical contexts relating to model's performance trained in these datasets, they provide researchers, particularly newcomers to the field, with a valuable overview.

Table 1: Pre-training datasets in urban analysis

Category	Year	Dataset Name and Reference	Resolution	Samples / pairs	Application
Vision-Language Datasets	2017	RSICD [136]	224 x 224 pixels	10,921	Image captioning
	2020	RSVQA [122]	15-cm - 10-m	10,659	GeoQA
	2021	WIT [137]	Text-Image-Pairs	37.6 M	VQA
	2021	FILIP [138]	Text-Image-Pairs	300 M	VQA
	2022	RSITMD [139]	23,715 captions	4,743	RS text–image retrieval
	2022	LEVIR-CC [140]	Mixed	10,077 50,385 pairs	Change captioning
	2022	WHU-OHS [141]	512 × 512 pixels 15 nm spectral resolution	7,795	HSI classification
	2022	LION5B [142]	Text-Image pairs	5 B	VQA
	2023	DIOR-RSVG [143]	Text-image pairs	17,402 38,320 pairs	Visual grounding and GeoVQA
	2023	RSICap [144]	Mixed	2,585 text-image pairs	RS image understanding
	2023	EarthVQA [123]	0.3m	6,000 208,593 pairs	GeoQA and GeoAI
	2024	UrBench [145]	Mixed	11.6K pairs	GeoQA and GeoAI
	2024	RemoteCLIP [146]	Mixed	165,745 images and 828,725 image-text pairs	Image-Text retrieval and other tasks
	2024	LHRS-Align [147]	Text-Image-Pairs	1,150,000	RS image understanding
	2024	hqDC [148]	Text-Image-Pairs	1.4 M	RS image understanding and VQA
	2024	GeoRSCLIP [149]	Text-Image-Pairs	5M	GeoVQA and GeoAI
	2024	RS5M [149]	Text-Image-Pairs	5 M	Vision-language tasks
	2025	DDFAV [150]	Mixed		GeoRSCLIP
	2025	SkyEyeGPT [151]	Mixed	968,000 pairs	Vision-language tasks
	2025	EarthReason [152]	Mixed	5,434 images, 30,000 pairs	Vision-language tasks
Multimodal-based RS Datasets	2019	iSAID [153]	512 × 512	2,806	Multiple RS tasks
	2020	AUAIR [154]	1920×1080 resolution	32,823	Visual object tracking
	2020	Earth on Canvas [155]	256 x 256 pixels	2,800	Inter-modal data retrieval
	2021	MRSSC [156]	40m, 100 m	12,000	Scene classification
	2021	BigEarthNet-MM [157]	10m–20 m Resolution	590,326	Classification
	2022	SEN12MS-CR-TS [158]	4000×4000 pixels	53	Multiple RS tasks

	2022	MMFlood [159]	20m	1748	Flood impact assessment
	2022	MULTISENGE [160]	256 x 256 pixels	8,157	Land use and land cover classification
	2023	C2Seg [6]	10m	413	Cross-city semantic segmentation
	2023	SSL4EO-S12 [161]	264 X 264 pixels	3M	Multiple RS tasks
	2023	SMARS [162]	30cm and 50cm	108 Synthetic tiles	Change detection, urban segmentation, and building extraction
	2023	MDAS [163]	Mixed	108K	Multimodal RS applications
	2024	MFED [164]	Mixed	1,419	Flood assessment
	2024	MMM-RS[165]	Mixed	2.1M Text-image pairs	RS image generation
	2024	DRIFT [166]	0.2 – 0.5m	25,000	Vegetation monitoring
	2024	RS-GPT4V [167]	Mixed	91,937 images 991,206 instruction-answer pairs	RS image understanding and VQA
	2014	PotsDam [168]	0.5m 6000×6000 pixels	38	Semantic Segmentation
	2014	Vaihingen [168]	0.3m	33	Semantic Segmentation
	2017	NWPU-RESISC45 [169]	0.2 m–30 m	31,500	Scene classification
	2017	AID [170]	600 × 600 pixels	10,000	Scene classification
	2018	FMoW [171]	Mixed	1,047,691	Multiple RS tasks
	2018	DeepGlobe Land Cover [172]	2,448 x 2,448 pixels	1,146	Multiple RS tasks
	2018	SpaceNet 2 [173]	0.3m	302,701	Building footprint detection
	2019	EuroSAT [174]	64 × 64 pixels	27,000	Land use and land cover mapping
	2019	XBD [175]	0.8 m/pixel	850,000	Multiple RS tasks
	2020	MLRSNet [176]	10m to 0.1m	109,161	Multilabel image segmentation
	2020	SECOND [177]	512 x 512 pixels	4,662 pairs	Change detection
	2020	Gaofen Image Dataset (GID) [93]	150 x 150 pixels	150	Land cover mapping
	2021	FloodNet [62]	1.5cm	2,343	Visual QA
	2021	SYSU-CD [178]	0.5m	20,000	Change detection
RS Datasets	2021	FAIRIM [179]	0.3m to 0.8m	15,000	Object recognition
	2021	LoveDA [180]	0.3m	5,987	Land cover mapping
	2021	EarthNet2021 [181]	20m	32,000	Multiple RS tasks
	2021	BigEarthNet [182]	10, 20, 60m resolution	590,326	Land cover mapping
	2021	LEVIR-KR [183]	Mixed	1,431,950	Geographical knowledge
	2021	Alsat-2B [184]	10m and 2.5m	13	Super-resolution construction
	2021	DOTA-v2.0 [121]	800x800 – 20,000x20,000 pixels	11,268	Object detection
	2022	CLCD [185]	0.5m to 2 m	600	Change detection
	2022	SpaceNet 8 [126]	0.3-0.8m	32,000	Multiple RS tasks
	2022	Landsat-SCD [186]	30m	8,468	Change detection
	2022	LIB-HSI [187]	512 x 512 pixels	513	Semantic segmentation on hyperspectral images
	2022	DynamicEarthNet [118]	3m	730	Semantic change detection
	2023	ChangeNet [188]	0.3m	31,000	Change detection
	2023	Billion Pixels [189]	4m	150	Land cover mapping
	2023	EGY-BCD [190]	0.25 m	6,091	Change detection

	2023	WHU-Mix [191]	Mixed	43,727	Building extraction
	2023	MillionAID [192]	Mixed	10,000	OD & SS
	2023	GeoImageNet [193]	DEM (10m) and NAIP (1m)	Not available	Object detection
	2023	HRCUS-CD [194]	0.5m	11,388	Change detection
	2023	UV6K [195]	0.1m	6,313	Urban vehicle segmentation
	2023	Satlas [196]	Mixed	302M	Multiple RS tasks
	2023	GVLM [197]	0.59 m	17 bitemporal very-high-resolution imagery pairs	Change detection, semantic segmentation, and landslide extraction
	2023	SAMRS [198]	Mixed	105,090	Object detection
	2024	Hi-CNA dataset [199]	0.8m	6797 pairs of dual-temporal images	Change detection
	2024	FMARS [200]	17,408 × 17,408	6,896	Disaster management
	2024	3D-GloBFP [201]	Various	Not available	Building footprint investigation
	2025	EarthView [202]	0.1, 10, 20, 60 m resolution	15 TB	Multiple RS tasks
	2025	S2-100K [203]	256×256 pixels	100,000	Multiple RS tasks
	Type	**Dataset Name and Reference**	**Resolution**	**Year**	**Application**
	LiDAR	USGS 3DEP [204] [205]	10m – 30m	2025	Precise 3D modeling.
		Global Ecosystem Dynamics Investigation (GEDI) [124]	1m (Altimetric resolution)	2022	Forest analysis
		UK Environment Agency LIDAR data [206]	50cm – 1m	2023	Precise 3D modeling.
		Toronto-3D LIDAR dataset [207]	<1m	2020	Urban modeling.
	DEM	Copernicus DEM [208]	30m – 90m	2022	Terrain modeling.
		ASTER Global [209]	30m	2020	Orthorectification.
		Shuttle Radar Topography Mission (SRTM) [210]	30m	2010	Elevation modeling.
Supplementary datasets	Vector	OpenStreetMap [211]	Global coverage	2009	Navigation and urban routing
		Global Google-Microsoft Open Buildings Dataset [212]	Various	2023	Building, mapping, and change detection
		Google Maps vector data [213]	Global coverage	2019	Navigation
	Trajectory	EuRoC MAV dataset [214]	Multimodal	2016	Vehicle navigation (Autonomous)
		Geolife [215]	17,621 trajectories	2024	Geolocation and tracking.
		ExactEarth Satellite AIS tracking system [216]	Global coverage	2024	Maritime traffic.
	Addresses	GeoNames [217]	11 million addresses.	2013	Geocoding and addressing systems.
		National address database (France) [218]	25 million addresses.	2024	Nationalwide addressing
		Australia Post's GNAF [219]	13 million addresses.	2016	Nationwide geocoding and addressing systems.
		ISPARK [220]	Istanbul City	2024	Parking lot

The number of training datasets referenced in Table 1 illustrates an upward trend in diversity, enabling pretrained models to tackle a broader spectrum of tasks. However, significant challenges exist in the current datasets used for GeoAI urban analysis. First, most training datasets are created without adhering to a standardized protocol or curation process. This raises a qualified concern about the quality of the datasets and the choice of benchmarks for model training. Furthermore, the diverse sizes of pre-training datasets and their imbalanced use in existing research pose challenges for assessing the impact of pre-training data on the adaptability of GeoAI models to downstream tasks [221]. Additionally, most domain-specific datasets are designed to train models for closed-world scenarios, which limits their generalization ability for environment-agnostic contexts [222].

To address these challenges, Li et al. and Fang et al. suggest developing large-scale multimodal corpora by assembling comprehensive collections of geospatial images (including satellite, aerial, and drone imagery) alongside corresponding textual descriptions, GIS metadata, and annotations. This approach emphasizes cross-domain diversity to improve generalization. Further, modalities can be paired and aligned with knowledge augmentation, integrating images or videos with knowledge-rich text or knowledge graphs (such as place descriptions and historical events) to facilitate cross-modal alignment [223, 224]. On the other hand, Oxori et al. argue the need for temporal sequencing with contextual narratives, linked to datasets that combine time-series geospatial imagery with mission logs or reports, to enhance temporal reasoning for change studies [225]. Subsequent sections address additional concerns related to pretraining datasets, such as regional socio-economic inequalities in urban spatial data, generalizability issues, bias, and data management.

In conclusion, future datasets should include explicit documentation and spatial-temporal pretext tasks while accounting for temporal and geographic diversity. Since the highlighted parameters can differ significantly across pre-training datasets, establishing a detailed framework for developing comprehensive, representative, and diverse geospatial datasets, along with practical training strategies, can substantially improve benchmarking for emerging urban geospatial models across diverse data modalities.

3.2 Data bias, incompleteness, and generalizability

GeoAI systems leverage spatial and multisource data, advanced through a model pipeline, to derive insights and context, enabling inferences and predictions. However, the increasing reliance on GeoAI across multiple data sources presents notable challenges, particularly in addressing data bias, missing observations that lead to incomplete spatial-temporal coverage, and data source fragmentation. Additional concerns stem from data heterogeneity, varying scales, and complexity in fusion and real-time inference constraints.

Several studies have explored explainable artificial intelligence (XAI) to identify biases, such as data- and model-bias, as well as other critical factors that lead to skewed predictions when designing GeoAI systems. Gao argues that assessing gradients and feature attributions may not be sufficient to uncover underlying or spatially scaled biases [7]. The study thus proposes developing a comprehensive framework to identify the forms and sources of bias. Some of the existing biases in machine learning inference include data bias, which relates to the representativeness of input data; model bias, which pertains to algorithmic preferences when computing weights during backpropagation; and perception bias, which concerns how humans interpret spatial cues when comparing GeoAI outputs to ground truth explanations [31, 59].

Data bias in GeoAI can arise from diverse causes, including the presence of non-representative samples (e.g., uneven ground truth), limitations inherent to sensors and vision systems, and sampling bias in crowdsourced, geo-constrained regions, or open data sources [7, 45, 226]. In city-to-city deployments, models can fail "out of distribution" robustness due to unseen elements and under-distribution biases caused by vast city morphological representation. Worse still, running bias-prone multisource geospatial data through data-driven ML models that may themselves be algorithmically biased can exacerbate these biases [227, 228]. When these biases infiltrate data and process pipelines, they affect interpretability, transferability, and accountability. In real-world GeoAI applications, misinterpretation of ground truth or misalignment with model objectives can amplify bias susceptibility and undermine trust in predictions [45, 229]. In a particular scenario, the Building and Establishment Automated Mapper (BEAM) demonstrated a promising 94% success rate in detecting building footprints after its deployment in informal settlements. However, over the years, the model's performance declined due to changes in weather, sensor parameters, and imaging protocols, necessitating costly retraining. [230]. This case aligns with Dank's assertion that the effectiveness and efficiency of AI tools and their algorithms are largely contingent upon the characteristics of the data used for their training. [231].

Another approach involves integrating physics-based models with data-driven GeoAI frameworks to ensure that predictions are consistent with established physical laws. This integration can reduce misleading biases inherent in purely data-driven methods and enhance adaptability across diverse environments [13, 232]. In light of the above, Scheider & Richter proposed a comprehensive strategy that highlights the importance of characterizing and auditing data biases. The framework's objective was to curtail bias propagation, thereby enhancing the reliability and fairness of GeoAI systems, thus improving the quality and promoting trustworthiness in decisions derived from geospatial data and AI technologies [228, 233].

Still, human dynamics and preference considerations are crucial while addressing perception bias, ensuring inclusive integration into decision-making processes, and maintaining trust in GeoAI systems [14, 22]. Jiao et al. and Jin et al. assert that developing explanations that account for geospatial scale, spatial relationships, and domain-specific semantics, and validating them with expert insights and real-world outcomes, can mitigate biases [31, 59]. For instance, location-based tasks can incorporate geospatial knowledge, such as the Geospatial Positions of point-of-interest objects (e.g., crater locations) in geospatial mapping, or hydrodynamic constraints in flood risk modeling, thereby enhancing robustness and reducing reliance on biased data alone [42]. Such practice, supported by governance frameworks with ethical guidelines, transparency, and evaluation protocols, can address biases and accountability gaps, particularly in understated regions or complex applications. Still, developing systems that combine process- and data-driven GeoAI models with open, scalable cloud-based architectures can support robust inference with bias checks across data sources, while facilitating model reusability and auditing [13, 234]. Further, fostering interdisciplinary collaboration among related disciplines, such as remote sensing, hydrology, urban studies, computer science, and policy, is reported to promote standardization of data, evaluation metrics, and bias-mitigation strategies [45, 226, 235].

Regarding data incompleteness and complexity, urban systems are inherently multimodal and characterized by feature-rich urban data repositories sourced from diverse origins. These systems integrate various data streams, including traffic patterns, pedestrian mobility traces, images, text, and sensor readings. This form of diversity provides feature-rich networks and indicators from diverse sources, enabling multimodal analyses that support objectives such as explanation, discovery, understanding, and generalization. However, data from different streams introduces diversity, raising challenges related to data constraints, quality, incompleteness, and complexity [22, 51].

To handle these challenges, some studies have automated the construction of knowledge graphs from multimodal inputs for retrieval, reasoning, and plan generation, facilitating tasks such as domain questioning and image-based plan synthesis [236]. Given that multimodal fusion occurs at multiple levels, researchers can leverage deep learning to integrate complementary information across modalities. Urban systems can deploy techniques that leverage text-image fusion to deliver assessments of urban recreation and environmental amenities, underscoring their benefits for location-based services [237]. Moreover, multimodal fusion can leverage visual context and textual cues via graph-based representations to model comprehensive situational understanding among entities.

For example, Wang et al. SMART-Plan exemplifies how knowledge graphs can be developed from multimodal data to aid in planning tasks and the creation of image-based plans. By integrating semantic graphs with multimodal embeddings, the framework enables reasoning about urban objects and their interconnections [236]. Additionally, domain-graph-enhanced multitask models can unify perception, enhance reasoning, and facilitate planning across various urban tasks by leveraging multimodal data and knowledge graphs. These models are applied to safety-critical scenarios and can help conduct integrity checks and validate data quality for localization in urban environments. Moreover, conducting coherence-based checks across modalities is crucial for identifying inconsistencies. This is especially necessary for mission-critical solutions such as emergency response or transit planning [238]. Notably, a robust GeoAI strategy should strike a balance between data integration and transparent modeling to advance societal and sustainability objectives by combining geospatial knowledge with data-driven learning while recognizing the limitations inherent in complex urban environments [12, 228, 239].

In a broader sense, generalizability encompasses the capacity to adapt across diverse geographic regions and data forms and to withstand spatiotemporal variations. The hydrological and urban studies conducted by Gonzales-Inca et al. recognize that, while GeoAI systems have the potential to reveal novel patterns and processes, they frequently encounter challenges related to low physical interpretability and limited generalization across different contexts, particularly when models are overly aligned to specific training datasets or scales [228]. Generalizability and reproducibility are further explored by Li et al.'s study, which underscores the trade-offs between non-linear predictive power and physical interpretability. Li emphasizes that models and evaluation protocols should prioritize generalization to new regions or temporal contexts, aligning with methodological rigor for broader scientific accountability [240]. To evaluate generalization, Deng et al. proposed a transformer-based model that emphasizes spatial context and examined its performance on synthetic and real-world datasets for spatial regression and interpolation. The results contend that spatial contexts are a crucial component of generalization and propose that XAI methods can aid in quantifying and communicating the capabilities of contextual generalization [241].

Further, recent evidence has highlighted the limitations of generalizing across cities when training models on specific urban environments. These models often struggle when applied to cities with varied morphological features. This observation also raises concerns about potential domain-shift limitations, particularly for models trained predominantly on datasets from the Global North when applied in Global South contexts, where urban settings exhibit extensive and diverse characteristics. [111]. Besides, many regions in the global South face significant limitations in digital infrastructure, including insufficient computing power, unreliable electricity, limited broadband connectivity, and inadequate data storage or cloud services.

These challenges restrict both institutional and regional capacity to utilize spatial-temporal data. Additionally, the majority of datasets are sourced from the Global North, raising concerns about financing, equity, and the unequal access to and distribution of research benefits [242-244].

In some instances, urban data generated by users in specific regions may be biased, incomplete, or unrepresentative of the broader population. For example, social media data collected in a city such as London is often derived from young, affluent, and educated individuals. This raises significant concerns regarding the generalizability of AI models trained in one urban context when applied to other regions with heterogeneous characteristics, including cultural, socioeconomic, and structural differences [245]. Further discussions on disparities in spatial data across regions, especially the global North and South, are extensively covered in reviews [246-248].

To address generalizability across cities, SERT employs a regional knowledge transfer technique to predict traffic flow in data-scarce environments [249]. This method establishes connections between source and target regions by integrating satellite images and Points of Interest (POI) data, thereby identifying region-specific characteristics and creating matched region pairs via contrastive domain adaptation. The goal is to align the features of matched regions, enabling knowledge transfer between cities and minimizing the feature distance of unmatched regions from noise from irrelevant data. Other methods to address city-city generalization limitations include Bayesian regularization, which exhibits lower error and confidence bounds [250]. In other studies, Uncertainty-aware Domain Generalization (UADG) uses specific urban features' “selective whitening” to separate city-specific style features from general content features, improving model transferability for unseen scenarios [251]. Surrogate models trained on multiple cities and later finetuned to predict target features in unseen urban contexts. These studies showcase approaches to strengthen generalizability and address incomplete data while addressing large, heterogeneous urban domains [252, 253]. However, there are still limitations for long-tailed data distributions in cities with rare elements, such as unique building scales, densities, and distributions, due to socioeconomic variance [254].

Addressing bias stemming from data sources is critical to ensuring the reliability and fairness of AI models, particularly in urban analysis. Data bias can arise from unrepresentative or incomplete datasets, which may disproportionately reflect certain populations, regions, or conditions, leading to skewed model outcomes [255]. This issue is compounded when models trained on data from specific cities or regions are applied elsewhere, as variations in demographics, socio-economic factors, and environmental conditions can limit their generalizability. Even when models perform well in their original context, they can fail to deliver accurate or equitable results in different geographic or cultural settings.

Techniques proposed and applied to mitigate these challenges have been outlined and discussed in recent studies, including domain adaptation and transfer learning to help models adapt to new regions by fine-tuning on localized data, thereby enhancing their applicability across different cities [45, 239, 256]. Additionally, incorporating fairness-aware algorithms and continuous monitoring for bias during model deployment ensures that disparities are identified and addressed proactively. These solutions, combined with strict data-quality controls and reporting on data limitations and model assumptions, can contribute to more equitable and generalizable AI applications across cities and regions [32].

3.3 Explainability, transparency, and trustworthiness

Urban analysis is gradually transitioning from isolated XAI practices to frameworks that prioritize human-centric approaches. The term "human-centric" in this article refers to methodologies, practices, technologies, and processes that prioritize not only the urban environment but also emphasize placing *people* at the core of the design and implementation of urban systems. Various sources define XAI as the development of AI systems that are focused on human needs, equity, interpretability, and policy relevance [22]. Thus, such frameworks must methodize data provenance and quality, inference process, contextual sensitivity, and user requirements into the design and evaluation of models.

Explainable GeoAI is crucial given the non-stationary and diverse nature of geospatial data, as well as the societal implications of predictions made by GeoAI systems. Both Hanny et al. and Liu et al. underscore the importance of exploring beyond gradient-based attributions to include spatial context in explanations (such as details of model development, data management, scale, and geographic specificity) when applying XAI to GeoAI [15, 32]. This viewpoint aligns with Roussel and Böhm's review of Geospatial XAI, which examines cutting-edge ML models and XAI techniques specifically for geospatial tasks. These studies underscore the importance of geospatially aware explanations [257]. In related studies, Liu et al. present a robust architecture for explainable spatial GeoAI by combining a graph neural network (GNN) with a graph-based XAI method (GNNExplainer) for urban analytics tasks, demonstrating how spatially explicit explanations can be generated via graph-based methods [32].

Beyond methodological advancements, other studies have emphasized human-centered and user-relevant explanations. Hanny et al. introduce an explainable GeoAI approach for the multimodal analysis of urban human dynamics, using COVID-19 in Rio de Janeiro as a specific case [15]. The proposed approach emphasizes the ranking of spatiotemporal features to facilitate transparent model building and interpretable predictions. Ye et al. underscore the importance of human dynamics in foundation models for GeoAI, arguing that geo-context and human-centered considerations are crucial for understanding and trusting large GeoAI systems [22]. Roussel et al. further highlight visualization challenges for XAI in GeoAI, noting that traditional plots lose geospatial context unless adapted for spatial plots [258]. These studies suggest that adequate GeoAI explanations require spatially aware visualization, explicit mapping of feature relevance to geospatial contexts, and consideration of human interpretability in design and evaluation phases.

Moreover, to enhance explainability, reproducibility, and trustworthiness in GeoAI systems, it is imperative to consider scientific rigor and social responsibility. For example, OpenStreetMap (OSM) serves as a fundamental data source for GeoAI model training; however, its quality and completeness can introduce biases into these models. To mitigate this scenario, Li and Zipf propose a conceptual framework for converting OSM contributions into geospatial machine-learning training data. The framework emphasizes historical data considerations, quality indicators, and error sources, and accounts for completeness, alignment, and variation [259]. Furthermore, the framework emphasizes the importance of incorporating data provenance and quality checks into GeoAI workflows to prevent misleading explanations and overconfident predictions. In related research, Saleh et al. present a comprehensive literature review that identifies limitations in GeoAI studies, including spatial data bias, the absence of ground truth, computational efficiency, ethical concerns, and interpretability. The study advocates for cross-domain collaboration and the establishment of ethical guidelines to ensure responsible deployment [45]. Further, Bordogna and Fugazza investigate the role of AI in managing multisource geospatial information, noting that the definitions and boundaries of GeoAI are evolving, thereby affecting transparency and methodological clarity [260]. Collectively, these works emphasize that transparent GeoAI necessitates clear data lineage, comprehensive documentation of dataset characteristics, and explicit consideration of biases and uncertainties arising from diverse data sources.

Roussel et al. introduced quality-aware explainable artificial intelligence (XAI) for geospatial analysis through the Q-GGXAI framework, which explicitly links model explanations to quality metrics, a crucial aspect for reliable applications in urban planning, health, and transportation [261]. This framework highlights the importance of geospatially aware visualization design for explanations, addressing the gap between standard machine learning and geospatial contexts. The study advocates integrated XAI-data quality pipelines and geospatial visualization tools to help stakeholders understand model decisions in a geographical context, a view supported by related studies [15, 22, 262].

In sum, GeoAI necessitates comprehensive strategies that identify and communicate uncertainty and data origins, generate explanations that preserve and represent spatial context, while prioritizing human decision-makers and ethical considerations. The findings of this review indicate that the majority of GeoAI research focuses on improving algorithmic accuracy and efficiency. However, there is a notable lack of critical examination of the analytical inferencing processes that generate these outputs, leading to opaque inferencing. Furthermore, there is insufficient information on budgetary decisions, data governance mechanisms, and regulatory procedures, all of which should be aligned with methodological innovation and policy directions. It is crucial that robust data governance mechanisms clearly define data ownership and interests, accountability, and compliance across the data processing pipeline while promoting secure data tracking, access controls, and auditable policies. Future GeoAI frameworks must attend to data quality, make spatially agnostic decisions, generate explanations and visuals, and exhibit robust generalization, while incorporating human-centered governance to ensure GeoAI deployments are transparent, trustworthy, and socially responsible.

3.4 Privacy, ethics, and safety

GeoAI analysis increasingly incorporates geospatial data into AI algorithms to derive insights from sensitive personal data and infer geospatial context. Crowdsourced data from social media, VGI, geotagged data, and metadata are fused with spatial data to reveal new urban insights. This trend raises critical concerns regarding privacy, ethics, and safety. This type of data contains rich metadata that can reveal sensitive information about individuals, households, and communities, thereby raising risks related to confidentiality and security. Therefore, the development and deployment of GeoAI systems require robust data governance, proactive privacy design principles, and clear safety procedures to prevent harm and protect user data rights and liberties [14, 38, 263]. This section presents recent studies on privacy, ethics, and safety in GeoAI analyses, drawing on insights from urban geospatial health, IoT and sensor ecosystems, and public welfare.

The ethical management of geographic data, known as GeoEthics, is crucial for the responsible governance of GeoAI across public and commercial domains. Privacy risks are exacerbated when private-sector geospatial data collection intersects with health analytics, mobility tracking, or environmental exposure assessments. Although the principles of privacy-by-design, data minimization, and purpose limitation have been advocated in the literature, concerns regarding GeoAI data obtained from IoT and connected devices in urban settings, such as location-based applications, preference mappings, and social media, amplify privacy concerns in the handling of personal data [38, 264]. Thus, ethical risk assessment and data governance are essential for the trustworthy implementation of IoT-enabled analytics, underscoring the importance of individual data autonomy and informed consent in data collection and use [265, 266].

In the field of health-oriented GeoAI, the responsible use of geospatial data in epidemiology and health disparities research is intrinsically linked to the implementation of privacy measures. These measures include averting the disclosure of precise geolocations and, where feasible, employing techniques such as aggregation, differential privacy, or secure multiparty computation to mitigate the risk of re-identification [264]. Inappropriate handling of user geospatial data can erode trust and lead to ethical violations, underscoring the necessity for defined privacy-preserving mechanisms during model architectural design and deployment. Agbese et al. and Machado et al. call for the development of ethical frameworks for urban GeoAI, emphasizing stakeholder engagement, risk assessment, and benefit appraisal. Such frameworks can minimize harm and promote Trustworthy practices, as established in the EU Trustworthy AI and Data Governance Charter [36, 37, 267]. Collectively, these studies stress that privacy, data governance, and the broader societal and environmental impacts are a core ethical obligation rather than a secondary consideration.

Research on robotic systems in care settings emphasizes the importance of integrating privacy safeguards and safety-by-design principles into system development, alongside stakeholder engagement and contextual risk assessments [268, 269]. In the context of GeoAI, these considerations necessitate that automated, location-based decisions prioritize patient autonomy and protect private data. The studies advocate for innovative, responsible frameworks that provide structures for evaluating privacy levels across diverse domains while observing ethical principles that promote accountability, transparency, and stakeholder participation in governance processes [264, 270]. Similar observations are made in safety engineering practice, where systematic mappings and reviews emphasize the need for tailored security standards and proactive safety engineering for AI-enabled health systems to guarantee safe operation, privacy protection, and public trust [271].

In recent studies, federated learning (FL) and decentralized AI have been proposed to address growing concerns over data privacy and real-time processing constraints [272]. FL addresses privacy concerns by enabling distributed AI training across multiple edge devices, allowing AI models to learn from localized data without exposing critical information [273, 274]. In so doing, the FL approach preserves data sovereignty. However, some studies contend that FL across heterogeneous urban contexts grapples with diverse data formats, interoperability issues, noisy data, and network synchronization, which affect the models' overall accuracy and performance [275].

Further, governance bodies comprising stakeholders, data scientists, and community representatives can evaluate data flows, de-identification strategies, and re-identification risks to promote aggregation, differential privacy, secure multiparty computation, and access controls. These steps can significantly reduce uncertainties related to re-identification risks while preserving analytical functionality. Additionally, incorporating fail-safes mechanisms, advancing explainability, and adopting human-expert-in-the-loop controls in contexts that utilize private data can effectively manage unforeseen risks. This approach prioritizes safety certifications, conducts field testing in controlled environments, and ensures continuous monitoring. [268, 271]. Lastly, cross-domain professionals require skills in governance, privacy, and data literacy to understand model workflows, data governance demands, and ethical responsibilities. The asymmetrical capacity in technical expertise not only affects effective data handling and algorithmic design but also influences the interpretation of outputs and the accurate communication of results, including potential assumptions, biases, and uncertainties, to policymakers. Upskilling such professionals can address knowledge gaps that hinder adoption and safe deployment in settings critical to public safety and privacy, and address the overreliance on external experts who may not fully contextualize local social, cultural, and historical realities [46, 276].

Addressing privacy, ethics, and safety in GeoAI analysis, particularly in the context of multi-source training datasets, is a pressing concern that demands a comprehensive, multi-layered approach. Candidate solutions should incorporate privacy-by-design, robust data governance, stakeholder engagement, and rigorous safety engineering. The reviewed studies identify GeoEthics as a foundational pillar that drives privacy and consent in geospatial contexts that utilize private data. Integrating privacy-preserving technologies, transparent governance, and human-centered design can enhance GeoAI urban analysis and interpretation while safeguarding individual rights and promoting public trust.

4. Applications of GeoAI in urban contexts

This section presents representative GeoAI applications, including urban investigation and mapping, precision and smart agriculture, and disaster management.

4.1 GeoAI in urban infrastructure investigation and planning

GeoAI is revolutionizing urban mapping and infrastructure research, thereby enhancing our understanding of complex urban systems. It also provides intelligent, data-driven insights that support critical decision-making in urban spaces.

GeoAI in urban analysis and planning extends beyond mere resource allocation and infrastructure development. It plays a significant role in modeling cities by integrating diverse data sources to optimize urban systems. For instance, GeoAI supports traffic patterns analysis, modeling public transportation routes, and investigating pedestrian flows to enhance urban mobility. This enables urban planners to design and implement efficient transportation networks that mitigate congestion and improve overall urban connectivity [32]. In the environmental impact evaluation of urban development, GeoAI analysis utilizes parameters such as settlement density and land surface temperatures to provide insights that support decisions on green spaces, energy-efficient building designs, and advancing sustainable urban growth strategies [277].

In cartography and mapping, high-resolution RS images are analyzed to produce maps that serve as imprints of city infrastructure networks [278]. Further, land cover mapping can be performed by generating thematic segmentation maps that distinguish elements such as buildings and infrastructure, land-use areas, and water bodies in urban areas. These maps are indispensable for improved urban planning, environmental monitoring, understanding urban dynamics, and supporting city planning and zoning. For instance, spatial data have been integrated with crowdsourced data to map green spaces in urban regions [279], extract of illegal buildings enabling city planners to update building databases [280], identifying renewal (retention, renewal, and demolition) areas in urban districts [281], investigate building footprints [282-284], interpret land use patterns [285], investigate urban growth patterns to project future ecological and environmental impacts [286]. In addition, leveraging textual descriptors paired with images from multiple sources, GeoAI achieves a profound understanding of geospatial context, supporting comprehensive modeling of urban areas [152, 287].

Still, GeoAI's ability to manage large volumes of spatial data significantly improves the precision and efficiency of topographic mapping and urban feature extraction. This capability is essential for maintaining infrastructure integrity within complex urban environments. Machine learning techniques, as expounded by Döllner et. al., are instrumental in processing

3D point clouds to generate geospatial digital twins [23]. These digital representations are invaluable to urban planners and infrastructure managers, enabling them to monitor infrastructure precisely and make informed decisions about the city's infrastructure. Moreover, integrating these innovative methodologies not only enhances modeling precision but also improves operational efficiency in urban contexts, thereby enabling more effective management of infrastructure resources.

Another notable feature of GeoAI is its adaptability and robustness, which enable it to incorporate real-time data, a critical capability for addressing the dynamic nature of urban infrastructure needs [277]. This capability allows city managers to respond promptly to changing conditions, whether driven by environmental factors, population shifts, or infrastructure deterioration. This provides accurate and up-to-date information to support the development of smarter, more adaptable urban environments that better serve their inhabitants and withstand various challenges [288].

In the realm of explainable models for GeoAI in urban infrastructure, Liu et al. observe that GeoAI holds substantial implications for urban governance and public engagement. By offering clear justifications for predictions and recommendations, XAI promotes transparent decision-making processes and cultivates trust between city authorities and residents. Liu notes that transparency in the design and deployment of such systems can enhance public participation in urban planning initiatives, since citizens are better equipped to comprehend and contribute to the planning process [32].

Investigated studies demonstrate the potential of GeoAI in tackling urban investigation and mapping. However, most current methods are still short of achieving complete autonomous spatial-temporal urban intelligence. Exploiting the potential of geospatial-temporal data and AI holds great promise for the design, planning, and management of future cities, as well as for accelerating the realization of full autonomy in the field.

4.2 GeoAI in traffic management and modeling

Multiple studies suggest that artificial intelligence systems utilizing historical, live sensor, and network data achieve improved traffic flow, reduced congestion, and increased travel efficiency compared to traditional approaches. Additionally, the fusion of varied data streams with machine learning techniques enhances the precision, adaptability, and scalability of urban traffic management strategies, including congestion reduction and dynamic routing [20, 52, 53, 289, 290]. This integration enables urban planners and traffic managers to understand, manage, and optimize these systems, thereby enhancing prediction, control, and resilience within transportation networks.

Recent investigations in urban analysis have focused on using spatially explicit GeoAI models to capture the heterogeneous nature of urban forms. More studies have focused on enhancing the interpretability and reliability of AI-driven systems that support on-demand, real-time traffic decision-making for congestion mitigation, route optimization, and planning [52, 289]. Techniques such as graph-based neural networks, geographic information system (GIS)-driven data fusion, and 3-D spatial simulations have shown potential to enhance traffic prediction accuracy and support adaptive signaling and simulations, thereby aiding urban planning decisions, especially under uncertain conditions. The net sum of integrating spatially explicit neural architectures with graph-based frameworks has bolstered interpretable traffic-relevant inference [20, 291].

To advance XAI in traffic modeling contexts, Liu et al. propose an explainable, spatially explicit GeoAI framework that merges a Graph Convolutional Network (GCN) with GNNExplainer to address node- and graph-level tasks in urban analytics, including traffic volume prediction and population estimation. The framework demonstrates that capturing network topology and spatial autocorrelation improves predictive performance and explains model decisions, which are essential parameters for policy-makers and traffic engineers [32]. In related studies, Dikshit et al. quantify the benefits of AI-driven routing through simulations and case studies, demonstrating reductions in travel time, fuel consumption, and emissions. The study findings establish a connection between traffic performance, environmental sustainability metrics, and economic viability for city-scale deployment [53]. Moscovici et al. examined the mitigation of traffic congestion using GeoAI. The study demonstrates that spatial data acquisition at traffic-light intersections supports the development of GIS for Timisoara city, Romania [292]. The proposed frameworks facilitate more effective signal coordination and congestion mitigation by contextualizing traffic dynamics at precise geographic locations, though they incur a computational burden in city-level deployments [293, 294].

In 3D urban traffic simulation and modeling, current technology advancements offer enhanced visual and analytical frameworks for examining network topology, traffic volume, and flow within realistic geometries. Feng et al. deployed a 3D simulation platform for urban traffic using Cesium, which enables spatially accurate representations of traffic dynamics and infrastructure interactions [295]. Feng's study demonstrates that a large-scale 3D road network generated from GIS data enables credible simulations by producing realistic network topologies and intersection configurations, which are essential for evaluating routing algorithms and signal timing strategies in virtual environments. These simulation tools complement data-driven models by supporting scenario testing under diverse conditions, including extreme circumstances and infrastructure modifications [296].

Further, agent-based modeling and multi-criteria decision analysis (MCDA) have been proposed as complementary methods for traffic management. Shaharuddin and Misro recommend agent-based modeling and simulation to address congestion in urban environments, demonstrating that analyzing mixed-traffic dynamics and cross-signal interactions can deliver robust control strategies [291]. Still, geospatial MCDA frameworks support surveillance and decision-making under spatial and temporal uncertainty. This can be critical in guiding transport planners when traffic risk factors intersect with other city parameter constraints. Integrating agent-based and MCDA paradigms with GeoAI frameworks can support interpretable, context-aware traffic management policies [297].

Studies cite computational infrastructure constraints as a significant challenge for GeoAI-enabled traffic management, particularly for near-real-time inference. To address the above challenge, the Traffic Analytics Development Kits (TADK) framework demonstrates that real-time artificial intelligence inference for networking workloads can be executed on standard hardware without specialized accelerators [298]. The framework supports edge and fog-based deployment of traffic analytics, allowing real-time routing and signal control decisions to be processed near sensors and actuators. This development aligns with the broader trend toward artificial intelligence of things (AIoT)- enabled smart traffic management, where live camera feeds and sensor data inform adaptive control systems that optimize vehicle throughput, reduce congestion, and minimize deployment costs [299].

Other studies have enhanced urban traffic models by integrating environmental factors such as noise and air pollution, thereby increasing the social and ecological relevance of GeoAI-based traffic management. Younes et al. use GIS and adaptive neuro-fuzzy inference systems to model traffic noise along urban corridors, demonstrating that spatially explicit modeling can inform noise mitigation strategies in urban design [300]. Similarly, GIS-based analyses of pollutant dispersal and exposure link traffic conditions to air quality outcomes, supporting urban planning that aligns traffic management with public health objectives [301]. Although these studies primarily address environmental externalities, they underscore the broader utility of GeoAI in comprehensive urban mobility planning.

Despite recent progress, significant challenges persist regarding data quality, spatiotemporal alignment, and large-scale interpretability. Accurately representing spatial heterogeneity, temporal dynamics, and network topology in unified GeoAI models calls for rigorous data fusion, feature engineering, and model design to prevent spurious correlations and ensure reliable explanations [59, 302]. The reviewed literature converges that advances in graph-based and contrastive learning methods for spatial data offer potential improvements in representation learning for traffic networks, thereby enhancing predictive accuracy and robustness against missing or noisy data. Additionally, integrating 3D GIS data and digital twin concepts can facilitate more comprehensive scenario analysis and policy evaluation for urban traffic systems. Lastly, the focus on explainability to address transparency in spatial predictions and justifying routing and signal-control recommendations to stakeholders remains a central concern.

GeoAI methodologies are making significant strides toward developing integrated, spatially aware, and interpretable systems for traffic analytics and management. The convergence of spatially explicit models, GIS-based data integration, 3D simulations, agent-based and multi-criteria planning, and scalable deployment architectures marks a mature evolution towards practical, policy-relevant, and environmentally sustainable urban traffic solutions. Future research should focus on enhancing robust explanation, integrating data from diverse sources, and effectively translating predictive insights into adaptive control within operational urban networks.

4.3 GeoAI in urban agriculture

The convergence of urban agriculture (UA), geospatial intelligence, and artificial intelligence underscores the transformative potential of these technologies to enhance food production in urban landscapes. Several studies have explored various GeoAI applications in urban farming and precision agriculture, as well as their integration into smart cities. The analyzed literature examines GeoAI's ability to address challenges in urban agriculture, including resource optimization, environmental stewardship, and improved food security.

With projections that 70% of the world's population will live in cities by 2050, and the consequential global trend of rural-to-urban migration as people seek jobs, education, improved services, and opportunities, the pressure to feed city dwellers is increasingly challenging. This has led to increased uptake of UA and signifies a pivotal direction in addressing the global challenge of feeding a burgeoning urban population [303]. Consequently, leveraging AI methodologies alongside geospatial data analysis can significantly enhance productivity, sustainability, and resource management. Open data, GIS-based tools, and AI-driven systems can support urban farmers in making informed decisions on crop selection, soil management, and resource allocation. These technologies enable urban farmers to operate more efficiently and sustainably, despite constraints such as land scarcity, unpredictable climatic conditions, and resource scarcity [114, 304].

The application of GeoAI in urban agriculture extends beyond basic site selection and crop management, encompassing a range of additional applications. It facilitates the development of innovative, controlled environments that maximize yield while minimizing resource inputs. Tamilkodi et al. argue that GeoAI has the potential to provide predictive insights to guide farmers in selecting the most suitable crops and farming methods for specific urban locations by analyzing complex datasets on soil quality, microclimate conditions, and market demand [305]. In other studies, Tamilkodi et al. assert that integrating GeoAI with urban informatics can deliver a robust framework for understanding and optimizing the entire urban food system from production to distribution. The framework can potentially revolutionize cities' approach to food security and sustainability [306]. According to Guechi et al., urban geospatial analysis helps assess land availability, market proximity, and infrastructure constraints, which are essential parameters to the viability of urban farming. Guechi et al. argue that multi-criteria assessment frameworks such as AHP-GeoTOPSIS can provide a structured framework for ranking urban sites by suitability, assisting planners in prioritizing locations for UA. The framework adopts transparent weighting criteria based on parameters such as soil, water, access to energy, flood risk, and policy context in urban growth and agricultural planning [307].

In the context of crop analysis and management, multi-source data from soil/plant health, sourced from sensors, remote sensing, and UAV imagery, form the foundation of GeoAI workflows and analytics. The analytical core for GeoAI-based urban precision agriculture includes GIS-based digital twins, AI/ML models for soil management, crop growth, and climate control, as well as geo-enabled data fusion that integrates multiple streams (IoT, UAV, satellite) into cohesive decision-support systems. The precision agriculture framework enhances these processes by using machine learning to identify complex, non-linear patterns in urban land gradients, population density, and environmental indicators, thereby improving predictive accuracy in suitability analyses [308-310].

On the other hand, GIS-based digital twin models can map solar radiation and assess microclimate conditions for UA design, guiding the placement of crops, control systems, and energy use in urban farms. Such models facilitate the simulation of shading, insulation, and seasonal variability, critical for urban growing environments [308]. Digital twins are integrated with GeoAI to enable scenario analysis. In turn, this can support the optimization of UA facility design, including rooftop and vertical farming, by linking geospatial inputs with agronomic models and energy balance calculations. Further, AI-enhanced soil management techniques, sensors, and data analytics support precision agriculture in both outdoor and indoor contexts [311]. In outdoor farming, AI aids in automated monitoring, predictive irrigation, nutrient management, and yield optimization. Conversely, indoor vertical farming employs AI to drive climate control, photonic management, and resource efficiency, leveraging data from sensors, cameras, and IoT devices [309, 312].

Studies in UA show that indoor smart gardens and vertical farming increasingly utilize AI-driven decision support to optimize growth environments, nutrient delivery, and lighting regimes, thereby enhancing productivity and resource efficiency in urban settings [313]. This approach complements outdoor urban agriculture strategies by providing scalable, space-efficient solutions in densely populated areas [309]. In this case, IoT and AI co-serve as the foundation of smart farming in urban environments, facilitating real-time monitoring of environmental conditions such as temperature, humidity, CO_2, moisture, and electrical conductivity (to measure nutrient and salt concentrations in soil or water), as well as other parameters such as plant health analysis and infrastructure performance indicators. In this case, GeoAI processes these continuous data streams to guide control actions, predict immediate budgets, and automate responses [314].

Other support infrastructure, such as UAVs and geospatial analytics, enhances field and peri-urban UA by delivering comprehensive surveillance, assessing crop health through multispectral imaging, and providing high-resolution spatial data for precise inputs and timely interventions. Studies show that UAV-based geospatial analytics are instrumental in managing irrigation, detecting pests, and monitoring crops on IoT-enabled platforms [306]. Moreover, open-source software and AI-powered GIS tools are essential for developing reproducible urban GeoAI workflows that enable the monitoring and analysis of environmental conditions and urban agricultural performance using scalable, configurable platforms. The benefits highlight the contribution of AI, GIS, big data, and open data ecosystems in actively empowering citizens and authorities to participate in urban agriculture planning and evaluation [314].

In assessing the productivity and impact of indoor farming, Mihailović et al. note that, in recent years, the number of indoor smart gardens has increased to enhance food security and urban resilience by providing locally grown produce in compact, climate-controlled settings, potentially located in supermarkets or basements. These gardens utilize AI-enabled automation to reduce labor needs and improve consistency [313]. This claim is supported by Bibri et al.'s submission, which states that smart gardens complement the broader smart city paradigm, where AI and IoT optimize services such as food production, energy use, and health outcomes [315]. However, both studies agree that human factors, such as skills gaps among unskilled farmers and the need for user-friendly control interfaces, significantly hinder the success of urban farming and require interventions. Singh et al. concur with previous studies that intelligent data analytics and decision-support systems can bridge knowledge gaps and enable effective management by non-specialists. The study also observes that leveraging spatial data with GeoAI can facilitate climate-neutral urban development and support transparent, data-driven decision-making for land-use and UA placement [314]. Other studies have demonstrated how geospatial platforms, web GIS, and citizen engagement can contribute to climate-conscious urban planning and agriculture [304, 316]. In contrast, government regulatory frameworks for urban farming, covering data privacy in edge AI deployments and the management of open data ecosystems, can support alignment with best practices to maximize positive outcomes [56].

Despite the success in exploiting AI systems for smart, precision agriculture, some emerging challenges worth exploring in future research relate to the disjointed nature of agricultural operations. These include the administration and operation of IoT/AI systems, remote sensing, environmental impact evaluation, data sharing and management, and interoperability. [317, 318]. Some studies on GeoAI for precision agriculture have been thoroughly reviewed [319-323].

4.4 GeoAI in disaster management

GeoAI models can help detect and manage natural disasters, demonstrating a significant advancement in risk management. However, acquiring geospatial data on natural catastrophes remains severely constrained because it must be collected precisely (in some cases, in real time) when the event occurs.

Prior studies have highlighted the potential of AI systems to enhance the management and governance of geospatial data, thereby facilitating environmental conservation and supporting the achievement of the Sustainable Development Goals (SDGs). AI systems, enhanced by multi-source big data, have successfully facilitated prompt responses to natural disasters, including wildfires, earthquakes, landslides, cyclones, and floods [324]. The task involves leveraging machine learning models and integrating multi-sourced data, which are then analyzed and processed by them. For example, **Fig. 5** illustrates earthquake imagery from Mexico City captured in 2019, along with the post-earthquake damage assessment results for the same region, using YOLOv4 [325]. The case study demonstrates the potential of GeoAI models in disaster investigation and assessment.

Several surveys have been conducted to explore the potential of AI in urban disaster management, aiming to facilitate faster, more concise, and more effective responses [324, 326, 327]. The consensus of these studies is that AI holds promise for disaster mitigation, management, and recovery. These studies emphasize integration of multimodal data with other big data sources, such as social media and IoT devices, at varying abstraction levels to provide broader insights. Furthermore, the studies highlight the importance of teamwork in disaster management, which is crucial for safeguarding lives, infrastructure, and the environment at all stages: mitigation, readiness, response, and recovery [328, 329].

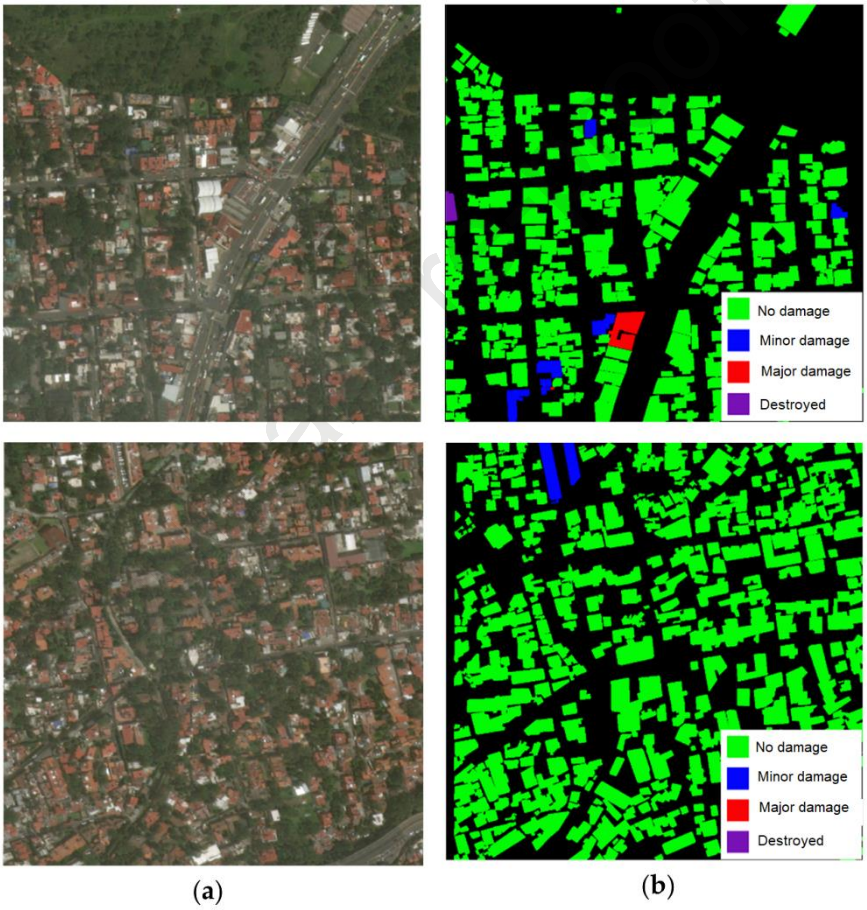


Fig. 5. Images of the Mexico City earthquake in 2017.
(a) Original and post-earthquake RS image.
(b) Segmentation maps showing Earthquake impacts [325]

RS data have supported GeoAI in pre- and post-disaster evaluation and management, with several methods recently developed under urban change studies and disaster management. Wu et al. proposed a Siamese network for evaluating the disaster status of buildings, including location recognition and classification of damaged structures [330]. BDANet uses a CNN network with two branches that accept pre- and post-disaster satellite images to correlate and assess building damage [331]. ChangeOS combines deep learning and OBIA to provide a building damage assessment system trained on global datasets [332].

Other disasters include floods, which are difficult to predict because they are triggered sporadically by climatic and environmental conditions, resulting in fatalities, infrastructure damage, and significant economic harm to the affected region. Since floods cannot be entirely avoided, governments and relevant organizations must take preventive measures to minimize their adverse effects. Furthermore, disaster management authorities ought to take precautions before floods occur to reduce risks and respond effectively when they do [333, 334]. Disaster preparation can involve using cutting-edge technologies to predict disasters in real time, enabling the implementation of necessary response measures before they occur. As a result, it is essential to expand the use of modern technologies for automated catastrophe prediction and forecasting, specifically RS data and GeoAI [335].

Recent studies have employed GeoAI models for flood assessments and mitigation. For example, Multi-Criteria Decision Analysis (MCDA) is a hybrid AI model that uses Adaboost and Bagging decision trees. This framework has successfully been used to map flood areas in Quang Nam, Vietnam [336]. In other studies, Rezvani et al. combined GeoAI and GIS to map flood hazards on Portugal's road networks, providing city transportation management with precise information on which roads were susceptible to damage following prolonged periods of rainfall [337]. These, among other studies, demonstrate the potential of GeoAI for disaster assessment and prevention [338-343].

5. GeoAI’s current trends and prospects in urban analysis

Urban ecosystems are best understood as coupled social-ecosystems in which dynamic processes involving climate dynamics, demographic details, economic structures, and urban governance interact across temporal and spatial scales. GeoAI is poised to revolutionize urban analysis further by providing scalable, explainable, and actionable insights across planning, governance, and resilience. This review reveals the following key trends: First, the advancement of GeoAI has significantly enabled greater accessibility to Internet-scale multi-source data. Second, the multisource data presents diverse challenges related to privacy, complexity arising from diversity, bias, incompleteness, and management. Therefore, there is a growing imperative to adopt responsible AI practices that address issues of privacy, ethics, and governance. Moreover, studies emphasize the significance of explainability, interpretability, and user trust across data management, processing, and inference pipelines. Third, advancements in urban analysis and 3D-geospatial modeling are increasingly supporting urban decision-making processes, driven by spatial-temporal-agnostic models leading to an increase in cross-disciplinary applications in areas such as urban planning, traffic management, urban agriculture, disaster management, and resilience. The progress has led to a utilitarian shift in urban infrastructure modeling, including the use of graph neural networks (GNNs), deep learning, and hybrid approaches that integrate data-driven and knowledge-driven methods.

Numerous sources emphasize the significance of each trend and delineate the evolving GeoAI landscape for urban environments, highlighting a notable increase in the scale and variety of multimodal and large-scale datasets. Various data-rich sources, including satellite and drone imagery, street-level views, sensor networks, user feedback, and urban ontologies, continue to enhance GeoAI methodologies, facilitating the expanded processing of diverse and extensive data. Li and Hsu document GeoAI’s capability for large-scale image analysis and rapid advancements across image types and data modalities, underscoring six strengths: scale, automation, accuracy, change-detection sensitivity, noise tolerance, and speed, that are particularly relevant to urban analytics [43]. This, in turn, supports a comprehensive analysis of land use, mobility, energy flows, and environmental conditions at city scales, thereby facilitating a range of downstream urban tasks. Following this trend, progress toward big-data urban analytics is reinforced by the convergence of geospatial science, AI, data mining, and powerful computing infrastructure, seeking to extract knowledge from vast geospatial datasets [23, 27]. Collectively, these studies suggest that future urban analysis will increasingly integrate multi-source data into GeoAI pipelines to provide timely, policy-relevant insights at the city level and beyond.

Further, explainability, interpretability, and human-centered GeoAI are becoming increasingly crucial for urban decision-making. As GeoAI becomes integral to urban planning and governance, researchers and stakeholders have extensively emphasized the need for transparency and interpretability. The broader literature notes that explainable GeoAI aims to render model outputs comprehensible to planners, policymakers, and the public, thereby ensuring accountability in decisions related to urban form and resources. Besides, explainability plays a critical role in policy settings, given that not all stakeholders and users of geospatial intelligence are technosavy in the domain. Thus, the need to clarify and justify predictions and recommendations to stakeholders to deliver urban designs and planning processes that are ethical, transparent, and integrated [7, 30, 344]. Reviewed studies concur that future GeoAI systems ought to incorporate interpretable architectures, post-hoc explanations, and decision-support interfaces that facilitate stakeholder understanding and integration into urban governance. Furthermore, digital twins, which utilize 3D geospatial modeling and 3D point clouds, can support urban simulation, thereby shaping a promising future for GeoAI-enabled analysis, predictive analytics, and scenario testing. These views are supported by Liu et al., who argue that digital twin frameworks can help evaluate traffic, air quality, noise, and urban spaces, providing decision-ready insights for future infrastructure planning, such as buildings, landscapes, and urban environments [345].

As GeoAI becomes increasingly prevalent in sensitive urban areas, governance emerges as a critical concern. He and Chen underscore the challenges and ethical considerations associated with applying AI to urban design and planning, including data privacy and the need for cross-disciplinary knowledge, and advocate for responsible digitalization in cities [33]. Further, the intersection of GeoAI with geo-big data platforms and data-sharing architectures necessitates robust, privacy-preserving methodologies and governance protocols to maintain public trust while enabling data-driven insights for urban areas. This calls for governance frameworks that address privacy, consent, data provenance, and equitable outcomes in AI-enabled urban services [27, 41]. Future GeoAI deployments are anticipated to incorporate privacy-preserving machine learning, data governance, and ethical safeguards as standard components to ensure secure data sharing and governance technologies. To enforce safety and privacy, approaches such as storing GeoAI data on blockchains have been proposed for GeoAI-based private and social media data. These technologies possess inherent privacy-preserving, decentralized data-sharing capabilities, leveraging Web3 and distributed ledger technologies to enhance provenance tracking, promote privacy, and ensure data integrity [346, 347].

In the domain of cross-disciplinary interdependencies, spatially explicit intelligence significantly augments capabilities. Biu et al. explore the evolving role of spatial AI and deep learning in urban security planning, risk management, and disaster response [40]. The study notes that in urban analysis, GeoAI integrates travel patterns, energy consumption, land use, and environmental impacts, thereby achieving time and resource efficiencies while equipping planners with comprehensive insights. On resilience and sustainable urban development, smart city big data, and digital twins analytics at neighborhood scales can support proactive processes that inform urban governance and resilience [348, 349]. As methodological advances in GeoAI progress beyond traditional GIS analytics toward graph-based neural networks, deep learning, and hybrid data-driven/knowledge-driven frameworks, robust GeoAI systems for urban analytics are emerging, enabling relational reasoning over spatial networks and spatiotemporal patterns. Future architectural designs and model training regimes need to lessen compute and memory footprints without sacrificing accuracy to accommodate efficient deployment in low-latency contexts to cater for regions with limited access to compute resources especially communities in the Global South [32].

In summary, the reviewed studies reveal a strong trend towards transitioning from image-centric analyses to extensive, multimodal urban analytics. This approach incorporates data from satellites, drones, street views, sensors, social media, IoT, and crowd-sourced information across different spatial dimensions. The momentum of multimodal analytics, propelled by multisource data, is accelerating as GeoAI proves beneficial for urban analysis, city planning, disaster management, and smart-city governance. However, challenges such as data gaps, socio-economic disparities, and the quality of data from varied sources continue to pose significant questions for investigation. Although these diverse sources introduce unprecedented data heterogeneity, the ongoing effort to harmonize geospatial data from various sources to address dynamic urban topologies and ensure effective, reliable urban intelligence remains a burgeoning area of research.

The growing adoption of GeoAI in shaping spatial decisions, urban space interactions, and investment decisions has long-term societal and political implications, raising critical concerns about control, fairness, and accountability. Further, explainable GeoAI and human-centered design, which touch on governance, privacy, and ethics, become a pivot, promoting responsible AI practices and ensuring transparent, accessible outputs. Real-world implementation will have to balance model accuracy, which most studies predominantly focus on, with the issues raised in this review to ensure fair and responsible GeoAI practices across research domains and multi-stakeholders, thereby enabling GeoAI to evolve and ultimately enhance its impact and acceptance in real-world scenarios.

6. Conclusion

In this review, we examine the development of multi-source big data, the evolution of the machine learning paradigm, and the advancement of GeoAI systems for urban analysis. We use the Web of Science and Scopus platforms as our literature sources and conduct a comprehensive literature review. We consider studies undertaken in recent years, assess the research landscape across multiple data sources, examine the evolution of machine learning in geospatial analysis, and explore human-centric practices in urban GeoAI contexts. The central themes that emerged from the reviewed literature were the implementation of scalable and interpretable GeoAI methods to manage multi-source big data for urban analysis; the development of spatially-agnostic GeoAI models to address the dynamic requirements of urban analysis and governance; the application of GeoAI in urban analysis to improve planning, management, resilience, and governance, while addressing ethical, privacy, and safety concerns; and emphasis on transparency, explainability, certainty in developing and deploying geospatial systems. Additionally, we share the datasets used for pretraining urban geospatial models and discuss the applications of GeoAI in urban infrastructure investigation, traffic management, urban agriculture, and disaster management. We conclude by summarizing key findings, sharing insights, and outlining future research directions.

Declaration of competing interest

The authors declare that they have no conflicts of interest.

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Declaration of Interest Statement

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