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Chapter 18
GeoAI and Urban Geography

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Abstract Recognising GeoAI as an emerging and rapidly evolving field that has been increasingly adopted in urban geography, this chapter provides an overarching overview of the GeoAI methods for urban analytics. It begins by revisiting the theoretical underpinnings of urban theory and mapping the evolution of urban spatial analytics, tracing the journey from traditional statistical methods to the cutting-edge AI-driven approaches reshaping the discipline today. Beyond examining the current state of GeoAI, the chapter also identifies current trending topics and investigates future directions for developing human-centric methodologies that prioritise the needs and experiences of urban residents. By emphasising the human dimension of urban analytics, the chapter seeks to contribute to the ongoing discourse on how GeoAI can be harnessed to enhance city governance, urban planning, and the overall quality of urban life.

Keywords GeoAI · Urban geography · Spatial analytics · Human-centric approaches · City governance

18.1 Introduction

Cities are inherently complex systems, characterised by entangled networks of people, infrastructure, and natural environments (Batty, 2009). Such urban systems are in a state of constant flux, continually evolving as a result of the

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ongoing interactions between social, economic, and environmental forces (Brenner & Schmid, 2015; Pred, 2017). Urban geography, a vibrant and dynamic sub-field of geography, seeks to understand the spatial structures, patterns, and processes that shape urban environments and people's lives within them (Hall & Barrett, 2012). It offers a spatial perspective on how human activities, infrastructure, and natural landscapes interact and shape in tandem with the multifaceted urban systems that define contemporary society (Pacione, 2009). As cities continue to expand and transform, they face a growing array of challenges, ranging from sustainability and resilience (Folke, 2006) to issues of equity and liveability (Ruth & Franklin, 2014), which are becoming increasingly complex. Addressing these challenges necessitates innovative approaches that capture, analyse, and interpret the vast quantities of information generated within urban environments.

In the era of big data (Kitchin, 2014), thanks to the increasingly accessible GPS-enabled devices and equipment, up to 80% of data produced every day is geo-referenced (Leszczynski & Crampton, 2016). Traditional approaches to studying urban geography have been profoundly transformed by the advent of new technologies, with GeoAI (Geospatial Artificial Intelligence) emerging as one of the most pioneering advancements. GeoAI harnesses the capabilities of artificial intelligence (AI), high-performance computing (HPC), and spatial big data (SBD), offering cutting-edge tools that allow for the enhanced and automated analysis of urban spaces with unprecedented precision and enhanced accuracy (Li, 2020; Janowicz et al., 2020; Liu & Biljecki, 2022). Through advanced AI-enabled methodologies, GeoAI enables novel use cases and provides invaluable insights into urban environments' complexities, facilitating more informed and effective urban planning and management strategies and, eventually, enhancing the quality of life for urban inhabitants.

This chapter offers a comprehensive overview of GeoAI as a cutting-edge collection of techniques within the field of urban geography. It begins by revisiting the theoretical foundations of urban theory and tracing the evolution of urban spatial analytics, from traditional statistical methods to the advanced AI-assisted approaches that are redefining the discipline today. The chapter also critically examines the uncertainties inherent in GeoAI analysis, highlighting the potential biases, limitations, and challenges that must be navigated when applying these technologies to urban studies. In addition to addressing the current state of GeoAI, this chapter explores future directions for developing human-centric GeoAI methodologies that prioritise the needs and experiences of urban residents. By focusing on the human dimension of urban analytics, the chapter aims to contribute to the ongoing discourse on how GeoAI can be leveraged to improve city governance, planning, and the overall quality of urban life.

18.2 Quantitative Evolution of Urban Geography

Urban geography has evolved significantly over the past century, with key milestones marking the development and transformation of this field, influencing both what and how geographic knowledge is produced for cities and the people living in them.

In the mostly descriptive and fieldwork-driven works in the early days (Reclus et al., [1876–94]; Sauer, 1941, 1952), geographers sought to catalogue instances of phenomena, ranging from physical landscape traits, to socioeconomic and cultural practices, and associate them with their locations and maps to narrate the distinct or similar features of different regions (Cope, 2010). Later, descriptive theories and models were developed in the early twentieth century to understand the spatial organisation, function, and processes of cities, such as the Concentric Zone Model (Burgess, 1925), the Sector Model (Hoyt, 1939), and the Multiple Nuclei Model (Harris & Ullman, 1945).

Meanwhile, much progress had been made in economic geography, spatial analysis, and quantitative social science, paving the way for what was later called the 'Quantitative Revolution' in geography in the 1950s and 1960s (Adams, 2001; Barnes, 2001). Influenced by works from other disciplines, such as the *Theory of Games and Economic Behavior* by von Neumann & Morgenstern (1944) and Human Behaviour and the Principle of Least Effort by Zipf (1949), quantitative techniques such as mathematical and statistical modelling began to gain interest among urban geographers to study the spatial arrangement of human activities (Garrison, 1959a,b, 1960; Isard, 1960; Burton, 1963).

The movement saw the re-introduction of location theory, which originated from the seminal work of Johann Heinrich von Thünen, 'The Isolated State' (1826), and laid the foundations for systematically understanding the principles of land use (Hoover & Giarratani, 1999). Benefiting from the development of location theory, the Central Place Theory developed by Christaller (1933) explained the spatial distribution and size hierarchy of human settlements, which were postulated to function as 'central places' to supply economic services to surrounding areas. Such work put forth new research agendas and methods and demonstrated the values of quantification to urban geographers—reproducible results, robust foundation for theory-testing, understanding and policy-making, and knowledge production that was cumulative instead of additive (Adams, 2001).

Another significant work that profoundly re-shaped the research methods in this field was Locational Analysis in Human Geography by Haggett (1965), which provided a thorough framework for understanding spatial patterns through quantitative methods. Such an exploration marked a milestone that transformed urban geography from a primarily descriptive field to one that is analytical, theoretical, and data-driven, and set the stage for modern spatial analysis and Geographic Information Systems (GIS), which have become important methods and tools to analyse urban phenomena.

Since the Quantitative Revolution, a range of statistical and mathematical techniques have been incorporated into the study of urban geography, including regression analysis (Barnes, 1998), factor analysis (Clark et al., 1974), and clustering methods (Webber & Craig, 1976). These methods enabled urban geographers to explore the relationships between different economic, social, and environmental variables, uncover their underlying patterns, and investigate their similarities and differences among spatial clusters of communities. Yet, even though the phenomena being studied are geographical, these modelling methods often do not take into account spatial information (e.g. coordinates, distances, topological relationships, interactions, and flows among spatial objects) and could overlook the spatial variability underlying the data (De Sabbata & Liu, 2023).

In 1970, Tobler's First Law of Geography was introduced. It states that 'everything is related to everything else, but near things are more related than distant things' (Tobler, 1970). This pivotal theory gave rise to the now fundamental concepts of spatial dependence and spatial autocorrelation, which underpin all spatial analysis. A range of spatial modelling and geostatistics techniques were developed, such as Inverse Distance Weighting and Kriging. These interpolation methods predict the values of unmeasured locations based on known data points by considering their distances and relative positions and have been useful in generating, from merely a set of sampled locations, detailed maps of certain urban variables such as population density (Liu et al., 2008; Wu & Murray, 2005), microclimate variables (Han et al., 2024), and air quality variables (Gardner-Frolick et al., 2022; Shukla et al., 2020; Jerrett et al., 2001).

As computers evolved rapidly, more advanced techniques became possible, such as agent-based modelling (ABM), cellular automata (CA), and spatial regression models. ABM and CA have been used to simulate urban growth, land use changes, and transportation systems by modelling the interactions of individual agents and cells, offering insights into urban sprawl and traffic dynamics (Batty, 1997; Clarke et al., 1997; Batty, 2005; Torrens, 2006; Crooks et al., 2008). Spatial regression models help analyse spatial dependencies in housing markets, crime patterns, and health outcomes, providing a deeper understanding of urban socio-economic and environmental dynamics (Fotheringham et al., 2003; Anselin, 1988; LeSage & Pace, 2009). Another analytical-computational technique developed in the late twentieth century is space syntax (Hillier et al., 1976; Hillier & Hanson, 1984), which is used to study the spatial configurations of built environments (e.g. street networks) and how these configurations influence societal behaviours within urban areas, such as human movement, accessibility, connectivity, and social interactions (Penn et al., 1998). Collectively, these techniques enable urban geographers to better model, manage, and plan urban environments.

Other than methodological advancements, technological progress has also brought forth a multitude of new data sources, ranging from satellite imagery to street view imagery, social media, and crowdsourced data. Long gone are the days when urban geographers were confined to fieldwork measurements or the often limited census survey data. With the advent of the 'digital turn' in geography (Ash et al., 2018a,b), researchers now tap into a burgeoning volume and variety of urban data that provides countless new ways and dimensions to measure human activities, urban characteristics, and social interactions. Yet, at the same time, such data is increasingly rapid, complex, noisy, and multi-sourced, and traditional modelling methods could face challenges in adapting to this era of spatial big data (Evans et al., 2014; Lee & Kang, 2015). GeoAI has emerged as a crucial and transformative element in urban geography research and applications. By integrating AI with spatial (and temporal) aspects, GeoAI offers promising solutions for mining, interpreting, and predicting urban and human dynamics (Gao, 2021; Gao et al., 2023), revolutionising ways to study complex urban systems.

18.3 Geospatial Artificial Intelligence

GeoAI is an interdisciplinary field representing the intersection of geography and AI (Gao, 2021). It empowers the research to investigate geospatial phenomena and enhance the understanding of human habitation (Liu & Biljecki, 2022; Mai et al., 2022).

At its core foundation, GeoAI builds on the principles and theories of GIS, automating the processing and analysis of vast and intricate geospatial datasets. Machine learning is integral to the functionality of GeoAI, providing the analytical power needed to handle the complexity and scale of modern geospatial data. However, conventional machine learning methods face limitations in interpreting the ever-growing and increasingly complex urban data, which often presents high-dimensionality and non-linear relationships that characterise the dynamic and complex nature of urban-human interactions. The rise of deep learning and neural networks has marked a turning point in addressing these challenges (Grekousis, 2019). Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have the ability to automatically learn hierarchical features from raw data, rendering them particularly well-suited for tasks involving large-scale and heterogeneous geospatial datasets. For instance, CNNs are highly effective in image recognition tasks, such as detecting urban scenes and objects from street view images (Biljecki & Ito, 2021; Ito et al., 2024), while RNNs excel at capturing temporal patterns in time-series data, such as predicting traffic flows (Medina-Salgado et al., 2022) or urban growth (Quadri et al., 2024).

Yet, GeoAI is more than merely applying deep learning methods to geographical problems. The emergence of graph neural networks (GNNs) has introduced a new dimension to GeoAI by integrating geographic theories directly into the models, thereby making them spatially explicit (Liu & Biljecki, 2022). While traditional deep learning techniques, such as CNNs and RNNs, have been effective in handling grid-based and sequential data, they often struggle to represent and analyse the complex, non-Euclidean structures inherent in certain types of geographic data. For example, urban networks, transportation systems, and social interactions are more accurately represented as graphs, where nodes correspond to entities like locations or individuals, and edges denote the spatial relationships or interactions between them. GNNs, which are able to process graph data, effectively address these limitations by providing a framework specifically designed to accommodate the irregular and interconnected nature of geospatial data (Mai et al., 2022). By incorporating geographic theories, such as Tobler's First Law of Geography, GNNs allow GeoAI models to account for essential spatial concepts like spatial autocorrelation, proximity effects, and network dynamics, allowing for a more robust understanding of geographic phenomena and deeper insights into a variety of complex issues (Liu et al., 2024; Lei et al., 2024).

The field of GeoAI is rapidly evolving, with ongoing advancements and continuous expansion of its capabilities. Emerging technologies, such as Large Language Models (LLMs) and other innovative approaches, provide geographers with unprecedented tools for analysing urban complexity. In the following sections, we offer a scoping review of how GeoAI has been integrated into urban geography, highlighting the opportunities that modern technologies present for an in-depth, in-situ understanding of urban environments, as well as examining their potential limitations.

18.4 GeoAI in Urban Geography: Integration and Applications

Figure 18.1 provides an overview of the key types of urban data, GeoAI approaches, and emerging trends and opportunities in this field. In the following sections, we will delve deeper into each of these components and their applications in urban geography.

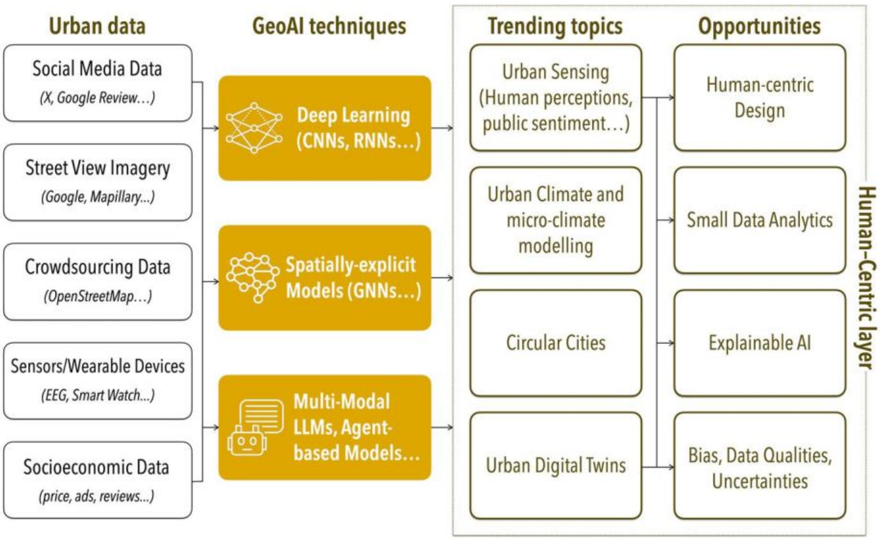

Fig. 18.1 Overview of key types of urban data, relevant GeoAI approaches, and emerging trends and opportunities

18.4.1 Emerging Urban Data

The evolvement of GeoAI techniques provides powerful tools to analyse complex urban spatial data, facilitating insights into urban dynamics and built environments that were previously unavailable and improving existing understandings by increasing spatial and temporal resolution and reliability. This section includes very recent examples of various developments, with a focus on novel sources or forms of urban data that have been leveraged with AI-assisted spatial analytics to support urban geography research.

Social media data has been spotlighted (Liu et al., 2015). For example, it has been used to understand urban park visitation (Wei et al., 2024) and park perception (Zhao et al., 2024), infer the design of riverscapes (Yang et al., 2022), predict traffic pollution (Zhang et al., 2024), and uncover semantic footprints (Berragan et al., 2024), among many examples in the past years.

Another prominent medium for urban studies in the past several years has been street view imagery (SVI) (Liang et al., 2024a; Liu & Sevtsuk, 2024). It has been used to map greenery and the urban form (Biljecki et al., 2023b), conduct virtual audits of dwellings (Yan et al., 2024), and assess walkability (Chen et al., 2024; Li et al., 2024). Sensing information on humans, facilitated by SVI, has also been the focus of many studies recently. For example, perception studies (Ito et al., 2024), which will be introduced more in the next section, have been commonly conducted in the past years thanks to the ease of reaching users around the world and providing the required data. The latest research efforts appear to be focused on change detection (Liang et al., 2023; Stalder et al., 2024), contributing to sensing the dynamics of cities and understanding the impacts of urbanisation.

Apart from the continued use of such data sources, there is a continuous trend of investigating the usability of latent urban data for urban sensing. For example, Liang et al. (2024b) demonstrated that scraping information on the website of a multi-purpose indoor arena in New York City can enhance human mobility prediction under public events. Such research has been facilitated by LLMs, demonstrating how emerging sources of data, coupled with new means to process information, can unlock new applications or enhance existing ones. Another relatively underutilised data source is real estate ads posted in online marketplaces. For example, they have been used to detect new buildings and amenities (Chen & Biljecki, 2022) and to understand decoration patterns across neighbourhoods and cities (Liu et al., 2019). In that space, Wang et al. (2023) have investigated the usability of reviews of homestays (Airbnb) to reveal the perception of neighbourhoods across multiple dimensions, for example, greenery, noise, and crime.

We outline a few trends that can be observed recently. First, urban analytics is becoming multi-modal, e.g. social media data is being fused with SVI to reveal new insights (Wang, 2024). Second, while in the past, a lot of such data was made available by governments and companies, now it is being increasingly crowdsourced. For example, weather data is progressively available from personal weather stations (Brousse et al., 2024), and crowdsourced data on buildings is becoming growingly available thanks to initiatives such as OpenStreetMap (Biljecki, Chow, & Lee, 2023a). Third, thanks to the wide availability of urban data and their harmonisation, research is becoming increasingly global and includes multiple cities (Hou et al., 2024). Finally, some of these lines of research have started being supported with open data, e.g. social media (Poorthuis et al., 2024) and real estate (Rey-Blanco et al., 2024), lowering the entry barriers for technical research and simplifying the process of obtaining relevant datasets.

18.4.2 Current Trends and Applications

The integration of GeoAI techniques has benefitted an array of urban geography studies. In particular, it has facilitated notable advancements in applications of rising importance, such as urban climate mitigation, circular cities, and urban perception, owing to the increasing focus on sustainable and inclusive urban development.

In the realm of urban climate, deep learning models are being leveraged to analyse complex environmental data and support decision-making processes (Patel et al., 2023). A notable development in this area is the use of Multimodal LLMs, which offer a comprehensive method for integrating diverse data types, including satellite imagery, SVI, and text descriptions, to measure urban environments holistically. For example, Fujiwara et al. (2024) developed a multimodal model that combines microclimate data with street-level and satellite imagery to predict microclimate variables (e.g. air temperature, relative humidity, wind speed, and global horizontal irradiance) at high spatial and temporal resolutions. These models allow researchers to consider more comprehensive features and depict cities as inherently complex systems, enhancing our understanding and management of urban spaces.

Benefiting from the recent trends of the digital twin and circular economy, GeoAI is poised to play a transformative role in advancing the circular digital built environment to enhance sustainability, efficiency, and resilience in urban spaces. One of the primary ways GeoAI contributes to this is through resource optimisation and lifecycle management (Mortaheb & Jankowski, 2023). For instance, it can model the potential effects of different urban layouts on energy consumption, waste generation, and resource use, enabling planners to design cities that are both efficient and resilient (Mortaheb & Jankowski, 2023). Additionally, GeoAI can aid in designing flood-resistant infrastructure that not only protects urban areas but also incorporates materials and designs that can be easily maintained, repurposed, or recycled (Zhou et al., 2023), thus contributing to a more liveable urban environment for the commonwealth of its residents.

While urban living conditions are impacted by external causes such as climate change and the increasing focus on circular economy development, human perception consistently shapes our understanding of the urban environment. Here, we feature the urban perception studies that apply perception-based labelling to images, providing a quantitative and extensive evaluation of human responses to built environments. These studies typically collect subjective impressions from participants using images, categorise the images with perceptual labels, and transform these labels into measurable attributes of urban environments (Ito et al., 2024). A foundational contribution to this field is the crowdsourced dataset known as Place Pulse 2.0, developed by Dubey et al. (2016). This dataset encompasses six attributes—depressing, boring, beautiful, safe, lively, and wealthy—and covers data from 56 cities, significantly expanding the scope of urban perception research. Not only has this dataset enabled extensive subsequent research on human perceptions across various regions (Zhang et al., 2018; Liang et al., 2023; Hou et al., 2024), but it has also broadened the urban perception framework to encompass other sectors of the built environment, such as soundscapes (Zhao et al., 2023), waterscapes (Luo et al., 2022), and building facades (Liang et al., 2024a).

Facing the growing need for comprehensive urban understanding, GeoAI, with its powerful capabilities to integrate and analyse multi-source data, is demonstrating significant potential in this evolving field. Meanwhile, due to the increasing attention on the concept of 'Technology for Social Good', which urges the shift from traditional top-down technological development that often focuses on big data analysis to individual-level 'small data' analytics, there is a growing need to bridge the technology on the urban-scale analysis to better support individuals' living experiences, thus enabling the GeoAI methods to be human-centric.

18.4.3 Towards Human-Centric Integrated GeoAI

The integration of GeoAI with human-centric approaches in urban geography is emerging as a crucial direction for future research. This convergence aims to bridge the gap between advanced technological capabilities and the nuanced understanding of urban systems that geographers and urban planners possess, to bring adequate attention to not only the *environment*, but also more importantly, the *people*.

Psychological-integrated urban sensing studies represent an evolving interdisciplinary field that synergises traditional psychological insights with cutting-edge urban sensing technologies. The psychological patterns embedded within urban environments offer a deeper understanding of how these patterns influence and shape the experiences and well-being of residents. Unlike conventional methods that primarily rely on SVI for urban observation, as discussed in the previous section, there is a noticeable shift towards incorporating psychological data, which underscores the growing recognition of the importance of human perception and mental states in shaping urban landscapes, leading to more nuanced analyses and interventions that consider both the physical and psychological dimensions of urban life (Helbich, 2018).

Wearable devices like smartwatches with sensors for tracking heart rate variability and skin conductance have become essential in urban sensing studies (Tartarini et al., 2023). These tools monitor stress levels as people move through the city, capturing real-time physiological responses alongside contextual data like temperature, noise, and air quality, allowing researchers to understand how urban environments impact well-being and identify stress patterns over time. Beyond stress monitoring, these devices evaluate urban design interventions aimed at improving comfort and reducing stress (Liu et al., 2023).

Additionally, sophisticated physiological devices like EEGs are increasingly used in urban research (Mavros et al., 2016). EEGs measure brain activity, offering insights into cognitive and emotional states in response to urban environments. Their portability and ease of use now allow data collection in real-world settings, enhancing our understanding of the relationship between the built environment and psychological well-being (Aspinall et al., 2015; Bolouki, 2023).

Through integrating physiological and machine insights, human-centric GeoAI approaches prioritise urban citizens' needs, behaviours, and experiences, ensuring that AI-driven analyses and solutions are technically sophisticated and socially relevant. A recent example proposed by Liu et al. (2023) constructs the pedestrians and their interactions with surrounding environments as human-centric dynamic graphs to study outdoor comfort. These graphs account for spatio-temporal variations observed in human walking patterns, including changes in sound levels, solar intensity, and visual perceptions. This research enables a two-way interaction between pedestrians and the GeoAI model, hence, providing individual tailored comfort prediction to navigate human outdoor activities.

18.4.4 Uncertainties

While the integration of AI with urban geography offers significant potential, it also introduces several uncertainties that researchers and practitioners must carefully consider. These uncertainties stem from various sources, including data quality, model limitations, and the inherent complexity of urban systems, necessitating a cautious and informed approach.

A primary source of uncertainty in GeoAI applications stems from the quality and representativeness of the data used (Crampton et al., 2013; Shelton et al., 2015; Poorthuis et al., 2023). Urban data, particularly when sourced from user-generated content or areas with limited digital infrastructure, can be incomplete, biased, inconsistent, or unrepresentative of the population. For instance, social media users in London are predominantly wealthy, young, and educated (Ballatore & De Sabbata, 2018). These limitations not only pose challenges in constructing accurate GeoAI models but also risk introducing biases in the interpretation of results (Graham et al., 2014). Furthermore, a study of OpenStreetMap's building data completeness reveals significant regional variability, with larger metropolitan areas typically having more complete datasets (Herfort et al., 2023). SVI also suffers quality and availability issues that are heterogeneous both spatially and temporally (Hou & Biljecki, 2022). Such variability in urban data raises crucial questions about the generalisability of AI models trained on data from one urban context to other cities with differing socio-economic, cultural, or physical characteristics, potentially limiting the broad applicability of GeoAI solutions.

Furthermore, the inherent complexity and unpredictability of urban systems add another layer of uncertainty. Cities are dynamic, adaptive systems influenced by countless interacting factors, many of which are difficult to quantify or predict. These factors include economic shifts, population movements, policy changes, and environmental conditions, all of which evolve in non-linear and sometimes unexpected ways (Jacobi et al., 2010). AI models, despite their sophistication, may struggle to capture the full complexity of urban phenomena, potentially overlooking important nuances or emergent patterns. For instance, social dynamics such as neighbourhood gentrification are subtle and multi-faceted processes that can be inadequately represented in datasets typically used for training AI systems. These intricacies challenge accurate modelling, often requiring advanced, context-specific adaptations that can complicate the development and scaling of general GeoAI solutions. A critical need remains for ongoing refinement of these data and modelling capabilities to better understand and capture a richer contextual representation of urban environments (Yap et al., 2023).

Addressing these uncertainties requires interdisciplinary collaboration, robust validation techniques, and a commitment to ethical and transparent AI practices. A notable effort towards this direction is the development of explainable AI (XAI) techniques specifically tailored for urban geographic applications enhancing the transparency and accountability of AI-driven urban research (Liu et al., 2024). As the field of GeoAI in urban geography continues to evolve, developing strategies to navigate these uncertainties will ensure that AI-driven approaches contribute positively to urban understanding and development.

18.5 Conclusion

The integration of GeoAI into urban geography marks a significant leap forward. It reforms the way we study how cities are constructed, governed, and experienced. By incorporating advanced computing techniques with domain knowledge, it became possible to analyse complex urban data with unprecedented precision, efficiency, and scale. Such an advancement facilitates more timely, granular, and data-driven insights that can fundamentally improve urban planning and decision-making, and, at the same time, enable a more humanistic focus. However, integrating GeoAI comes with challenges, particularly in managing the uncertainties inherent in data quality, model transparency, and the dynamic nature of urban environments. To fully leverage the potential of GeoAI, it is crucial to adopt strategies that enhance data reliability, adequately quantify and communicate uncertainty, and ensure that AI models are both interpretable and contextually relevant. This will help GeoAI provide more accurate and actionable insights, ultimately leading to more informed and effective urban planning and policy-making.

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