GeoAI for Urban Sensing

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ABSTRACT
Urban sensing has been an important topic in the past decades, and research has been amplified in the last several years with the emergence of new urban data sources and advancements in GeoAI. This chapter gives a high-level overview of the applications of GeoAI for urban sensing, which have multiplied across various domains. It reviews four examples of GeoAI applied for urban sensing, which span a variety of data sources, techniques developed, and application domains such as urban sustainability. Concluding this topic, several challenges and opportunities for future research are discussed, such as ethics and data quality.

1. Introduction

Urban sensing can be defined as a collection of methods and techniques to sense and obtain information about the built environment and human activities in cities (Shi 2021). It is a major pillar of urban analytics, and it involves the collection and management of both static (e.g. buildings, road infrastructure) and dynamic (e.g. traffic, social media, noise) phenomena in urban areas. It has permeated through numerous domains and tasks pertaining to cities, from transportation, tourism and social networks to disaster management, air quality and foodscapes (Bai *et al.* 2022, Abirami and Chitra 2022, Xu *et al.* 2022b, Andris and Lee 2021, Shin *et al.* 2015, Yang *et al.* 2023, Liang and Andris 2021, Calabrese *et al.* 2013, Xu *et al.* 2022a).

Following decades of developments, urban sensing remains a vital topic in spatial information sciences and urban management. Many technologies, such as lidar and satellite-based remote sensing, have been developed and employed in urban sensing. These approaches allow processing of data to extract knowledge, leading to meaningful and actionable insights. It has been attracting growing interest thanks to several continuously developing factors. In particular, in the past few years, these factors have multiplied: the increased volume of existing data (e.g. coverage, longitudinal acquisition), proliferation of sensors and supporting platforms (e.g. sensor-equipped vehicles), increasing quality of existing data (e.g. resolution of satellite imagery, accuracy of positioning), emergence of new sources and types of data (e.g. social media data, street-level imagery), the rise of citizen science and crowdsourcing (e.g. the success of OpenStreetMap), and greater computing power to process large amounts of data (Gao *et al.* 2021, Biljecki and Ito 2021, Lai 2021, O'Keeffe *et al.* 2019, Tu *et al.* 2021, Yan *et al.* 2020, Duarte and Ratti 2021, Hu *et al.* 2015, Psyllidis *et al.* 2022,

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deSouza *et al.* 2020). As a result, it is not surprising that GeoAI techniques, powered by developments in computer science, have flourished in urban sensing. GeoAI aims to make sense of the vast and diverse data, and it helps enhancing our understanding of urban environments. It has become a dominant topic in journals and conferences, giving impetus to new opportunities, use cases, and sensing insights in cities (Gao *et al.* 2023, Liu and Biljecki 2022, Li 2020, Janowicz *et al.* 2019, Kang *et al.* 2019, Das *et al.* 2022).

This chapter gives a brief overview of some developments of GeoAI in urban sensing, together with an overarching overview beyond specific AI techniques to give a broader understanding such as use cases, data, and challenges and opportunities. Considering the large volume of papers published on this topic, covering all aspects would be beyond the scope of a single book chapter. Further, specific GeoAI techniques, datasets, and use cases have been subject of many review papers (Ghahramani *et al.* 2020, Chen *et al.* 2023, Ibrahim *et al.* 2020, Biljecki and Ito 2021, Shahtahmassebi *et al.* 2021, Yan *et al.* 2020, Martí *et al.* 2019, Shi 2021, Song *et al.* 2023, Liu *et al.* 2015, Hsu and Li 2023, Richter and Scheider 2023, Li and Hsu 2022, Lu *et al.* 2023). Thus, this chapter focuses on a selected set of insights that capture the general trends and landscape of the GeoAI developments supporting urban sensing in the ever-growing complexity and scope of urban environments. It focuses on examples of research conducted at my research group, which reflect the developments described above, and it gives a diversity of high-level examples of various GeoAI techniques used, input data, and solutions to challenges across multiple domains.

2. Recent examples of GeoAI for urban sensing – case studies in Singapore

This chapter reviews a few use cases developed at the research group Urban Analytics Lab at the National University of Singapore to give an overview of recent applications of GeoAI for urban sensing. These use cases are based on a variety of types of input data and techniques to process them, and they span diverse application domains that benefit from novel urban sensing approaches.

2.1. *Sensing rooftops from high-resolution satellite images*

Roofpedia is a project described in Wu and Biljecki (2021), focused on mapping the content of rooftops of one million buildings around the world, in the context of sustainable development. It has been developed against the backdrop of the increasing volume of studies focused on understanding the potential of rooftops in cities for the installation of solar panels (Bódis *et al.* 2019, Han *et al.* 2022). It identifies a gap that — while a large volume of papers has been published with the purpose of measuring the space provided by rooftops and assessing their potential — not many studies have established the current utilisation of rooftops, e.g. understanding how many rooftops have already been used for such purpose. The same goes for rooftops that have greenery, i.e. green roofs.

The developed workflow uses satellite imagery and image segmentation to automatically identify rooftops that are vegetated and/or have photovoltaic system installations, and measure their extent. In the preprocessing stage, the developed workflow uses building footprints sourced from OpenStreetMap to delineate portions of the imagery that represent buildings, in order to detect only photovoltaic panels and green

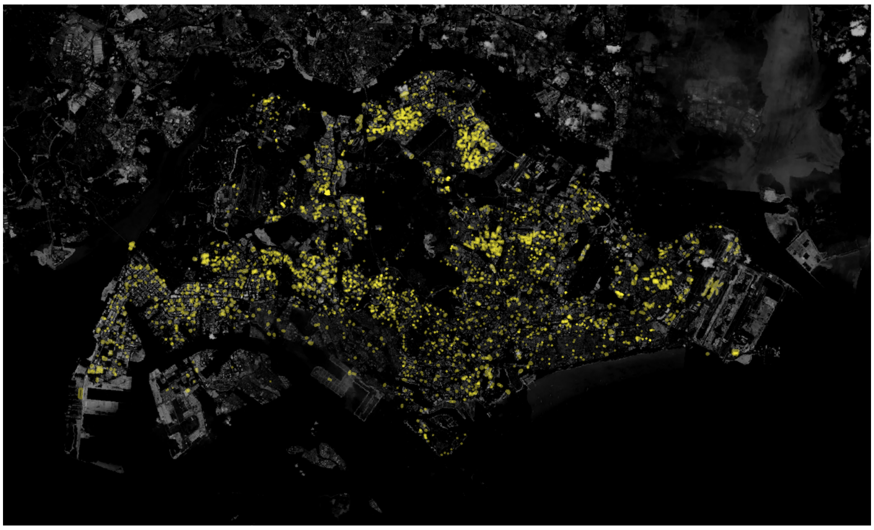

Figure 1. Locations of buildings in Singapore that have been detected to have photovoltaic installations on rooftops, using GeoAI techniques. Source: (Wu and Biljecki 2021).

roofs that are located on buildings, and exclude such features that are not on rooftops.

It is an example of research that engages primarily existing data (optical satellite imagery) but introduces a novel use case, thanks to its increasing quality (resolution, coverage) and accessibility, and developments in artificial intelligence. At the same time, it leverages crowdsourced data, an emerging data source, to support the mapping of rooftops.

Since the study is conducted at the city-scale for dozens of cities worldwide, it can be used for urban scale analyses (Figure 1) and understanding the penetration of sustainable rooftops. It also includes an index that quantifies the rooftop utilisation rate in cities, which can be considered a proxy to gauge how successful cities are when it comes to unlocking the space provided by rooftops.

Such research is an example of urban sensing that has potential to be linked to urban policies and lead to actions, e.g. understand whether policies to install solar panels in residential buildings have had an effect, and whether there is a particular area in a city that did not experience an uptake of rooftops for such purposes.

2.2. *Sensing urban soundscapes from street-level imagery*

Street-level imagery has been used extensively in the past few years in combination with GeoAI techniques (Biljecki and Ito 2021, Kang *et al.* 2020b, Zhang *et al.* 2023a). It is a quintessential example of an emerging data source for urban sensing and it has greatly benefited from the advancements in GeoAI. For example, it has been used for understanding human perception (Kruse *et al.* 2021), mapping street-level greenery (Yang *et al.* 2021), understanding factors driving house prices (Kang *et al.* 2021), generation of 3D city models (Pang and Biljecki 2022), inferring urban density (Garrido-Valenzuela *et al.* 2023), and discovering inconspicuous but interesting places in cities (Zhang *et al.* 2020).

The work developed by Zhao *et al.* (2023) is a new application of GeoAI for urban sensing — predicting the intensity and nature of sounds in urban areas at a large-scale from street view imagery. The key motivation for this work is the increasing importance of soundscapes in the development and management of smart cities. How-

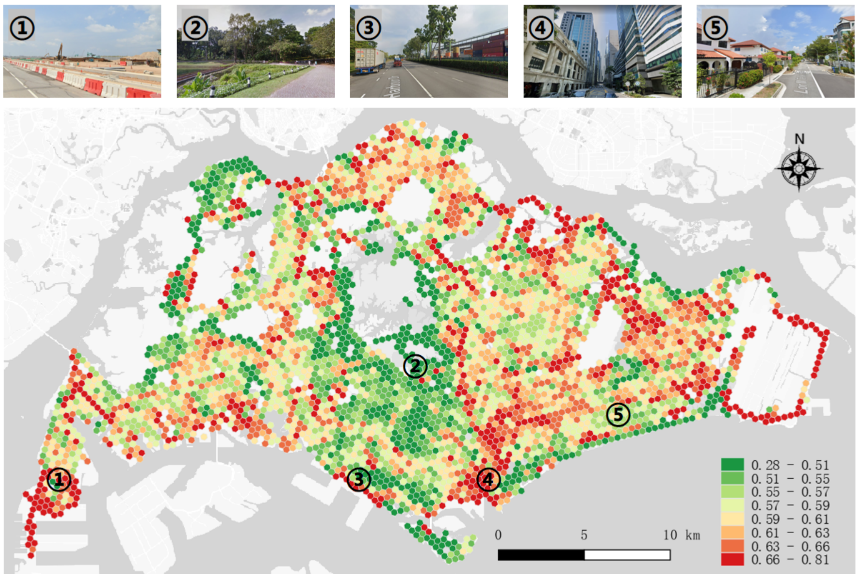

Figure 2. Predicted sound intensity from street view imagery across Singapore at high resolution. Adapted from: (Zhao *et al.* 2023).

ever, techniques to sense the acoustic environment have been limited, especially at a high resolution. Thus, this work establishes a hypothesis that visual representations of streets may suggest the nature and intensity of noise, which can be leveraged by the increasing availability of street view imagery and advancements in GeoAI.

The developed approach uses street view imagery and computer vision to extract relevant visual features, doing so at multiple levels: pixel-level, object-level, semantic-level, and scene-level visual features. For example, the semantic-level feature is the proportion of 19 semantic features in an image, such as sky and vegetation, which was derived thanks to the DeepLabV3+ model trained on the Cityscape dataset (Chen *et al.* 2018, Cordts *et al.* 2016). After the visual features have been determined, the work establishes relationships using Gradient Boosted Regression Trees to infer the soundscape at the city-scale at a high resolution (Figure 2). The results have been validated using field audio measurements.

This work demonstrates how an emerging dataset in conjunction with GeoAI techniques can uncover a new use case and be leveraged to fill data gaps and derive new insights for multiple domains, i.e. enable inferring urban soundscapes for purposes such as measuring liveability, understanding impact on house prices, and support urban planning.

2.3. *Sensing and understanding human comfort using smartwatches and other sensors*

Walkability and outdoor comfort have been topical subjects in urban planning, and GeoAI techniques have been used to assess them (He and He 2023). A recent paper by Liu *et al.* (2023a) is an example of GeoAI engaged for sensing and understanding human comfort — it introduces GraphSAGE-LSTM (GraphSAGE (Hamilton *et al.* 2017) and Long short-term memory network (LSTM) (Hochreiter and Schmidhuber 1997)) on crowdsourced data and computer vision to predict human comfort on the sidewalks.

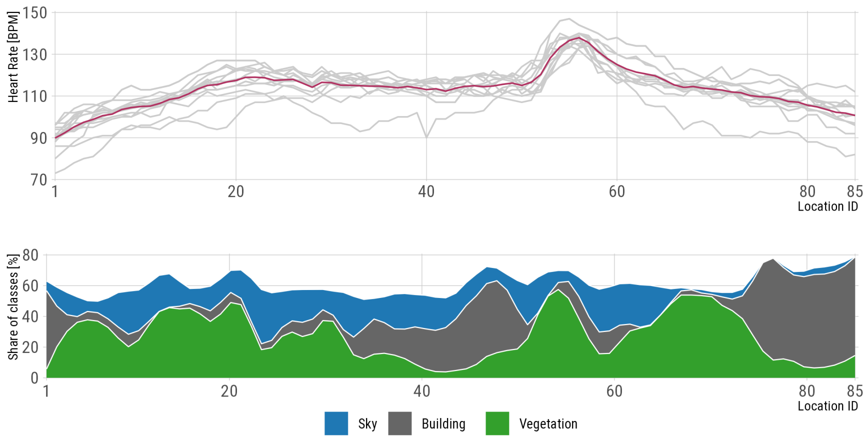

Figure 3. Collecting a variety of sensory experiences of dozens of people during walking through a specific path: their heart rate (top plot) and what they see (bottom plot), which was collected using different sensors. GeoAI techniques have been used to understand the dynamic interactions between the environment and individual factors in the context of walkability and outdoor comfort. The plots have been generated using the data collected in the experiment conducted by Liu *et al.* (2023a).

A particularity of the work is that it combines multiple datasets (Figure 3): it collects data from a wearable device (smartwatch) and a developed app to gather physiological data and human comfort (Tartarini *et al.* 2022, Jayathissa *et al.* 2019), and couples it with a variety of environmental data such as noise, solar irradiation, and street-level imagery (which was used to establish what pedestrians see at a particular location).

The developed GeoAI model is spatio-temporal-explicit because it captures the interactive nature of humans and surrounding built and unbuilt environments to predict human comfort through sequential movements. It is an example of a study that demonstrates the superiority of GeoAI approaches for urban sensing as it delivers substantially better accuracy than traditional machine learning models and some state-of-art deep learning frameworks.

The work also sets the scene for the consideration of dynamic data and GeoAI in urban digital twins, as it may help establishing the integration of GeoAI-empowered models in digital twins to achieve location-attentive predictions and human-centric simulations.

2.4. *Sensing the perception and quality of underinvestigated urban spaces*

Street-level imagery, an emerging dataset overviewed in Section 2.2, has been largely confined to roads due to being acquired from cameras mounted on cars, affecting downstream analyses that have almost always considered only driveable streets instead of the entire urban environment.

Luo *et al.* (2022b) noticed that in platforms offering street-level imagery (e.g. Google Street View and Mapillary), in some cities, imagery has been collected also from boats (e.g. on water bodies such as urban rivers). The paper dubs such data as ‘water view imagery’, and positions it in the broader context of sensing urban waterscapes, an increasingly relevant topic in urban planning.

The paper presents a comprehensive perception study of multiple dimensions of waterfronts using GeoAI. It performed semantic segmentation of water level scenarios using SegFormer (Xie *et al.* 2021), and developed a comprehensive set of indexes for urban waterscape evaluation. These are then linked to the perception of these scenes,

Figure 4. An unconventional street-level image, taken on a footpath by a pedestrian in the Botanic Gardens in Singapore, as opposed to the typical imagery collected from cars on driveable roads. New forms of existing types of data open new opportunities for urban sensing, which need to be accompanied by the development of new GeoAI approaches to extract reliable insights from such unorthodox platforms. Source: Mapillary.

which were collected through a survey. Thanks to the large-scale availability of data and AI techniques employed, for the first time, a global study was conducted. Its findings are several — the analysis reveals the heterogeneity of riverscapes around the world, and based on the analyses of the relationship between the developed indexes and the subjective visual perception, it finds the drivers of appealing urban waterscape design.

The work of Chen and Biljecki (2023) has focused on 'off-road' imagery, a growing subset of street-level imagery that covers public open spaces such as parks, largely enabled by the emergence of crowdsourced street-level imagery, in which contributors use heterogeneous approaches, equipment, and platforms to collect imagery in cities (Figure 4). This example doubles as one that reflects another trend mentioned in the Introduction — it is an image that has been obtained from a crowdsourced platform (Mapillary), which has been seeing a surge in volume and coverage (Hou and Biljecki 2022, Ding *et al.* 2021, Juhász and Hochmair 2016, Ma *et al.* 2019), and it is increasingly used in urban studies (Yap *et al.* 2022).

Thanks to such data, a method, which relies on computer vision techniques, was developed to establish an automated approach to evaluate public open spaces and understand their quality from the human perspective. In a case study conducted across two cities, 800 public open spaces have been evaluated using traditional geospatial and remote sensing data, with the addition of street-level imagery. Thanks to GeoAI, the work shows that this emerging dataset can be used to automatically sense the rarely considered off-road areas, and it provides a convincing advancement over traditionally used data, potentially contributing to policy-making related to public open spaces.

3. Challenges and opportunities

Quality of data The reliability of GeoAI techniques in urban sensing much relies on the quality of data. However, quality is not a topic that is often mentioned in papers, thus, there is an impression that it is usually taken for granted. This matter is especially important considering the increasing use of data that has a crowdsourced provenance, such as OpenStreetMap. Further, there is a lack of data quality standards and assessment procedures tailored for emerging urban datasets (but also some traditional data), which hinders understanding and quantifying the level of quality of data. Such may be relevant for establishing data requirements for certain GeoAI approaches.

On the flip side, in general, we are witnessing an increasing quality of urban data. Various data sources have been increasing in completeness. Further, thanks to the advancements in sensors, remotely sensed data has been increasing in resolution. Such developments will benefit the application of GeoAI, and may potentially lead to the introduction of new use cases (such as the one described in Section 2.1) and increased reliability.

In terms of quality, some datasets are also increasing in timeliness, i.e. the temporal resolution, reflecting urbanisation and the dynamic nature of urban environments. These may present an opportunity for further use cases. For example, as some cities have been imaged multiple times in the past decade, street-level imagery is often available across multiple epochs. However, very few studies take advantage of the availability of historical data (Li *et al.* 2022, Byun and Kim 2022, Zhang *et al.* 2023b). Moving forward, certain GeoAI techniques may need to be improved to cater to temporal studies, especially as some may require an increased level of reliability for detecting subtle changes between two periods in time.

Emerging data streams A notable development in urban sensing, and one that has implications for GeoAI, is the multiplication of the types and sources of urban data in the last several years. Besides examples of datasets described earlier in the chapter, emerging urban data streams such as ground-based infrared thermography sensing the cityscape (Martin *et al.* 2022, Dobler *et al.* 2021, Arjunan *et al.* 2021), crowdsourcing indoor images (e.g. from Airbnb listings) to understand local culture (Liu *et al.* 2019), using takeout data to extract dietary patterns across different population groups in a city and link dietary habits to the sense of place (Xu *et al.* 2022b), text-mining hotel reviews to learn environmental quality complaints at a large-scale (Ma *et al.* 2023) and scraping real estate listings (text and photos) to collect data on buildings (Chen and Biljecki 2022), are just examples among many instances. These datasets provide new perspectives and insights that contribute to understanding urban environments and more reliable decision-making, but at the same time, provide also certain challenges. Further, new variants of existing data, such as the one presented in Figure 4 and Section 2.4, present particular challenges and opportunities as well.

Some of the challenges include the integration of such data with traditional urban data, entailing the development of data fusion techniques, and the lack of understanding of quality and bias, and data requirements for the development of GeoAI techniques. The two case studies described in Section 2.4 demonstrate that there are large and distinct unexplored subsets of data, which may necessitate the adaptation of GeoAI workflows to suit them. While focusing on ‘off-road imagery’, the work of Chen and Biljecki (2023) uses well established approaches developed to extract insights from standard street-level imagery collected on driveable roads, but it reveals limitations as they are not perfectly adequate for such data and use case, e.g. many facilities in public open space, such as amenities for children in parks are difficult to be detected by existing models developed for streetscapes. It calls attention to the development of methods specifically developed for such type of imagery. Next, some emerging data sources should not be taken for granted. Researchers focusing on social sensing have benefited greatly from the availability of social media about a decade ago, but since then, such platforms have experienced curbs and restricted access, depriving an entire research line of suitable data. Finally, because of the novelty of such data streams, privacy and bias that GeoAI models might introduce may not be fully understood yet.

However, opportunities are several. As exemplified earlier in the chapter and with dozens of references, emerging datasets, coupled with GeoAI, enable penetrating into new application areas and developing new use cases previously not possible or bringing considerable improvement to existing ones. The novelty of some of these developments also offers an opportunity to establish data standards and benchmarks, which have been common in traditionally used datasets and have been used to support the development of AI techniques (Rottensteiner *et al.* 2014). The development of standardised data formats and data structures, and accompanying elements such as metadata, may foster data interoperability, which might be relevant for reproducibility and collaboration. Finally, some of the emerging datasets can provide a better insight into the citizenry: their perception and behaviour. GeoAI may amplify such benefit by extracting more human-centric insights, which has been exemplified in Section 2.3 with an application on sensing outdoor human comfort thanks to the development of a novel GeoAI technique and crowdsourced data together with a few other emerging data sources such as wearables.

Reproducible workflows and open data Reproducibility is an increasingly important topic in GIScience (Wilson *et al.* 2020), and it is described later in the book in a chapter specifically dedicated to this topic.

Reviewing the publications presenting applications of GeoAI for urban sensing, there is an impression that the research community has room for improvement regarding reproducibility. For example, a recent review of 250 papers using street-level imagery for urban sensing (Biljecki and Ito 2021), a prominent and emerging data source in this domain (e.g. see Section 2.2), revealed that only a fraction of the studies has shared data and/or code openly, and there is often little information for reproducing the methods.

While recently there has been momentum in releasing open data related to urban sensing obtained with GeoAI techniques or developed to support them (Kang *et al.* 2020a, Luo *et al.* 2022b, Ju *et al.* 2022, Zhang *et al.* 2022, Wu *et al.* 2023, Piadyk *et al.* 2023, Luo *et al.* 2022a), such efforts are still scarce, and an increasing number of studies employing GeoAI techniques for urban sensing calls attention to open data (He and He 2023). Such matter is hindered by the fact that much of the developments rely on proprietary data, which limits their sharing, but also technical challenges — some workflows may simply be too complex and too computationally intensive to be reproduced by many others, especially those with limited resources, which may also impact equity in GeoAI research.

This aspect offers lots of opportunities for advancements. Researchers may adopt reproducible research practices and help ensure that the GeoAI workflows can be reproduced.

Ethical concerns and bias Ethical concerns and bias are being increasingly discussed in the GeoAI community (Janowicz 2023), with many concerns applicable in the domain of urban sensing. This is in particular important in research that includes human-related aspects, such as perception, as GeoAI can perpetuate biases present in the data. Recent work commenced investigations in this line, e.g. Kang *et al.* (2023) worked on understanding the local variations of human perception of safety (i.e. comparing safety perception scores of people living in the study area versus using a global model), tackling potential ethical issues in GeoAI such as population bias.

With the increasing deployment of sensors and increasing data quality, privacy is another concern. GeoAI researchers need to ensure to employ techniques that guarantee the protection of personal data. Further, as a large number of studies involves human participants (e.g. to collect data on perception), researchers need to ensure that they have obtained informed consent and the approval from institutional review boards.

Many of potentially sensitive datasets are collected and managed by corporations, which is a point raised also by Duarte and Ratti (2021), and which may present an opportunity for the development of legal and regulatory acts to safeguard privacy and safety.

Capacity building and domain knowledge GeoAI for urban sensing requires an intricate set of skills. These are not only related to artificial intelligence and geospatial data, but include also domain knowledge, which may often not be available. As such combination is rare and unique, entry barriers remain high. Further, urban sensing research involving GeoAI benefits from understanding the entire geospatial process, which does not include only processing and analysing data, but also considering its provenance and quality. An opportunity is the development of educational initiatives to support the development of holistic skills.

4. Conclusion

This chapter has discussed recent trends and developments of applications of GeoAI for urban sensing across multiple types of data, urban challenges, and application domains. While a single book chapter cannot give justice to all the GeoAI-powered research related to urban sensing, it gives a high-level overview of a few recent efforts that are representative of the use of GeoAI for advancing urban sensing under the umbrella of urban informatics.

The proliferation of urban sensing and GeoAI techniques, while providing unprecedented opportunities and advancements, entails some challenges and issues, such as privacy and ethics concerns. The aspects described in the previous section are by no means complete. There are many further topics that require attention and may represent viable research directions.

The lack of interpretability and the ‘black-box’ nature of existing GeoAI approaches has spurred discussions on the need for explainable GeoAI (GeoXAI) (Xing and Sieber 2023, Hsu and Li 2023). This topic is certainly relevant for urban sensing as well. Some of the recent urban sensing work involving GeoAI started tackling this matter (Liu *et al.* 2023b).

Much of emerging datasets are textual, which may be propelled with the recent popularity of large language models, that is, their improved text analysis capabilities may enable deriving more reliable and meaningful insights from such data, leading to the improvement of applications or introduction of new use cases.

Generalisation of GeoAI models is another important topic. Much of the approaches have been developed in a single or a few cities, and may not be fully generalised elsewhere. Further, some GeoAI approaches that are ostensibly designed to be global may have a variable performance across cities, and potentially introduce bias towards certain geographies and types of urban areas.

Finally, while GeoAI and urban sensing have made great strides in the past few years, research rarely translates into actionable policies and adoption by policy makers. At the moment, it appears that the gulf between the two is too wide to be bridged in many cases, and it can be attributed to issues such as limited capacity of policymakers to implement GeoAI-based solutions, regulatory barriers, lack of trust of reliability of the approaches, and limited interpretability of GeoAI models.

In conclusion, GeoAI, largely thanks to developments in computer science, proliferation of emerging datasets and increasing computational resources, continues to revolutionise urban sensing, by introducing more efficient, more comprehensive, and more accurate insights and analyses of urban environments. It holds immense potential for supporting the development of sustainable and liveable cities with continued methodological advancements, inclusion of stakeholders from multiple domains, growing efforts of integrating data sources, and increasing consideration of ethical considerations.

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