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# A review of spatially-explicit GeoAI applications in Urban Geography

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ABSTRACT

Urban Geography studies forms, social fabrics, and economic structures of cities from a geographic perspective. Catalysed by the increasingly abundant spatial big data, Urban Geography seeks new models and research paradigms to explain urban phenomena and address urban issues. Recent years have witnessed significant advances in spatially-explicit geospatial artificial intelligence (GeoAI), which integrates spatial studies and AI, primarily focusing on incorporating spatial thinking and concept into deep learning models for urban studies. This paper provides an overview of techniques and applications of spatially-explicit GeoAI in Urban Geography based on 581 papers identified using a systematic review approach. We examined and screened papers in three scopes of Urban Geography (Urban Dynamics, Social Differentiation of Urban Areas, and Social Sensing) and found that although GeoAI is a trending topic in geography and the applications of deep neural network-based methods are proliferating, the development of spatially-explicit GeoAI models is still at their early phase. We identified three challenges of existing models and advised future research direction towards developing multi-scale explainable spatially-explicit GeoAI. This review paper acquaints beginners with the basics of GeoAI and state-of-the-art and serve as an inspiration to attract more research in exploring the potential of spatially-explicit GeoAI in studying the socio-economic dimension of the city and urban life.

## 1. Introduction

Urban Geography is concerned with the study of cities and urban life from a geographical perspective (Hall and Barrett, 2012). It seeks to analyse, explain, and forecast changes in urban forms as well as the socio-economic structures. As a specialised discipline within Human Geography, Urban Geography addresses urban issues from political, socio-economic and ecosystem aspects at various scales (Smelser et al., 2001). The scientific results of urban studies have increasingly supported public investment, resource allocations, and urban planning (Mills, 1967; Thumboo et al., 2003; Oliveira and Pinho, 2010; Fan et al., 2014; Bukuluki et al., 2020). Facing the rapid speed of urbanisation and increasingly abundant data, the bigness of cities often only can be explained through the bigness of data produced from them (Shelton, 2017). Emerging sources of so-called "Big Data" and revolutionary technologies including high performance computing (HPC) and Artificial Intelligence (AI) (Li, 2020) enabling new kinds of discoveries of previously unforeseen knowledge unhampered by longstanding theoretical approaches.

In the era of "Big Data" (Kitchin, 2014), up to 80% of big data is "spatial" with locational components attached (Leszczynski and Crampton, 2016). With the advanced development in remote sensors, GPS-enabled applications and the popularity of mobile devices, as well as increasingly affordable data storage and computational technologies, data are produced from a wide range of disciplines from commercial business to scientific research and engineering. Such geotagged data in large volume, high velocity, and abundant variety that exceed the capacity of current common spatial computing platforms are defined as *spatial big data* (SBD) (Jiang, 2016). The recent breakthrough in machine learning, or more generally AI and more specifically deep learning, enables a new research paradigm of data-driven science to analyse, mine, and visualise massive SBD that are difficult to handle using traditional spatial analysis methods (Li, 2020).

AI is a term frequently applied to machine learning or deep learning algorithms aiming to simulate the intellectual processes of humans, for example, the capability of reasoning, meaning discoveries, generalisation, or learning from previous experience. The interplay of AI and geography is not entirely new. The early thoughts trace back to 1984 when Smith (1984) first proposed the idea of applying AI-based techniques in geo-spatial problem-solving tasks. Later in the 90s, Openshaw and Openshaw (1997) published their influential book entitled "Artificial Intelligence in Geography", which marked the beginning of the AI revolution in geography and prompted the use of Artificial Neural Networks (ANNs) within the discipline, which later

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formulated the foundations for the research theme of GeoAI. Nowadays, AI in general, deep learning in particular, have been widely adopted to address many geographical problems, from spatial object detection for satellite imagery (Li et al., 2021b; Wu and Biljecki, 2021; Li et al., 2022) to urban traffic forecasting (Li et al., 2018; Vázquez et al., 2020). It is important to note that although AI methods may not necessarily refer to deep learning-based approaches, for the scope of this paper and also to following the recent trend of GeoAI development within the GIScience discipline (Zhu et al., 2018; Li, 2020; Janowicz et al., 2020; Mai et al., 2022), we will focus on papers in which (deep) neural network-based methods are involved.

GeoAI functions as a promising solution technology for data or compute-intensive geospatial problems with the help of AI, HPC, and SBD. Many research projects have successfully applied AI for geospatial problems by using models and algorithms from computer science with no or minor modifications (Huang et al., 2018; Pereira et al., 2019; Zhu et al., 2020a; Wu and Biljecki, 2022). However, such models and algorithms by design do not explicitly adopt locations as parts of the feature input; thus, they are rather formalised as a one-way direct import from AI to Geography (Li, 2020; Janowicz et al., 2020). Those conventional GeoAI methods have been massively contributing to the understanding of urban issues in the past decade, such as urban function recognition through remote sensing images (Zhou et al., 2020), understanding geodemographics of urban and national populations (Singleton and Longley, 2015; Gale et al., 2016), and urban gentrification (Reades et al., 2019). However, although the models were applied to the spatial data, the locational information of the data were not directly used by the models. Taking unsupervised clustering methods in geodemographic classifications (Singleton and Longley, 2015; Gale and Longley, 2013) as an example, conventional classification methodologies lack any explicit use of information on the geospatial context of an area. The central "control by aggregation" concept of geodemographics (Farr and Webber, 2001) is usually only applied to data attributes during the clustering process, without accounting for the geospatial relationships among area units. That is, conventional clustering algorithms account only for proximity in the data attribute space but not in the geographic space. As such, areas are essentially treated independently from their neighbours. Thus, despite the term, geodemographic classifications discussed in the academic literature are often *a-(geo)spatial* in their implementations.

Location is a key to synthesising multi-source spatial data and geographic domain knowledge; spatial concepts contribute to different contextual platial understanding (e.g. mobility space and social space), which were often neglected in much existing research (Goodchild, 2001). Li (2020) emphasised the importance of two-way knowledge transfer from both "AI" to "Geo" and "Geo" to "AI", which stressed the idea of incorporating location and domain-specific spatial concepts or rules (e.g. the first law of geography) into the AI models (Goodchild, 2001; Janowicz et al., 2020). More specifically, spatially-explicit GeoAI is defined as those models that can satisfy four requirements (Goodchild, 2001): *invariance test (the results of the models are not invariant if the studied issues are relocated)*, *representation test (spatial representations of the coordinates, spatial relations, etc.)*, *formulation test (formulations of the algorithms makes use of spatial concept)* and *outcome test (the input spatial structures are different from the output)*. As such, spatially-explicit GeoAI models straightforwardly adopt locational information from the data in the computational process, taking into account spatial dependence and heterogeneity, to address the "speciality of spatial" in geospatial problems (Gao, 2021). The spatially-explicit GeoAI models have proved to outperform traditional non-spatial machine/deep learning models in many geography-related tasks, such as image classification (Li et al., 2014; Chen et al., 2022; Ma and Li, 2022), geographic knowledge graph summarisation (Yan et al., 2019), terrain features detection (Zhou et al., 2021a), urban ecology (Zhang and Xie, 2022), urban climate (Yu et al., 2021), geographic question-answering problems (Mai et al., 2019), and social sensing (Liu and De Sabbata, 2021; Yin et al., 2021).

In the existing review papers, an extensive summary of deep neural networks in various aspects of Urban Geography is presented in Grekousis (2019). The paper broadly covers a wide range of urban geography tasks using deep neural networks, from extensive urban land cover change to urban socio-economic studies. However, most papers reviewed focus on addressing geographic questions using or developing deep learning techniques with no account of spatial components in the AI models. Moreover, although the author included the socio-economic aspect as one of the themes to review, the paper identifies a clear research gap in utilising socio-economic data to analyse the social dimension of the cities, which, however, should be one of the significant focuses of urban geography studies (Castree et al., 2013). Considering that rapid urbanisation often results in substantial changes of urban socio-economic fabrics (Turok and McGranahan, 2013), more demanding analysis and interdisciplinary studies using progressively sophisticated GeoAI methods are necessary in the era of "Big Data" to address complex urban socio-economic issues (Leitner, 1989).

This study fills the gap in the existing reviews where social dimensions of the cities are often a neglected topic in (deep learning-based) GeoAI-involved quantitative urban studies (Grekousis, 2019) and GIScience (Janowicz et al., 2020; Li, 2020; Mai et al., 2022). Therefore, this paper provides a complementary scope of the GeoAI in Urban Geography, focusing on the development and the use of spatially-explicit GeoAI in studying the socio-geographical dimension of the city and city life. Urban socio-geographical studies seek to understand the interactions between human and urban spaces and environment on socio-economic levels in the phrase of consistent urban development (Jabareen and Eizenberg, 2021), and how urban places are understood through human everyday activities (Agnew and Livingstone, 2011). Therefore, we follow three independent but also interconnected scopes to perform the review:

- Urban Dynamics: includes studies of urban development (e.g. urban growth/sprawl) and the changing flow of everyday urban population and socio-economic activities.
- Social Differentiation of Urban Areas: includes studies related to population demographic analysis (e.g. geodemographics), segregation and social area analysis.
- Social Sensing: includes studies focusing on understanding urban places described through people's activities, in particular with the help of SBD (e.g. social media, volunteered geographic information).

Fig. 1 illustrates how the three chosen scopes are connected. The social differentiation of urban areas is often a consequence of urban dynamics (Mack and McElrath, 1964), resulting in different living experiences for the residents in the cities and influencing how places are socially sensed by everyday activities. In turn, such platial understandings of the inhabitant impact how cities will evolve into (Shao et al., 2021) and the dynamics of the population flows (Guo et al., 2021). The rest of the paper will briefly introduce deep neural networks and spatially-explicit GeoAI in Section 2; methods used for our systematic review in Section 3; the survey and results of the review output in Section 4, with discussions and conclusions presented in Section 5.

## 2. Deep neural networks and spatially-explicit GeoAI

In this section, we give a brief overview of the topic to readers who may not be fully acquainted with the concepts in focus.

### 2.1. Neural networks, GeoAI and location encoding

In the short term, a simple neural network is a mathematical model with connections and weights that takes inputs and delivers outputs as a network of nodes organised in layers. As shown in the right part (neural network in the box of *Downstream Tasks*) of Fig. 2, the neural network consists of an input layer, an output layer, and two columns

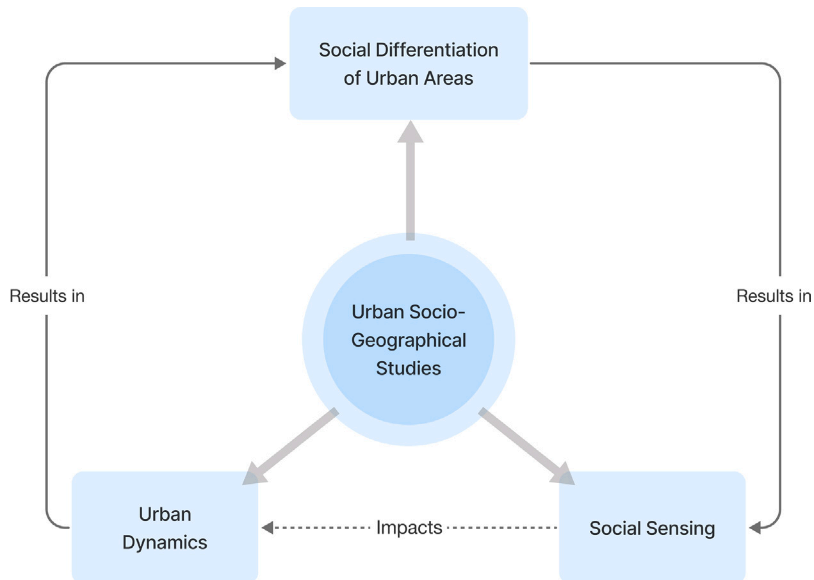


**Fig. 1.** Three connected scopes in urban socio-geographical studies.

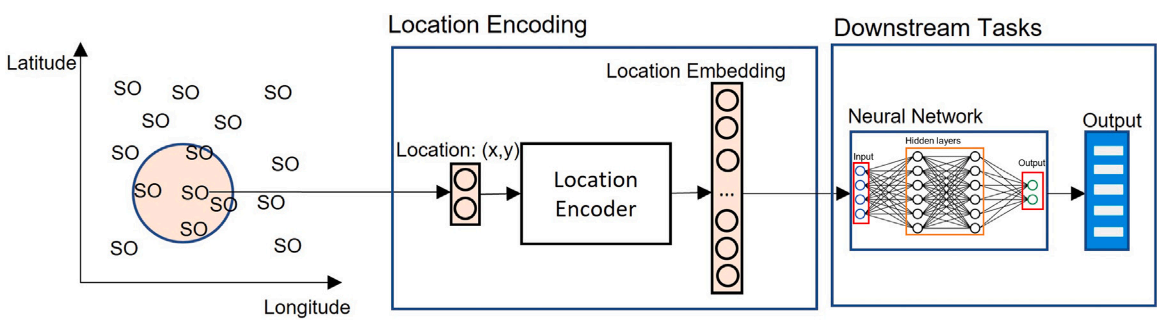


**Fig. 2.** Location Encoding process, which converts locations of spatial objects (SO) into embedding space which can later be adopted in the neural networks for downstream tasks. This image is a reproduction of Fig. 1 in Mai et al. (2022).

of hidden layers in between. Each layer has nodes called neurons coupled through connections with initial weights. Through an iterative process with a feedback mechanism (i.e. back-propagation), the neural network adjusts the weights to minimise some pre-defined error (i.e. loss) to satisfy specific termination or stopping criteria so that the model performance is expected to be increased. The number of neurons and layers can be modified depending on the complexity of the tasks or requirements. The more complex the data, the more probable the neural network will require additional neurons and hidden layers. A simple neural network can be further developed into a deep neural network by adding up more layers and neurons.

GeoAI further develops AI-based methods to imitate human perception in spatial reasoning, and the discoveries of spatial phenomena and geographic dynamics (Gao, 2021). The trending question of "why spatial is special" (Egenhofer, 1993; Gao, 2021) emphasises the importance of location, spatial dependence and heterogeneity in the GeoAI, and it drives spatial thinking and the use of spatial concepts crucial when developing spatially-explicit AI models (Zhu et al., 2018; Janowicz et al., 2020). Fig. 3 demonstrates a comparison between a conventional GeoAI method and a spatially-explicit GeoAI. The key difference between the two methods is that spatially-explicit GeoAI includes a step of location encoding so that both the data features and locational information can be fed into a AI method for the learning tasks.

Location encoding is considered to be an essential step when designing and developing spatially-explicit GeoAI models (Mai et al., 2022). The general framework is shown in Fig. 2. Location encoding is designed to represent (or encode) different spatial data types into embedding (dense numerical representations expressed as a vector) so that deep neural networks can use them. Those spatial data include, for example, points of interest (PoI), travel trajectories (i.e. polylines), postcode areas (i.e. polygons), streets and roads (represented by graphs or networks), or satellite images (i.e. raster). As pointed out by Janowicz et al. (2020) and Mai et al. (2022), raster data are easy to be encoded because the regular grid organisation can be straightforwardly used by existing models such as convolutional neural networks (CNNs, example shown in Fig. 4). Recent years have also witnessed a rising number of sophisticated location encoding methods (e.g. Sinusoidal location encoders (Qi et al., 2017; Mai et al., 2020), graph encoders (Cai et al., 2020; Zhao et al., 2022), kernel-based location encoders (Yin et al., 2019)) to represent locations in other spatial organisations (e.g. points, graphs) into a high dimensional vector space through which to incorporate different spatial information (e.g. distance, direction) into the AI models.

### *2.2. Towards spatially-explicit GeoAI in urban socio-geographical studies*

Mai et al. (2022) provided a comprehensive survey about the current landscape of location encoding techniques in GeoAI. As comprehensive as their literature review is, they focus on GeoAI models in a broad scope of the whole discipline of GIScience, which provides some, however, limited, insights into urban socio-geographics oriented studies, especially on the studies that have socio-economic perspectives. Our paper focuses on spatially-explicit GeoAI applications in Urban Geography, particularly with studies involving human and socio-economic

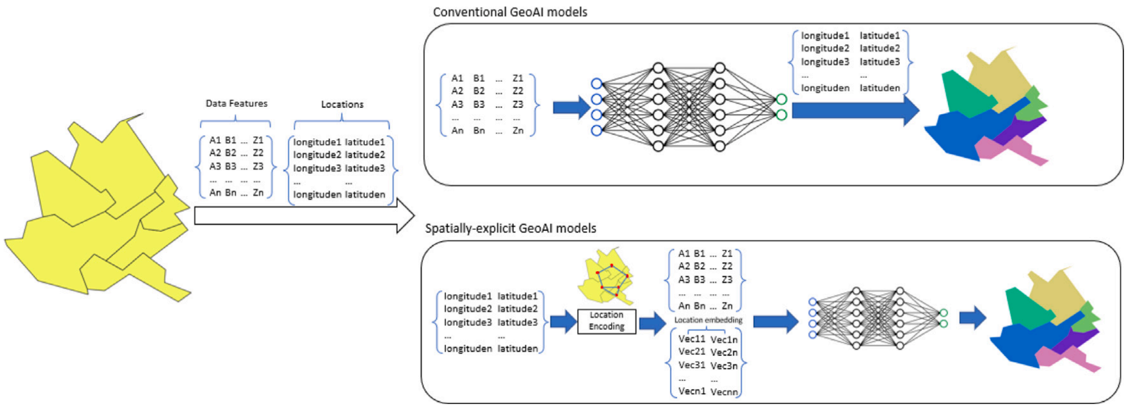


**Fig. 3.** Conventional GeoAI and spatially-explicit GeoAI.

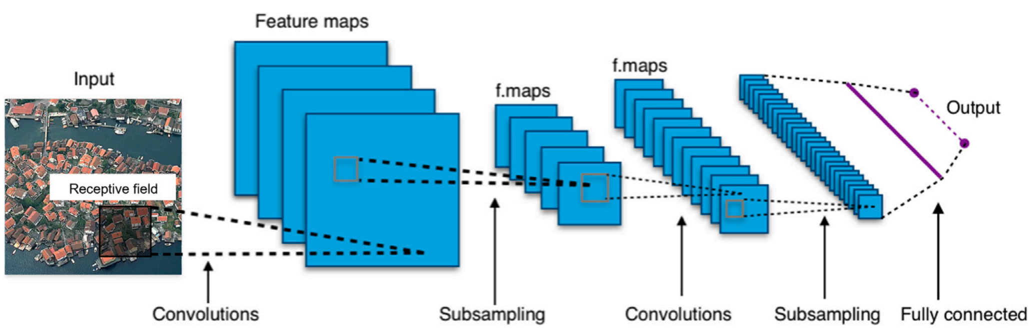


**Fig. 4.** A typical CNN. The receptive field of a CNN aggregates spatial information from the raster data. *Source:* (Satellite image adapted from Jan Norrman, via Wikimedia Commons, CC BY-SA 4.0; CNN adapted from Aphex34, via Wikimedia Commons, CC BY-SA 4.0.)

aspects in the urban context, which aims to provide a complimentary scope of how spatial and spatio-temporal components can be included in GeoAI models addressing urban socio-geographic-related questions.

## 3. Review methodology

### 3.1. Overview

For the scope of this review paper, we include the location encoding concept to identify papers that are spatially-explicit GeoAI models relevant and with a focus on Urban Socio-geographical studies. To keep the scope reasonable and to avoid simply reviewing the same papers as in existing studies (Grekousis, 2019; Yang, 2021), we specifically exclude the GeoAI models that were developed for remote sensing data analysis. Thus, we focus on models developed or used with vector data (i.e. points, polylines, polygons and graphs or networks) that are spatially organised in more irregular formats. As our review paper focuses on spatially-explicit GeoAI models and applications in Urban Geography (with the three main scopes defined in Section 1) rather than reviewing technological innovations of the models, we will not further classify papers based on the location encoder types which defined in Mai et al. (2022). Instead, we focus on how authors use or develop those models and what tasks are they addressing.

We pursued the standard systematic review methodology in the discipline (Biljecki and Ito, 2021; Berthon et al., 2021; Yap et al., 2022) to select papers relevant for this review, and the overall workflow for the paper retrieval is outlined in Fig. 5. We developed applicable keywords to fetch the initial collection of papers from the *Web of Science* (WOS) from which we extracted information. To gather state-of-the-art, we focused on papers published in the last four years (2018, 2019, 2020, and 2021). Because the concept of spatially-explicit GeoAI is developed fairly recently, to ensure that our review is adequately diverse and covers the most spatially-explicit GeoAI models in Urban Geography, we also included a screening of four academic conferences to select relevant papers: *International Conference on Geographic Information Science*, *International Conference on Geocomputation*, *ACM SIGSPATIAL International Conference on Advances in Geographic Information System*, *The Association of Geographic Information Laboratories in Europe (AGILE)*. We only considered long/full papers published in the conference proceedings in the review because the short papers and abstracts may lack necessary details of their methods and studies (Scherer and Saldanha, 2019). For papers by the same authors published both in conferences and journals, we consider only the latter.

### 3.2. Eligibility criteria

We investigated WOS for all recent publications based on predefined search syntax of keywords to identify an initial collection of journal papers. The search syntax consists of two sets of keywords. The first set fetched papers focusing on cities and the urban context, and the second delineated publications involving deep neural network models. Their intersection points out the direction of our review.

We set the expression “Urban* OR City* OR Place* OR Soci* OR Census* OR Human* OR Population* OR Flow” as the first group of keywords. The asterisk expands the search to include variations of the key search terms, covering words such as “Urban areas” or “Place understanding”. The search syntax broadly covers studies about the cities’ social or socio-economic dimensions (related to the scopes defined in Section 1). Because the keywords filtered out at this step appeared in other domains that are irrelevant to the scope of this review paper, we further limit the search to the following subject categories in WOS: *Environmental Studies*, *Geography Physical*, *Geography*, *Engineering Civil*, *Urban Studies*, *Regional Urban Planning*, *Sociology and Social Science Mathematical Methods*.

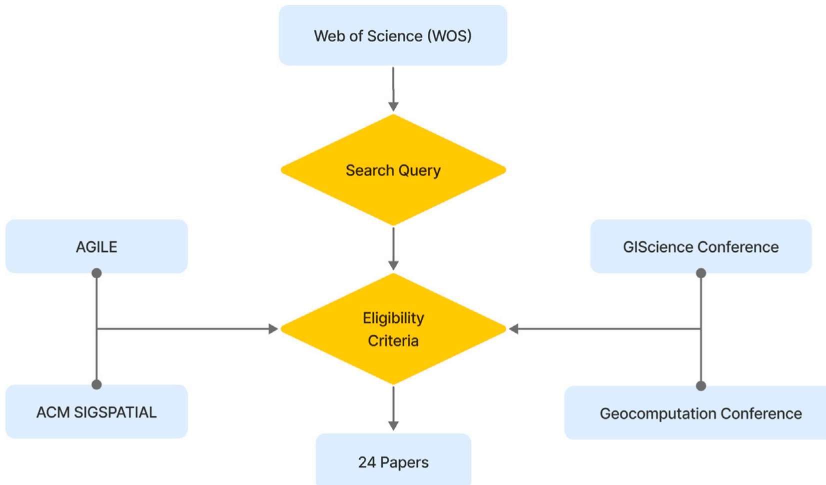


**Fig. 5.** The overall workflow for the systematic review.

The second set of keywords aims to identify articles that use deep neural networks. We set the keywords as "GeoAI OR Deep Learning OR Neural Network OR Embedding" for this step. It is important to note that at this step, we did not only target spatially-explicit models but to include all papers that involved deep neural networks. This decision is because we notice the fact that although many papers are using or developing spatially-explicit GeoAI models (e.g. Liu and De Sabbata (2021), Zhu et al. (2021)), the authors will only put either "deep learning" or "GeoAI" or "neural network" or all of them in the keywords to increase the visibility of their research. We included peer-reviewed papers written in English and published in academic journals in the selection pool (including early-access papers), finally collecting 581 papers from 2018 to 2021 (the final search was executed in the first half of 2022). However, as the scope of this review paper focuses on spatially-explicit GeoAI models, a further screening to decide whether the papers are within the scope of this study is required.

After obtaining the initial literature pool, we proceeded to select those relevant for our review manually: we screened the titles, abstracts and methodologies of papers to assess their relevance. We set up the following criteria for a paper to be included for this review:

- The (case) study area is an urban or peri-urban region.
- The paper is using or developing neural network-based GeoAI methods to address social or socio-economic research questions in the urban context within the scope defined in Section 1 (*Urban Dynamics*, *Social Differentiation of Urban Areas*, and *Social Sensing*).
- The methods proposed in the study are spatially explicit, which incorporate the component of location encoding or include spatial thinking and concepts (spatial dependencies or heterogeneity) that can address the irregular organisation of the spatial data (as mentioned in Section 2) in the development of deep learning-involved models and systems. This criterion is particularly crucial in this review because although many papers put "GeoAI" as one of their keywords to draw visibility and attention to their work, the methods they adopted are non-spatial.

We took forward 22 papers that satisfy the criteria above after screening the papers in the initial pool. Less than 4% of papers selected (22 out of 581) show that the development of spatially-explicit GeoAI in Urban Geography is still in its early phase. In addition, following the same criteria, we included two papers published in the conference proceedings. As such, we examined 24 papers, as shown in Table 1. Detailed survey and analysis of the literature will be presented in Section 4.

**Table 1**
List of the reviewed papers. (ANN—Artificial Neural Network; DNN—Deep Neural Network; CNN—Convolutional Neural Network; GNN—Graph Neural Network; CA—Cellular Automata.).

| Paper | Methods |
|---|---|
| **Urban Dynamics (urban development)** | |
| He et al. (2018) | CNN+CA |
| Xu et al. (2019) | ANN+CA |
| Ou et al. (2019) | Autoencoder+CA |
| Lu et al. (2020) | ANN+CA |
| Zhai et al. (2020) | CNN+CA |
| Rana and Sarkar (2021) | ANN+CA |
| Gantumur et al. (2022)[a] | ANN+CA |
| **Urban Dynamics (urban population flows)** | |
| Zhang and Cheng (2019) | CNN |
| Huang (2019) | GNN |
| Yao et al. (2020) | GNN |
| Zhang and Cheng (2020) | GNN |
| Hu et al. (2021) | GNN |
| Yang et al. (2021) | GNN |
| Liu et al. (2021b) | GNN |
| Xia et al. (2021) | GNN |
| Li et al. (2021a) | GNN |
| Zhu et al. (2022)[a] | GNN |
| **Social Differentiation of Urban Areas** | |
| Gervasoni et al. (2018) | CNN |
| De Sabbata and Liu (2019) | Geoconvolution+DNN |
| Monteiro et al. (2019) | CNN |
| Zhang et al. (2021) | CNN |
| Social Sensing | |
| Zhu et al. (2020b) | GNN |
| Liu and De Sabbata (2021) | GNN |
| Zhu et al. (2021) | GNN |

[a] Indicates early access.

## 4. A survey on literature

### 4.1. Spatially-explicit GeoAI for urban dynamics

Urban dynamics seeks to evaluate the main components initiating or being influenced by changes in urban areas. Among the numerous factors impacting urban dynamics, the dynamics of urban development (e.g. growth/sprawl) (Docampo, 2014), and the everyday transportation or travel activities of the population in the cities (Manley et al., 2018) are of high significance. The former focuses on a long-term temporal urban change, while the latter studies the more recent dynamics with a high temporal resolution. Urban development is or can be a spatial process (Sanders and Sanders, 2004), whereby once an area changes, neighbouring areas can be affected by that process independently or in conjunction with other factors. Research studying the process of urban development and changes using machine learning models indicates that the model performance can be enhanced by adding spatial components into the model (e.g. Reades et al. (2019), Rigolon and Németh (2019)), which suggests the potential of developing spatially-explicit GeoAI models.

The change in land-use patterns has long been a vital proxy to show and predict urban development. Cellular automata (CA), a set of early-stage AI methods (from the 1980s) (Gao, 2021) with the ability to simulate urban development through a set of transition rules among neighbourhoods and parameters (i.e. driving factors), has been widely adopted within urban-related studies (Noszczyk, 2019). In recent years, numerous research seeks the possibility of integrating neural network-based methods mining suitable transition rules for the CA models better to simulate the urban development or growth process (see Table 1, under *Urban Dynamics (urban development)*) (He et al., 2018; Ou et al., 2019; Xu et al., 2019; Lu et al., 2020; Zhai et al., 2020; Rana and Sarkar, 2021; Gantumur et al., 2022), incorporating socio-economic indicators (e.g. accessibility to the point of interests, the spatial distribution of infrastructures). CA-based models simulate the urban changes at the (pre-defined) neighbourhoods levels, which take the locations of each area into account; thus, the neural network-integrated methods are naturally spatially-explicit. However, it is important to notice that most research only adopted neural networks (e.g. multi-layer artificial neural networks, unsupervised autoencoder) (Ou et al., 2019; Xu et al., 2019; Lu et al., 2020; Rana and Sarkar, 2021; Gantumur et al., 2022) for mining transition rules for the CA. They treated each area independently rather than taking the spatial dependency (e.g. distance, directions of the changes) of areas into the model; thus, the neural networks they used did not have the step of location encoding for the study areas. He et al. (2018) and Zhai et al. (2020) tried to incorporate spatial dependency of the areas by using convolutional neural networks (CNN). However, the receptive field used by CNN as grids to aggregate spatial information failed to address the irregular and complex structures of the spatial data. However, given the complexity of urban development and the spatial dependency and heterogeneity of the spatial components and objects involved (Longley and Tobón, 2004), we fail to see many spatially-explicit GeoAI models developed other than the CA and neural network-integrated methods.

In contrast, the studies on urban population flows have attracted a wider interest in developing spatially-explicit GeoAI models. They often fall into the discipline of *Transportation*, which heavily involves traffic analysis (e.g. traffic congestion and prediction, road planning and optimisation and traffic speed) and optimisation, which is not within the scope of this review. Comprehensive reviews can be found in (Do et al., 2019; Tedjopurnomo et al., 2020; Liu and Tan, 2021; Jiang and Luo, 2021). Instead, we focus on reviewing papers that analyse the implication of everyday urban population flows with spatially-explicit GeoAI models on the urban environment understanding, which may eventually improve urban life (e.g. crime reduction, green sustainable development).

Travel patterns and the travel mode choice is a valuable proxy to indicate urban socio-demographics (Lu and Pas, 1999; Xie et al., 2016). Zhang and Cheng (2019) introduced an approach that adopted smart card data (SCD) and a household survey, using a proposed CNN-based method, to predict a passenger's employment status. First, the passenger's weekly travel patterns (classified in different modes) were extracted from the raw SCD into a three-dimensional image. In other words, the temporal travel patterns between destinations are converted into an image-like tensor representation which later is used for the downstream classification task. Then, a thresholding multi-channel CNN was introduced to infer an individual's employment status. In this study, the temporal patterns of travel behaviours were the focus of the encoding phase, while the tensor only inherently represented geo-locations of travel destinations; thus, the deep learning model presented was not a spatially-explicit GeoAI defined in this review paper per se. However, the efforts to develop such a model that could incorporate spatio-temporal information into a deep learning model were nevertheless innovative and inspirational, which can be considered an early effort in developing a spatially-explicit GeoAI model. Such methods have proved to be practically helpful, and the authors later employed similar methods to study geodemographics (which also link to the discussion in Section 4.2) (Zhang et al., 2020), and urban traffic flows (Ren et al., 2020).

Meanwhile, we have witnessed the vast majority of research incorporating spatial and spatio-temporal information of the urban crowd flows and people's everyday activities into their deep learning model using graph representations (Mai et al., 2022), especially after the recent proliferation of graph neural networks (GNNs) (Wu et al., 2020). Graph neural networks handle the input of graph representation as an adjacency matrix that can straightforwardly encode each spatial object's location as a node and the spatial dependency of the nodes as links (see example in Fig. 6). In addition, the extensibility of GNNs to either integrate with neural networks that can handle temporal variations (e.g. LSTMs) or build a gated attention module in the networks offers the possibility to include temporal information in the model, which can greatly benefit the studies of urban dynamics. Huang (2019), Yao et al. (2020), Liu et al. (2021b), Yang et al. (2021), Xia et al. (2021), Li et al. (2021a) (see Table 1, under *Urban Dynamics (urban population flows)*) adopted and developed graph-based neural networks to analyse crowd flows that can be performed on much downstream analysis based on the graph representations of street networks (e.g. bus lines) or irregular structure of mobile data flows, such as human activity community identification, everyday travel patterns analysis, etc. In particular, Huang (2019), Yao et al. (2020), Li et al. (2021a) encode the crowd flow analysis as a static graph which encodes the direction and locations of the destination while Liu et al. (2021b), Yang et al. (2021), Xia et al. (2021) additionally incorporate the temporal variations of the population flows. Zhang and Cheng (2020), Zhu et al. (2022) can be considered a practical use of GNNs to address urban issues (i.e. regional crime forecast) with dynamic human activities datasets, which reinforces the importance of spatio-temporal information incorporation in the model.

### 4.2. Spatially-explicit GeoAI for social differentiation of urban areas

The rapid urban development process not only changes the scale of the urban spatial organisation but also leads to an alteration in the social organisation of people's activities, which consequently results in the evident clustering of groups of people sharing similar socio-economic characteristics (as well as ethnics and cultures) into particular parts of the cities. Those spatial clusters were famously (although controversially) described as "ghettos" (Van Liempt, 2011; Walks, 2020) and have long been observed in many metropolitan and economically active cities. Therefore, the social differentiation (e.g. population demographics, segregation) of areas is often a consequence of the urban development and growth (i.e. urbanisation) (Mack and McElrath, 1964).

Geodemographic classification, socio-economic characterisation, and quantitatively learning segregation are often a way to study such systems of differentiation at the urban or national scale. Those methods are often created to summarise indicators for small areas' (e.g. pre-defined neighbourhoods) socio-economic, demographic and built-environment characteristics (Harris et al., 2005), and have been heavily relied on the clustering methods (e.g. k-means clustering (Singleton and Longley, 2015; Gale et al., 2016)) or shadow (one-layer) neural network (e.g. self-organising map (Olteanu et al., 2020)). Although some research investigated the possibility of using street view images with computer vision techniques to analyse the social differentiation

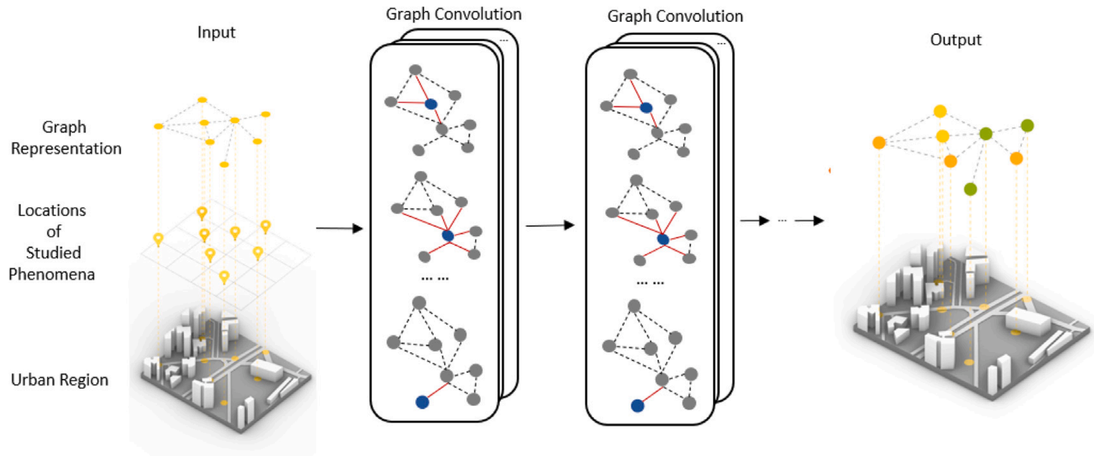


**Fig. 6.** A typical GNN, inspired by Zhu et al. (2021). Graph convolution, in general, is defined as a filter moving over the graph's nodes. It determines the area captured by the filter by screening through the adjacency matrix. An intuitive understanding of the convolution process is for each node in the graph, and the graph convolution will aggregate the information from its connected neighbours. By propagating through the hidden layers, GNN is able to produce useful feature representations of nodes in the graph, thus benefits further downstream tasks, such as classification, link prediction or the generation of graph embeddings. The illustration contains a base map from OpenStreetMap, under CC BY-SA.

of urban areas (Gebru et al., 2017), those methods are considered as a direct import from AI to geography (as mentioned in Section 1), and they are out of the scope of this review paper. Limited research has applied or developed deep learning-based spatially-explicit methods to those topics.

As outlined in Table 1 (*Social Differentiation of Urban Areas*), CNNs have been identified as a primary tool used for research exploring the potential of AI-based methods on social differentiation of urban areas (Gervasoni et al., 2018; Monteiro et al., 2019; Zhang et al., 2021). However, as discussed previously in Section 4.1, the receptive field used by CNN as grids requires spatial data in the organisation of grids leading to a failure to address the irregular and complex structures of the spatial data, in particular, the neighbouring effect of the small areas (Reades et al., 2019). De Sabbata and Liu (2019) is the only paper that occurred trying to incorporate the spatial information into the deep learning models to analyse the small areas of social differentiation. They proposed the idea of "geographic convolution" (geoconvolution) to explore the potential contribution of geo-spatial patterns in creating geodemographic classifications, example output is shown in Fig. 7. Geoconvolution is defined by including neighbourhood averages of the features (input values, pre-processed census data) representing area objects in the learning process. However, geoconvolution is a computationally heavy approach, and preliminary results do not demonstrate a clear advantage in implementing geoconvolution.

The lack of research on spatially-explicit GeoAI models in quantitatively studying the urban social differentiation is for many reasons, for example, the lack of consistently updated in-situ data (Gale and Longley, 2013; Gray et al., 2019), the debate of quantitative–qualitative divisions (Bryman, 2003; Morgan, 2013). However, the increasingly abundant SBD (e.g. SCD as mentioned in Zhang et al. (2020)) is nevertheless seeking new models and research paradigms to address such a limitation.

### 4.3. Spatially-explicit GeoAI for social sensing

The urbanisation and the resulting social differentiation of urban areas can lead to different living experiences for the residents in the cities. Analysing how places are perceived and represented is crucial to interpreting the underlying social and spatial practices involved with enriched human activities such as political, social and economic activities in space. The analysis of human conceptualisations of the space often involves categorisations of some kind. Such summarisation and categorisation processes of representative geographical phenomena inform us of the understanding of socio-spatial practices in the places of a given space. Thus, understanding the representation of place is a central problem in geographical studies (Purves et al., 2019), and in particular crucial for Urban Geography studies (Short, 2017). Place representation has a strong connection with information science and information systems (Purves et al., 2019), and it often refers to the overall information presented in an area with a given dataset (Ballatore and De Sabbata, 2018). According to Graham et al. (2015), 'information has always had geography. It is from somewhere; about somewhere; it evolves and is transformed somewhere; it is mediated by networks, infrastructures, and technologies: all of which exist in physical, material places'. In the past two decades, thanks to the development of digital devices and the world wide web, human society has witnessed a radical change in the information availability; such phenomena are termed as "information revolution" (Floridi, 2014) or "data revolution" (Kitchin, 2014). Although there remain concerns regarding the bias of human participation on the Internet due to uneven geographies of the ICT access (Graham et al., 2014), Fuchs (2008) and Shirky (2010) suggest that the digitally mediated participation allows residents to play a more pivotal role in creating and shaping the content and augmentations for place understanding.

Given the proliferation of digital platforms and the increasing amount of data production of activity-related user-generated content (UGC), numerous research has adopted AI-based methods, particularly deep neural networks, to study the places of spaces through UGC production (Verma et al., 2018; Kang et al., 2021), or to monitor social events and natural harassment (Frias-Martinez and Frias-Martinez, 2014; Sechelea et al., 2016; Zahra et al., 2017). Many of the research apply deep neural networks on geo-referenced text (Hu et al., 2019; Liu et al., 2022) or images (Jones et al., 2018; Zhang et al., 2018; Kruse et al., 2021) to understand the semantics and activities of human everyday life and the places, and a comprehensive survey can be found in Janowicz et al. (2020), Liu et al. (2021a). However, research towards spatially-explicit GeoAI model development using UGC to study residents' activities and urban places is still at an early phase. As shown in Table 1 (*Social Sensing*), Liu and De Sabbata (2021) by far is the only research that occurred using the GNN-based method to encode text and image of social media posts as nodes and the spatio-temporal distances among the posts as graphs to classify the activity types of users at the urban scale. Their research shows that spatio-temporal information can benefit activity learning through a quantitative model and proves a clear advantage of spatially-explicit GeoAI modes compared with conventional AI-based methods. Zhu et al. (2020b) introduced a GNN-based approach incorporating the spatial

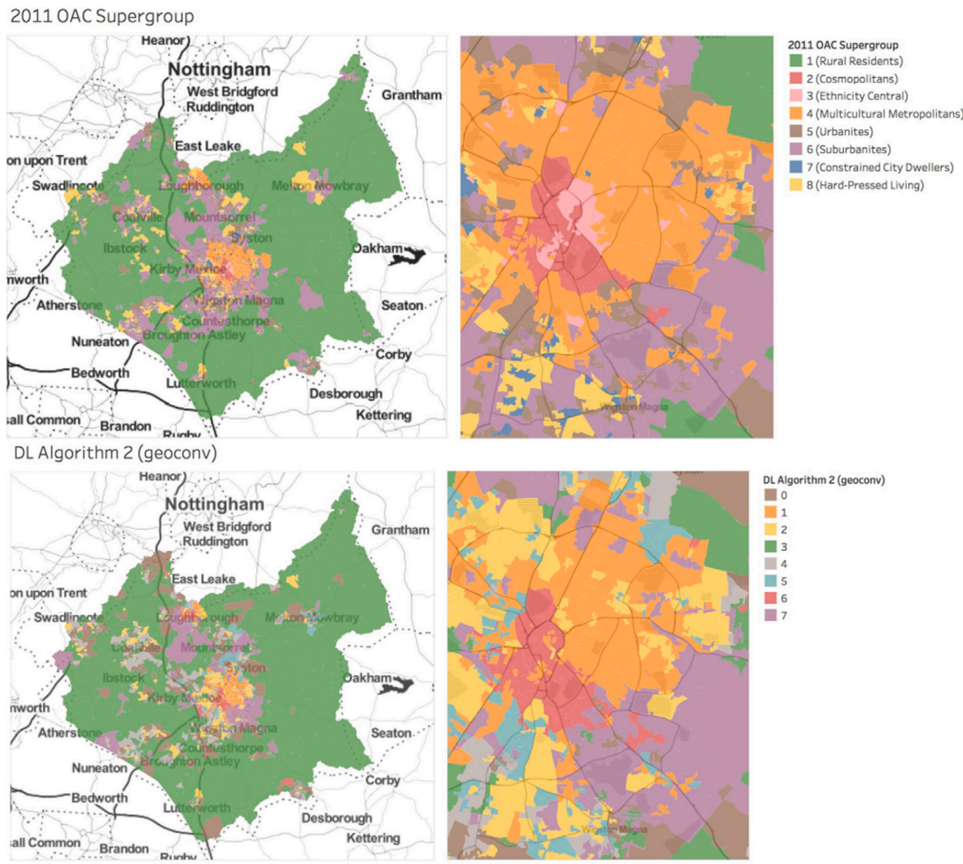


**Fig. 7.** Geodemographic classification comparisons between Gale et al. (2016) and the geoconvolution model's output in Leicester, United Kingdom.
*Source:* Image adopted from De Sabbata and Liu (2019).

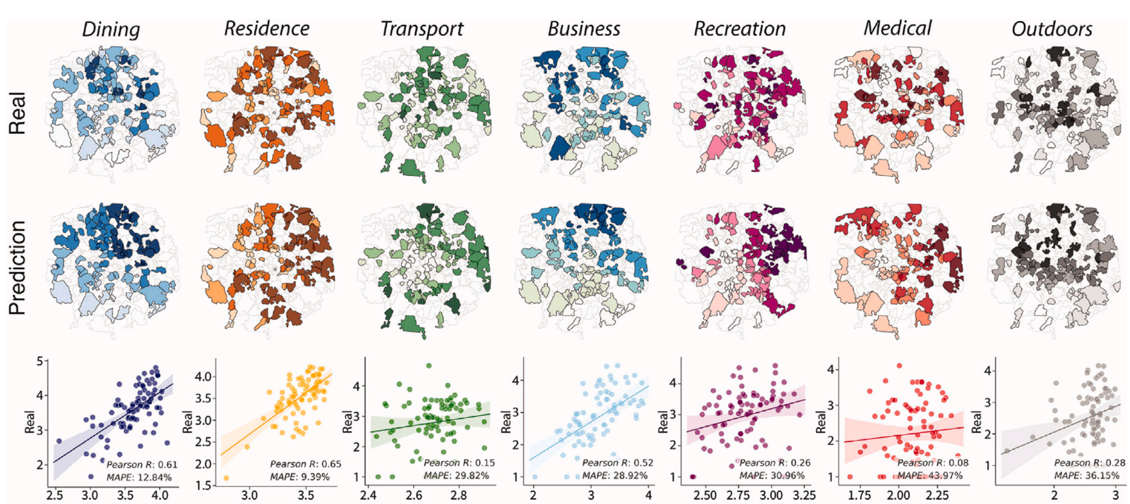


**Fig. 8.** An example of quantifying place characteristics in urban areas using spatially-explicit GeoAI approach (i.e. GNN).
*Source:* Image adopted from Zhu et al. (2020b).

connections among places (the delineated places based on point-of-interest data) to quantify place characteristics using both street view images and check-in activities from social media, which is a typical example of studies contributing to the quantitative understanding of urban places (Fig. 8). The authors later proposed a spatial regression GNN to address various geographical questions where regression modelling and predictions are needed for multivariate spatial data (Zhu et al., 2021). The authors validated their model using check-in activities from social media, and they proved that the spatially-explicit GeoAI model, which incorporates conventional concepts of spatial analysis techniques (i.e. geographically weighted regression), has a tremendous potential in studying distribution patterns of everyday human activities; thus, contributing to the study of urban places.

## 5. Discussion and conclusions

The purpose of this review was to summarise the scope and essence of spatially-explicit deep learning models in Urban Geography topics, in particular focusing on the socio-economic aspects, such as urban dynamics (e.g. urban growth, population flow analysis), social differentiation of urban areas and social sensing, allowing common threads to emerge. Embracing the recent trend of "AI for social good" (Tomašev et al., 2020), it is important to notice that we have chosen a somewhat specific scope of this study by reviewing papers that only use or develop spatially-explicit models for the research to analyse the social dimension of urban issues; thus, bridging the gap between the existing literature that motivated by the engineering-driven urban questions (e.g. Transportation, Construction) (Ma et al., 2019; Razavi, 2021; Khallaf and Khallaf, 2021; Kumar and Raubal, 2021) and urban socio-geographical studies. Pioneer reviews focused on reviewing the use of AI-based methods in Urban Geography in general (Grekousis, 2019), we are rather looking at papers using or developing spatially-explicit GeoAI methods, which is currently a new and trending research topic in Geography.

As a trending topic within Geography, the development and the use of spatially-explicit GeoAI models in Urban Geography are in their early phases even though the use of AI-based methods has been proliferated. It is identified by the fact that we started from a literature pool with 581 papers between 2018 and 2021 but only 22 papers were selected for the final reviewing process. This is not only because the use of GeoAI is still a relatively new field in geography but also because the social dimension of Urban Geography traditionally is often conducted through qualitative and resource-intensive approaches. However, the digital revolution of the spatial phenomena with a vast amount of SDB production daily requires researchers to seek new research methods to address urban issues.

As also pointed out by the previous review papers (Janowicz et al., 2020; Li, 2020; Mai et al., 2022), graph representations of the spatial data have opened up the opportunities to encode spatial and spatio-temporal information intuitively, especially facing the irregular structures of spatial data in nature so that the GNNs can handle such data formats directly or injunctions with other methods. The papers we reviewed also highlight the importance of incorporating a spatial component in the graph-based deep learning models, thus, setting forth the future research directions and objectives to devise spatial models.

However, there are some limitations rooted in the nature of such research:

- *Data*: the development of deep learning-based methods requires abundant and high-quality data. Traditionally, urban research heavily relied on coarse aggregate statistics (often published by the official channels, e.g. census) and smaller-scale surveys (Glaeser et al., 2018). Although those data are high in quality and spatial resolution, they are collected periodically (e.g. census data are collected every ten years). As noted in Section 4.2, the lack of consistently updated in-situ data is a barrier to developing quantitative GeoAI models to understand or predict short-term and long-term urban social differentiation. Nowadays, the increasingly accessible SBD, particularly UGC, serves as a crucial data source for urban studies. However, such data are produced voluntarily by the web or application users. The uncontrolled data quality and uneven representation of the population (e.g. social media users in London tend to be wealthy, young and educated) (Ballatore and De Sabbata, 2018) are critical issues not only for the development of GeoAI models but also introducing bias in the interpretations of the results (Graham et al., 2014).
- *Scale*: scale is a missing point which was not explicitly discussed in most of the research reviewed in this paper except Zhu et al. (2020b). The research was claimed to be conducted at the neighbourhood or small areas level. However, the choice and the impact of the neighbourhood size remain inadequately discussed. The lack of in-depth discussion of the scale issue is in particular problematic for studies that use CA-based methods where the variation of the geographical size could heavily impact the model performances (Li et al., 2020).
- *Modifiable Areal Unit Problem (MAUP)*: MAUP is the statistical bias that can affect the hypothesis tests' results immensely. MAUP affects results when spatial phenomena in the form of point-based measures are aggregated into districts, and the consequent summary values, such as totals, proportions, and densities, are impacted by the aggregation unit' shape and scale (Wong, 2004). The MAUP are generally an issue for location encoding methods using CNNs which require socio-economic data organised and aggregated in the format of grids.
- *Deep learning as black box*: although many of existing research in this paper have proven the deep learning-based GeoAI approaches in spatial analysis useful, other researchers are criticising deep learning for creating models that are black boxes. Therefore, the models produce results but do not explain phenomena, and sometimes cannot be examined (Krishnan, 2019). Such a limitation heavily impacts the use of GeoAI in modelling urban changes, where the explanation of which factors correlates to the changes are often needed. Moreover, the uncertainties within the data can propagate through the learning process of the models and further impact the accuracy of the results (Xing and Sieber, 2018). The deep learning-based models developed and adopted in the papers that we reviewed are still in the face of such a "black box" issue, which impacts the confidence in models' output and leads to uncertainties in the results.

Inspired by the recent development of *Explainable* AI (XAI) (Zhou et al., 2021b), we argue those limitations bring up a new research direction that multi-scale explainable spatially-explicit GeoAI models should be developed to address urban issues. Meanwhile, we have also witnessed the use of GeoAI models and spatial data in other domains, for example, Architecture. These research lines often integrate data collected from qualitative experiment-based methods investigating the interaction between human and the built environment into the model development (Abdelrahman et al., 2022; Abdelrahman and Miller, 2022), which have proved to be effective in improving model performance. Thus, we argue that the future development of GeoAI in quantitative urban socio-geographical studies could also use qualitative methods (e.g. walking interviews) to capture the interaction between human and urban spaces to better study the socio-economic aspects of city life. This paper provides a complementary scope of the GeoAI in Urban Geography, and we hope it will encourage more studies exploring spatially-explicit GeoAI models to analyse the social and socio-economic problems in the urban context.

## CRediT authorship contribution statement

**Pengyuan Liu:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Filip Biljecki:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

## Declaration of competing interest

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

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