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Applications of Geospatial AI in Human Geography and Spatial Networks: A Literature Review

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ABSTRACT

GeoAI is the internationally recognized term that describes the powerful nexus of artificial intelligence, spatial science, and big data analytics presents new and innovative avenues for understanding and addressing the challenges and opportunities faced by human societies at a geographic scale. This literature review aims to consolidate the key applications of GeoAI specifically for human geography and spatial networks, demonstrating its revolutionary potential in fields such as urban planning, population mobility, social network analysis, health geography, or environmental justice. The review describes the methodologies used from machine and deep learning to graph neural networks and the enabling geospatial technologies, which include GIS, remote sensing and spatial databases. Here we summarize our comprehensive review of existing studies, their limitations, challenges in the field such as spatial data bias, absence of ground truth, computation efficiency, ethical issues, and interpretability of AI models. Other emerging approaches such as real-time GeoAI, smart cities and digital twins' integration, explainable AI and human-centered approaches are also covered. Findings This review highlights the importance of cross-domain collaboration and ethical guidelines to ensure GeoAI technologies not only bring the best technical expertise, but also are responsibly and inclusively embedded into geographic decision-making.

1. INTRODUCTION

GeoAI, the intersection of Artificial Intelligence (AI) with geospatial technologies, has evolved as an interdisciplinary field that merges AI, spatial science, and big data analytics. The integration of GeoAI into research has opened new frontiers in the study of spatial phenomena impacting a range of fields, particularly in human geography, where understanding both spatial relationships and human-environment interactions is central to the discipline. Instead, GeoAI is the use of machine learning (ML), deep learning (DL) and other such techniques to analyze and interpret complex geographic data sets [1]. These new capabilities reveal new insights into spatial behavior, mobility patterns, and socio-economic dynamics that were previously not easy to quantify using traditional GIS tools [2].

Human geography studies the spatial aspects of human existence such as population distribution pattern, urban development, migration and socio-economic disparities, etc. The incorporation of AI into human geography makes it possible to analyze these phenomena in ways that are more dynamic, predictive, and scalable. [3] Researchers can model human behavior in urban spaces, detect patterns in social and spatial (human-) networks, and identify transitioning demographics. The shift from describing the process to performing predictive modeling represents a paradigm shift in the field supported by data availability from remote sensing, mobile apps, and social media platforms [4].

Spatial networks, which are defined by nodes representing human or spatial entities, and edges representing connections (e.g. transportation systems, social ties, migration flows), are fundamental structures through which we understand spatial organization and interactions. AI applications for analysis of such networks, especially with graph theory and neural network models, have also demonstrated significant success in discovering hidden relationships and predicting future network connectivity scenarios [5]. And there are examples applied in urban planning, in disaster prevention and response,

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in optimization of transport infrastructure, regional development studies, etc. Hence, GeoAI offers the methods to go beyond static spatial analysis and towards dynamic modeling of interdependent human systems.

Reviewing the applications of GeoAI in human geography and spatial networks is important because there is a burgeoning body of literature and tools for researchers to leverage. However, despite successful results found in isolated field studies, whether on land use classification, population mobility modeling, or crime mapping, a holistic synthesis and integration of these works has yet to be done. We seek to gap that by exploring more detailed applications, methods, data, and challenges owed to human geo- and network-based phenomena in this sub-perspective of GeoAI [3], [6]. This review also discusses how GeoAI enhances spatial decision making and planning. To add context to this discussion. The framework to ensure the linkage of theory to practice of this literature review is as described in Figure. 1. It emphasizes that AI technologies (e.g., machine learning, deep learning, and computer vision) and geospatial tools (e.g., GIS, remote sensing, and spatial data mining) are integrated together and jointly applied to multiple domains of human geography and spatial networks. This perspective diagram provides a basic insight into the methodological universe discussed in subsequent worlds.

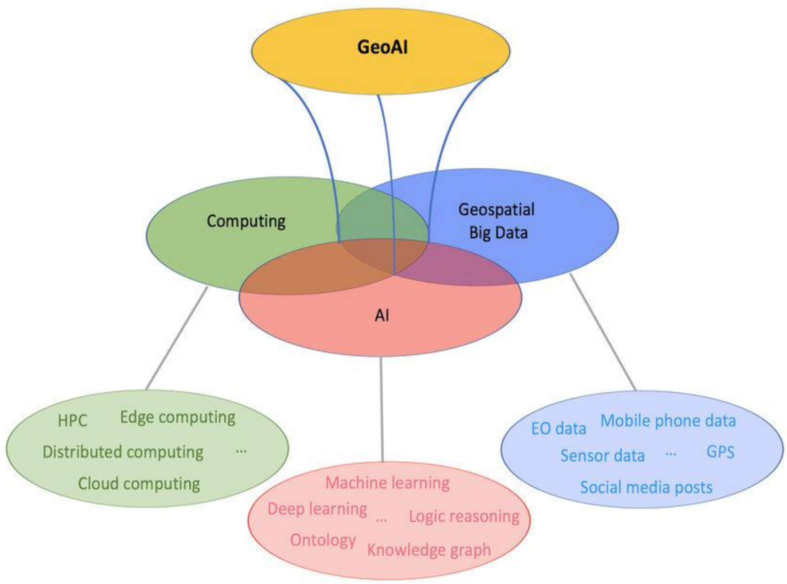

Fig. 1. Conceptual framework showing the intersection of AI, Geospatial Big Data, and Computing in the formation of GeoAI, with relevant techniques and data sources.

2. RELATED WORKS

The past few years have seen ample research around the convergence of geospatial technologies and artificial intelligence. Initially applied to human geography, GeoAI brought methods of machine learning and statistical modeling to automate existing spatial analysis techniques. At [7] proposed a fundamental framework combining spatial statistics and deep learning for human mobility pattern exploration in urban space. They highlighted the significance of spatially explicit data in improving AI predictions and paved the way for building sophisticated GeoAI systems that can make inferences about complex geographic relationships.

One of the important research fields of GeoAI is urbanization and land use classification. As an example, [8] used CNNs along with high-resolution satellite images for urban growth boundary classification. Their results showed that AI models can achieve high levels of spatial accuracy, comparable to traditional remote sensing methods. Similarly, [9] leveraged random forest algorithms (Breiman et al., 2001) to map urbanization trends across Asia, demonstrating that ensemble learning techniques can efficiently ingest heterogeneous geospatial datasets.

GeoAI has also opened up new avenues within the field of population mobility and movement research, relying on mobile phone use, GPS trajectory data and social media activity for modeling human mobilities. At [10] applied spatial-temporal clustering and deep learning to model daily migration flows in megacities, which improved urban planning and transport modeling. Their work highlights how AI-driven models can manage live, dynamic geospatial data to better assist human geographic research. Similarly, [11] lists RNNs used for temporal prediction toward inter-city population flow, showing significantly better time-series forecasting accuracy than classical time-series models.

AI Applications in Mapping Social Interaction and Networks within Human GeographyAI techniques have also been transformative for social network analysis within human geography. At [12] explored spatial social networks through graph neural network (GNN) along with geographic information system (GIS), which will identify central actors and spatial clusters in urban communities. Their approach opened a pathway to explore not just the topology of networks but also the spatiality of human interconnectedness which is a critical aspect of our understanding of urban coalescence, urban fracture and information diffusion in smart cities. These lines of research show potential to integrate spatial measures with social connectivity.

In another area, GeoAI is particularly important in disaster management and spatial risk assessment. At [13] proposed that AI-augmented risk maps be generated based on the combination of geospatial big data, LIDAR, and deep learning classifiers to identify flood vulnerability. The framework enabled quick and automatic assessment of high-risk regions that could help local authorities in both pre-disaster preparedness, and emergency response. Meanwhile, other AI models have been adapted for forecasting the propagation of fires, disease outbreaks, and pollution, demonstrating the utility of GeoAI for spatial risk analytics.

However, multiple studies point to some challenges of applying AI to human geography. This exacerbates challenges related to biases in spatial data, interpretability of models, a lack of true-label data, and ethical issues - including privacy and surveillance concerns. With [14] stressed that when models guiding public policy or community development decisions are used on spatial research, such research should use explainable AI. In addition, researchers [15] encourage the development of hybrid models leading to rule-based spatial theory combined with data-driven AI methods that can maintain both veracity and theoretical soundness.

In addition, we provide a summary of the diversity of studies on the uses of Geospatial AI in human geography and spatial networks, shown in Table I, to supplement the narrative review discussed in this section. The table summarizes the scope of each study, the methodology or AI model implemented, the form of geospatial data employed, and the key findings or contributions. This comparative perspective casts into relief both the range of fields that have been the subject of GeoAI research, and the methodological innovation that has occurred in the last few years.

TABLE I. SUMMARY OF KEY STUDIES ON GEOSPATIAL AI APPLICATIONS IN HUMAN GEOGRAPHY AND SPATIAL NETWORKS

Study Reference	Focus Area	Methodology/Model	Type of Geospatial Data	Key Findings
[7]	Human movement modeling	Deep learning, spatial statistics	Urban spatial data	Proposed foundational GeoAI framework; enhanced interpretation of human mobility
[8]	Urban land use classification	Convolutional Neural Networks (CNN)	High-res satellite imagery	Accurate classification of urban areas compared to traditional RS methods
[9]	Urban expansion analysis	Random Forest	Satellite imagery	Mapped long-term urban growth trends in Asia with high efficiency
[10]	Population mobility modeling	Spatio-temporal clustering, Deep Learning	Mobile GPS data, social media	Tracked daily human mobility in cities for better urban planning
[11]	Migration forecasting	Recurrent Neural Networks (RNN)	Social media & temporal data	Achieved high prediction accuracy of inter-city migration flows
[12]	Social network analysis	Graph Neural Networks (GNN), GIS	GIS + Social connectivity data	Detected spatial clusters and key actors in urban social networks
[13]	Disaster risk mapping	Deep learning classifiers, LIDAR	Geospatial big data, LIDAR	Automated high-risk zone identification for emergency planning
[14]; [15]	Methodological challenges	Explainable AI, Hybrid models	Mixed spatial datasets	Addressed bias, interpretability, and ethical issues in spatial AI

3. METHODOLOGIES AND TECHNOLOGIES IN GEOAI

The convergence of innovative AI techniques with geospatial technologies has led to the emergence of Geospatial Artificial Intelligence (GeoAI). It reviews important computational methods, including machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs), in addition to the technologies that make them possible, such as geographic information systems (GIS), remote sensing, spatial databases, and high-performance computing (HPC). Collectively these methods and approaches facilitate the analysis and modeling of complex spatial phenomena important to human geography and spatial networks.

3.1 Machine Learning and Deep Learning in GeoAI

Machine learning is the engine of many GeoAI applications, including models that can "learn" from spatial data and recognize patterns without needing to be programmed explicitly. Common supervised learning techniques for land use classification, socio-spatial modeling and population prediction include support vector machines (SVM), decision trees, and ensemble methods such as random forests [1]. In detecting spatial patterns and anomalies in migration or mobility data [16], unsupervised techniques, particularly the k-means and DBSCAN clustering techniques, are applied.

Deep learning, a subset of the greater ML framework, allows for more intricate spatial representations through hierarchical feature learning. Convolutional neural networks (CNNs) are commonly used to address image-based geospatial tasks, particularly urban area detection, land cover mapping, and building extraction with high-resolution remote sensing images [17]. Recurrent neural networks (RNNs), especially long short-term memory (LSTM) networks, have proven to work well for modeling temporal geospatial sequences, e.g. migration flows [17] or traffic dynamics [18]. Such models can also capture spatial and temporal dependencies and are thus well suited for studies of dynamic human geographies.

3.2 Graph Neural Networks and Network-Based Modeling

Graph neural networks in human geography graph learning architectures: new solution to spatial and social networks. Spatial entities like urban zones or communities are modelled as nodes in GNN-based models, and their relationships (e.g. transport links or migration paths) as edges. These models have shown success in detecting influential network actors, community clusters, and variations in spatial connectivity over time [19]. GNNs naturally model the non-Euclidean structures which is a significant paradigm shift away from classical pixels/raster type data heliocentric-models or vector type data based centripetal models.

For example, [20] used GNNs on social network data with embedded geographic coordinates which revealed spatial clustering in urban interactions. Such approaches are relevant to the study of urban segregation, social capital, and infrastructure access & vulnerability. GNNs are a suitable candidate for spatial behavior analysis and geospatial predictive modeling because they merge the structure of network topology with spatial information.

3.3 Geospatial Technologies: GIS and Remote Sensing

GIS is the key technology used to store, manage, and analyze spatial data. GIS technologies enable data preprocessing, spatial querying, and visualization; thus, they are an integral part of the GeoAI pipeline [21]. Automation of tasks like geocoding, spatial interpolation, proximity analysis, etc. is possible through the integration with AI algorithms. Also, GIS is sometimes used as a post-processing tool to interpret and contextualize AI model outputs in space.

Multispectral and hyperspectral imagery are some of the remote sensing technologies through which crucial geospatial data inputs for AI models can be generated. Fine-grained spatial analysis over time is facilitated by satellite images from Landsat, Sentinel, and commercial satellite suppliers. Remote sensing with AI has also been used in monitoring urban sprawl, and environmental change and resource distributions [22]. Moreover, using time-series remote sensing imagery with DL models significantly improve change detection in urban and rural landscapes.

3.4 Spatial Databases and Big Data Infrastructure

GeoAI relies on spatial databases that are designed to handle the enormous scale and diversity of geospatial data. Spatial indexing, topology processing, and real-time data integration are also supported by the systems [23] including PostGIS, Oracle Spatial, Spatiality. These databases facilitate fast searching of location-based datasets and are playing an increasing role in AI pipelines that preprocess data and extract features on the fly.

The same goes for big data infrastructure—the use of distributed computing frameworks like Apache Hadoop and Spark—continuing to be a crucial element to supporting GeoAI workflows. Such systems allow parallel processing over these terabyte-scale data sets like mobile phone records or LiDAR data or social media check-ins. Together with GPU-accelerated computation, high-performance computing (HPC) platforms further enable such training of complex DL models over large spatial-temporal datasets at scale [24].

3.5 Comparative Overview

Table II provides a comparative overview of the major AI methodologies and geospatial technologies used in human geography and spatial network analysis. It summarizes their typical applications, data requirements, and strengths in the context of GeoAI.

TABLE II. COMPARATIVE OVERVIEW OF AI METHODS AND GEOSPATIAL TECHNOLOGIES IN GEOAI APPLICATIONS.

Method / Technology	Typical Applications	Data Requirements	Key Strengths
Machine Learning (ML)	Land use classification, demographic modeling	Structured spatial/tabular datasets	Easy to implement, interpretable models
Deep Learning (DL)	Image classification, feature extraction, pattern detection	High-resolution imagery, time-series data	Captures complex spatial and temporal features
Convolutional Neural Networks (CNNs)	Urban boundary detection, building extraction	Satellite or drone imagery	Excellent in handling spatial data with imagery
Recurrent Neural Networks (RNNs / LSTM)	Migration and mobility prediction, temporal trends	GPS traces, time-tagged population data	Effective in modeling sequential spatial data
Graph Neural Networks (GNNs)	Social network analysis, infrastructure modeling	Network topology, relational spatial data	Captures spatial and topological relationships
GIS (Geographic Information Systems)	Mapping, spatial analysis, proximity evaluation	Vector/raster spatial datasets	Powerful in visualization and spatial querying
Remote Sensing (RS)	Land cover change, urban sprawl, resource mapping	Multispectral and hyperspectral imagery	Long-term Earth observation and monitoring

Spatial Databases	Data management, spatial indexing, spatial joins	Geospatial records with location attributes	Enables efficient spatial querying and storage
Big Data & HPC Platforms	Large-scale mobility analysis, real-time processing	Massive geolocation/social media datasets	Scalable for complex and high-volume computation

4. DOMAINS OF APPLICATION IN HUMAN GEOGRAPHY

The emergence of geospatial artificial intelligence (GeoAI) has immensely magnified analytical power in human geography as it allows automated, scalable, and dynamic spatial analysis. It is used in a wide range of important fields, from urban planning and population mobility to public health, and environmental justice. GeoAI has already begun fundamentally reshaping the way we think about geographic inquiry here in the 21st century, which is evident in the following sections that identify significant contributions by GeoAI to other fields.

4.1 Urban Planning and Land Use

One of the most prominent domains for GeoAI applications has been Urban planning. Satellite imagery could provide much information for urban land-use classification and monitoring of city growth, and deep learning models, particularly convolutional neural networks (CNNs), have often been applied in these researches. For example, [25] employed CNNs with high-resolution Landsat such as Sentinel-2 imagery to identify urban expansion changes, and it attracted higher accuracy compared to classification techniques. Additionally, this information has been used with spatial-temporal models to predict future urban sprawl, enabling planners to evaluate infrastructure needs and maximize land use [26]. The integration of AI with GIS systems has also opened up for interactive planning dashboards so that policy makers can test zoning, transportation planning and green space distribution scenarios.

4.2 Population Mobility and Migration

Insights on human mobility behavior are pivotal reconstructions for infrastructure construction, transport planning, and disaster preparedness. GeoAI tools have facilitated more spatially refined and timely flow analysis based on mobile GPS data, transport card data, and geotagged social media (Khalil et al. 2023). developing a deep learning framework to generate daily mobility patterns of megacities at [27], contributing to better traffic management and emergency evacuation planning. Another example [28] used recurrent neural networks (RNNs) to predict inter-city migration from historical population data and location-based service (LBS) activity, allowing for improved accuracy of migration predictions over time. This is critical for real-time analysis applications in smart cities.

4.3 Social Network and Spatial Behavior Analysis

[44] Spatial social network analysis GeoAI allows for a deeper understanding of individual and group activity and interaction in space. GIS data combined with graph neural networks (GNNs) allow scholars to examine social cohesion, urban segregation, and the spatial diffusion of behaviors. We [29] used GNNs to model spatially embedded social networks in urban neighbourhoods, and discovered communities of social interaction, which showed close alignment with patterns in the demographics and infrastructure. Connecting all of this to the real world allows for implementation in urban design, community outreach programs, and policies towards social equity.

4.4 Health Geography and Epidemiology

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4.5 Environmental Justice and Spatial Inequality

GeoAI helps identify and address spatial inequalities associated with environmental hazards, resource distribution and socio-economic status. By analyzing satellite imagery and socio-demographic data, AI models can identify inequities in access to green space, exposure to air pollution or susceptibility to climate risks. To illustrate, AI-integrated spatial analysis [32] was leveraged to analyze mapping with respect to urban environmental injustice, uncovering patterns of disproportionate exposure among marginalized communities. GeoAI also makes it possible to create spatial equity indices that allow decision makers to create informed policies that target at-risk communities. AI-enabled crowd-sourced mapping has also enhanced underserved areas in the Global South [33]. Thus, GeoAI has become a disruptive revolutionary in human geography, unlocking unprecedented potential for spatial insight and foresight. The next section will touch on the limitations and ethical considerations surrounding these technological advancements to provide a broader perspective on the opportunities and pitfalls of GeoAI. Table III summarizes the dominions, AI methodologies, data sources and their impacts of GeoAI in human geography therefore serves as a synthesis of GeoAI and fills the gap in human geography. Data-driven insights are enriched by GeoAI over the many elements of human life and spatial organization.

TABLE III. SUMMARY OF GEOAI APPLICATIONS ACROSS HUMAN GEOGRAPHY DOMAINS.

Domain	AI Techniques Used	Data Types Used	Key Impact
Urban Planning and Land Use	CNN, ML classification, DL	Satellite imagery (Sentinel, Landsat), GIS layers	Accurate urban mapping, future land use prediction
Population Mobility and Migration	RNN (LSTM), clustering, DL	GPS data, LBS data, mobile phone records, social media	Real-time mobility modeling, migration forecasting
Social Network and Spatial Behavior	GNN, network analysis, GIS	Social graphs, spatial interaction data, demographic layers	Revealed urban social patterns, informed urban design
Health Geography and Epidemiology	Risk modeling, CNN, mobility AI	Mobility data, environmental sensors, demographic indicators	Tracked disease spread, assessed healthcare accessibility
Environmental Justice & Inequality	AI-based spatial analysis, DL, GIS	Remote sensing, census data, environmental exposure layers	Identified spatial inequalities, supported policy decisions

5. CHALLENGES AND LIMITATIONS

In spite of the potential benefits of Geospatial Artificial Intelligence (GeoAI) to human geography, several challenges still prevent its wider use and its effective use. These challenges cover everything from data-related issues through to computational hurdles, ethical level concerns, and the interpretability of AI models. Here the limitations are highlighted to offer a comprehensive perspective on the current status of GeoAI integration.

1. Spatial Data Bias and Noise: A primary challenge in GeoAI applications is the presence of bias and noise in spatial datasets. Geospatial data from mobile phones can be used to extract useful information, but mobile phones are not equally owned across the population, introducing potential biases in the data [32]; geospatial data pulled from social media can also misrepresent reality given that lower-income or isolated populations may lack access to social media [33] and volunteered geographic information [34] suggested that these kinds of data only becomes available if a population has the means to involve themselves. Middle classification zones are overrepresented in deals, while rural areas often do not have enough data points. Spatial noise can be introduced via sensor errors, GPS drift, or disparate data formats, which can reduce the ability of AI models to make reliable predictions [35]. These biases may cause incorrect decision making in domains like disaster management, health resource assignment, or social equality explorations.
2. No Ground Truth and Labelled Data: Most AI models especially supervised learning models depend on accurate ground truth data for training and validation purposes. In geospatial contexts, though, obtaining labeled datasets at fine spatial and temporal resolutions is typically hard or impossible [36]. This is particularly pronounced in the Global South, where up-to-date census information, combined with maps of urban spaces or mobility records, may not even exist. Improper or partial labeling results in poor generalization of the model and low trust in GeoAI systems. Standardized, openly accessible ground truth data still lacks and this has been touted as one barrier for reproduction of practical and scalable applications in this area.
3. Computational Complexity and Infrastructure Demands: GeoAI methods especially deep learning models like CNNs, RNNs, GNNs demand considerable computational power, particularly when dealing with massive spatial-temporal datasets, which involve high costs for the algorithms' training and inference processes. Tiling high-resolution satellite images, processing LiDAR point clouds, or using dynamic mobility datasets requires high-performance computing (HPC) environments, GPU acceleration, and efficient data management protocols [16]. For researchers and organizations who lack access to such infrastructure, the computational complexity is a bottleneck. Moreover, the storage and preprocessing of all heterogeneous geospatial data results in increased system overhead and implementation time.
4. Ethical Concerns: Privacy, Surveillance and Data Misuse: Ethical issues have been increasingly discussed in GeoAI research, especially privacy and surveillance problems. When combined with personal information from mobile phones or social platforms, geospatial data can enable intrusive profiling, tracking of user location, and prediction of user behaviour all without the informed consent of users [26]. There are also concerns surrounding the potential abuse of a surveillance system by ehierarchical regimes, or by powerful monied interests. There are no clear ethical guidelines for deploying location-based AI models in practice, creating issues with data ownership, consent and transparency. In addition, biased data can contribute to spatial injustice because they maintain systemic inequalities in service provision and urban planning [17].
5. Explainability and Interpretability of AI Models: Although GeoAI systems can provide high predictive accuracy, they often lack transparency. The majority of deep learning model architectures are described as "black boxes," which means that it is very complicated to know how to make spatial decisions and why certain regions are tagged as high-

risk or underserved [18]. Such opacity limits their applicability to the domains of policymaking and public-sector planning, where explainability is integral to building trust with stakeholders. Explainable artificial intelligence (XAI) techniques, including SHAP and LIME, have been incorporated by some researchers into GeoAI workflows to explain model decisions, but these efforts are still in the developmental realm of geospatial applications [19].

To summarize the notable multiplicative challenges exists in the integration of GeoAI into human geography, we present here in Figure 2 a conceptual flowchart with five key issues: data bias and noise, lack of ground truth, computational demands, ethical concerns and explainability issue. These challenges affect the overall modeling accuracy of GeoAI systems and directly influence trust in AI-assisted spatial decision-making. The diagram serves as a conceptual model for understanding the interplay between technical and ethical limitations in limiting the effectiveness and adoption of GeoAI approaches.

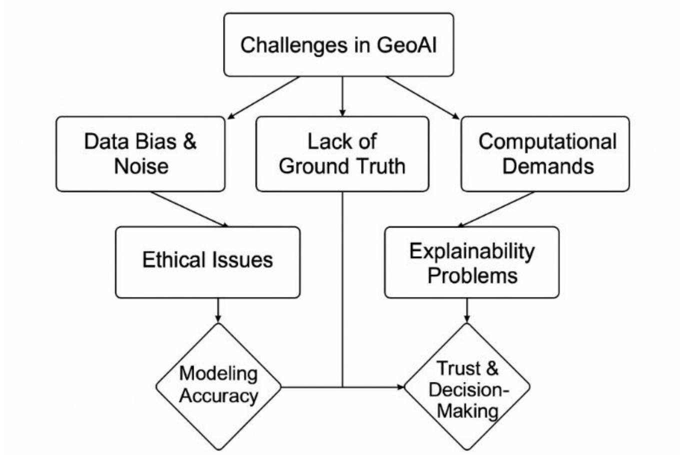

Fig. 2. Key Challenges in the Integration of GeoAI into Human Geography Applications

6. EMERGING TRENDS AND FUTURE DIRECTIONS

With the rapid development of Geospatial Artificial Intelligence (GeoAI), we will continue to see an unprecedented application of GeoAI in human geography by integrating real-time data streams with human-centered AI designs and intelligent infrastructure. Here are a number of transformative trends and trajectories of noteworthy interest that we foresee will shape spatial analysis, and with-it urban governance and equity-driven geographic decision-making, in the years to come.

As a part of 5G-enabled services, Real-time GeoAI means that AI models generating can be processed and analyzed with geospatial data on the go and most importantly at real-time in a dynamic environment. IoT refers to such systems by integrating sensor networks, mobile GPS, and video surveillance, and facilitates HD mapping and highways of human mobility, environmental changes, and infrastructure performance in real-time [11]. In the field of emergency response, for instance, real-time GeoAI has been applied to identify flash floods, crowd movements, and evacuation pathways. Accordingly, the integration of streaming data and edge computing is a key requirement in order to bring about these capabilities, specifically in smart city applications where spatial events are highly dynamic with respect to time [21].

A new frontier is emerging in the application of GeoAI to urban planning and simulation: GeoAI-driven digital twins. AI-powered spatial data can be applied to these models so cities can build simulations for various socio-spatial situations, from traffic management, to energy deployment [13]. GeoAI in smart cities: Processes raw data coming from IoT devices, environmental sensors, and autonomous systems to understand the real-world, and enabling prediction of events, automation and improved governance. Cities such as Singapore and Dubai have piloted projects using AI-assisted geospatial data as their digital twins to optimize a range of services and inform infrastructure development [14].

In the wake of rising calls to make the algorithms running AI transparent and accountable, scholars are finding common ground in Explainable Spatial AI (XGeoAI), which seeks to decode and visualize how geospatial models decide. Methods like SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-agnostic Explanations), and saliency maps are being adapted for spatial datasets [15] in order to increase transparency of the models. XGeoAI is especially crucial in the fields of urban governance and public health, where decisions need to be data-driven as well as justifiable. Next steps are likely to include making XAI work in a spatial setting, helping policy-makers to audit model behavior for potential algorithmic bias [16].

The integration of GeoAI with Internet of Things (IoT) devices, 5G networks, and blockchain technologies will create well-connected, secure, and responsive spatial ecosystems. IoT devices stream geospatial data continuously over vehicles, infrastructure, and personal devices. Even at scale, thanks to the low latency and high bandwidth that 5G offers, real-time GeoAI applications, including those for autonomous navigation, crowd management, and disaster monitoring, can now be realized [17]. Blockchain can provide secure and transparent handling of location data, improving data provenance and privacy protection in geospatial applications [18]. These combinations represent the emergence of decentralized, but smart spatial systems.

As the field of GeoAI evolves, future trends will align with human-centered design practices, focusing on equitable, inclusive, and community (co-)production of outcome-based spatial decisions. Human-centered GeoAI: participatory mapping, co-designed data platforms, localized AI models respecting socio-cultural context. This strategy responds to ongoing criticisms of spatial data colonialism and enables the use of GeoAI for good within underrepresented groups [19]. Moreover, the importance of fairness in spatial AI outputs has also emerged as an important part of research with frameworks developed to audit spatial bias, improve transparency and ensure algorithmic accountability for geography and space-based choices [10]. These emerging trends collectively show that GeoAI is increasingly more technically sophisticated as well as increasingly responsive to social needs. The future of GeoAI involves connecting real-time analytics to human values providing not just the tools. To effectively synthesize the GeoAI trajectory, Table IV compares future directions and trends, technologies, and human geographical impacts of GeoAI. These trends are indicative of a shift toward real-time responsiveness, ethical modeling, and deeper integration of AI with urban systems and societal needs.

TABLE IV. EMERGING TRENDS AND FUTURE DIRECTIONS OF GEOAI IN HUMAN GEOGRAPHY

Trend / Direction	Key Technologies Involved	Potential Impact in Human Geography
Real-Time Geospatial AI	Edge computing, mobile sensors, AI pipelines	Enables real-time mobility tracking, emergency response, dynamic planning
Integration with Digital Twins & Smart Cities	IoT, GIS, simulation models, AI	Supports predictive urban modeling, infrastructure optimization
Explainable Spatial AI (XGeoAI)	SHAP, LIME, interpretable ML/DL	Enhances transparency, trust, and accountability in spatial decisions
Integration with IoT, 5G, and Blockchain	IoT devices, 5G networks, distributed ledgers	Secures geospatial data flows; improves latency and real-time analytics
Human-Centered GeoAI	Participatory mapping, equity frameworks	Promotes inclusive and ethical spatial decision-making

7. CONCLUSION

This literature review has explored the wide evolution of Geospatial Artificial Intelligence (GeoAI) in human geography and spatial networks. GeoAI has synergized the latest AI approaches including machine learning, deep learning and graph neural networks with geospatial technology systems such as GIS, remote sensing and spatial databases, facilitating the development of more dynamic, predictive and scalable models for understanding complex human-environment interactions. It provided an in-depth examination of four key application domains, namely urban planning, population mobility, social network analysis, health geography, and environmental justice illustrating GeoAI's capacity to transform theoretical and practical aspects of spatial analysis. Despite the promising potential of GeoAI, several challenges exist for widespread adoption. These include spatial data bias, lack of ground truth, computational demands, and increasing ethical issues relating to privacy, fairness, and transparency. Another aspect is the interpretable nature of AI models which is still an important challenge especially with regards to public-sector applications where decisions need to be explainable and justifiable. Understanding these limitations is a prerequisite for building robust, responsible, and equitable all-encompassing GeoAI systems. These are exciting times for geospatial technology and, indeed, its future is fusing with the very fabric of many modern technologies that humanity needs to survive in this world. Solving these technical and societal challenges will depend heavily on interdisciplinary collaboration, mixing geography, computer science, data ethics, and urban studies. Andrea and collaborators argue for a more human-centered GeoAI that serves as the pathway to an understanding of issues such as equity and transparency via participatory design. Finally, GeoAI is a new paradigm within human geography, and offers new opportunities with regard to evolution within direct evidence and innovative evidence. Future work in this area must create more of the scalable, invariably ethical and explainable methods necessary to use geographic knowledge to inform decision-making in the real world that responsibly advances our understanding of geography.

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