International Journal of Geo-Information

MDPI

Editorial

Advancing AI-Driven Geospatial Analysis and Data Generation: Methods, Applications and Future Directions

Hartwig H. Hochmair [1,*], Levente Juhász [2] and Hao Li [3]

[1] Geomatics Sciences, Fort Lauderdale Research and Education Center, University of Florida, Davie, FL 33314, USA
[2] Geographic Information Systems (GIS) Center, Florida International University, Miami, FL 33199, USA; ljuhasz@fiu.edu
[3] Department of Aerospace and Geodesy, Technical University of Munich, 85521 Ottobrunn, Germany; hao_bgd.li@tum.de
* Correspondence: hhhochmair@ufl.edu

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Received: 28 January 2025
Accepted: 29 January 2025
Published: 1 February 2025

Citation: Hochmair, H.H.; Juhász, L.; Li, H. Advancing AI-Driven Geospatial Analysis and Data Generation: Methods, Applications and Future Directions. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 56. https://doi.org/10.3390/ijgi14020056

1. Introduction

Recent years have witnessed a revolution of artificial intelligence (AI) technologies, highlighted by the rise of generative AI and geospatial artificial intelligence (GeoAI). Unlike generic AI, GeoAI is distinct in its integration of geographic knowledge, positioning it at the intersection of geospatial scientific research, AI technologies, and high-performance computing. This fusion is critical for tackling data- and computation-intensive geospatial challenges [1,2]. These advancements are fueled by the massive volume of available geospatial data, advancements in machine learning (ML) hardware and GeoAI models, and the growing need for innovative analytical methods to address critical knowledge gaps in social and environmental research [3,4]. As a result, we have seen substantial progress in the mapping, extraction, generation, and analysis of spatial information. The Special Issue (SI) "Advances in AI-Driven Geospatial Analysis and Data Generation" seeks to showcase the efforts of the geographic information science (GIScience) community in leveraging cutting-edge computing technologies—particularly AI—to solve complex geographic problems. In line with this trend in GIScience research, several related Special Issues have been organized in prominent journals, such as *the International Journal of Geographic Information Science*, *GeoJournal*, *Geoinformatica*, *Geographies*, or *Applied Sciences*. These collections focus on spatially explicit models [1,2] and applications in urban analytics [5], image classification and land cover mapping [6], crowd-sourced image and text analysis [7], natural resource management [8] and infrastructure monitoring [9,10].

In addition, recent systematic literature reviews have also highlighted the growing use of GeoAI across related disciplines. For example, human geographers have leveraged GeoAI to explore urban functional zones, urban dynamics, human behavior, and social sensing using large-scale spatiotemporal data [11,12]. This integration has equipped the traditional field with powerful new tools, enabling large-scale, quantitative analyses. GeoAI is also emerging as a key frontier in physical geography research, with applications in areas such as geohazard assessment, environmental change simulation, biodiversity monitoring, and planetary science [13]. In cartography, GeoAI is being used to enhance geographic output evaluation and map quality, as well as to improve image object detection, map generalization, and map design [14]. Furthermore, the development and availability of spatially explicit GeoAI models have significantly enhanced accuracy in addressing complex challenges, such as urban growth, socio-economic biases, and social sensing. These models achieve improvements by directly incorporating spatial dependencies and heterogeneity into analytical frameworks [12]. This includes encoding spatial data structures, integrating space-aware loss functions and pooling layers in neural networks, incorporating spatial predicates into knowledge graphs, and using spatial transformers to model directed spatial dependencies with self-attention mechanisms [15]. Other major directions in the current GeoAI research landscape include remote sensing, urban computing, earth system science, and geospatial semantics [4].

However, despite the clear advantages of GeoAI in GIScience, several challenges remain that warrant further exploration. These include issues related to the geographic nature of the underlying data and processes—such as geographic scale, biases, the modifiable areal unit problem (MAUP)—as well as broader scientific concerns like the lack of explainability in AI models [12], reproducibility and replicability in advancing open science [16] and the ethical and privacy considerations that arise in this new era of AI-driven research [17].

Contributions to this Special Issue span four continents—Asia, Australia, Europe, and North America—though contributions from Africa and South America are notably absent. This mirrors the publication trends observed in GIScience journals in recent years [18], pointing towards an underrepresentation of research from the Global South in the field of GeoAI. This may be attributed to limited access to resources and technology for certain parts of the world that are necessary to conduct data collection and research, a phenomenon sometimes called the digital divide [19]. Notably, only two papers (14%) resulted from international collaboration, a figure that falls well below the average for GIScience journals, where over 30% of articles have been published by international research teams in recent years [18]. Interestingly, India, South Korea and Iran appear to be one of the most studied areas using GeoAI in human geography (4th, 6th and 7th place, respectively) [11], despite ranking 14–16th in overall GIScience journal article output [18], which may suggest a specialized focus on emerging technologies, including GeoAI, in these countries. The majority of authors contributing to this Special Issue are affiliated with geospatial sciences (broadly defined to include fields such as geography, GIS, geoinformatics, geomatics, and remote sensing) and computing sciences. However, several contributors come from related disciplines, including architecture, agricultural sciences, criminology, information sciences, and public safety. This diversity highlights the interdisciplinary nature of GIScience and GeoAI in general [20].

The following sections of this Editorial summarize the contributions to this SI with a focus on the AI methods used (Section 2) and the application areas explored (Section 3). In Section 4, we discuss future directions and emerging trends, drawing insights from this Special Issue and beyond.

2. AI Methods in the SI

The AI methodologies utilized in this SI can be broadly categorized into four groups: machine learning (ML), deep learning (DL), large language models (LLMs), and genetic programming (GP).

Machine Learning: The four papers in this category utilize classical and interpretable ML methods to tackle various geospatial tasks. For example, the GraviGBM model by Liu et al. combines a gravity model with gradient-boosting decision trees to simulate population mobility flows, while the use of SHAP (SHapley Additive exPlanations) enhances the model's interpretability and explainability. Graph-based learning approaches are also employed for tasks like crime prediction (Gu et al.). The remaining two papers focus on ML algorithms for agricultural and environmental applications: Puttinaovarat et al. use Random Forests, Decision Trees, and Support Vector Machines for oil palm ripeness classification, and Q. Wang et al. optimize rice yield through the Geographically Optimal

Zone-based Heterogeneity (GOZH) model. Overall, these studies highlight the versatility of ML methods in addressing a wide range of complex geospatial analysis challenges.

Deep Learning: DL models are the primary AI technique employed in five papers, addressing a range of tasks including traffic anomaly detection, image fusion, and semantic segmentation. For example, Traffic-ConvLSTM, developed by Mao et al., combines convolutional neural networks (CNNs) with long short-term memory networks (LSTMs) to detect urban traffic anomalies across both spatial and temporal scales. The U-Net model is adapted by Farmakis-Serebryakova et al. to generate scale-sensitive shaded reliefs, while Jin et al. enhance pansharpening by fusing multispectral and panchromatic images using unsupervised generative adversarial networks (GANs). In another study, the Bi-LSTM-CRF method, which integrates bidirectional LSTMs with the Conditional Random Fields (CRFs) algorithm, is employed for disaster response, demonstrating DL's ability to model the relationships between spatial and contextual data (S. Li et al.). Finally, Yu et al. focus on semi-supervised learning to improve road extraction models using the Asymmetric Consistent Co-training (ACCT) framework, which reduces reliance on labeled data and increases efficiency in resource-limited settings.

Large Language Models: The four contributions employing LLMs highlight their application in geospatial contexts. Zeng and Boehm introduce an open-vocabulary, multimodal foundation model for semantic segmentation of street-level images, bridging DL and LLMs by integrating both visual and textual inputs. Another paper demonstrates that LLMs can be fine-tuned and guided through prompt engineering and retrieval-augmented generation (RAG) to produce structured outputs such as GeoJSON and XML (D. Li et al.). This contribution also proposes a method that combines spatial indexing, RAG, and R-trees, building on fine-tuned LLMs to optimize query efficiency and the generation of JSON outputs. Xu and Tao evaluate the multimodal LLM GPT-4V(ision) for its map-reading and interpretation capabilities, leveraging pretrained geographic knowledge. They assess the model's ability to interpret three types of maps—choropleth maps, graduated symbol maps, and dot density maps—each representing different themes such as population, unemployment rate, and per capita income. Finally, W. Wang and Osaragi apply a transformer-based model to learn and predict daily human mobility patterns, using self-attention-based embeddings alongside generative pre-trained transformers (GPTs) to suggest the potential of LLM-like frameworks for spatiotemporal analysis, offering an alternative to traditional traffic modeling techniques like the four-step model, Markov Chain models, and activity-based models.

Genetic Programming: Kotze et al.'s contribution utilizes GP for trajectory optimization focusing on robustness, speed and automatization for unmanned aerial vehicles. GP is an AI method within the field of evolutionary computation that simulates the process of natural selection using crossover and mutation. It is often used for complex optimization problems that differ from predictive tasks in ML, pattern recognition tasks in DL and natural language tasks in LLMs. Unlike ML, DL, and LLM, GP does not require labeled data or text corpora for training and works with limited data for a specific optimization problem.

3. AI Applications in the SI

Applications of AI presented in the 14 papers of this SI can be grouped into four topics as follows: (1) mobility, (2) natural resource and disaster management, (3) cartography and mapping, and (4) geospatial data handling and curation.

Mobility: Human mobility research uses a diverse array of location-based data (e.g., GPS trajectories, traffic data) to gain insights into urban human dynamics. This SI explores various aspects of human mobility, including simulating population migration during COVID-19 (Liu et al.), identifying large-scale traffic anomalies (Mao et al.), and predicting daily spatiotemporal mobility patterns (W. Wang and Osaragi). Kotze et al. addressed the optimization task for 3D trajectory data to minimize the route cost, in terms of energy or time, and restricted flight zones. Related tasks in spatiotemporal AI for mobility and transportation research include predicting traffic variables such as flow, density, and travel times, optimizing traffic networks (e.g., controlling signal timings, scheduling urban transit systems, managing supply chains, and vehicle routing), and utilizing computer vision for sensing and analyzing complex urban environments [21].

Natural Resource and Disaster Management: Previous research highlights how AI applications can enhance the monitoring and management of natural resources, contributing to environmental preservation and advancing progress toward achieving the Sustainable Development Goals [22]. AI systems have also proven effective in supporting timely responses to and management of natural disasters, such as forest fires, earthquakes, and floods. This includes using deep learning techniques for semantic segmentation of airborne sensor data and applying various ML methods for extracting information from social media posts [23,24]. In this SI, Puttinaovarat et al. compare several ML methods for classifying the ripeness of oil palm bunches from images captured with smartphones and tablets. Similarly, Q. Wang et al. examine the spatial determinants of rice yields in China (e.g., climate, soil, and vegetation types) using an ML approach. S. Li et al. improve real-time demand estimation for disaster relief supplies by mining social media data with a deep learning model. These case studies suggest that further integration of AI-based solutions holds significant potential for improving efficiency and accuracy in fields such as natural resource management and disaster response.

Cartography and Mapping: Yu et al. enhance road network mapping accuracy by incorporating unlabeled aerial imagery into the learning process. To improve street-level crime mapping, Gu et al. developed a graph representation learning approach that enhances crime occurrence classification within a megacity in China. Additionally, Farmakis-Serebryakova et al. automated the relief shading process for maps at arbitrary scales by training an encoder–decoder deep learning model on existing map products (e.g., SwissALTI3D DEM), significantly reducing the time and effort required for future large-scale map updates. Moreover, Xu and Tao evaluated the map-reading and analysis capabilities of state-of-the-art multimodal LLMs (e.g., GPT-4V). These findings highlight the potential for advanced AI solutions to further empower traditional cartographic analysis (e.g., map generation, historic map digitization) and design, as also suggested by related research [14].

Geospatial Data Handling and Curation: Geospatial analysis relies on data from diverse sources, where data quality can become a challenge when the information varies in format, standards, and scale [25]. As a result, AI techniques have become increasingly important in improving data quality, data handling, and data curation. For example, Jin et al. propose an unsupervised pansharpening method using a GAN to enhance the spatial-spectral resolution of remote sensing images. Zeng and Boehm introduce a data enrichment approach based on the Grounded Segment Anything Model (SAM) to enable open-vocabulary semantic segmentation with textual input, demonstrated on street scene imagery. D. Li et al. focus on tabular-based spatial data and develop a benchmark dataset to assess the ability of LLMs to generate structured spatial outputs. This contribution therefore underscores the potential of AI-driven technologies to simplify complex, time-consuming manual workflows in geospatial analysis.

The broad and diverse range of application topics covered in this SI suggests that AI-driven advancements and GeoAI are becoming increasingly accessible, with widespread domain-specific adaptation likely in the near future.

4. Future Directions

Despite the rapid advancements in AI technologies, foundation models, and generative AI, which have significantly expanded their applicability to geographic problem-solving, several critical challenges persist in the development of next-generation GeoAI frameworks [4]. Further progress will necessitate the integration of spatial thinking into the design of GeoAI models, substantial improvements in theories, methods, and experiments, and a collaborative approach to the development of open data, benchmarks, and evaluation methodologies. In the realm of spatial representation learning, one of the key challenges lies in creating an effective location decoding model that can accurately capture feature distributions based on user inputs, such as images or text. Additionally, there is a need to develop a unified representation learning model that accommodates various vector data formats (point, line, polygon) to support subsequent analysis tasks.

Current large pre-trained foundation models (PFMs) are typically trained in a task-agnostic manner. While artificial general intelligence (AGI) that can effectively generalize across all tasks remains a distant goal, PFMs have demonstrated success in fields like Natural Language Processing and Computer Vision. However, their ability to handle geospatial data and related tasks is still limited [26] as they lack the inherent capability to fully comprehend and address geospatial challenges [27]. Geospatial tasks often require substantial prior knowledge, making the integration of GIS theories and spatial knowledge into the hierarchical features of deep learning a key challenge for the future development of GeoAI.

A current research direction aimed at addressing the limitations of PFMs is the development of geo-foundation models (GeoFMs), which are specifically tailored to geoscience questions. These models can be obtained through fine-tuning existing foundation models on new geospatial tasks, developing them from scratch, or leveraging LLMs as AI agents to perform geospatial tasks by utilizing third-party geospatial tools. However, the development of GeoFMs faces several challenges, including managing the diverse data modalities associated with geospatial tasks—such as geospatial vector data, network data, geospatial knowledge graphs, satellite imagery, elevation models, and environmental sensing data—to broaden the scope of tasks they can address. While most current GeoFMs focus on geospatial image and geo-text data, pioneering efforts like CSP [28] and CityFM [29] have explored the integration of unique geospatial data modalities into GeoFM development. Additionally, since geospatial tasks vary across both spatial and temporal scales, GeoFMs must be capable of processing geospatial data at different spatial levels (from street-level to global) and temporal resolutions (ranging from minutes to years) [27].

LLMs have demonstrated a wide range of capabilities in addressing spatial tasks, including code generation and interpretation, GIS concepts and spatial literacy [30,31], toponym recognition [32], spatial reasoning [33], enriching maps with scene content from street-level images [34] and breaking down spatial analysis questions into spatial operations to synthesize geoprocessing workflows [35]. While these findings provide useful examples, there is a need to develop an LLM agent capable of answering arbitrary spatial questions. Advancing multimodal models that integrate spatial, temporal, and semantic data could help overcome current limitations and enable more comprehensive geospatial analyses [27]. Moreover, the black-box nature of LLMs, which makes their predictions and outputs difficult to interpret and validate, poses a significant concern, particularly in geospatial applications where accuracy, reliability, and consistency are crucial [36]. Future research should focus on developing robust validation frameworks tailored to geospatial contexts to address inconsistencies and ensure outputs align with established geospatial standards. Recent models have started to incorporate the role of location and spatial relationships in model explanations by quantifying their impact on the predicted variable of interest [37], marking a crucial step toward more transparent and interpretable geospatial predictions.

As highlighted in previous GIScience publications [18], we observe a continued underrepresentation of the Global South in this SI and in published GeoAI research [4]. While this trend is prevalent across scientific publishing as a whole, there are additional barriers to the adoption of GeoAI technologies in resource-constrained environments [38] that may exacerbate this disparity. It is also crucial to ensure that cutting-edge GeoAI research is conducted collaboratively in a multi-disciplinary environment, rather than in research silos.

To provide an alternative platform for disseminating pioneering GeoAI research that addresses current challenges, we have organized a follow-up SI (https://www.mdpi.com/journal/ijgi/special_issues/g2vcj097om) (accessed on 28 January 2025) in the same journal. One of the key objectives of this SI is to increase the participation of researchers from the Global South through targeted initiatives, such as directly reaching out to active researchers via email and discussion forums, and offering fee waivers for invited contributions. Additionally, while the practical application of AI and GeoAI to geographically relevant problems is valuable and necessary, more synergistic research that advances both AI and geospatial sciences is essential to fully realize their potential [39,40]. This type of research is especially encouraged in the follow-up SI.

Author Contributions: All authors contributed equally to the conceptualization and writing of this editorial. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: We want to express our congratulations to the authors of the papers of this Special Issue for their scientific contributions; to the referees whose help made it possible to improve the contents of these papers; and finally, to the editorial staff of the *ISPRS International Journal of Geo-information* for their assistance in producing this Special Issue.

Conflicts of Interest: The authors declare no conflicts of interest.

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