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Advances in geocomputation and geospatial artificial intelligence (GeoAI) for mapping

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ABSTRACT

Geocomputation and geospatial artificial intelligence (GeoAI) have essential roles in advancing geographic information science (GIS) and Earth observation to a new stage. GeoAI has enhanced traditional geospatial analysis and mapping, altering the methods for understanding and managing complex human–natural systems. However, there are still challenges in various aspects of geospatial applications related to natural, built, and social environments, and in integrating unique geospatial features into GeoAI models. Meanwhile, geospatial and Earth data are critical components in geocomputation and GeoAI studies, as they can effectively reveal geospatial patterns, factors, relationships, and decision-making processes. This editorial provides a comprehensive overview of geocomputation and GeoAI applications in mapping, classifying them into four categories: (i) buildings and infrastructure, (ii) land use analysis, (iii) natural environment and hazards, and (iv) social issues and human activities. In addition, the editorial summarizes geospatial and Earth data in case studies into seven categories, including in-situ data, geospatial datasets, crowdsourced geospatial data (i.e., geospatial big data), remote sensing data, photogrammetry data, LiDAR, and statistical data. Finally, the editorial presents challenges and opportunities for future research.

1. Introduction

Geocomputation and Geospatial Artificial Intelligence (GeoAI) represent innovative approaches that promote Geographical Information Science (GIS) and Earth Observation into a new stage. Geocomputation has the advantage of using computational methods and tools to explore geospatial and Earth data, and generating new knowledge (Longley et al., 1998; Fischer, 2006). Meanwhile, GeoAI provides powerful learning algorithms such as machine learning, deep learning, and transfer learning, to develop effective and innovative solutions for geospatial and Earth issues (Smith, 1984; Janowicz et al., 2020; VoPham et al., 2018). Mapping is an essential component of GIS and Earth observation that helps in understanding natural and built environments. Traditionally, spatial analysis based on the theories of spatial statistical inference is used for mapping. The issues of spatial analysis can be classified into the following categories: identifying spatial patterns (Thach et al., 2018), exploring spatial factors (Luo et al., 2022a; Zhang et al., 2022b; Song et al., 2020; Song and Wu, 2021), spatial interpolation and prediction (Luo et al., 2022b; Song, 2022a,b), spatial simulation (Crooks and Castle, 2011; Castle and Crooks, 2006), and geographical decision making (Song et al., 2021). Despite differences in scope and focus, geocomputation and GeoAI have significantly enhanced the traditional methods of geospatial analysis and mapping in recent years. They have the potential to transform the way we understand and manage the complex interactions between human and natural systems in the world.

Geocomputation and GeoAI have greatly improved the approach to addressing complex geospatial and Earth-related challenges. The integration of advanced computational tools provides more opportunities for innovative applications of geospatial artificial intelligence (GeoAI) and Earth observation. These advanced computational tools include big data analysis (Li et al., 2016), cloud computing (Yao et al., 2019) (such as Google Earth Engine Gorelick et al., 2017), knowledge graphs (Ma, 2022), natural language processing (Sit et al., 2019), etc. The integration of these advanced computational tools with geospatial analysis and Earth observation has led to essential advancements in geospatial big data (Yang et al., 2020), geospatial cloud computing (Yao et al., 2019), geospatial knowledge graphs (Chadzynski et al., 2021), and geocomputation for social sciences (Qin et al., 2022). GeoAI has been a driving force in these advancements (Janowicz et al., 2020).

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Despite the growing implementations of geocomputation and GeoAI in mapping, there is still an increasing need to examine their applications from various perspectives. First, it is increasingly important to understand the geospatial implications of the methods and outcomes generated by geocomputation and GeoAI. Currently, from the perspective of algorithms or models, geocomputation and GeoAI predominantly involve applying computational and learning methods directly to geospatial data, leading to a relatively simplified integration of geospatial characteristics and spatial association in the models. Traditional spatial analysis techniques leverage various geospatial characteristics, such as spatial autocorrelation for measuring the similarity between neighboring observations (Cliff and Ord, 1970), spatial heterogeneity for describing the variation of geospatial data across space (Goodchild, 2004; Wang et al., 2010; Luo et al., 2022b), spatial singularity and anomaly for detecting unusual and rare observations (Cheng, 2007), and geographical similarity and complexity for measuring the similarity (Zhu et al., 2018; Song, 2022a) and complexity (Manson, 2007; Zhang et al., 2023) of geospatial data based on their geographical configurations, respectively. However, these unique geospatial features are currently not widely incorporated in the algorithms of GeoAI. Despite some recent studies characterizing the spatial dependence using the relationship between data and their neighbors (Liu and Biljecki, 2022), the incorporation of these geospatial features is still limited. In addition, geospatial and Earth data are complex and diverse, with a wide range of sources and types such as satellite images, aerial images, photogrammetry data, geospatial data, and location data from social media. However, they are often treated as samples or images similar to other fields, ignoring their unique geospatial features. As we know, geospatial and Earth data can accurately describe geospatial information with various spatial types (e.g., point, polyline, area, and grid) and at different scales, in addition to the location itself such as longitude and latitude. Therefore, there is a need to integrate these unique geospatial features into the algorithms and models of geocomputation and GeoAI to fully use their capabilities in solving geospatial and Earth-related challenges.

This special issue aims at providing a comprehensive overview of geocomputation and GeoAI in mapping, including the latest applications and approaches to understanding various types of geospatial and Earth data in the studies. The special issue contains a review of GeoAI and a collection of case studies conducted across 20 countries that have been classified into four categories: buildings and infrastructure, land use analysis, natural environment and natural hazards, and social issues and human activities. This Editorial categorizes the applications of geocomputation and GeoAI into these four categories, providing readers with a clear understanding of the fields of the latest applications. In addition, we provide a summary of the geospatial and Earth data in these case studies, which is critical for understanding the data from a geospatial perspective and integrating geospatial characteristics of data in future computational and GeoAI methods. Finally, we summarize the challenges and opportunities identified in the publications to inform future research in this field.

2. Applications of geospatial artificial intelligence

2.1. Applications

The applications of this special issue demonstrate the global trends of GeoAI and geocomputation, with studies conducted across 20 countries in North America, South America, Europe, Africa, and Asia, including the United States, Canada, Brazil, Spain, the United Kingdom, Denmark, Germany, Switzerland, Italy, Ghana, Tanzania, South Africa, Israel, China, South Korea, Myanmar, Thailand, Laos, Cambodia, and Vietnam (Fig. 1). The studies contain a diverse range of topics, which we have classified into four categories: buildings and infrastructure, land use analysis, natural environment and natural hazards, and social issues and human activities (Fig. 1). These categories reflect the broad applicability of geocomputation and GeoAI in solving complex geospatial and Earth-related problems. In the following subsections, we provide a summary of the applications within each of these categories.

2.1.1. Buildings and infrastructure

The applications of geocomputation and GeoAI in building and infrastructure studies can be broadly classified into three categories. First, for buildings, deep learning techniques have been utilized to detect spatial structures of undocumented buildings (Li et al., 2022) and roof structure lines (Qian et al., 2022) using remote sensing images. These approaches effectively address challenges caused by diverse roof sizes and shapes, as well as significant class imbalances, ultimately improving identification accuracy and providing reliable urban building structure datasets. Meanwhile, the integration of deep learning and geospatial information provides powerful tools, such as the Multi-Scale Geoscience Network (MS-GeoNet) (Liu et al., 2022) and Momentum and Spatial-Channel Attention RFANet (MSCA-RFANet) (He et al., 2022a), which improves the accuracy and enhances building footprint extraction using high-resolution remote sensing images.

In addition, deep learning is a powerful tool for road-related studies. Guan et al. (2022) develops the attentive capsule feature pyramid network (ACapsFPN) to enhance road marking extraction accuracy from UAV images. The ACapsFPN is more robust in the UAV-based road marking extraction compared to existing approaches, effectively dealing with complex conditions by extracting and integrating high-quality, multi-level, and multi-scale capsule features. Jiao et al. (2022) extracts roads from historical maps using a fast and effective deep learning that automatically generates training data through symbol reconstruction. By implementing and comparing different training scenarios using the Swiss Siegfried map, the results indicate that imitation maps generated by symbol reconstruction enhance the performance of road extraction models.

Finally, GeoAI can address issues related to infrastructure in addition to buildings and roads, such as oil well sites and points of interest (POIs) of facilities. In He et al. (2022b), oil well sites can be automated identified and extracted from high-resolution satellite images using a modified Mask R-CNN architecture, which integrates D-LinkNet and a semantic segmentation branch, significantly improving the accuracy and effectiveness compared to the original Mask R-CNN. Yu et al. (2022b) infers labels of facility POIs with unbalanced data distribution by employing a hierarchical learning model based on multi-level POI categories, which can provide a balanced division of geospatial data across the POI category tree structure.

2.1.2. Land use analysis

GeoAI has made significant contributions to urban land use studies by employing advanced learning techniques and integrating diverse geospatial and Earth data. Yao et al. (2022b) identifies urban land use patterns using a neural network (TR-CNN) that explores the fusion of remote sensing data and high-spatial and temporal resolution time-series electricity data that capture socioeconomic attributes. Yang et al. (2022) classifies urban functional regions using an ensemble classification method that combines vector-based buildings and POIs, and an improved graph convolutional neural network (GCNN) and a Word2Vec model, achieving higher classification accuracy than single-source data applications and existing multisource data integration methods. Gevaert and Belgiu (2022) performs land use classification and identifies buildings in three African cities using a supervised classification model, i.e., Fully Convolutional Network (FCN), which employs landscape metrics to assess the similarity between training and testing images. Pan et al. (2022) assesses urban expansions using an integration of a convolutional neural network (U-Net) and a recurrent neural network (LSTM), which provides high-accuracy land use classification due to the multiscale neighborhood information provided by U-Net and the time series information of historical urban expansion revealed by LSTM.

In addition to urban land use classification, GeoAI is also implemented in the land use analysis in other typical regions, such as coastal lands and wetland. For instance, De Carvalho et al. (2022) identifies objects in beach settings using multispectral panoptic segmentation

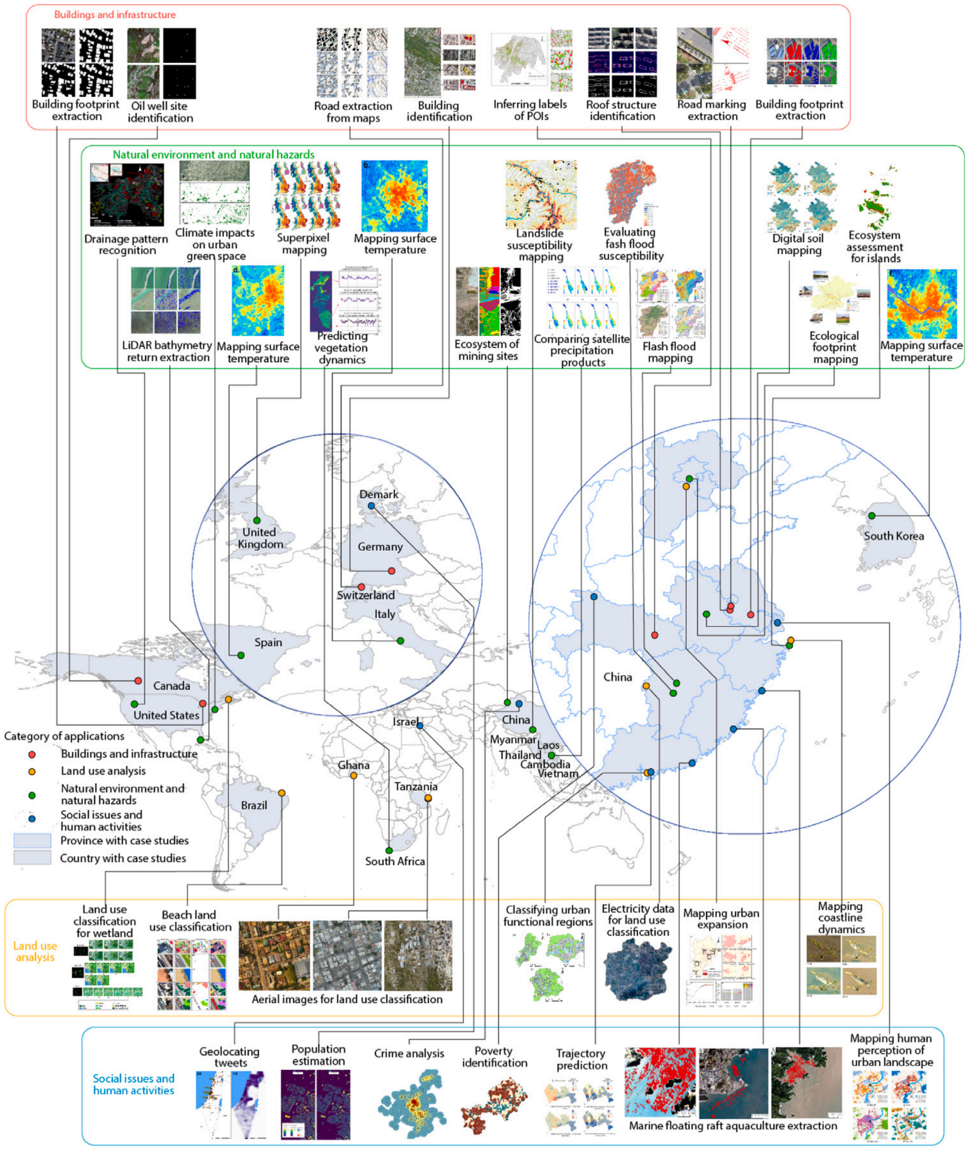

Fig. 1. A summary of applications of geocomputation and geospatial artificial intelligence (GeoAI) in buildings and infrastructure, land use analysis, natural environment and natural hazards, and social issues and human activities in the special issue. Small figures of case studies are reproduced from articles published in the special issue, including (Hu et al., 2022; Wang et al., 2021; Cheng et al., 2022; Zohar, 2021; Fibæk et al., 2021; Yu et al., 2022a; Yao et al., 2022b; Guan et al., 2022; Tan et al., 2022; Wei et al., 2022b; Chen et al., 2022; Huang and Xu, 2022; Lowell and Calder, 2022; Zhang et al., 2022a; Qian et al., 2022; Yu et al., 2022b; He et al., 2022b; Jiao et al., 2022; Yang et al., 2022; Ye et al., 2022; Liu et al., 2022; Wei et al., 2022a; He et al., 2022a; Yoo et al., 2022; Hou et al., 2022; Li et al., 2022; Yao et al., 2022a; Fan et al., 2022; De Carvalho et al., 2022; Nowosad and Stepinski, 2022; Gevaert and Belgiu, 2022; Pan et al., 2022; Jamali et al., 2022; Xu et al., 2023; Ma et al., 2022; Le et al., 2023).

with WorldView-3 images, enabling the detailed mapping and counting of tourist infrastructure and background features at beach areas. Chen et al. (2022) extracts coastline information and analyzes the spatial and temporal evolution of archipelago coastline using tasseled cap transformation and morphology analysis of multi-temporal remote sensing images. The method effectively addresses the suspended sediments and complex coastlines, and provides insights into coastal resource protection in the archipelago. Jamali et al. (2022) conducts wetland classification with limited training samples using a deep learning framework based on 3D Generative Adversarial Networks (3D GAN) and Vision Transformers, which has a great potential for large-scale remote sensing wetland classification.

2.1.3. Natural environment and hazards

GeoAI has been widely implemented in the study and management of natural environments and hazards, such as climate, ecosystems, vegetation, water resources, soil, terrain, geology, and the mitigation of various natural hazards. Here we divide the applications of GeoAI for natural environment and hazards into four categories: climate, ecosystem, natural environment sectors, and natural hazards. First, GeoAI can enhance the understanding of climate issues. For instance, Yoo et al. (2022) downscales MODIS nighttime land surface temperatures (LSTs) in urban areas using a local linear forest (LLF) method with ASTER thermal data, which demonstrates high accuracy and effective description of thermal spatial patterns in the downscaling. Le et al. (2023) conducts bias-correction and improves the accuracy of daily multisatellite precipitation products using a deep learning framework that combines convolutional neural networks and encoder–decoder architecture. The deep learning model decreases the spatial–temporal difference between the four satellite-based precipitation products and a site observation-based product, ensuring the reliability of the products in diverse climatic regions. Nowosad and Stepinski (2022) provides a case study of accurately identifying Great Britain's climates using an extended Simple Linear Iterative Clustering (SLIC) superpixel algorithm with non-imagery geospatial raster data.

Table 1
Summary of geospatial and Earth data used in the applications of geospatial artificial intelligence (GeoAI).

Category	Geospatial and Earth data (references show the applications)
In-situ data	Water quality monitoring collected by handheld terminals and fixed sensors (Tan et al., 2022); in-situ air temperature collected from weather stations (Yoo et al., 2022); soil organic matter samples (Fan et al., 2022); WorldClim gridded climate data (interpolation data based on in-situ climate observations) (Huang and Xu, 2022; Nowosad and Stepinski, 2022); APHRODITE precipitation data (Le et al., 2023); other rainfall datasets (Wei et al., 2022b; Zhang et al., 2022a); aridity index and PET from the Global Aridity and PET Database (Huang and Xu, 2022)
Geospatial datasets	Hydrography dataset (surface water features) (Yu et al., 2022a; Zhang et al., 2022a); river dataset (Wei et al., 2022b; Yao et al., 2022a); landslide inventory (Wei et al., 2022b); road dataset (Wei et al., 2022b); geology dataset (e.g, lithology and fault) (Wei et al., 2022b); historical flash flood events (Zhang et al., 2022a); soil types (Zhang et al., 2022a); scanned maps (Jiao et al., 2022); population raster data products (Ye et al., 2022; Yoo et al., 2022); digital cadastral map (i.e., 2D building database) (Li et al., 2022); rainfall spatial data (Yao et al., 2022a)
Crowdsourced geospatial data (i.e., geospatial big data)	POI from Gaode Map (Hu et al., 2022; Cheng et al., 2022), GeoNames (Zohar, 2021), OSM (Zohar, 2021), AutoNavi (Yu et al., 2022b), and Amap (Yang et al., 2022); road network from OSM (Hu et al., 2022; Cheng et al., 2022; Qian et al., 2022; Yang et al., 2022; Yoo et al., 2022); buildings from GeoDenmark and OSM (Fibæk et al., 2021) and multiple public building datasets (e.g., Massachusetts Building Dataset, WHU Building Dataset, and Waterloo Building Dataset) (He et al., 2022a); drainage from OSM (Yu et al., 2022a); geocoded crime records (Cheng et al., 2022); mobile phone location and user data (Cheng et al., 2022); geolocated tweets (Zohar, 2021); Addresses WebAPI (Fibæk et al., 2021); geocoded residential electricity data (Yao et al., 2022b); urban landscape ratings collected from MIT "Place Pulse 2.0" crowdsourcing platform (Wei et al., 2022a); trajectory data (Xu et al., 2023)
Remote sensing data	Land use generated from Gaofen (Hu et al., 2022; Tan et al., 2022), Landsat (Wang et al., 2021; Tan et al., 2022; Chen et al., 2022), Sentinel (Fibæk et al., 2021), Google Earth (Yao et al., 2022b; Qian et al., 2022), MODIS images (Ye et al., 2022), and PROBAV images (Nowosad and Stepinski, 2022); Land use datasets of Global Land Cover (Wei et al., 2022b) and other products (Pan et al., 2022); terrain from ALOS DEM (Hu et al., 2022; Wei et al., 2022b), SRTM DEM (Huang and Xu, 2022; Yoo et al., 2022), ASTER GDEM (Zhang et al., 2022a), CopernicusGLO-30 DEM (Nowosad and Stepinski, 2022), and DEM data products (Yao et al., 2022a); DSM (Li et al., 2022); NDVI from Sentinel (Hu et al., 2022), Landsat (Wei et al., 2022b; Yao et al., 2022a), MODIS (Yoo et al., 2022; Ma et al., 2022), NAIP images (Huang and Xu, 2022), and NDVI data products (Zhang et al., 2022a); NPP from MODIS (Ye et al., 2022); nighttime light intensity (Huang and Xu, 2022); Sentinel images (Jamali et al., 2022); RapidEye images (He et al., 2022b); WorldView images (He et al., 2022b; De Carvalho et al., 2022); OCO-2 carbon data (Ye et al., 2022); Superview images (Liu et al., 2022); aerial images (He et al., 2022a); MODIS Terra nighttime LST and ASTER nighttime LST (Yoo et al., 2022); ZY1-02D hyperspectral satellite images (Hou et al., 2022); TRMM, CMORPH, CHIRPS, and PERSIANN-CDR precipitation products (Le et al., 2023)
Photogrammetry data	UAV images and orthomosaics (Guan et al., 2022; Tan et al., 2022; Gevaert and Belgiu, 2022); street-view images (Wei et al., 2022a)
LiDAR	LiDAR data (Lowell and Calder, 2022)
Statistical data	Poverty incidence derived from the total and poverty population at the village level (Hu et al., 2022); population statistics at the parish level (Fibæk et al., 2021); yield and consumption of biological and energy resources at the city level (Ye et al., 2022)

Abbreviations:
ALOS DEM: Advanced Land Observing Satellite digital elevation model
APHRODITE: Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources
ASTER GDEM: Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model
CHIRPS: Climate Hazards Group InfraRed Precipitation with Station data
CMORPH: CPC Morphing Technique
DSM: digital surface model
MODIS: Moderate Resolution Imaging Spectroradiometer
NAIP: National Agriculture Imagery Program
NDVI: Normalized Difference Vegetation Index
NPP: Net Primary Productivity
OSM: OpenStreetMap
PERSIANN-CDR: Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks - Climate Data Record
PET: potential evapotranspiration
PROBAV: Project for On-Board Autonomy - Vegetation
SRTM DEM: Shuttle Radar Topography Mission digital elevation model
TRMM: Tropical Rainfall Measuring Mission

Second, GeoAI is increasingly used in the ecosystem management, enabling more informed decision-making and sustainable development. Wang et al. (2021) estimates the value of regional ecosystem services of an archipelago using satellite images and identifies the correlations between ecosystem services and socio-economic conditions. Tan et al. (2022) develops a communication-navigation-remote sensing-integrated ecological environment emergency monitoring chain (CN-RIEEEMC) for tailings areas, providing a framework for automatic and intelligent ecological environment emergency monitoring. Ye et al. (2022) introduces high-resolution mapping of ecological footprint using GeoUNet, an AI-based end-to-end multi-scale prediction approach with multi-source data, which can generate more accurate downscaling maps for fine-scale spatio-temporal analysis.

Third, GeoAI is also employed in various aspects of natural environment. For instance, Huang and Xu (2022) examines spatial patterns of urban green space coverage (UGSC) using high-resolution remote sensing images and explores main factors influencing these patterns. Results show that climatic factors are the primary drivers of UGSC spatial patterns, while socio-economic and terrain factors have fewer impacts. Ma et al. (2022) forecasts the vegetation dynamics in open ecosystems using deep learning with environmental variables such as precipitation, fire history, and temperature. Yu et al. (2022a) recognizes drainage patterns using a graph convolutional network (GCN), which provides more accurate drainage pattern recognition than machine learning algorithms. Fan et al. (2022) conducts large-area digital soil mapping for soil organic matter content using improved individual predictive soil mapping (iPSM) approaches, which provide more accurate predictions than the original iPSM and random forest kriging models. Lowell and Calder (2022) effectively extracts bathymetric soundings from LiDAR point clouds using a combined density- and clustering-based approach and a machine learning algorithm. Wei et al. (2022b) provides landslide susceptibility mapping using a deep learning framework that integrates spatial response features and machine learning classifiers (SR-ML), which can more accurately classify images than random forest.

Finally, GeoAI has been implemented in studies of natural hazards, such as floods. Zhang et al. (2022a) presents a flash flood regionalization study using machine learning, including exploring flash flood factors, identifying clustered homogeneous regions, and generating flash flood maps. Yao et al. (2022a) assesses flood risks for disaster prevention and control using a stacking and blending ensemble learning approach, which is more accurate in estimating flood potentials than linear regression, K-nearest neighbors, support vector machine, and random forest.

2.1.4. Social issues and human activities

GeoAI plays an essential role in addressing social issues and assessing human activities. From the perspective of social issues, Fibæk et al. (2021) predicts areas, volumes, and population of human-made structures with high accuracy using Inception-ResNet inspired deep learning and Earth observation data; Zohar (2021) inspects geolocations of tweets using information from tweet meta-fields, GeoNames, and Open Street Map (OSM) datasets; Cheng (2007) estimates urban burglary risks using a multiscale feature extraction and scale optimization framework that defines neighborhoods and optimizes spatial scales for neighborhood environment variables; and Hu et al. (2022) identifies village-level poverty using machine learning, high-resolution remote sensing images, and geospatial data, such as POIs, OSM, and digital surface model (DSM) data, showing the potential of GeoAI in identifying areas required policy interventions.

From the perspective of human activities, Hou et al. (2022) accurately extracts and maps floating raft aquaculture using a hyperspectral index for floating raft aquaculture (HSI-FRA) and a decision tree classification; Xu et al. (2023) predicts human travel behaviors using a GeoAI approach that fuses multispectral observations and trajectories geocomputation; and Wei et al. (2022a) maps human perception of urban landscape, including security, depression, vitality, and aesthetic perceptions, across different land use types using deep learning and street-view images, contributing to the sustainable development of human settlement.

2.2. Geospatial data

Table 1 provides a comprehensive overview of the various types of geospatial and Earth data used in GeoAI studies. These data are classified into seven categories: in-situ data, geospatial datasets, crowdsourced geospatial data (i.e., geospatial big data), remote sensing data, photogrammetry data, LiDAR data, and statistical data. These diverse data types play a fundamental role in the GeoAI applications shown in Section 2.1. Among the seven categories of geospatial and Earth data, remote sensing data is most commonly used in GeoAI studies, followed by crowdsourced geospatial data and in-situ data. By using these various types of data, GeoAI studies can enhance our understanding of spatial relationships, forecast future patterns, and make better decisions for sustainable development. The integration of these geospatial and Earth data with GeoAI methods significantly improves GIS and remote sensing research. The integration also provides new insights into the study of buildings and infrastructure, land use analysis, natural environments and hazards, as well as social issues and human activities.

2.3. Challenges and opportunities

This special issue published a review of GeoAI applications in urban geography (Liu and Biljecki, 2022). The systematic review assesses 581 research articles about GeoAI in urban dynamics, social differentiation of urban areas, and social sensing. The study reveals a growing applications of GeoAI methods, such as deep neural networks within urban geography research. However, the review highlights three challenges in current GeoAI models: limited interpretability, difficulties in multi-scale data integration, and the necessity for more spatially-explicit models. This review demonstrates the potential of GeoAI to improve our understanding of urban dynamics, social differentiation in urban areas, and social sensing. The review recommends the development of multi-scale, explainable, and spatially-explicit GeoAI models in future studies.

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References

Castle, C.J., Crooks, A.T., 2006. Principles and Concepts of Agent-based Modelling for Developing Geospatial Simulations. Centre for Advanced Spatial Analysis (UCL), London, UK.

Chadzynski, A., Krdzavac, N., Farazi, F., Lim, M.Q., Li, S., Grisiute, A., Herthogs, P., von Richthofen, A., Cairns, S., Kraft, M., 2021. Semantic 3D city database—An enabler for a dynamic geospatial knowledge graph. Energy AI 6, 100106.

Chen, C., Liang, J., Xie, F., Hu, Z., Sun, W., Yang, G., Yu, J., Chen, L., Wang, L., Wang, L., et al., 2022. Temporal and spatial variation of coastline using remote sensing images for Zhoushan archipelago, China. Int. J. Appl. Earth Obs. Geoinf. 107, 102711.

Cheng, Q., 2007. Mapping singularities with stream sediment geochemical data for prediction of undiscovered mineral deposits in Gejiu, Yunnan province, China. Ore Geol. Rev. 32 (1–2), 314–324.

Cheng, J., Zhang, X., Huang, J., 2022. Optimizing the spatial scale for neighborhood environment characteristics using fine-grained data. Int. J. Appl. Earth Obs. Geoinf. 106, 102659.

Cliff, A.D., Ord, K., 1970. Spatial autocorrelation: a review of existing and new measures with applications. Econ. Geogr. 46 (sup1), 269–292.

Crooks, A.T., Castle, C.J., 2011. The integration of agent-based modelling and geographical information for geospatial simulation. In: Agent-Based Models of Geographical Systems. Springer, pp. 219–251.

De Carvalho, O.L.F., de Carvalho Júnior, O.A., De Albuquerque, A.O., Santana, N.C., Borges, D.L., Luiz, A.S., Gomes, R.A.T., Guimarães, R.F., 2022. Multispectral panoptic segmentation: Exploring the beach setting with worldview-3 imagery. Int. J. Appl. Earth Obs. Geoinf. 112, 102910.

Fan, N.-Q., Zhao, F.-H., Zhu, L.-J., Qin, C.-Z., Zhu, A.-X., 2022. Digital soil mapping with adaptive consideration of the applicability of environmental covariates over large areas. Int. J. Appl. Earth Obs. Geoinf. 113, 102986.

Fibæk, C.S., Keßler, C., Arsanjani, J.J., 2021. A multi-sensor approach for characterising human-made structures by estimating area, volume and population based on sentinel data and deep learning. Int. J. Appl. Earth Obs. Geoinf. 105, 102628.

Fischer, M.M., 2006. Spatial Analysis and Geocomputation: Selected Essays. Springer Science & Business Media.

Gevaert, C.M., Belgiu, M., 2022. Assessing the generalization capability of deep learning networks for aerial image classification using landscape metrics. Int. J. Appl. Earth Obs. Geoinf. 114, 103054.

Goodchild, M.F., 2004. The validity and usefulness of laws in geographic information science and geography. Ann. Assoc. Am. Geogr. 94 (2), 300–303.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ. 202, 18–27.

Guan, H., Lei, X., Yu, Y., Zhao, H., Peng, D., Junior, J.M., Li, J., 2022. Road marking extraction in UAV imagery using attentive capsule feature pyramid network. Int. J. Appl. Earth Obs. Geoinf. 107, 102677.

He, H., Gao, K., Tan, W., Wang, L., Chen, N., Ma, L., Li, J., 2022a. Super-resolving and composing building dataset using a momentum spatial-channel attention residual feature aggregation network. Int. J. Appl. Earth Obs. Geoinf. 111, 102826.

He, H., Xu, H., Zhang, Y., Gao, K., Li, H., Ma, L., Li, J., 2022b. Mask R-CNN based automated identification and extraction of oil well sites. Int. J. Appl. Earth Obs. Geoinf. 112, 102875.

Hou, T., Sun, W., Chen, C., Yang, G., Meng, X., Peng, J., 2022. Marine floating raft aquaculture extraction of hyperspectral remote sensing images based decision tree algorithm. Int. J. Appl. Earth Obs. Geoinf. 111, 102846.

Hu, S., Ge, Y., Liu, M., Ren, Z., Zhang, X., 2022. Village-level poverty identification using machine learning, high-resolution images, and geospatial data. Int. J. Appl. Earth Obs. Geoinf. 107, 102694.

Huang, C., Xu, N., 2022. Climatic factors dominate the spatial patterns of urban green space coverage in the contiguous United States. Int. J. Appl. Earth Obs. Geoinf. 107, 102691.

Jamali, A., Mahdianpari, M., Mohammadimanesh, F., Homayouni, S., 2022. A deep learning framework based on generative adversarial networks and vision transformer for complex wetland classification using limited training samples. Int. J. Appl. Earth Obs. Geoinf. 115, 103095.

Janowicz, K., Gao, S., McKenzie, G., Hu, Y., Bhaduri, B., 2020. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond.
Jiao, C., Heitzler, M., Hurni, L., 2022. A fast and effective deep learning approach for road extraction from historical maps by automatically generating training data with symbol reconstruction. Int. J. Appl. Earth Obs. Geoinf. 113, 102980.
Le, X.-H., Van, L.N., Nguyen, D.H., Nguyen, G.V., Jung, S., Lee, G., 2023. Comparison of bias-corrected multisatellite precipitation products by deep learning framework. Int. J. Appl. Earth Obs. Geoinf. 116, 103177.
Li, S., Dragicevic, S., Castro, F.A., Sester, M., Winter, S., Coltekin, A., Pettit, C., Jiang, B., Haworth, J., Stein, A., et al., 2016. Geospatial big data handling theory and methods: A review and research challenges. ISPRS J. Photogramm. Remote Sens. 115, 119–133.
Li, Q., Taubenböck, H., Shi, Y., Auer, S., Roschlaub, R., Glock, C., Kruspe, A., Zhu, X.X., 2022. Identification of undocumented buildings in cadastral data using remote sensing: Construction period, morphology, and landscape. Int. J. Appl. Earth Obs. Geoinf. 112, 102909.
Liu, P., Biljecki, F., 2022. A review of spatially-explicit GeoAI applications in urban geography. Int. J. Appl. Earth Obs. Geoinf. 112, 102936.
Liu, T., Yao, L., Qin, J., Lu, N., Jiang, H., Zhang, F., Zhou, C., 2022. Multi-scale attention integrated hierarchical networks for high-resolution building footprint extraction. Int. J. Appl. Earth Obs. Geoinf. 109, 102768.
Longley, P.A., Brooks, S., Macmillan, W., McDonnell, R., 1998. Geocomputation: A Primer. Wiley.
Lowell, K., Calder, B., 2022. Operational performance of a combined density-and clustering-based approach to extract bathymetry returns from LiDAR point clouds. Int. J. Appl. Earth Obs. Geoinf. 107, 102699.
Luo, P., Song, Y., Huang, X., Ma, H., Liu, J., Yao, Y., Meng, L., 2022a. Identifying determinants of spatio-temporal disparities in soil moisture of the northern hemisphere using a geographically optimal zones-based heterogeneity model. ISPRS J. Photogramm. Remote Sens. 185, 111–128.
Luo, P., Song, Y., Zhu, D., Cheng, J., Meng, L., 2022b. A generalized heterogeneity model for spatial interpolation. Int. J. Geogr. Inf. Sci. 1–26.
Ma, X., 2022. Knowledge graph construction and application in geosciences: A review. Comput. Geosci. 105082.
Ma, Y., Hu, Y., Moncrieff, G.R., Slingsby, J.A., Wilson, A.M., Maitner, B., Zhou, R.Z., 2022. Forecasting vegetation dynamics in an open ecosystem by integrating deep learning and environmental variables. Int. J. Appl. Earth Obs. Geoinf. 114, 103060.
Manson, S.M., 2007. Challenges in evaluating models of geographic complexity. Environ. Plan. B: Plann. Des. 34 (2), 245–260.
Nowosad, J., Stepinski, T.F., 2022. Extended SLIC superpixels algorithm for applications to non-imagery geospatial rasters. Int. J. Appl. Earth Obs. Geoinf. 112, 102935.
Pan, X., Liu, Z., He, C., Huang, Q., 2022. Modeling urban expansion by integrating a convolutional neural network and a recurrent neural network. Int. J. Appl. Earth Obs. Geoinf. 112, 102977.
Qian, Z., Chen, M., Zhong, T., Zhang, F., Zhu, R., Zhang, Z., Zhang, K., Sun, Z., Lü, G., 2022. Deep roof refiner: A detail-oriented deep learning network for refined delineation of roof structure lines using satellite imagery. Int. J. Appl. Earth Obs. Geoinf. 107, 102680.
Qin, K., Lin, H., Yang, Y., Zhang, F., Gong, J., 2022. Spatial humanities and geo-computation for social sciences: Advances and applications. J. Geod. Geoinf. Sci. 5 (2), 1.
Sit, M.A., Koylu, C., Demir, I., 2019. Identifying disaster-related tweets and their semantic, spatial and temporal context using deep learning, natural language processing and spatial analysis: a case study of Hurricane Irma. Int. J. Digit. Earth 12 (11), 1205–1229.
Smith, T.R., 1984. Artificial intelligence and its applicability to geographical problem solving. Prof. Geogr. 36 (2), 147–158.
Song, Y., 2022a. Geographically optimal similarity. Math. Geosci. 1–26.
Song, Y., 2022b. The second dimension of spatial association. Int. J. Appl. Earth Obs. Geoinf. 111, 102834.
Song, Y., Thatcher, D., Li, Q., McHugh, T., Wu, P., 2021. Developing sustainable road infrastructure performance indicators using a model-driven fuzzy spatial multi-criteria decision making method. Renew. Sustain. Energy Rev. 138, 110538.
Song, Y., Wang, J., Ge, Y., Xu, C., 2020. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: Cases with different types of spatial data. GISci. Remote Sens. 57 (5), 593–610.
Song, Y., Wu, P., 2021. An interactive detector for spatial associations. Int. J. Geogr. Inf. Sci. 35 (8), 1676–1701.
Tan, X., Jiao, J., Zhong, Y., Ma, A., Xu, Y., Sha, Z., Huang, F., Wan, Y., Hu, W., 2022. The CNRIEEEMC: A communication-navigation-remote sensing-integrated ecological environment emergency monitoring chain for tailings areas. Int. J. Appl. Earth Obs. Geoinf. 108, 102710.
Thach, N.N., Ngo, D.B.-T., Xuan-Canh, P., Hong-Thi, N., Thi, B.H., Nhat-Duc, H., Dieu, T.B., 2018. Spatial pattern assessment of tropical forest fire danger at Thuan Chau area (Vietnam) using GIS-based advanced machine learning algorithms: A comparative study. Ecol. Inform. 46, 74–85.
VoPham, T., Hart, J.E., Laden, F., Chiang, Y.-Y., 2018. Emerging trends in geospatial artificial intelligence (geoAI): potential applications for environmental epidemiology. Environ. Health 17 (1), 1–6.
Wang, L., Chen, C., Xie, F., Hu, Z., Zhang, Z., Chen, H., He, X., Chu, Y., 2021. Estimation of the value of regional ecosystem services of an archipelago using satellite remote sensing technology: A case study of Zhoushan Archipelago, China. Int. J. Appl. Earth Obs. Geoinf. 105, 102616.
Wang, J.-F., Li, X.-H., Christakos, G., Liao, Y.-L., Zhang, T., Gu, X., Zheng, X.-Y., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. Int. J. Geogr. Inf. Sci. 24 (1), 107–127.
Wei, R., Ye, C., Sui, T., Ge, Y., Li, Y., Li, J., 2022b. Combining spatial response features and machine learning classifiers for landslide susceptibility mapping. Int. J. Appl. Earth Obs. Geoinf. 107, 102681.
Wei, J., Yue, W., Li, M., Gao, J., 2022a. Mapping human perception of urban landscape from street-view images: A deep-learning approach. Int. J. Appl. Earth Obs. Geoinf. 112, 102886.
Xu, C., Li, F., Xia, J., 2023. Fusing high-resolution multispectral image with trajectory for user next travel location prediction. Int. J. Appl. Earth Obs. Geoinf. 116, 103135.
Yang, C., Clarke, K., Shekhar, S., Tao, C.V., 2020. Big spatiotemporal data analytics: A research and innovation frontier.
Yang, M., Kong, B., Dang, R., Yan, X., 2022. Classifying urban functional regions by integrating buildings and points-of-interest using a stacking ensemble method. Int. J. Appl. Earth Obs. Geoinf. 108, 102753.
Yao, X., Li, G., Xia, J., Ben, J., Cao, Q., Zhao, L., Ma, Y., Zhang, L., Zhu, D., 2019. Enabling the big earth observation data via cloud computing and DGGS: Opportunities and challenges. Remote Sens. 12 (1), 62.
Yao, Y., Yan, X., Luo, P., Liang, Y., Ren, S., Hu, Y., Han, J., Guan, Q., 2022b. Classifying land-use patterns by integrating time-series electricity data and high-spatial resolution remote sensing imagery. Int. J. Appl. Earth Obs. Geoinf. 106, 102664.
Yao, J., Zhang, X., Luo, W., Liu, C., Ren, L., 2022a. Applications of stacking/blending ensemble learning approaches for evaluating flash flood susceptibility. Int. J. Appl. Earth Obs. Geoinf. 112, 102932.
Ye, R., Huang, Z., Li, L., Shan, X., 2022. GeoUNet: A novel AI model for high-resolution mapping of ecological footprint. Int. J. Appl. Earth Obs. Geoinf. 112, 102803.
Yoo, C., Im, J., Cho, D., Lee, Y., Bae, D., Sismanidis, P., 2022. Downscaling MODIS nighttime land surface temperatures in urban areas using ASTER thermal data through local linear forest. Int. J. Appl. Earth Obs. Geoinf. 110, 102827.
Yu, H., Ai, T., Yang, M., Huang, L., Yuan, J., 2022a. A recognition method for drainage patterns using a graph convolutional network. Int. J. Appl. Earth Obs. Geoinf. 107, 102696.
Yu, W., Chen, J., Wei, C., 2022b. A hierarchical learning model for inferring the labels of points of interest with unbalanced data distribution. Int. J. Appl. Earth Obs. Geoinf. 108, 102751.
Zhang, R., Chen, Y., Zhang, X., Ma, Q., Ren, L., 2022a. Mapping homogeneous regions for flash floods using machine learning: A case study in Jiangxi province, China. Int. J. Appl. Earth Obs. Geoinf. 108, 102717.
Zhang, Z., Song, Y., Luo, P., Wu, P., 2023. Geocomplexity explains spatial errors. Int. J. Geogr. Inf. Sci. http://dx.doi.org/10.1080/13658816.2023.2203212.
Zhang, Z., Song, Y., Wu, P., 2022b. Robust geographical detector. Int. J. Appl. Earth Obs. Geoinf. 109, 102782.
Zhu, A.-X., Lu, G., Liu, J., Qin, C.-Z., Zhou, C., 2018. Spatial prediction based on third law of geography. Ann. GIS 24 (4), 225–240.
Zohar, M., 2021. Geolocating tweets via spatial inspection of information inferred from tweet meta-fields. Int. J. Appl. Earth Obs. Geoinf. 105, 102593.