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Artificial Intelligence: New Horizons in Geography Education and Geographical and Earth Science Research

ABSTRACT

In recent years, the application of artificial intelligence (AI) has become increasingly widespread in scientific research, including geography and the Earth sciences, offering new opportunities while simultaneously raising methodological challenges. The concept of producing research results through algorithm- and model-based machine processing with diminishing levels of human intervention has been present in the Earth sciences for some time. The analysis of the rapidly growing volume of geographical data can now be supported in novel ways by artificial intelligence, which not only facilitates the automated identification of specific spatial patterns from satellite imagery but also contributes to the exploration and interpretation of complex spatial processes. Its application enables, for example, the prediction of dynamic processes and the reconstruction of the former states of certain regions. The aim of this paper is to provide an overview of the potential applications of artificial intelligence in geographical research and education, illustrated through both national and international examples. The analysis also highlights that many methodological approaches currently classified under the umbrella of AI in geography have already been in use for some time; however, the broader and more integrated application of AI may lead to dynamic developments in geographical and Earth science research, as well as in geography education. Given that the range of methodological possibilities offered by AI is continuously expanding, this study does not seek to present all potential applications. Instead, following a general overview, the topic indicated in the title is illustrated through a selection of representative examples from the field of geography.

Keywords: artificial intelligence, GeoAI examples, geography education, geoscience

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INTRODUCTION

The rapid spread of artificial intelligence (AI) in the twenty-first century has been facilitated by its ability to perform complex tasks efficiently (Norvig & Russell, 2023). Such tasks include, for example, the automation of processes without direct human intervention, as well as the replacement of human labour in time-consuming and monotonous activities, such as processing large volumes of data, identifying trends and patterns, making predictions, and detecting potential risks. Consequently, the application potential of AI is extensive, ranging from healthcare (e.g. diagnostic procedures) and economic analysis to the optimization of decision-making processes. AI-based statistical methods are widely employed not only by private companies but also by governmental bodies and institutions, for instance to enhance administrative efficiency. Today, artificial intelligence is also firmly embedded in the scientific domain, with numerous universities and research institutes actively engaged in its research and development (Janowicz et al., 2020).

The growing use of AI over the past 10–15 years can largely be attributed to its capacity to efficiently predict future trends in complex processes or to characterize areas with unknown attributes based on sample areas. This includes, for example, the identification of similar patterns within large datasets using data-characterized patterns observed in training areas (Hengl et al., 2017; Wadoux et al., 2020). In the present study, artificial intelligence (AI) is understood as a set of computer-based solutions built on algorithms and models capable of identifying patterns in data, generating predictions, and supporting complex decision-making tasks, with particular emphasis on the processing of spatial and spatio-temporal data (Li & Hsu, 2022).

Over the past decade, the application of AI has become increasingly influential across numerous subfields of geography, ranging from remote sensing and environmental modelling to urban and regional analysis (Bastin et al., 2025; Bui & Mucsi, 2021; Hengl et al., 2017; Kosuri et al., 2025; Lifelo et al., 2024; Szilassi et al., 2019; Tölgyesi et al., 2025; Wadoux et al., 2020). Drawing on examples from geographical research and education, this study outlines both the possibilities and the limitations of AI applications, with particular emphasis on methodological characteristics and interpretability. The aim of the following—by no means exhaustive—overview is not to provide a detailed technical description of specific AI-based algorithms, but rather to demonstrate how AI can be integrated into geographical thinking and to explore the role it may play in future research and educational practice.

This paper is a focused narrative review that maps how artificial intelligence (AI) is currently used in geographical and Earth science research, as well as in geography education, with an emphasis on methodological characteristics (data types, model families, interpretability, and validation constraints) and representative application domains (e.g., remote sensing, spatio-temporal prediction, hazards, soil and ecosystem modelling, urban analyses, and educational practice).

METHODS

The narrative review design deliberately prioritises conceptual synthesis and methodological comparability over exhaustive coverage. The literature base was assembled through a structured keyword search combined with iterative snowballing from reference lists and highly cited synthesis papers.

Search terms targeted both general and domain-specific labels, including artificial intelligence, machine learning, deep learning, GeoAI, spatial prediction, remote sensing, GIS automation, explainable AI, generative models, large language models, and AI in geography education. Inclusion criteria were: (1) peer-reviewed journal articles, scholarly books or handbooks, and authoritative institutional sources; (2) clear relevance to geospatial or Earth-science data and workflows, or to teaching and learning contexts in geography; (3) explicit discussion of methods, data, and/or evaluation (rather than general claims only); and (4) the inclusion, as illustrative examples, of selected results from our own research. Given the rapid acceleration of the field, the search prioritised recent work (primarily from the last 10–15 years), while also retaining seminal publications that anchor key concepts and research trajectories.

To ensure a balanced coverage of the literature used in the study, the final compilation deliberately combines the international literature with Hungarian and regional case studies that demonstrate the relevance of AI-based methods in the earth sciences, including geography and geography education, and exemplify the practical feasibility of these methods.

RESULTS

The Methodological Framework of AI in Geographical Research

The essence of an AI system lies in equipping computers with technical "knowledge" (i.e. software programs) that enables them to imitate aspects of human intelligence and behavioural patterns. A key characteristic of such systems is continuous learning (self-improvement), through which data processing can become increasingly efficient, allowing AI to autonomously automate and partially optimize tasks. For example, based on large volumes of data (big data), AI systems are able to construct their own models (algorithms), the application of which enables them to perform tasks in a partly autonomous manner. Moreover, through repeatedly executed algorithms, the system can learn and evolve over time, adjusting and refining its own models. In this way, AI becomes capable of recognizing patterns, forecasting processes, and developing new models without direct human intervention. Unlike earlier approaches, in which models were explicitly designed by human programmers, these models are now generated by AI systems themselves.

To understand the geographical and Earth science applications of artificial intelligence, it is essential to clarify the conceptual foundations of the most frequently used methodological approaches (Figure

1). In practice, the vast majority of solutions classified as AI fall within the methodological framework of machine learning (ML), which encompasses algorithms capable of identifying patterns in data and making predictions without the rule system being explicitly predefined. Classical ML algorithms commonly applied in Earth science and geographical research—such as decision trees, Random Forests, and support vector machines—have the advantage of operating efficiently with structured spatial data and relatively small datasets, while maintaining a relatively high level of interpretability.

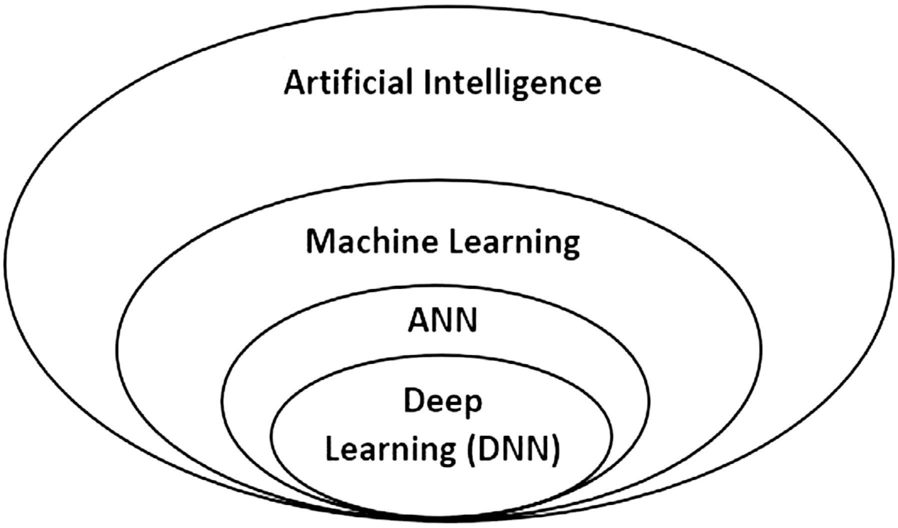
Deep learning (DL) is a specific subfield of machine learning based on multilayer artificial neural networks (ANNs). It is important to emphasize that not every neural network qualifies as a deep learning model; however, all deep learning approaches are based on neural networks. DL methods are particularly effective when large volumes of data are available and are especially well suited to image-based and complex pattern-recognition tasks, such as the processing of satellite and drone imagery (e.g. Sentinel-2 MSI, Sentinel-1 SAR, WorldView-2/3; RGB, multispectral, and hyperspectral drone sensors). As a result, deep learning has gained a prominent role in applications related to remote sensing and urban geography; however, the interpretability of DL models is often more limited than that of classical ML approaches.

In geographical research practice, machine learning and deep learning should be regarded as complementary rather than mutually exclusive toolsets. The choice of method is determined by the nature of the geographical problem, the type and volume of available data, and the required level of interpretability of the results. These methodological foundations also underpin the most recent generative and language models (Large Language Models, LLMs), which can be considered specialized applications of deep learning and primarily offer new opportunities for processing textual, visual, and multimodal data. Generative and language models thus constitute a complementary toolkit for geographical research and education rather than a replacement for classical GIS or remote sensing analyses. Their role is mainly associated with enhancing the efficiency of information processing and knowledge transfer (Edureka, 2019; Lavallin & Downs, 2021).

Many forms of deep learning rely on neural networks, large volumes of data, and substantial computational capacity to learn how to recognize patterns across a wide range of fields, from economics and the natural sciences to some of the most widely used language-based applications (e.g. OpenAI, Midjourney.ai, Anthropic.ai, Fireflies.ai). Among software solutions capable of analysing images or social relationships, the language models developed by OpenAI were among the first to achieve widespread adoption (from 2018 onwards) and have therefore become the most widely known (https://openai.com/chatgpt).

The meaning of GPT (Generative Pre-trained Transformer) indicates, on the one hand, that the model is *generative*, meaning that it is capable not only of processing, translating, and answering questions based on existing texts, but also of creating new textual content. On the other hand, the term *pre-trained* refers to the fact that these capabilities are based on prior training using sample texts or, more broadly, predefined training domains. The extremely rapid diffusion of language-based applications can be explained by the availability of several hundred thousand books' worth of digitised textual data used to train deep learning language models.

Figure 1. The Relationship Between Artificial Intelligence, Machine Learning, Artificial Neural Networks (ANN), and Deep Learning (Deep Neural Networks, DNN).



Source: Lavallin & Downs, 2021; Ramlakhan et al., 2022

The technological foundation of deep learning lies in neural networks—algorithms designed to mimic, in a highly simplified manner, the functioning of the human brain's neural system and its neurons. In simplified terms, a language application operates by taking an initial keyword, letter, or textual unit (token) and continuing text generation by selecting the most probable subsequent letter or word. Through this iterative process, new text is produced. Using the same logic, such models are also capable of interpreting and analysing relationships within existing texts.

To illustrate this with a geographical example, if the word *"Alföld"* (Great Hungarian Plain) is entered as a prompt on chatgpt.com, together with a few key concepts, the system may generate a coherent text of 3,000–5,000 characters describing the region's location, relief, climatic conditions, economic characteristics, cultural and historical traditions, settlement patterns, and related features. Naturally, this presupposes the availability of sufficiently large word-based datasets (e.g. geography textbooks, regional descriptions, and geographical studies) used to train the underlying deep learning algorithms.

However, AI-based methods also have certain limitations. For instance, there is no inherent weighting of input information: all data are treated as equally important, with mathematical optimisation taking precedence, while domain-specific expertise is not explicitly embedded in the process. The verification and validation of AI-generated results may therefore be problematic, as these tasks cannot be delegated to the AI itself. In addition, copyright-related issues arise, particularly with regard to the ownership of texts or images generated by AI-based systems.

The Most Widely Used AI-based Methods in Geography and Earth Sciences

AI methods applied in geography can be classified into numerous categories; however, in simplified terms, computer-based simulation is more effective than manual calculation, and analytical workflows based on AI algorithms are even more efficient. One of the most common application domains is image analysis, which includes image segmentation as well as the recognition and identification of objects within images. Convolutional neural networks (CNNs)—which operate on the similarity of images or image patches and on convolution operations (essentially a generalisation of averaging)—are widely used to address problems such as the identification of areas threatened by inland excess water (Kajári et al., 2024).

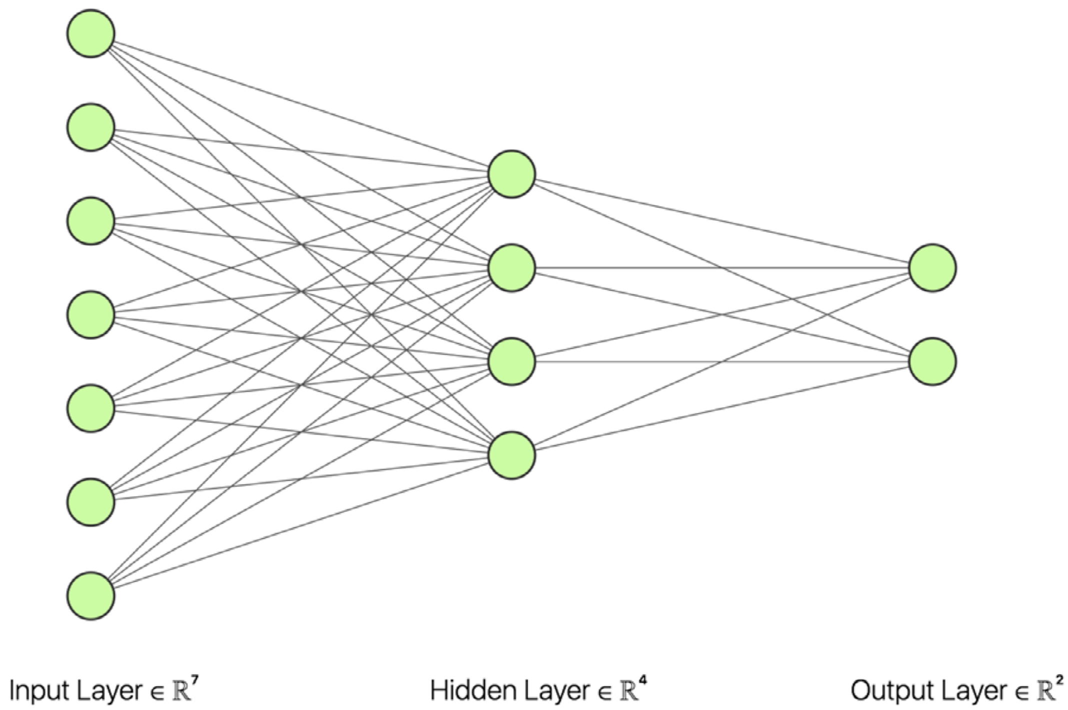
The use of traditional artificial neural networks is well established in geographical research, for example in the monitoring of inland water bodies (van Leeuwen, 2012), while classical machine learning approaches (e.g. support vector machines and artificial neural networks) have been successfully applied to the identification of invasive plant species at the individual level (Papp et al., 2021).

One of the most widely used neural network architectures is the fully connected neural network, which is capable of capturing complex non-linear relationships between input and output variables (Figure 2). However, this architecture has two major limitations. First, input nodes often need to be defined manually, which may require substantial expert knowledge and preprocessing effort. Second, to achieve adequate predictive performance, multiple neural layers must be stacked in order to learn increasingly complex non-linear relationships between the independent (input) and dependent (output) variables.

In the application of neural networks, it is also possible to analyse how computational models enable the retrieval of visually similar images from the internet simply by uploading a reference photograph. Such functionalities are typical examples of computer vision. Recurrent neural networks (RNNs) are designed to process sequential (temporal or ordered) data, as they take into account not only the current input at each step but also the hidden state from the previous step. A specific variant of this architecture is Long Short-Term Memory (LSTM), which is capable of learning long-term dependencies and is therefore particularly suited to time-series analysis. These methods operate on univariate or multivariate time-series data to learn recurring patterns (Brownlee, 2018). Typical applications include the forecasting of river water levels, meteorological parameters, or the future evolution of inland excess water coverage.

Generative adversarial networks (GANs) are paired AI systems whose designation reflects the adversarial competition between two networks involved in the generation of artificial data (Nelson, 2020). GANs represent a branch of machine learning in which neural networks are able to generate new data and images based on existing datasets (e.g. image databases). A GAN consists of two opposing components: a generator and a discriminator. The discriminator's task is to determine whether an output is real or artificially generated, while the generator continuously produces increasingly realistic synthetic data until the discriminator can no longer reliably distinguish generated outputs from original data. Common applications include image-to-image translation, such as converting sketches or drawings into photorealistic images (Isola et al., 2018), text-to-image generation, and image editing. In geographical research, these methods can be applied, for example, to the comparison of current and projected images (scenarios) of urban environments, the analysis of landscape change, or various forms of image enhancement.

Figure 2. A Feed-Forward Artificial Neural Network With Three Fully Connected Layers: Input Layer With 7 Nodes (A), Hidden Layer With 4 Nodes (B), and Output Layer With 2 Nodes (C) for Binary Classification



Source: After Li-Hsu 2022

Artificial intelligence technologies are applied not only in geography but also across other Earth science disciplines, including the analysis of geological structures, atmospheric dynamics, and hydrological and water-system characteristics. AI substantially enhances traditional geographical capacities for data collection, analysis, and integration, for instance through the application of neural network–based methods. Early applications of AI focused on traffic monitoring, urban planning, and cartography; however, with the advancement of deep learning, cartography has also benefited from the precise identification of the spatial positions of historical geographical features on scanned historical maps (Jakab et al., 2025). Within cartography, AI further enables the automation of cartographic generalisation workflows, including polygon simplification and aggregation, as well as the simplification and connectivity-based integration of road networks (Zhou, 2023).

For professional spatial data analysis, LLM-based tools such as Google Geospatial Reasoning can be applied; for geoinformatics solutions, tools such as GeoGPT; and for research support, applications including NotebookLM.

Table 1. Main Types of Artificial Intelligence and Their Typical Application Domains in the Geosciences

Classical machine learning (Machine Learning)	Environmental modelling, soil science and agricultural research, ecological analyses	Analysis of structured spatial data, prediction, relatively good interpretability
Deep learning (Deep Learning)	Remote sensing, urban analysis, disaster and risk research	Image and pattern recognition, handling large volumes of data
Graph-based learning (Graph AI)	Hydrology, urban planning, geological networks	Modelling spatial, topological, and relational structures
Spatio-temporal models (Spatio-temporal AI)	Climate modelling, hydrology, mobility and traffic analysis	Forecasting time-varying spatial data
Bayesian and probabilistic AI	Environmental modelling, geology, decision support	Handling uncertainty, risk analysis
Generative and language models (GANs, LLMs, diffusion models)	Automated GIS processing, data imputation, visualisation	Generation of synthetic spatial data and descriptions
Hybrid GeoAI systems	Complex Earth science and environmental systems	Integrated application of multiple AI approaches

The aim of the present study is to provide a structured—though by no means exhaustive—overview of the AI-based research trends most commonly applied in geography and the Earth sciences. A detailed discussion of individual AI-based methods is not attempted, both because of their rapid and ongoing development and due to the length constraints of this paper. Accordingly, the examples presented do not focus on specific algorithms but rather on broader methodological directions, which are supported by an extensive international body of literature and by numerous applications in the Earth sciences published in leading international journals.

Some Case Studies of AI in Geographical and Earth Science Research

According to many scholars, the use of AI is transforming geographical research and may herald a new golden age for the discipline (Kantor, 2024). There is little doubt that AI provides highly effective tools for exploring complex relationships, such as interactions between landscape-forming factors or the comprehensive geographical analysis of intertwined natural and social processes. Geography underwent a similarly promising transformation in the 1990s, when the rapid diffusion of geographic information systems (GIS) and remote sensing techniques fundamentally reshaped the field. The expansion of geoinformatics from the 1990s onwards opened new horizons in geography and the Earth sciences, comparable in significance to the invention of the microscope in biology or the telescope in astronomy. Thus, geography has relied on computer-based technologies, particularly GIS methods, for nearly three decades; however, the development of artificial intelligence may further expand the possibilities for the processing and analysis of spatial data.

Building on this perspective, an integrative initiative aimed at strengthening the links between the Earth sciences and artificial intelligence was launched in the United States under the name

Geospatial Artificial Intelligence (GeoAI) (American Geographical Society, 2022). In brief, GeoAI refers to the integration of geospatial data and artificial intelligence methods (Li & Hsu, 2022). Its primary objective is to enable more efficient and faster analysis of geographical information, as well as to support the production of more accurate predictive maps and climate scenarios.

Different application domains within GeoAI are distinguished primarily not by the algorithms employed, but by the nature and scale of the geographical problems under investigation. GeoAI should therefore not be regarded as an independent methodological paradigm, but rather as an integrative framework within geographical research, linking large-volume spatial datasets with the analysis of complex environmental and social processes (Table 2).

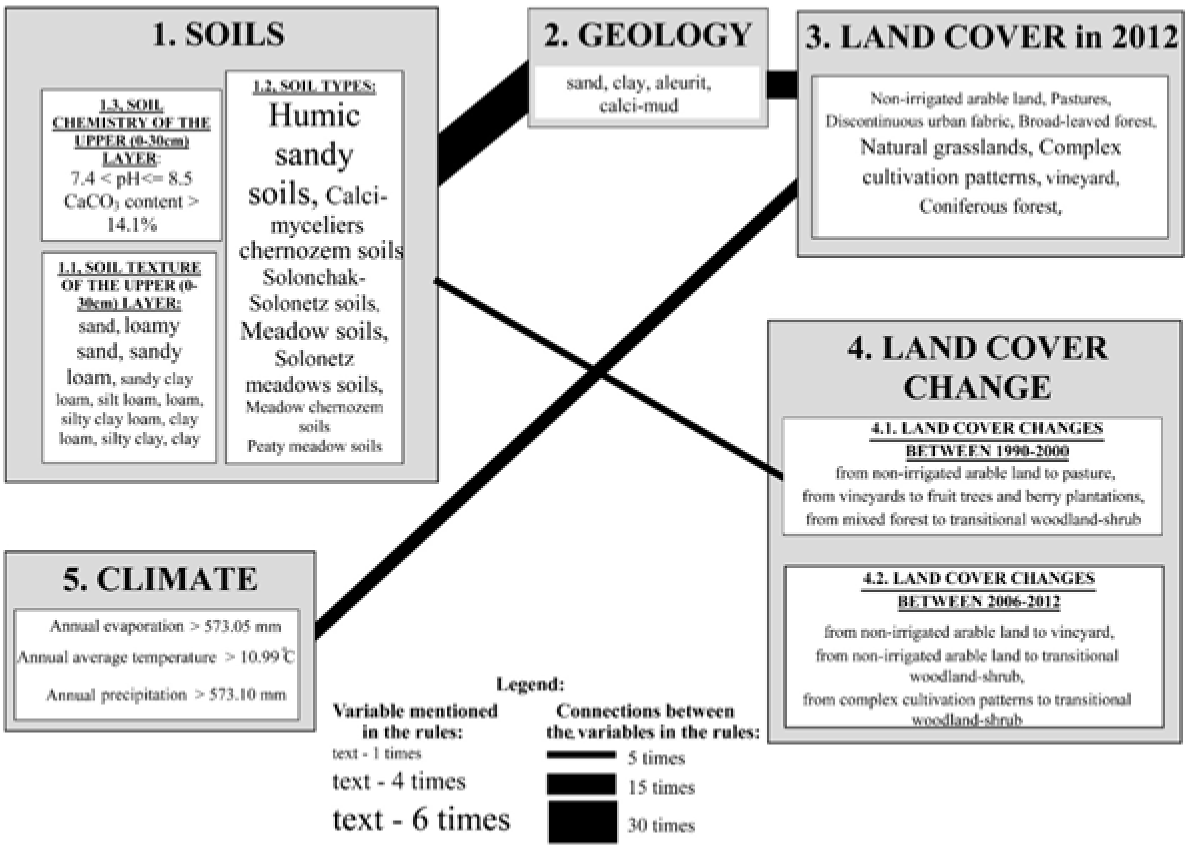
Table 2. Main Application Areas of Artificial Intelligence in Geographical Research

Remote sensing and Earth observation	Automatic interpretation of satellite and drone imagery; recognition of land cover and objects	CNN, U-Net, Vision Transformer	Land cover and land use classification, deforestation detection, analysis of urbanisation processes
Spatio-temporal prediction	Prediction of dynamic natural and social processes in space and time	LSTM, TCN, Graph Neural Networks	Air pollution and traffic forecasting, hydrological and flood modelling
Disaster and risk analysis	Identification of natural hazards; mapping vulnerability and risk	Deep learning, anomaly detection	Flood, wildfire and landslide susceptibility maps, damage assessment
Environmental and ecological modelling	Spatial assessment of ecosystems, soil conditions and carbon cycling	Random Forest, XGBoost, Bayesian models	Habitat and ecosystem modelling, estimation of soil organic carbon, prediction of soil degradation
Urban and regional modelling (Urban GeoAI)	Analysis of urban structure, mobility and environmental pressures	GNN, reinforcement learning, agent-based models	Urban growth trends, traffic regulation, energy management
Precision agriculture	Spatial optimisation of production processes	CNN, clustering, reinforcement learning	Crop yield prediction, crop condition and stress detection, input optimisation
Geological and geophysical analysis	Recognition of geological structures and patterns	CNN, graph-based models, unsupervised learning	Seismic data analysis, ore deposit potential estimation, lithological classification
Data fusion and multimodal integration	Joint processing of geospatial data from different sources	Multimodal learning, transfer learning, knowledge graphs	Integration of satellite, sensor and social data, digital twin systems
GeoAI-based decision support	Interpretation of predictions, uncertainty and impacts in decision-making	Explainable AI, ensemble modelling	Environmental risk maps, sustainability and land-use decision support
Automated GIS processing	Automation of GIS workflows	NLP, generative models (LLMs, diffusion models)	Metadata generation, automatic map description, generation of synthetic geospatial data

Several authors have synthesised the highly diverse geographical and Earth science applications of GeoAI in special journal issues (Janowicz et al., 2020), while others have addressed the topic in standalone volumes (Gao et al., 2023). Hungarian studies also demonstrate that GeoAI algorithms are capable of detecting changes on the Earth's surface—such as land-use transformations and shifts in environmental conditions—using satellite and drone imagery. For example, Bui and Mucsi (2021) applied AI-based methods to produce a large-scale land cover map of Hungary, while Farmonov et al. (2023) employed similar approaches to estimate crop yields (Bui & Mucsi, 2021; Farmonov et al., 2023). In research on the impacts of climate change in Hungary, AI-based GIS analyses have likewise proven effective for forecasting certain meteorological patterns and modelling the long-term effects of climate change, including drought and inland excess water (Kajári et al., 2024).

GeoAI also provides valuable support for land-use planning by facilitating the selection of land-use types that best match specific landscape characteristics, such as soil properties and climatic conditions. Moreover, AI-based methods are well suited to exploring the geographical background and underlying causes of environmental and nature conservation issues, including the spread of invasive plant species or levels of urban particulate matter. These methods enable the identification of geographical factors influencing the magnitude and spatial distribution of such phenomena—such as the occurrence of invasive species or temporal variations in PM10 concentrations—the assessment of the relative importance (weight) of these factors (Figure 3), and the exploration of the relationships among them (Papp et al., 2021; Sohrab et al., 2024; Szilassi et al., 2019).

Figure 3. The Weight of Environmental Variables Affecting the Presence of an Invasive Plant (Asclepias Syriaca) and Those Variables' Relationship to One Another



Source: Papp et al. 2021

The application of GeoAI in the study of natural hazards is widespread worldwide, particularly in the spatial prediction of flood, landslide, and erosion risks, where machine learning enables the integrated evaluation of complex environmental factors (Akinci et al., 2022; Band et al., 2020; Choi et al., 2025).

AI-based modelling is also gaining increasing importance in the forecasting of large-scale environmental processes. A recent study provides a representative example: the future spatial distribution of four major ecosystem types was predicted using a Random Forest algorithm under different climate change scenarios (Tölgyesi et al., 2025). The model inputs primarily consisted of climatic, bioclimatic, and environmental variables, while the outputs represented the projected global redistribution of ecosystem types. Based on the AI-derived classification results, the authors subsequently estimated future global carbon sequestration potential, thereby demonstrating the extent to which ecosystem shifts may influence the Earth's carbon cycle. Similar AI-based approaches are increasingly applied in global-scale ecosystem and biosphere modelling, where machine learning supports the prediction of climate change impacts as well as the spatial dynamics of ecosystem functions and the carbon cycle (Ahlström et al., 2017; Bastin et al., 2025; Forkel et al., 2019; Huang et al., 2023).

GeoAI and machine learning are likewise becoming increasingly influential in soil science research, particularly in the fields of digital soil mapping and the spatial estimation of soil functions. Numerous recent studies have shown that Random Forest and other machine learning algorithms can be effectively applied to predict soil properties, soil organic carbon content, and related indicators by integrating large environmental covariate databases. AI-based models are able to capture complex non-linear relationships among soil characteristics, topography, and climate, often providing more accurate estimates than traditional statistical methods, even at regional and national scales (Csikós et al., 2023; Sohrab et al., 2025; Szatmári & Pásztor, 2025). These findings clearly demonstrate that GeoAI is not merely a descriptive mapping tool but also plays a crucial role in analysing future changes in soil conditions, soil functions, and carbon sequestration. At the international level, digital soil mapping and the modelling of soil functions represent one of the most dynamically developing areas of GeoAI application, where machine learning methods have consistently been shown to outperform conventional statistical approaches (Hengl et al., 2017, 2018; Sun et al., 2023; Taghizadeh-Mehrjardi et al., 2020; Wadoux et al., 2020).

GeoAI and AI-based geospatial data processing are also gaining increasing importance in the analysis of urban environments, particularly in the domains of urban green infrastructure and high-resolution spatial mapping. Several studies have introduced treetop detection methods based on airborne LiDAR data that reliably identify individual woody vegetation, even in low-resolution laser-scanned datasets and under complex, multilayered urban canopy conditions. The practical applicability of these methods is further enhanced by their availability as reproducible, open-source R packages. Other research has examined the effects of Structure from Motion (SfM) processing techniques and various UAS-based data acquisition strategies on the accuracy of urban land-use mapping, as well as evaluated the quality of orthophotos and digital surface models (DSM) using explainable AI metrics. GeoAI-based approaches are also increasingly applied in studies of the urban heat island effect, where machine learning models integrate satellite-derived land surface temperature data with urban structural parameters to reveal the non-linear relationships governing thermal stress, thereby supporting climate adaptation strategies and urban planning decisions. Globally, AI-based urban environmental analysis is expanding rapidly, particularly through the integrated processing of high-resolution remote sensing data (LiDAR, UAS) and detailed urban structural information, opening new opportunities for the quantitative assessment of urban environmental processes (Chen et al., 2022; Kosuri et al., 2025; Lifelo et al., 2024; Xu et al., 2019; Zhang et al., 2025).

Within European Union research programmes, artificial intelligence now appears not only as an applied methodological component but also explicitly at the project title level, clearly indicating the institutionalisation of GeoAI. A prominent example is the *AI4SoilHealth* project (https://ai4soilhealth.eu/), which develops AI-based solutions for the spatial assessment and monitoring of soil condition, soil functions, and soil health by integrating diverse Earth observation, soil, and environmental data sources. A comparable initiative is the *AI4Copernicus* project (https://ai4copernicus-project.eu/), which prioritises AI-driven processing of Copernicus Earth observation data, enabling faster and more accurate spatial analyses of land cover change, environmental processes, and climate change impacts. These projects clearly demonstrate that AI is becoming a key integrative technology in European geographical and environmental research, particularly in the analysis of large-volume and complex spatial systems.

Finally, AI-based methods can also be effectively applied to the visualisation of maps and other types of spatial data, for example in the reconstruction of historical landscapes from archival cartographic sources such as the First Military Survey (Figure 4).

In recent years, AI-based literature search and research support tools have emerged and are increasingly applied in Earth science research. Tools such as Scopus AI and the Web of Science Research Assistant facilitate literature discovery, the preparation of thematic summaries, and the identification of key publications based on natural-language queries. Similarly, scite.ai analyses citation context by distinguishing between supporting, contrasting, and methodological citations, which is particularly useful for critical literature evaluation. In addition, AI-based research support functionalities have been integrated into the Nature portfolio, providing authors with assistance in literature exploration and manuscript preparation. However, these solutions are dependent on the underlying databases, their output is not fully transparent, and the generated summaries require careful verification; therefore, they should be regarded primarily as complementary rather than substitutive tools.

AI has thus become suitable for the semantic classification of texts—including scholarly articles, regional descriptions, textbook content, and news reports—as well as for the statistical analysis of the frequency of user-defined words and phrases, and for extracting generalisable relationships from such analyses. For example, by examining publications produced by geographers over recent decades, it is possible to identify changes in authors' publishing practices, shifts in the prevalence of specific research topics (e.g., landscape geography or environmental geography), temporal trends in particular research directions and methods, and developments in the philosophy of science (Boros et al., 2025; Szilassi et al., 2024).

Figure 4. Figure 4. Nagy-Nádas Swamp at Farmos before water regulations. (a) Detail of the First Military Survey (1782–1785) Map that Serves as a Compositional Model; (b) AI-generated Image

Source: Jakab et al., 2025

Primarily in human geography and integrative approaches, the 2023 AI volume (Gao et al., 2023) presents a wide range of practical applications. Moreover, Wang and colleagues analysed 1,516 human geography studies published over the past two decades and sourced from the Web of Science that employed GeoAI methods. This corpus includes a substantial number of interdisciplinary studies leveraging integrated research platforms, encompassing fields such as public health, environmental science, and medical science (Wang et al., 2024).

Challenges and Limitations of Applying AI in Geography and Earth Sciences

The geographical application of AI is accompanied by several generally recognised challenges and limitations, including issues related to model interpretability, potential biases, and limited suitability for specific research questions. AI models typically require region-specific data, and the availability and applicability of data across different areas often constitute major constraints. Because the quality of input data strongly influences the reliability of model outputs, problems frequently arise due to data errors, limited accuracy, restricted spatial or temporal validity, or insufficient alignment with the requirements of geographical analysis. From a results perspective, biased validation procedures may introduce additional uncertainty, which can be further amplified during algorithmic processing.

It is important to note, however, that AI does not necessarily function as a complete "black box" in which only inputs and outputs are observable while internal processes remain entirely opaque. Explainable AI (xAI) approaches have been developed precisely to enhance transparency; examples include methods such as LIME and SHAP, which are applied, for instance, in image analysis.

The current heightened interest in AI is likely partly attributable to its demonstrated success in applications such as weather forecasting and COVID-19 prediction. At the same time, many GeoAI applications essentially perform operations that, from a GIS perspective, amount to spatial—and sometimes temporal—searches, that is, the identification of cases and patterns that satisfy predefined criteria. A limitation of such approaches is that they may amount to little more than a sophisticated form of reclassification. In some instances, GeoAI has been employed solely to generate visually compelling but scientifically limited representations of landscapes, contributing minimally to the advancement of geographical knowledge (Hu et al., 2024).

The use of GeoAI is further complicated by differences in legal and regulatory frameworks governing data access across countries; for example, a river and its catchment area may span multiple states, each with distinct data governance regulations.

Artificial Intelligence in Geography Education

When considering the application of AI in geography education, key questions include why AI should be taught, who it affects, which methods are most appropriate, and what content should be delivered. This overview is not intended as technical instruction at the university level; it does not focus on mathematical details but, building on secondary-level knowledge, aims to illustrate how subject-specific understanding can open new avenues for problem-solving and development in geographical applications.

As demonstrated in the examples above, AI in geography primarily supports the comprehension of patterns and relationships. A major contribution lies in the use of interactive visualisations and realistic simulations, which integrate geographical locations and natural phenomena into the learning process. The growing array of AI-based visualisation tools can make teaching and learning more efficient, intuitive, and engaging. Furthermore, incorporating AI into geography classes facilitates discussion of broader educational questions, such as the limits of knowledge transmission and the degree to which students and teachers are motivated to learn about and utilise AI, particularly GeoAI.

Teachers can leverage AI to design personalised learning plans, enhance educational experiences, provide intelligent learning analytics, and improve overall learning efficiency. However, the effective implementation of AI in geography education—including public education, where geography encompasses Earth sciences—requires the active engagement of all participants (teachers, lecturers, students, and pupils) and the availability of necessary resources, including hardware, software, data, and expertise. AI automation can reduce teacher workload and improve instructional effectiveness, for example by assisting in the evaluation of assignments and reports.

In traditional teaching, educators devote significant time to tasks such as question design, grading, performance evaluation, and test analysis. AI technologies—including image recognition, predictive systems, and virtual reality—can not only generate examination questions but also automatically grade homework and tests, thereby increasing assessment efficiency. Continuous assessment, feedback, and progress monitoring are particularly important for maintaining educational quality. While some educators may perceive AI as a potential threat to their professional role, it simultaneously enables new pedagogical approaches, such as virtual field trips and immersive virtual classrooms. These approaches allow for the simulation of difficult-to-observe geographical processes and the visualisation of natural phenomena that are otherwise inaccessible (Rakuasa, 2023). In this way, AI functions as a powerful tool for supporting critical thinking, learning, and curriculum development.

AI-generated teaching materials can be customised to individual learners' needs, supporting personalised instruction. It is important to note, however, that not all topics benefit from AI integration, particularly certain social topics. Integrating AI into existing geography curricula represents a significant challenge, as curricula must remain flexible enough to accommodate emerging technologies. Teacher training—including the preparation of trainers—is therefore essential. AI can also support adaptive learning, adjusting the difficulty of materials, tasks, tests, and exercises to individual learners (Huang et al., 2021). Such adaptation should encompass both content and methodology, including data mining, intelligent tutoring systems, and learning analytics.

GeoAI, through cloud-based geospatial databases, enables students to quickly and efficiently access large volumes of geographical data and to explore realistic, visually represented maps, locations, natural phenomena, virtual fieldwork, and interactive simulations (Wilby & Esson, 2024).

Beyond curriculum content and infrastructure, a critical future consideration is whether teacher education equips educators with sufficient knowledge and experience to use AI effectively and responsibly. A clear limitation is exemplified by the widespread use of language models such as ChatGPT: although these tools can generate text, they often fail to properly address spatiality, territoriality, temporality, and scale—core concepts in geography. Their outputs are generated through probabilistic text continuation based on keywords rather than conventional scientific methods. Earlier limitations included the lack of access to real-time information, raising concerns about reliability. For these reasons, it is essential that students not only rely on AI tools but also understand the underlying geographical concepts and processes. Developing critical thinking skills among both students and teachers is therefore fundamental to avoid uncritical reliance on AI-generated outputs.

The use of AI in education also raises pedagogical, legal, and ethical questions. For AI-generated teaching materials, issues of authorship and intellectual property arise: who owns the curriculum, the lesson plan, or the content, and whose name should be associated with it? This also prompts organisational questions within educational institutions (Zawacki-Richter et al., 2019). Additional ethical concerns relate to ownership of AI-generated outputs, particularly in contexts where even a lecturer's voice can now be digitally cloned. Despite these challenges, LLMs present opportunities to reduce regional socio-economic disparities in educational quality.

CONCLUSIONS

The emergence of artificial intelligence in geography can be traced back to Dobson's 1983 work *Automated Geography* and Openshaw's 1997 volume *Artificial Intelligence in Geography*. One of the primary drivers of the rapid development of GeoAI over the past decade is the availability of user-friendly Python and R libraries, which enable practical applications even for users with basic programming skills. Concurrently, AI-based applications have gained traction in human geography, particularly in research on settlements, mobility, the environment, and medical geography (Biljecki, 2023).

An interesting experiment involves asking ChatGPT to generate a summary of the ideas presented in this paper and comparing it with the authors' own text. The AI produced a text structured into two chapters based on a few keywords. One chapter, titled *Geographical Research*, focused on GIS (data processing and analysis, image recognition, forecasting and modelling, particularly of natural hazards), environmental monitoring (climate change, pollution), and urban studies (urban development, transport systems). The second chapter, titled *Geographical Education*, addressed interactive learning tools (virtual and augmented reality, smart maps), personalised learning (adaptive platforms, automated assessment), data visualisation, and interactive mapping.

Based on the national and international examples presented, several key trends in the application of AI in Earth sciences are evident. The most dynamic growth occurs in subfields of geography characterised by large volumes of spatially and temporally variable data, particularly remote sensing, urban studies, natural hazard research, and soil and ecosystem modelling. A common feature of current developments is the increasing use of data fusion, i.e., the integrated processing of datasets from diverse sources (satellite, field, sensor, statistical), as well as a growing emphasis on spatio-temporal prediction. Attention to uncertainty management and interpretability is also rising, as reflected in the proliferation of explainable AI approaches.

In this context, GeoAI represents not only a new analytical toolkit but also a broader shift in the epistemological orientation of Earth science research. Alongside descriptive mapping, process-oriented, function-oriented, and decision-support analyses are becoming increasingly prominent. From the perspective of education and research, AI should therefore not be viewed merely as a technological innovation, but rather as an integrative methodological framework that facilitates the understanding of complex spatial systems. We are confident that AI-based methods will collectively stimulate a rethinking of the role, focus, and objectives of geography in the 21st century.

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