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Artificial intelligence and GIS: Transforming spatial analysis—A review

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Abstract
Artificial Intelligence (AI) has emerged as a transformative technology across numerous scientific disciplines, with Geographic Information Systems (GIS) being one of the most significantly impacted fields. The integration of AI with GIS has revolutionized spatial data acquisition, processing, analysis, and visualization by enabling automated pattern recognition, predictive modeling, and intelligent decision-making. This review examines the convergence of AI and GIS, highlighting recent developments in machine learning, deep learning, computer vision, natural language processing, and reinforcement learning within geospatial applications. The paper discusses key application domains, including urban planning, environmental monitoring, disaster management, transportation, precision agriculture, and public health. Furthermore, it explores current challenges related to data quality, interpretability, computational requirements, ethics, and privacy. Finally, the review outlines emerging research directions, emphasizing explainable AI, digital twins, edge computing, cloud GIS, and generative AI as promising areas that will shape the future of intelligent spatial analysis.

Keywords: Artificial intelligence, geographic information systems, GIS, spatial analysis, machine learning, deep learning, remote sensing, geospatial intelligence

Introduction

Artificial Intelligence in Geographic Information Systems (GIS)

Geographic Information Systems (GIS) have become indispensable tools for collecting, managing, analyzing, and visualizing geographically referenced information. Traditionally, GIS relied heavily on statistical analysis, rule-based modeling, and expert interpretation for extracting insights from spatial data. However, the rapid growth of geospatial datasets generated from satellites, drones, sensors, mobile devices, and Internet of Things (IoT) technologies has created unprecedented challenges in handling large-scale, heterogeneous, and dynamic spatial information (Malaker & Meng, 2026) [9].

Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), offers powerful computational techniques capable of automatically identifying patterns, learning from complex datasets, and making intelligent predictions. The integration of AI with GIS has significantly enhanced spatial analysis by improving automation, prediction accuracy, and decision support (Malaker & Meng, 2026) [9].

This review explores how AI is transforming GIS methodologies, summarizes recent technological advances, identifies application areas, and discusses existing challenges and future opportunities.

Evolution of GIS and Artificial Intelligence

Geographic Information Systems (GIS) originated in the 1960s as computerized systems designed for storing, managing, and analyzing spatial information. Initially focused on digital mapping and basic spatial analysis, GIS has evolved significantly over the decades into advanced platforms capable of integrating spatial databases, remote sensing data, Global Positioning System (GPS) technologies, web-based mapping services, cloud computing, and three-dimensional (3D) visualization. Parallel to this evolution, Artificial Intelligence (AI) has progressed from early rule-based expert systems to more sophisticated machine learning algorithms, deep learning architectures, reinforcement learning techniques, and, most recently, generative AI and foundation models. These advances have greatly enhanced the ability of AI to process large and complex geospatial datasets, recognize spatial patterns, automate feature extraction, and generate predictive insights. The convergence of GIS and AI has transformed conventional GIS from a descriptive mapping and visualization tool into an intelligent spatial decision-support system capable of learning from data, adapting to dynamic environments, and supporting evidence-based decision-making across diverse fields such as urban planning, environmental monitoring, disaster management, transportation, agriculture, and public health (Malaker & Meng, 2026) [9].

Artificial Intelligence Techniques in GIS

1. Machine Learning

Machine Learning (ML) is one of the most widely adopted branches of Artificial Intelligence in Geographic Information Systems (GIS), enabling computers to identify patterns, make predictions, and improve performance through experience without being explicitly programmed. By learning from historical and spatial datasets, ML algorithms can effectively analyze complex geospatial relationships and generate accurate predictive models. Commonly used machine learning techniques in GIS include Decision Trees, Random Forests, Support Vector Machines (SVM), Gradient Boosting, K-Nearest Neighbors (KNN), and Naïve Bayes classifiers. These algorithms are particularly effective in handling large and multidimensional geospatial datasets, making them suitable for a wide range of spatial analysis tasks (Belgiu & Drăguț, 2016; Mountrakis *et al.*, 2011) [2, 11].

Applications of machine learning in GIS include land-use and land-cover classification, soil property mapping, habitat suitability modeling, flood susceptibility assessment, urban growth prediction, groundwater potential mapping, and environmental risk analysis. Compared with traditional statistical and rule-based methods, machine learning techniques can provide automated approaches for modeling complex nonlinear relationships, although performance depends on training data, feature selection, model specification, and validation (Belgiu & Drăguț, 2016; Mountrakis *et al*., 2011) [2, 11]. As the availability of high-resolution satellite imagery, remote sensing data, and spatial big data continues to increase, machine learning has become an important tool for enhancing spatial decision-making and reducing the need for extensive manual interpretation in geospatial analysis (Malaker & Meng, 2026) [9].

2. Deep Learning

Deep Learning (DL), a specialized subset of machine learning, has revolutionized geospatial analysis by enabling the automatic extraction of complex and hierarchical spatial features from large-scale datasets. Unlike conventional machine learning methods that rely on manually engineered features, deep learning models learn multiple levels of data representation through multilayer neural networks, resulting in improved accuracy and robustness in spatial analysis tasks (Ma *et al*., 2019; Zhu *et al*., 2017) [18, 20]. Several deep learning architectures have demonstrated success in GIS and remote-sensing applications, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Transformer-based models (Ma *et al*., 2019; Zhu *et al*., 2017) [20].

CNNs are particularly effective for processing high-resolution satellite and aerial imagery and are widely used for land-use and land-cover classification, object detection, building footprint extraction, road network mapping, and semantic segmentation (Ma *et al*., 2019). RNNs and LSTM networks are suited to temporal and sequential data, while GNNs can represent relationships among interconnected spatial entities. Transformer architectures have also expanded the capabilities of large-scale image interpretation and multimodal analysis by modeling long-range dependencies (Kipf & Welling, 2017; Vaswani *et al*., 2017) [6]. Overall, deep learning has enhanced the automation, precision, and scalability of geospatial analysis, reducing the need for manual feature extraction and enabling analysis of increasingly complex Earth-observation datasets (Ma *et al*., 2019; Zhu *et al*., 2017) [20].

3. Computer Vision

Computer Vision (CV) is a rapidly advancing field of Artificial Intelligence that enables computers to automatically interpret, analyze, and extract meaningful information from visual data such as satellite imagery, drone images, and aerial photographs. In Geographic Information Systems (GIS), computer vision techniques have enhanced the automation and accuracy of image interpretation, reducing dependence on manual digitization and visual inspection (Ma *et al*., 2019; Zhu *et al*., 2017) [20]. By combining advanced image-processing methods with deep learning algorithms, computer vision can identify and classify geographic features from remote-sensing imagery. Its applications include feature extraction, infrastructure mapping, forest and vegetation monitoring, coastal erosion assessment, illegal mining detection, glacier and snow-cover monitoring, urban expansion analysis, and disaster damage assessment. Modern object-detection and image-segmentation models, such as You Only Look Once (YOLO) and Mask Region-Based Convolutional Neural Network (Mask R-CNN), have improved the detection and delineation of buildings, roads, water bodies, and other land features from high-resolution imagery (He *et al*., 2017; Redmon *et al*., 2016) [4, 12]. As the availability of high-quality Earth-observation data continues to grow, computer vision is becoming increasingly valuable for efficient geospatial analysis and environmental monitoring (Ma *et al*., 2019) [18].

4. Natural Language Processing (NLP)

Natural Language Processing (NLP) is an important branch of Artificial Intelligence that enables computers to understand, interpret, and analyze human language from unstructured textual data. Within Geographic Information Systems (GIS), NLP facilitates the extraction of geographic information from diverse text sources, including social media posts, government reports, scientific publications, news articles, disaster reports, and citizen-generated content. Techniques such as text mining, named entity recognition, sentiment analysis, and language modeling can identify geographic locations, events, and spatial relationships embedded in textual information (Hu, 2017) [16].

Typical GIS applications include automated geocoding, place-name recognition (toponym detection), disaster monitoring, public sentiment mapping, crisis response, and location-based information retrieval. During natural disasters and public emergencies, NLP can support the rapid analysis of large volumes of textual information to identify affected areas and emerging needs. Recent advances in transformer-based language models have further expanded NLP capabilities, including natural-language interaction with geospatial information systems and the integration of textual and spatial information (Hu, 2017; Vaswani *et al*., 2017) [16].

5. Reinforcement Learning

Reinforcement Learning (RL) is a branch of Artificial Intelligence in which an intelligent agent learns to make decisions by interacting with its environment and receiving feedback in the form of rewards or penalties. Unlike supervised learning, which relies on labeled datasets, reinforcement learning improves a decision-making policy through interaction and trial-and-error learning, making it relevant to dynamic and uncertain environments (Yau *et al*., 2017) [19].

In Geographic Information Systems (GIS), RL has gained attention for complex spatial optimization and real-time decision-making problems. Its applications include traffic signal optimization, emergency evacuation planning, autonomous vehicle and drone navigation, resource allocation, logistics optimization, and smart-city management. For example, RL-based traffic-management systems can dynamically adjust traffic-signal timings according to changing traffic conditions (Miletić *et al*., 2022; Yau *et al*., 2017) [10, 19]. Similarly, RL can be investigated for adaptive routing and resource-allocation problems in dynamic environments. As computational power, simulation environments, and real-time geospatial data continue to evolve, reinforcement learning has potential for supporting adaptive and autonomous GIS applications (Miletić *et al*., 2022; Yau *et al*., 2017) [10, 19].

AI-Driven Spatial Analysis

Artificial Intelligence (AI) has fundamentally transformed traditional spatial analysis by enabling Geographic Information Systems (GIS) to identify complex spatial patterns, generate predictions, detect changes, and support spatial optimization more efficiently than many conventional approaches. AI-based pattern-recognition methods can uncover relationships and spatial structures within large and heterogeneous datasets, supporting applications such as disease-cluster identification, crime-hotspot analysis, urban expansion monitoring, and vegetation-pattern assessment (Malaker & Meng, 2026; Zhu *et al*., 2017) [9, 20]. Machine learning techniques can also be used for spatial prediction, allowing researchers and planners to model and forecast spatial phenomena such as flood susceptibility, landslide occurrence, deforestation, population growth, and urban sprawl by learning relationships between historical observations and relevant environmental or socioeconomic variables (Belgiu & Drăguț, 2016; Mountrakis *et al*., 2011) [2, 11]. Another important application is change detection, where deep learning models automatically compare multi-temporal satellite and remote-sensing imagery to identify changes in forest cover, coastal environments, urban areas, agricultural land, and glaciers, thereby reducing the need for extensive manual image interpretation (Bai *et al*., 2023; Kaur & Afaq, 2024) [1, 5]. In addition, AI and reinforcement-learning approaches are increasingly being investigated for spatial optimization problems, including facility-location decisions, route planning, transportation management, resource allocation, and logistics, where algorithms can learn or identify efficient solutions under complex spatial and operational constraints (Wang & Tang, 2021; Xiao & Murray, 2019) [17, 18]. Overall, the integration of AI into spatial analysis is enabling GIS to move beyond conventional descriptive analysis toward more predictive, automated, and optimization-oriented decision-support capabilities.

Applications of AI in GIS

1. Urban Planning

Artificial Intelligence (AI) integrated with Geographic Information Systems (GIS) has become an important approach in urban planning by enhancing spatial analysis, prediction, and data-driven decision-making for sustainable urban development. AI and GeoAI techniques can process large volumes of spatial and temporal information from satellite imagery, sensor networks, mobile devices, and Internet of Things (IoT) systems to identify urban growth patterns, predict development trends, analyze land-use changes, and support infrastructure planning (Sevinç *et al*., 2026) [14]. Machine learning and deep learning can also contribute to traffic prediction, transportation planning, infrastructure management, population analysis, and land-use optimization. In addition, the integration of AI, GIS, real-time sensor data, and simulation environments can support digital-twin approaches in which planners evaluate alternative development scenarios and assess infrastructure and environmental impacts before implementing interventions. Overall, the combination of AI and GIS provides urban planners with more automated and data-driven tools for understanding complex urban systems and supporting resilient and sustainable city development (Sevinç *et al*., 2026) [14].

2. Environmental Monitoring

AI has significantly strengthened environmental monitoring by enabling GIS and remote-sensing systems to process and interpret large volumes of spatial and temporal data more efficiently. Machine learning and deep learning methods can be applied to satellite, UAV, and sensor data for monitoring vegetation, forests, water resources, land-cover change, and other environmental conditions (Zhu *et al*., 2017) [4]. In particular, AI-based image analysis can support the detection of forest-cover changes and other landscape transformations from multi-temporal remote-sensing imagery. Deep learning is also increasingly used to extract environmental features automatically from remotely sensed data, supporting applications in ecosystem monitoring, climate-related assessment, and natural-resource management (Ma *et al*., 2019; Zhu *et al*., 2017) [20]. By integrating multiple geospatial datasets, AI-driven GIS can therefore improve environmental assessment and provide more timely information for conservation planning, natural-resource management, and evidence-based environmental decision-making.

3. Disaster Management

The integration of AI and GIS has important applications in disaster management because it enables the rapid analysis of large volumes of spatial information before, during, and after hazardous events. Machine learning and deep learning can process satellite imagery, UAV observations, weather information, sensor measurements, and other geospatial datasets to support hazard assessment, disaster detection, damage mapping, and emergency response (Zhu *et al*., 2017) [20]. AI-based remote-sensing methods can assist in identifying affected areas and extracting damaged buildings, roads, vegetation, and other features following disasters, thereby reducing the time required for manual interpretation (Ma *et al*., 2019). GIS further enables these outputs to be integrated with information on infrastructure, population, transportation networks, and accessibility to support emergency planning and resource allocation. Consequently, AI-driven GIS can improve the speed and analytical capacity of disaster-response systems and contribute to more effective risk reduction and emergency decision-making.

4. Precision Agriculture

Artificial Intelligence integrated with GIS and remote sensing has become an important component of precision agriculture by supporting spatially targeted monitoring and management of agricultural resources. Remote sensing and GIS provide information on crop health, soil conditions, water status, vegetation characteristics, and yield variability, while machine learning and deep learning can analyze these data to identify patterns and generate predictive information for farm management (Sangeetha *et al*., 2024) [13]. AI-driven systems can support crop-health monitoring, disease and pest detection, yield estimation, soil-moisture assessment, irrigation management, and variable-rate application of agricultural inputs. UAV-based remote sensing further provides high-resolution imagery that can be analyzed using deep-learning techniques for crop monitoring and the detection of agricultural stress (Liu *et al*., 2021) [7]. By integrating these technologies, precision agriculture can improve the spatial and temporal precision of agricultural decision-making while contributing to more efficient use of water, fertilizers, pesticides, and other resources (Sangeetha *et al*., 2024) [13].

5. Transportation

AI integrated with GIS has significantly expanded the capabilities of transportation planning and management by enabling the analysis of large volumes of spatial and temporal mobility data. Machine learning and other AI techniques can be applied to traffic data to identify travel patterns, forecast congestion, optimize routes, and support intelligent transportation systems. GeoAI applications in smart cities increasingly include transportation management, navigation, route analysis, and the integration of spatial information with real-time data (Sevinç *et al*., 2026) [14]. AI can also support dynamic traffic management by analyzing changing traffic conditions and assisting with route and network optimization. In addition, the integration of GIS, computer vision, sensors, and high-resolution spatial information contributes to autonomous-vehicle navigation and localization. Overall, AI-driven GIS provides analytical capabilities that can help improve transportation efficiency, mobility planning, and the management of increasingly complex urban transportation networks (Sevinç *et al*., 2026) [14].

6. Public Health

The integration of AI with GIS has become increasingly valuable in public health because spatial analysis can reveal geographic patterns in disease, environmental exposure, healthcare accessibility, and population vulnerability. GIS-based public-health approaches can integrate epidemiological, demographic, environmental, and healthcare data to support disease surveillance, spatial risk assessment, healthcare-accessibility analysis, and resource planning (Stasinos *et al*., 2026) [15]. AI and machine-learning methods can further assist in identifying spatial patterns and relationships within large health-related datasets, supporting disease-risk assessment and evidence-based decision-making. GIS can also be used to evaluate the geographic distribution of healthcare facilities and populations, helping identify areas with limited access to health services. The growing integration of geospatial technologies with AI therefore provides an important foundation for spatial epidemiology, healthcare planning, and public-health decision support (Stasinos *et al*., 2026) [15].

Emerging Technologies

Several emerging technologies are expanding AI-enabled GIS capabilities.

Cloud GIS

Cloud computing provides scalable infrastructure for processing large geospatial datasets.
Examples include cloud-based geospatial platforms that enable collaborative analysis and large-scale satellite data processing.

Internet of Things (IoT)

IoT sensors continuously generate spatial data for:

- Smart cities
- Environmental monitoring
- Transportation
- Agriculture
- Utilities

AI processes these streaming datasets for real-time decision-making.

Edge Computing

Edge computing reduces latency by processing spatial information closer to data sources, making it valuable for autonomous vehicles, drones, and disaster response.

Digital Twins

Digital twins integrate AI, GIS, IoT, and simulation models to create dynamic virtual representations of real-world environments for planning and management.

Generative AI

Generative AI and large language models are increasingly being integrated with GIS to:

- Generate spatial reports
- Automate geospatial workflows
- Support natural language querying of maps
- Assist in geospatial programming
- Summarize spatial datasets

These capabilities lower technical barriers and improve accessibility for non-specialist users.

Model Generalization

Models trained in one geographic region may perform poorly in different environmental or socioeconomic contexts, highlighting the need for transferable and adaptable learning methods.

Future Research Directions

The integration of Artificial Intelligence (AI) and Geographic Information Systems (GIS) continues to evolve rapidly, creating new opportunities for advancing spatial analysis and intelligent decision-making. Future research is expected to focus on developing Explainable Artificial Intelligence (XAI) techniques to improve the transparency, interpretability, and trustworthiness of AI-driven spatial models, particularly in critical applications such as disaster management, urban planning, and environmental monitoring. Privacy-preserving approaches, including federated learning, are also gaining importance as they enable collaborative geospatial analytics across distributed datasets without compromising sensitive location-based information. Another promising direction is the integration of foundation models and large language models (LLMs) with GIS workflows, enabling automated geospatial analysis, natural language querying of spatial databases, and intelligent generation of maps and analytical reports. AI-powered digital twins are expected to play a significant role in sustainable urban management by creating dynamic virtual representations of cities that support real-time monitoring, infrastructure planning, and scenario simulation. Furthermore, advances in edge AI will facilitate real-time geospatial intelligence by processing spatial data closer to its source, thereby reducing latency and improving the responsiveness of applications such as autonomous vehicles, disaster response, and smart infrastructure. Multi-modal learning, which combines satellite imagery, textual information, sensor observations, and spatial databases, is another emerging research area that promises more comprehensive and context-aware geospatial analysis. Future studies are also likely to emphasize AI applications for climate resilience, biodiversity conservation, sustainable resource management, and environmental risk assessment to address the growing impacts of climate change. Additionally, greater attention will be given to human–AI collaboration, where AI systems complement human expertise by providing interpretable insights and decision support rather than replacing human judgment. Collectively, these emerging research directions are expected to transform GIS into more intelligent, adaptive, and collaborative systems capable of addressing increasingly complex environmental, social, and economic challenges while supporting sustainable development and informed policymaking.

Conclusion

The integration of Artificial Intelligence with Geographic Information Systems represents one of the most significant advances in modern spatial science. AI enhances GIS by automating feature extraction, improving predictive accuracy, enabling real-time analytics, and supporting intelligent decision-making across a broad spectrum of applications. From urban planning and environmental conservation to disaster management, transportation, agriculture, and public health, AI-driven GIS has become an essential component of data-driven policy and resource management.

Nevertheless, important challenges remain, including data quality, computational demands, interpretability, ethical considerations, and privacy protection. Addressing these issues through explainable, transparent, and responsible AI will be critical for ensuring trustworthy geospatial systems. As cloud computing, IoT, digital twins, and generative AI continue to mature, the synergy between AI and GIS is expected to redefine the future of spatial analysis and contribute significantly to sustainable development and informed decision-making.

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