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AI and Machine Learning in Geospatial Analysis: Advances, Biases, and Future Directions (2020–2026)

R. S. Daniel [1]

ABSTRACT

The rapid integration of artificial intelligence and machine learning into geospatial analysis (2020–2026) has transformed spatial research through cloud computing, advanced deep learning architectures, and foundation models. Yet, technical progress frequently outpaces critical evaluation of spatial validity, equity, and reproducibility. This review synthesizes contemporary GeoAI developments using a PRISMA-guided scoping framework and critical narrative analysis. We examine paradigm shifts from rule-based statistics to self-supervised learning, map domain-specific applications across environmental, urban, and human geography, and interrogate systemic challenges including spatial sampling bias, algorithmic opacity, and commercial data monopolies. Findings reveal that while predictive accuracy has improved dramatically, models often fail to capture place-based context, scale dependencies, and socio-political data realities. We advocate for standardized geospatial benchmarks, transparent validation protocols, hybrid process-AI frameworks, and participatory governance to mitigate geographic inequities. Ultimately, responsible GeoAI requires sustained interdisciplinary collaboration that aligns computational innovation with rigorous spatial theory, ethical data stewardship, and actionable policy implementation globally.

Keywords: *Geospatial AI, Machine Learning, Spatial Bias, Foundation Models Reproducibility, Ethical Governance*

Over the past decade, geospatial analysis has undergone a profound transformation driven by the rapid integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques. Traditionally, spatial analysis relied heavily on deterministic models, statistical inference, and rule-based Geographic Information Systems (GIS), where human expertise played a central role in defining relationships between spatial variables. However, the increasing availability of high-resolution satellite imagery,

[1] Research Scholar, Palamuru University, Mahbubnagar, Telangana, India

sensor networks, and large-scale geospatial datasets has shifted the paradigm toward data-driven methodologies. In this emerging framework, AI/ML models are capable of learning complex spatial patterns, nonlinear relationships, and temporal dynamics directly from data, thereby significantly enhancing predictive and analytical capabilities. The period from 2020 to 2026 marks a critical phase in the evolution of geospatial AI. This era has been characterized by the proliferation of cloud-based geospatial platforms such as Google Earth Engine, the rapid expansion of satellite constellations like Planet Labs, and the adoption of advanced deep learning architectures including Vision Transformers (ViTs) and foundation models. These developments have enabled unprecedented scalability in geospatial data processing, allowing researchers to analyze petabyte-scale datasets in near real-time. Simultaneously, increasing global attention to AI governance, ethical concerns, and regulatory frameworks has brought issues such as algorithmic transparency, data privacy, and fairness into sharper focus.

Despite these advances, significant research gaps persist within the domain of geospatial AI/ML. Existing review studies tend to focus either on specific algorithmic developments—such as convolutional neural networks (CNNs) for image classification—or on domain-specific applications like land use mapping or disaster prediction. However, there remains a lack of comprehensive synthesis that critically examines the intersection of methodological innovation with systemic challenges, including data bias, spatial heterogeneity, reproducibility limitations, and geographic inequality in data representation. In particular, many models trained on data-rich regions fail to generalize effectively to data-scarce areas, raising important concerns about the global applicability and equity of AI-driven geospatial insights. Furthermore, the unique characteristics of spatial data—such as spatial autocorrelation, scale dependency, and non-stationarity—introduce complexities that are often inadequately addressed by conventional machine learning frameworks. These challenges necessitate a more nuanced understanding of how AI/ML techniques interact with geographic principles, and how methodological choices influence both analytical outcomes and policy implications.

In light of these considerations, this review paper seeks to address the following research questions:

- What are the dominant advances in AI and ML applications within geospatial analysis during the period 2020–2026?
- How do different forms of bias-data bias, algorithmic bias, and spatial bias-manifest in geospatial AI systems?
- What ethical, governance, and methodological challenges remain unresolved in current research?
- What future research directions can provide actionable guidance for both geographers and data scientists working at the intersection of AI and spatial analysis?

The scope of this review encompasses a broad range of applications across GIS and remote sensing, including urban analytics, environmental monitoring, climate modeling, and human geography. Studies that integrate spatial data with machine learning techniques are included, while purely computational or algorithmic studies lacking explicit geographic context are excluded. This boundary ensures that the analysis remains grounded in the spatial sciences while engaging critically with advances in AI. The remainder of this paper is structured as follows: Section 2 outlines the methodological framework used for literature selection and analysis. Section 3 presents the conceptual foundations of geospatial AI, including data types and model architectures. Section 4 reviews recent advances in AI/ML applications across various geospatial domains. Section 5 critically examines biases and challenges inherent in these approaches. Section 6 provides a comparative analysis of different methodologies, followed by Section 7, which discusses future research directions and emerging opportunities. Finally, Section 8 concludes the paper by synthesizing key insights and outlining implications for future research and practice.

METHODOLOGY

Review Design

This study adopts a PRISMA-guided scoping review combined with critical narrative synthesis to systematically examine the evolution of Artificial Intelligence (AI) and Machine Learning (ML) in geospatial analysis from 2020 to 2026. A scoping review is particularly suitable for emerging and interdisciplinary domains such as GeoAI, where the objective is to map key concepts, research trends, and knowledge gaps rather than to evaluate narrowly defined hypotheses (Arksey & O'Malley, 2005). The integration of a critical synthesis approach further enables the identification of structural issues such as bias, reproducibility challenges, and spatial inequities within the literature, aligning with recent calls for more reflexive and responsible AI research (Kitchin, 2017).

Data Sources and Search Strategy

The literature search was conducted across multiple multidisciplinary and domain-specific databases to ensure comprehensive coverage of both geospatial and computational research.

Table 1

Data Sources and Search Strategy

Component	Description
Databases	Scopus, Web of Science, IEEE Xplore, arXiv
Domain-Specific Journals	ISPRS Journal of Photogrammetry and Remote Sensing, International Journal of Geographical Information Science (IJGIS), Remote Sensing
Search Keywords	(“machine learning” OR “deep learning” OR “artificial intelligence” OR “foundation model”) AND (“geospatial” OR “GIS” OR “remote sensing” OR “spatial analysis” OR “earth observation”)
Time Frame	2020–2026
Search Enhancements	Backward and forward citation tracking
Rationale	Captures interdisciplinary research across geography, remote sensing, and AI domains

The search string was designed to maximize both recall and precision by combining broad AI-related terms with geospatial-specific keywords. The selected time frame reflects the rapid advancement of deep learning architectures, cloud-based geospatial platforms, and large-scale Earth observation systems during this period.

Inclusion and Exclusion Criteria

A structured set of inclusion and exclusion criteria was applied to ensure the relevance and quality of the selected studies. Only peer-reviewed articles and high-quality conference papers published in English between 2020 and 2026 were considered. Studies were required to explicitly integrate geospatial data such as GIS layers, satellite imagery, or spatial datasetswith AI/ML techniques, and to present empirical findings or methodological contributions.

Conversely, studies were excluded if they focused solely on machine learning without a spatial context, were published prior to 2020, or lacked methodological transparency. While grey literature was generally excluded, key policy documents and AI governance reports were selectively included due to their relevance in addressing ethical and regulatory dimensions of GeoAI. This approach ensures a balance between academic rigor and policy relevance (Goodchild & Li, 2021).

Screening and Data Extraction

The screening process followed a multi-stage workflow consistent with PRISMA guidelines. Initially, all retrieved records were imported into reference management software, and duplicates were removed. This was followed by title and abstract screening to eliminate irrelevant studies. The remaining articles underwent full-text review to assess their eligibility against predefined criteria. To improve transparency and reduce selection bias, tools such as Rayyan were used to facilitate systematic screening and decision tracking. Data extraction was performed using structured templates in spreadsheet-based environments, capturing key attributes such as study objectives, spatial scale, data sources, machine learning techniques, evaluation metrics, and reported limitations. Subsequently, a thematic coding process was applied to categorize studies into meaningful clusters, such as deep learning applications, bias in geospatial datasets, and scalability challenges. This step enabled the identification of recurring patterns and conceptual linkages across the literature (Braun & Clarke, 2006).

Synthesis Approach

This review employs a thematic and critical synthesis approach, moving beyond descriptive summarization toward comparative and analytical evaluation. Studies were grouped into thematic domains and assessed across multiple dimensions, including model performance, interpretability, spatial generalizability, and data dependency. This approach facilitates the identification of cross-cutting insights and trade-offs within the literature. For instance, while deep learning models often demonstrate high predictive accuracy, they may also suffer from reduced interpretability and increased susceptibility to data bias. By synthesizing findings across studies, the review provides a more holistic understanding of both the capabilities and limitations of AI/ML in geospatial analysis (Yuan et al., 2020).

Limitations

Several limitations of this review must be acknowledged. First, the restriction to English-language publications introduces language bias, potentially excluding relevant research conducted in other linguistic contexts. Second, the rapid pace of AI development—particularly the widespread use of preprint platforms such as arXiv—poses challenges in balancing timeliness with peer-reviewed reliability. Additionally, disparities in computational resources, data availability, and research funding contribute to geographic representation bias, with studies from technologically advanced regions being overrepresented. Finally, reproducibility remains a significant concern in GeoAI research due to limited access to proprietary datasets, lack of standardized benchmarks, and insufficient reporting of model architectures and hyperparameters. These challenges underscore the need for more transparent and inclusive research practices in the field (Reichstein et al., 2019).

Evolution of AI/ML in Geospatial Analysis (2020–2026)

Table 02

Evolution of AI/ML Paradigms in Geospatial Analysis

Phase	Time Period	Key Techniques	Characteristics	Limitations
Traditional Spatial Methods	Pre-2020	Spatial statistics, GWR, regression	Rule-based, interpretable, domain-driven	Limited scalability, linear assumptions
Classical ML	~2015–2020	Random Forest, SVM	Better prediction, handles non-linearity	Feature engineering required
Deep Learning (CNN Era)	2020–2022	CNN, RNN	Automatic feature extraction, image-based analysis	High data & compute demand
Transformer Era	2022–2024	Vision Transformers (ViT)	Captures global spatial dependencies	Computationally expensive
Foundation Models	2024–2026	Pretrained GeoAI models	Transfer learning, multi-task capability	Data bias, lack of interpretability

Paradigm Shift

Geospatial analysis has shifted from traditional statistical models to advanced AI-driven approaches. Earlier methods relied on predefined relationships and strong assumptions, whereas modern models learn patterns directly from data. The introduction of CNNs enabled automated extraction of spatial features from satellite imagery, significantly improving accuracy in tasks such as land-use classification. More recently, transformer-based models have enhanced the ability to capture long-range spatial dependencies, while foundation models aim to generalize across tasks and regions. This transition reflects a broader movement from rule-based reasoning to data-driven intelligence (Zhu et al., 2017; Dosovitskiy et al., 2021).

Infrastructure and Ecosystem

The growth of GeoAI has been strongly supported by cloud computing platforms such as Google Earth Engine and Microsoft Planetary Computer, which provide scalable access to geospatial data and processing tools. Open satellite datasets from NASA and European Space Agency (e.g., Landsat, Sentinel) have further expanded data availability. Together with cloud-based ML pipelines and GPU acceleration, these developments have enabled large-scale, real-time geospatial analysis, significantly lowering technical barriers (Reichstein et al., 2019).

Disciplinary Adoption Trends

AI/ML techniques have been widely adopted across multiple branches of geography. In physical geography, they are used for hydrological modeling, climate analysis, and ecosystem monitoring. In human geography, they support studies on mobility, urban inequality, and population dynamics using spatial big data (Batty, 2020). Urban and regional planning has benefited from AI-driven mapping and smart city applications, while disaster and climate science increasingly relies on ML for early warning systems and risk assessment. This widespread adoption highlights the versatility of GeoAI across both natural and social systems.

Open Science vs Commercialization

The GeoAI ecosystem reflects a growing tension between open science and commercialization. Open-source tools and datasets promote transparency and accessibility, enabling wider participation in research. However, proprietary platforms and high-performance computing resources are often controlled by private organizations, creating an accessibility divide. This imbalance can limit participation from resource-constrained regions and influence the direction of research. Addressing this issue requires a balance between open collaboration and technological innovation, along with efforts to ensure equitable access to data and computational resources (Kitchin, 2014).

Key Technological Advances & Applications

Table 3

AI/ML Advances Across Geospatial Domains

Subsection	Geographic Domain	Typical ML Techniques	Example Use Cases
Earth Observation & Remote Sensing	Land cover, deforestation, agriculture, disaster mapping	CNNs, U-Net, Vision Transformers	Crop yield forecasting, flood extent mapping
Urban & Human Geography	Informal settlements, mobility, spatial inequality, smart cities	GNNs, Spatio-temporal LSTM, Graph ML	Transit optimization, slum upgrading prioritization
Environmental & Climate Geography	Carbon flux, glacier retreat, species distribution, soil moisture	Physics-informed NNs, Hybrid ML, Bayesian DL	Permafrost thaw modeling, biodiversity hotspots
Emerging Architectures	Cross-domain, multi-modal analysis	Foundation models, Self-supervised learning	Zero-shot land use classification, few-shot change detection

Earth Observation & Remote Sensing

Earth observation is a major area of AI/ML application due to abundant satellite data. Models like CNNs and U-Net improve image classification and mapping tasks such as land cover, deforestation, and agriculture. Recently, Vision Transformers enhance large-scale analysis by capturing global spatial patterns, supporting applications like flood mapping and crop prediction (Zhu et al., 2017; Dosovitskiy et al., 2021).

Urban & Human Geography

AI/ML helps analyze complex urban systems. Graph Neural Networks model spatial relationships such as transport networks, while LSTM models capture temporal patterns like traffic and mobility. These techniques are used in urban planning, slum detection, and inequality analysis (Batty, 2020).

Environmental & Climate Geography

AI/ML supports environmental modeling where systems are complex and nonlinear. Physics-informed neural networks integrate physical laws, while hybrid and Bayesian models improve prediction and uncertainty analysis. Applications include climate modeling, glacier studies, and biodiversity assessment (Reichstein et al., 2019).

Emerging Architectures

New approaches like foundation models (e.g., Prithvi, SatMAE) and self-supervised learning enable analysis with limited labeled data. These models support tasks like zero-shot classification and few-shot learning, making GeoAI more scalable, though challenges of bias and interpretability remain.

CRITICAL CHALLENGES: BIASES, DATA, AND REPRODUCIBILITY

Spatial & Sampling Biases

Geospatial AI datasets often suffer from spatial and sampling biases, particularly due to the overrepresentation of data from developed regions and underrepresentation of the Global South. This imbalance leads to models that perform well in data-rich areas but fail in data-scarce regions. Additionally, an urban–rural divide exists, where high-quality data is more available for urban areas than rural ones. Variations in sensor coverage and inconsistent temporal data further introduce bias, reducing the reliability of spatial predictions.

Algorithmic & Model Biases

Biases also arise from model design and behavior. A key issue is poor cross-region generalization, where models trained in one region do not perform well in others. Scale mismatch between training and application data further affects accuracy. Moreover, many AI models function as black boxes, limiting interpretability and trust. Errors in labeled data can also introduce confirmation bias, reinforcing incorrect patterns. These challenges highlight the need for more explainable and geographically aware models.

Reproducibility & Benchmarking

Reproducibility is a major limitation in GeoAI due to the lack of standardized benchmarks and variations in datasets and methods. Limited access to open data and code further restricts validation. Computational inequality also affects research outcomes, as not all institutions have access to advanced resources. Additionally, common evaluation metrics often ignore spatial properties like autocorrelation, leading to overestimated model performance. Standardization and open research practices are essential to address these issues.

Integration with Traditional GIS

Integrating AI/ML with traditional GIS remains challenging due to workflow fragmentation and compatibility issues with legacy systems. A significant skill gap exists between geographers and data scientists, affecting model development and interpretation. Furthermore, there is a trade-off between interpretability and accuracy, where traditional GIS is more transparent but less powerful than AI models. Bridging this gap requires integrated tools and interdisciplinary approaches.

ETHICAL, GOVERNANCE, AND SOCIETAL IMPLICATIONS

Privacy and Surveillance Risks

The integration of AI with high-resolution geospatial data has significantly increased concerns related to privacy and surveillance. Modern satellite imagery and sensor data, when combined with machine learning, enable the tracking of human activities at fine spatial and temporal scales. This creates risks of unauthorized monitoring of communities, particularly in sensitive contexts such as informal settlements or conflict zones. AI-driven geospatial systems can inadvertently enable mass surveillance, where individuals or groups are monitored without consent. The issue is further amplified when data is combined with mobile or social datasets, raising serious ethical concerns about individual privacy and collective rights. Addressing these risks requires stricter data governance frameworks and the incorporation of privacy-preserving techniques in GeoAI systems.

Geopolitical Control and Data Sovereignty

Another critical issue is the geopolitical concentration of data and computational power. Much of the global geospatial data infrastructure is controlled by large technology platforms such as Google Earth Engine and Microsoft Planetary Computer. This creates dependency on cloud-based ecosystems, where access, pricing, and data governance are often determined by private entities. Such concentration raises concerns about data sovereignty, particularly for developing countries that may lack control over their own spatial data. Licensing restrictions and unequal access to high-performance computing further deepen global inequalities. These challenges highlight the need for decentralized data systems and stronger national spatial data infrastructures to ensure equitable access and control.

Policy Landscape and Governance Frameworks

In response to growing ethical concerns, several international and national policy frameworks have emerged to regulate AI and geospatial technologies. The EU AI Act emphasizes risk-based classification of AI systems and mandates transparency and accountability. Similarly, UNESCO has developed global guidelines on AI ethics, focusing on human rights, inclusiveness, and sustainability. At the national level, spatial data infrastructures and open science mandates aim to improve data accessibility and standardization. However, the implementation of these frameworks remains uneven across regions. Effective governance requires not only regulatory policies but also institutional capacity, technical expertise, and international collaboration.

Role of Geographers and Inclusive Approaches

Geographers play a crucial role in bridging the gap between technical AI development and place-based, socially grounded analysis. Unlike purely computational approaches, geography emphasizes context, scale, and human-environment interactions. This perspective is essential for ensuring that AI applications are socially relevant and ethically grounded. Participatory approaches, including community engagement and co-design, are critical for responsible GeoAI development. Incorporating indigenous spatial knowledge can further enrich datasets and improve the cultural relevance of models. At the same time, ensuring algorithmic accountability—through transparency, auditing, and explainability—is necessary to build trust and support informed decision-making.

FUTURE RESEARCH DIRECTIONS & ROADMAP

The rapid evolution of AI and Machine Learning (ML) in geospatial analysis has created significant opportunities, but also highlighted critical gaps that must be addressed to ensure sustainable, equitable, and scientifically robust development. This section outlines a multi-horizon roadmap short-term, mid-term, and long-term focusing on actionable research and policy directions.

Short-Term (1–3 Years)

In the short term, the priority should be to improve the reliability, transparency, and reproducibility of GeoAI systems. There is a strong need for standardized geospatial ML benchmarks, which can ensure fair comparison of models across regions and datasets. Along with this, the development of bias auditing tools is essential to detect spatial inequalities such as urban–rural gaps and regional underrepresentation. Academic journals should enforce open science practices, including mandatory code and data availability. An important step would be requiring “spatial bias statements”, where researchers clearly report dataset limitations. Additionally, hybrid ML–process models should be promoted, as they combine machine learning with physical or geographic knowledge, improving both interpretability and accuracy (Reichstein et al., 2019; Karpatne et al., 2017).

Mid-Term (3–5 Years)

In the mid-term, research should focus on developing more context-aware and efficient AI systems. One key direction is the use of causal and physics-informed GeoAI, which goes beyond simple correlations to understand underlying spatial processes. Another important area is federated and privacy-preserving learning, which allows models to be trained without sharing sensitive geospatial data. This helps address privacy and data sovereignty issues. At the same time, edge AI systems should be developed to support analysis in low-resource regions, reducing dependence on cloud infrastructure. Equally important is improving AI literacy in geography education, ensuring that future researchers can effectively combine spatial thinking with machine learning skills (Li et al., 2020).

Long-Term / Systemic

In the long term, the focus should shift toward building inclusive, ethical, and globally equitable GeoAI systems. This includes developing participatory governance frameworks, where local communities are involved in data collection and decision-making. There is also a need to adopt decolonial data practices, which address historical biases and incorporate indigenous and local knowledge systems. Ensuring equitable access to data and computational resources is critical to prevent widening global inequalities. Finally, future research must focus on integrating AI uncertainty into policy and planning. Instead of treating AI outputs as exact predictions, decision-makers should consider uncertainty to make more robust and informed spatial decisions (Kitchin, 2014).

CONCLUSION

The integration of artificial intelligence into geospatial analysis between 2020 and 2026 has fundamentally transformed spatial research. Advanced architectures, cloud computing, and foundation models now enable rapid, large-scale monitoring of environmental and urban systems. Yet, computational progress does not inherently guarantee geographic robustness or spatial equity. High-accuracy models frequently obscure place-based contexts, scale dependencies, and socio-political data realities, producing outputs that are statistically optimized but theoretically disconnected. Bridging this divide requires urgent attention to bias mitigation, reproducibility, and ethical governance alongside algorithmic innovation. Researchers must rigorously adopt spatially explicit validation protocols, standardized benchmarking, and transparent data documentation to systematically address sampling asymmetries and cross-regional generalization failures. Mandating open code, equitable compute access, and systematic bias audits will prevent the institutionalization of persistent geographic inequities. Ethical considerations must be embedded in research design and policy implementation from the outset.

Realizing responsible GeoAI demands sustained interdisciplinary collaboration. Geographers, data scientists, policymakers, and local communities must co-develop analytical frameworks that balance predictive performance with spatial causality and contextual relevance. Transparent governance, participatory validation, and regulatory accountability are essential for ensuring AI-driven spatial decisions serve public interests. The future of geographic AI will not be measured by algorithmic complexity, but by its alignment with spatial justice, methodological transparency, and democratic stewardship. Moving forward, institutional support, curriculum reform, and sustained funding for open geospatial science will ensure technological innovation remains firmly anchored in geographic wisdom—producing spatial analytics that are intelligent, equitable, and deeply responsive to the places and populations they aim to serve.

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