Int. J. Econ. Environ. Geol., Vol. 17, Issue 2, 2026, 131-136 doi: 10.46660/int.j.econ.environ.geol.v17i2.719.
Journal home page: www.econ-environ-geol.org

Short Communication

ADVANCES IN GEOAI FOR ENVIRONMENTAL MONITORING AND EARTH OBSERVATION DATA ANALYSIS

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Received: *21 January, 2026* ***Accepted:*** *26 April, 2026*

Abstract: The last five years have witnessed a rapid transformation in environmental monitoring driven by the convergence of geospatial science and artificial intelligence, commonly referred to as GeoAI. The exponential growth of Earth Observation (EO) data from satellite constellations, unmanned aerial systems, and in-situ sensors has created unprecedented opportunities for large-scale, high-frequency environmental analysis, while simultaneously exposing the limitations of traditional analytical methods. Recent advances in deep learning architectures—particularly transformer-based models—multimodal data fusion, self-supervised learning, and privacy-preserving collaborative frameworks have significantly enhanced the accuracy, scalability, and operational relevance of environmental monitoring systems. This paper presents a comprehensive review and discussion of GeoAI advances between 2020 and 2025, focusing on their application to land-cover dynamics, disaster monitoring, hydrological systems, biodiversity assessment, and atmospheric observation. Emphasis is placed on methodological innovations, data challenges, operational deployment, and the emerging role of explainable and trustworthy AI in environmental decision-making. While GeoAI has demonstrated transformative potential, persistent challenges remain in data bias, generalization across regions, model interpretability, and energy-efficient deployment. The paper concludes with recommendations for advancing GeoAI research and strengthening its adoption in operational environmental monitoring frameworks.

Keywords: GeoAI, geospatial, artificial intelligence, earth observation, environmental monitoring.

Introduction

Sustainable development, climate change adaptation, disaster risk reduction, and natural resource governance all critically depend on robust environmental monitoring systems (Reichstein *et al*., 2019; Li *et al*., 2020). Historically, monitoring relied on in-situ measurements, expert interpretation of aerial and satellite imagery, and physics-based numerical models, which provided valuable insights but suffered from limited spatial coverage, low temporal frequency, and high operational costs (Reichstein *et al*., 2019). The emergence and maturation of Earth Observation (EO) satellite missions such as Landsat and Copernicus Sentinel, complemented by commercial high-resolution constellations, have radically increased the availability of multispectral, hyperspectral, synthetic aperture radar (SAR), and LiDAR data for continuous environmental observation at multiple spatial and temporal scales (Zhu *et al*., 2021; Li *et al*., 2020).

However, the resulting data volume, velocity, and heterogeneity far exceed the capacity of manual interpretation and classical statistical or rule-based approaches to capture complex, nonlinear, and multi-scale environmental dynamics (Reichstein *et al*., 2019; Li *et al*., 2020; Li, 2025). Earth Observation (EO) systems have experienced a high growth in the last 20 years. The decades-old state missions like Landsat and Copernicus Sentinel, supported by commercial high-resolution satellite constellations, currently provide streams of multispectral, hyperspectral, synthetic aperture radar (SAR), and LiDAR data. Such data allow tracing the dynamics of land-use, hydrology, atmospheric processes, and changes in the ecosystems at a level of spatial and time resolution previously unknown (Zhu *et al*., 2021). This shift between the occasional snapshots of the environment to the continuous time-series measurements of the environment has radically changed the scale, on which the analysis of the environment can be performed.

Nevertheless, the rapid increase in EO data has also posed major problems in the analysis. The size, speed, and non-homogeneity of EO data is much beyond the reach of an old fashioned analytical workflow. The interpretation of images manually is no longer a viable choice to monitor the continent or world as a whole, whereas classical statistical and rule-based models have difficulties with capturing the nonlinear, multi-scale interactions that the environmental systems have (Li *et al*., 2020). As an illustration, the interaction of climatic, socio-economic and biophysical processes that change over space and time contributes to land-cover change, which generates complex patterns that cannot be well resolved by

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the linear or threshold approach. Such constraints have inspired the use of data-driven approaches that are capable of acquiring rich representations directly off the EO data.

Emergence of GeoAI

To address these concerns, geospatial Artificial Intelligence (GeoAI) has been developed as a method of taking the developments in artificial intelligence and applying them in conjunction with spatial science concepts to improve the analysis of EO data. In contrast to generic AI applications, GeoAI directly uses spatial dependency, spatial heterogeneity, temporal dynamics, and geophysical constraints, inherent to environmental phenomena (Li *et al*., 2020). Deforestation, flooding, drought propagation, glaciers retreat, urban growth processes are strongly autocorrelated spatially and persist in time, and cannot be modeled by relatively simplistic learning models that focus on pixel-wise responses.

After 2020, methodological advances in GeoAI have been faster because of the growth of deep learning architectures, especially convolutional neural networks (CNNs), vision transformers, and hybrid CNN transformer architectures. Transformer based architectures, which were initially designed to process natural language, have been proven more superior in capturing long range spatial dependency and multi temporal relationships in EO imagery (Wang *et al*., 2024). These models have shown to be better than the traditional CNNs in land-cover classification, semantic segmentation and change detection, particularly in high-resolution and hyperspectral data, where contextual information is essential.

Simultaneously, self-supervised and weakly supervised learning paradigms have become popular, and they respond to the fact that the availability of labeled EO data remains limited. These methods lower the cost of annotation of large amounts of unlabeled images, and enhance the cross-regional and sensor cross-modal model generalization (Zhu *et al*., 2021). Moreover, the multimodal data fusion (optical, SAR, LiDAR and auxiliary geospatial data) has been found to be more robust to different environmental and atmospheric conditions and provided the capability to monitor all weather and day-night conditions.

Taken together, these innovations have made GeoAI one of the key instruments of contemporary environmental surveillance, realizing EO analysis as a descriptive mapping tool that can be transformed into the predictive, adaptive, and near-real-time decision support system (Ma *et al*., 2023).

GeoAI has been proposed as a unifying paradigm that couples advances in artificial intelligence and machine learning with geospatial concepts such as spatial dependence, temporal autocorrelation, and physical constraints inherent in environmental systems (Li *et al*., 2020; Reichstein *et al*., 2019). GeoAI explicitly embeds spatial structure, neighborhood context, and domain knowledge into learning processes, enabling more realistic representation of processes such as deforestation, urban expansion, floods, drought propagation, and glacier retreat compared with generic AI workflows (Li *et al*., 2020; Ma *et al*., 2023). Since 2020, rapid progress in deep learning architectures—most notably convolutional neural networks (CNNs), vision transformers, and hybrid CNN–transformer models—together with multimodal data fusion, self-supervised learning, and federated training frameworks has significantly expanded the scope and performance of GeoAI in environmental monitoring (Zhu *et al*., 2021; Wang *et al*., 2024; Ben Youssef *et al*., 2024).

Motivation and Research Gap

Several recent surveys have discussed AI and GeoAI applications in Earth and environmental sciences, including broad overviews of AI in Earth system science, geoscience, and climate-related mapping (Li *et al*., 2020; Ma *et al*., 2023; Reichstein *et al*., 2019; Li, 2025). These works typically focus on high-level trends, conceptual opportunities, or domain-specific use cases (for example, hydrology or urban analytics) but often treat model architectures, learning paradigms, and operational deployment aspects in a relatively generic or fragmented manner (Ma *et al*., 2023; Reichstein *et al*., 2019). In addition, many earlier reviews predate the widespread adoption of transformer architectures, large-scale multimodal fusion strategies, and federated learning frameworks in remote sensing, and therefore only partially capture the methodological shift that has occurred since 2020 (Wang *et al*., 2024; Li, Y., Zhang, & Chen, 2025; Ben Youssef, Aouinti, & Lefèvre, 2024).

Although the methodological development is rapid, the introduction of GeoAI in the areas of environmental monitoring is still disproportionate and scattered. Most of the state-of-the-art models are trained with geographically constrained data sets and when transferred to other geographic areas with varying climatic, ecological, or socio-economic characteristics, they perform poorly. It is also restrictive of GeoAI systems in global environmental studies, as well as in areas that lack cross-regional generalization, which are usually the most susceptible to environmental change (Ma *et al*., 2023).

Moreover, the growing dependence on more and more complicated deep learning models has attracted an interest in the notion of model transparency, model interpretability, and model trustworthiness. Black-box predictions do not work well in regulatory and policy environments, where one needs to be able to explain and make scientifically defensible predictions. Environmental decision-makers need the accurate prediction, as well as the clear insights into the drivers and uncertainties behind the model outputs (Reichstein *et al*., 2021). More problems with GeoAI implementation include algorithmic bias (due to the disproportionate representation of geographic data) and the environmental impact of training large-scale AI models.

The other gap that is critical is collaborative and privacy-enabling GeoAI frameworks. Multi-agency and cross-border data sharing is frequently part of environmental monitoring, which is limited by legal, political and security factors. Despite the recent research demonstrating the effectiveness of federated learning and privacy-preserving methods, their use in workable EO systems is minimal (Ben Youssef *et al*., 2024).

This review aims to address these gaps by providing a focused, methodologically explicit synthesis of GeoAI advances for environmental monitoring and EO data analysis between 2020 and 2025 (Li, 2025; Ma *et al*., 2023). Specifically, it (i) emphasizes model-level innovations such as transformers, hybrid architectures, and temporal models; (ii) analyzes multimodal EO data fusion strategies; (iii) examines privacy-preserving and federated learning frameworks; and (iv) discusses explainability, trustworthiness, and energy efficiency as cross-cutting concerns (Wang *et al*., 2024; Li, Y., Zhang, & Chen, 2025; Ben Youssef, Aouinti, & Lefèvre, 2024). By linking these advances to concrete environmental monitoring tasks and systematically discussing their advantages, limitations, and open challenges, the paper offers a more critical and integrated perspective than existing narrative summaries (Li *et al*., 2020; Reichstein *et al*., 2019; Zhu *et al*., 2021).

Innovations in GeoWalking Model Architectures

Recent advances in GeoAI have been strongly driven by innovations in deep learning architectures for EO data, particularly CNNs, vision transformers, and hybrid CNN–transformer models (Zhu *et al*., 2021; Wang *et al*., 2024). Early GeoAI studies relied predominantly on CNNs, which are effective at extracting local spatial features but can struggle to capture long-range contextual dependencies that characterize heterogeneous landscapes and multi-scale environmental processes (Ma *et al*., 2023; Zhu *et al*., 2021). Since 2020, transformer-based architectures and hybrid designs have gained prominence in remote sensing tasks such as land-use/land-cover classification, semantic segmentation, and change detection, owing to their self-attention mechanisms that model global spatial relationships (Wang *et al*., 2024; Li, Y., Zhang, & Chen, 2025).

Hierarchical vision transformers and multi-scale transformer variants have shown improved performance on high-resolution and hyperspectral imagery by integrating fine-scale details with coarse-scale context (Wang *et al*., 2024; Li, Y. *et al*., 2025). Hybrid architectures that combine CNN backbones with transformer layers leverage the efficient local feature extraction of CNNs while adding attention mechanisms for long-range dependencies, yielding a balanced trade-off between accuracy and computational cost in operational environmental monitoring systems (Ma *et al*., 2023; Wang *et al*., 2024).

Table 1. Comparison of GeoAI model architectures.

Model	Strengths	Limitations	Applications
CNN	Efficient, low computation	Limited global context	Classification
Transformer	Global modeling	High computation	Change detection
Hybrid	Balanced performance	Complexity	Large-scale monitoring

The Multimodal Data Fusion Earth Observation

Environmental processes are inherently complex and cannot generally be characterized by a single EO modality; for example, optical imagery provides spectral information but is sensitive to cloud cover, SAR offers all-weather observations but can be noisy, and LiDAR captures three-dimensional structure (Li, Y., Zhang, & Chen, 2025; Ma *et al*., 2023). Recent GeoAI research has increasingly focused on multimodal data fusion, combining optical, SAR, LiDAR, hyperspectral, and ancillary geospatial data (e.g., DEMs, climate reanalysis products) to produce more robust and informative representations for tasks such as flood mapping, vegetation monitoring, urban growth analysis, and habitat assessment (Li, Y. *et al*., 2025; Zhu *et al*., 2021).

Deep learning-based fusion strategies, particularly feature-level fusion and attention-based fusion, have been effective at integrating heterogeneous data sources by learning modality-specific feature spaces and then combining them in a task-aware manner (Li, Y. *et al*., 2025). These multimodal GeoAI systems demonstrate improved resilience to missing data, cloud contamination, and sensor artifacts, and are especially valuable in persistently cloudy regions and highly dynamic environments where single-sensor approaches are unreliable (Ma *et al*., 2023; Li, Y. *et al*., 2025).

Weakly and Self-Supervised Learning

The scarcity and high cost of well-annotated EO datasets remain major bottlenecks for supervised GeoAI applications (Zhu *et al*., 2021; Ma *et al*., 2023). To address this, recent work has explored self-supervised learning (SSL) techniques, such as contrastive learning and masked image modeling, which allow models to learn transferable representations from large archives of unlabeled satellite imagery (Zhu *et al*., 2021). These representations can then be fine-tuned on modest labeled datasets, substantially reducing annotation demands while enhancing cross-regional and cross-sensor generalization (Zhu *et al*., 2021; Li, Y., Zhang, & Chen, 2025).

Weakly supervised approaches have also gained traction, leveraging coarse or noisy labels derived from auxiliary sources such as land registries, crowdsourced maps, or low-resolution land-cover products to support large-scale monitoring tasks (Ma *et al*., 2023). When combined with SSL and domain adaptation, these methods enable practical deployment of GeoAI systems in data-sparse regions and emerging monitoring programs where high-quality ground truth is limited (Li *et al*., 2020; Li, Y. *et al*., 2025).

Federated and Privacy-Preserving GeoAI

Environmental monitoring frequently involves cross-institutional and cross-border collaboration, but legal, political, and security constraints can restrict centralized data sharing (Ben Youssef, Aouinti, & Lefèvre, 2024). Federated learning offers a promising paradigm in which models are trained collaboratively across multiple institutions while raw EO data remain local, thereby complying with data sovereignty and privacy requirements (Ben Youssef *et al*., 2024). Recent studies demonstrate that federated GeoAI models can approach the performance of centrally trained models, provided that heterogeneity in local datasets is properly managed and communication-efficient aggregation strategies are employed (Ben Youssef *et al*., 2024).

Nevertheless, federated learning in remote sensing faces challenges related to sensor variability, uneven label quality, non-IID data distributions, and limited bandwidth in operational settings (Ben Youssef *et al*., 2024). Addressing these issues requires advances in personalized federated learning, robust aggregation rules, and domain-adaptive model components tailored to EO data characteristics (Ben Youssef *et al*., 2024).

Explainable Artificial Intelligence and Reliability

As GeoAI models become increasingly complex, concerns about transparency, interpretability, and trustworthiness have intensified, particularly in high-stakes environmental and policy contexts (Reichstein *et al*., 2019; Li, 2025). Explainable AI (XAI) techniques such as saliency maps, attention visualization, and feature attribution are being integrated into EO modeling workflows to reveal which spatial regions, spectral bands, or temporal patterns drive model predictions (Reichstein *et al*., 2019). These tools can support expert validation, reveal potential biases, and enhance stakeholder confidence when GeoAI outputs inform regulatory decisions (Reichstein *et al*., 2019; Li, 2025).

However, many existing XAI methods were originally developed for generic computer vision tasks and do not explicitly account for spatial autocorrelation, geophysical consistency, or underlying process dynamics in environmental systems (Reichstein *et al*., 2019). Explanations may highlight statistically important features without necessarily aligning with causal environmental mechanisms, underscoring the need to integrate XAI with domain knowledge, uncertainty quantification, and physics-aware constraints in future GeoAI research (Reichstein *et al*., 2019; Li, 2025).

Despite the rapid development of GeoAI since 2020, the major gaps exist. There is a lack of geographic spread of generalization, bias due to unbalanced data availability, large model computational and energy expenses, and poor standardization of benchmarks and evaluation protocols. To ensure fair and sound application of GeoAI in functional environmental surveillance, there is a need to address the challenges.

Materials and Methods

Data Sources

Environmental monitoring systems based on modern GeoAI are based on the combination of various Earth Observation (EO) and other auxiliary geospatial information. The common inputs of core EO are multispectral optical imagery (e.g., Sentinel-2, Landsat-8/9), synthetic aperture radar (SAR) data (e.g., Sentinel-1) to have all-weather coverage, and terrain characterization with the use of digital elevation models (DEMs). Climate reanalysis products (e.g., ERA5) and land surface temperature datasets, as well as in-situ data, such as meteorological station records and field surveys. Recent GeoAI processes are giving more emphasis to the temporal depth, working by using dense time series to record seasonal cycles, long term trends, and extreme events. It is this richness of time that is required by applications like drought monitoring, flood dynamics, deforestation monitoring, and urban growth analysis, where environmental processes are changing at a variety of time scales (Zhu *et al*., 2021).

Preprocessing and Data Harmonization

Preprocessing remains a critical component of GeoAI pipelines due to sensor noise, atmospheric interference, geometric distortions, and missing data in EO imagery (Li, Y., Zhang, & Chen, 2025; Ma *et al*., 2023). Standard steps include radiometric calibration, atmospheric correction, cloud and shadow masking, and spatial resampling to a common grid and resolution, while SAR data require additional processing such as speckle filtering and terrain correction to ensure consistent geometry and radiometry across scenes (Li, *et al*., 2025).

Recent work has increasingly focused on inter-sensor harmonization, enabling data from multiple platforms and missions to be used jointly in training and inference (Wang *et al*., 2024; Ma *et al*., 2023). Techniques such as cross-sensor normalization, domain adaptation, and feature alignment help mitigate distribution shifts across sensors and time periods, enhancing the robustness and transferability of GeoAI models deployed across regions, seasons, and sensor generations (Wang *et al*., 2024; Li, Y. *et al*., 2025).

Modeling Paradigms

Current frameworks of GeoAI modeling are characterized by a prevalence of hybrid deep learning systems who integrate attention-based systems with convolutional neural network (CNNs) architectures. CNN molecules are effective feature extractors of local geometries and transformer-based attention layers are effective feature extractors on long-range geometries and distant contextual and relations across extensive geographic scopes (Wang *et al*., 2024). This mixed architecture has been used in land-cover classification, semantic segmentation and environmental change detection problems.

Models of temporal dynamics can be based on recurrent neural networks (RNNs), long short-term memory (LSTM) networks or more recently, temporal transformers, which are more appropriate for long and irregular time series. Commonly used training techniques are based on pretrained weights based on large EO benchmark datasets, and train them either via transfer learning or fine-tuning to downsample data requirements and enhance convergence. It is also common now to pretrain self-supervision to utilize huge archives of unlabeled EO data (Zhu *et al*., 2021).

Evaluation and Validation

Strong assessment of GeoAI models needs approaches that indicate the spatial and temporal framework of environmental information. The separation of training and testing samples by geographic location instead of randomly is increasingly being used as a form of spatial cross-validation which is designed to test how well the true performance of generalization is and to minimize spatial autocorrelation bias (Ma *et al*., 2023).

Depending on the task, model performance is normally measured by the use of statistical values that include accuracy, F1-score, intersection-over-union (IoU), and root mean square error (RMSE). Nevertheless, statistical performance is not adequate to apply to the environment. Thus, outputs can be usually compared to independent in-situ measurements, expert interpretations, or standard environmental data to determine ecological or physical plausibility. The combined assessment methodology would increase the element of trust and facilitate the operational application of GeoAI in the context of monitoring different environment and decision-making (Reichstein *et al*., 2021).

Results and Discussion

Greater Accuracy and Generalization

The latest developments in GeoAI have resulted in significant enhancement of the quality and stability of environmental monitoring activities based on Earth Observation (EO) information. According to the comparative literature, the models of deep learning, especially the ones that use the transformer-based attention mechanisms, outperform traditional convolutional neural networks (CNNs) in the real-life field of land-use/land-cover classification, semantic segmentation, and detecting environmental changes (Wang *et al*., 2024). This is because of the capacity of mechanisms of attention to focus on long-range spatial dependencies so that heterogeneous landscape can be interpreted in a more coherent way and minimizes the effects of local noise and sensor artifacts.

Besides that, the combination of temporal modeling structures (e.g. temporal transformer, recurrent neural network) have improved the ability to detect slower-gradient environmental variations, as well as extreme events. Multi-temporal EO models that are trained on the multi-temporal EO datasets show enhanced generalization between seasons and climatic regimes, which is a major shortcoming of previous single-date or region-based models (Ma *et al*., 2023). These advantages indicate that GeoAI can now be used to perform environmental analyses of a large scale and across regions.

Operational Impact

GeoAI has moved beyond the largely experimental use of the technology to operational use in a number of environmental monitoring fields. In the systems of both the government and the business, AI-powered EO analytics are now the foundation of near-real-time flood mapping, wildfire detection, deforestation alerts, and agricultural stress monitoring (Zhu *et al*., 2021). GeoAI pipelines are designed to be automated and scalable, which in turn allows responding to environmental hazards much faster, eliminating the need to rely on manual interpretation and making a decision faster.

The combination of optical and SAR data has been particularly advantageous to the operational systems since it guarantees continuity even during poor weather. Continuous monitoring on regional or global scale is also provided with the help of cloud-based infrastructures and automated preprocessing pipelines. The developments prove the usefulness of GeoAI in the context of disaster risk reduction strategies, food security strategies, and climate adaptation strategies.

Interpretability and Trust

Although the benefits of the model are huge in terms of performance, the interpretability of the model is a major issue of concern, particularly in policy-related environmental contexts. Deep learning models are black-box, which can make them scientifically unacceptable and restrict their application into regulatory systems. As a reaction, explainable AI (XAI) methods, including saliency maps, attention visualization, feature attribution, and others, are becoming part of GeoAI processes to provide information about the model decision-making processes (Reichstein *et al*., 2021).

Although these techniques enhance transparency, the power of explanation is not necessarily in agreement with either physical or ecological causality. Interpretations can bring out statistically significant features, but not necessarily represent underlying environmental processes. This is leading to increased appreciation of the necessity to implement XAI together with domain insight, uncertainty quantification, and physics-conscious limitations in an effort to increase the level of trust and interpretability in operational environments.

Limitations and Challenges

Despite the recent developments, various limitations still exist in order to broaden the use of GeoAI in environmental monitoring. A major problem is model bias whereby training data tends to be geographically clustered in data-rich areas with lower performance in the underrepresented ecosystems. This disproportion is dangerous to add to the current inequalities of environmental monitoring and decision-making (Ma *et al*., 2023).

There is also difficulty in the computational cost and environmental footprint. Models with large transformers need a lot of energy sources to be trained and deployed, which makes sustainability and availability of concern. Moreover, the need to keep up with the changing nature of an environment necessitates constant retraining and performance drift checking. To make GeoAI systems objective, fair, comprehensible, and green, it will be critical to tackle these constraints and make sure that they are not merely accurate.

Conclusion

Geospatial Artificial Intelligence (GeoAI) has been a revolutionary technology that has been able to scale, automate and provide high-resolution analysis of Earth Observation (EO) data. The combination of the most recent machine learning solutions with the geospatial principles has overcome the numerous shortcomings linked to handshaking interpretation and classical statistical modeling. Significant progress (especially in transformer-based architecture, multimodal data fusion, and self-supervised learning) has been achieved to the accuracy, robustness, and generalization of the EO-learned environmental understanding between 2020 and 2025.

The results of these developments have increased both the scientific knowledge and the capacity of operations in a variety of applications such as land-use change detection, disaster monitoring, ecosystem assessment and climate impact analysis. Near-real time decision-making and large scale environmental evaluations that previously were impossible to conduct are now supported by geoAI systems. However, interpretability issues, bias, cost of computation, and fair access remain a challenge. All these issues need to be resolved to make sure that GeoAI is a reliable, sustainable, and policy-relevant instrument of worldwide environmental monitoring.

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