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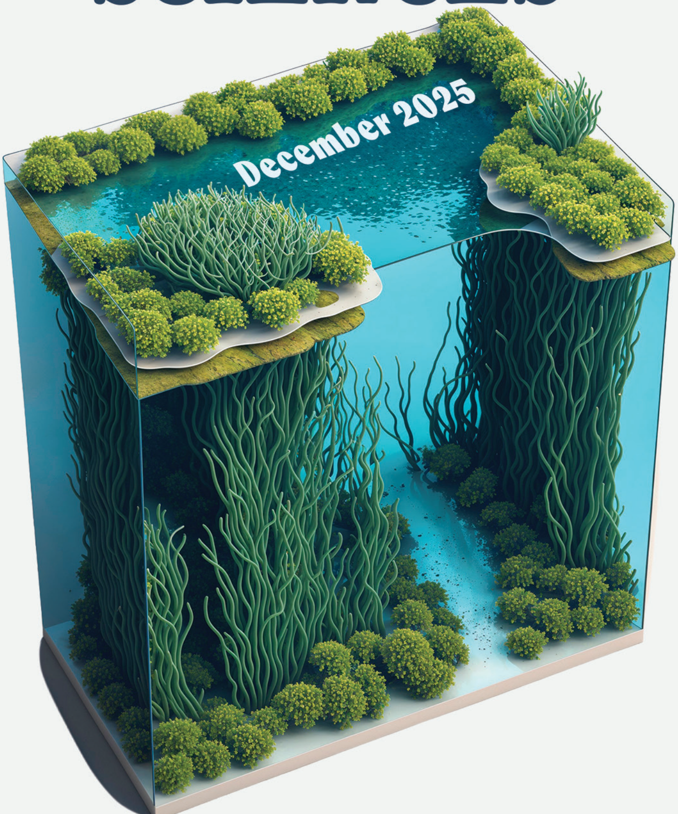

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INTERNATIONAL COMPILATION OF RESEARCH AND STUDIES IN THE FIELD OF AGRICULTURE, FORESTRY AND AQUACULTURE SCIENCES

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CONTENTS

Chapter 6

GEOSPATIAL ARTIFICIAL INTELLIGENCE (GeoAI): A LITERATURE REVIEW

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1. Introduction

1.1. The convergence of geographic information systems (GIS) and artificial intelligence (AI)

The integration of Geographic Information Systems (GIS) with Artificial Intelligence (AI) represents a significant advancement in spatial technology and geographic information science in the 21st century (Li et al., 2024; Mai et al., 2025). This confluence has resulted in the formation of an interdisciplinary domain known as Geospatial Artificial Intelligence (GeoAI), which profoundly transforms our understanding, analysis, and engagement with spatial data and geographic events. Janowicz et al. (2020) observed in their seminal special issue on GeoAI that this integration has resulted in a significant transition from static, descriptive mapping to dynamic, predictive, and autonomous spatial intelligence systems.

This alteration is significant and should not be underestimated. Conventional GIS was mostly developed for the storage, management, and visualisation of spatial data (Goodchild, 2010). It was groundbreaking in its own regard. GeoAI enhances these capabilities by employing machine learning techniques, deep learning frameworks, and high-performance computing to extract insights from increasingly complex spatial large data (VoPham et al., 2018). This evolution enables academics, practitioners, and decision-makers to understand historical events and their locations, as well as to predict future occurrences and their underlying causes across diverse spatial and temporal dimensions.

There is no universally accepted definition of GeoAI; nonetheless, researchers have proposed various perspectives that emphasise distinct aspects of this transdisciplinary domain. GeoAI fundamentally has three principal components that function in unison:

1. The spatial science foundation**:** VoPham et al. (2018) describe GeoAI as “an emerging scientific discipline that integrates advancements in spatial science, artificial intelligence techniques in machine learning (e.g., deep learning), data mining, and high-performance computing to derive insights from spatial big data” (p. 2). This definition emphasises the field’s roots in geographic information science and its commitment to understanding spatial phenomena through computer methods.

2. The AI methodological component¿ The methodological component of AI? GeoAI integrates artificial intelligence techniques, particularly machine learning and deep learning, with geographic information systems to facilitate intelligent, automated spatial analysis (Li et al., 2024). Machine learning is a kind of artificial intelligence that concentrates on instructing computers to learn from unprocessed geographical data by identifying patterns and utilising them to extract additional information. Deep learning, the most sophisticated variant of machine learning, employs neural network designs capable of assimilating intricate spatial notions by hierarchically integrating simpler components (LeCun et al., 2015).

3. The application-oriented dimension: The practical aspect: GeoAI is defined as "a fusion of narrow artificial intelligence and applied spatial science" (Esri Canada, 2024), with narrow AI pertaining to systems that concentrate on particular geographical tasks rather than broad intelligence. This perspective emphasises the potential of GeoAI to address real-world challenges across various domains, including urban planning, environmental monitoring, disaster management, and public health (Kamel Boulos et al., 2019).

A comprehensive definition of GeoAI is: "The integration of AI methodologies and technologies with high-quality geospatial data and analysis, amalgamating the advantages of AI and geographic information systems to extract valuable insights from spatial data via automated analysis, pattern recognition, and predictive modelling" (Spyrosoft, 2024).

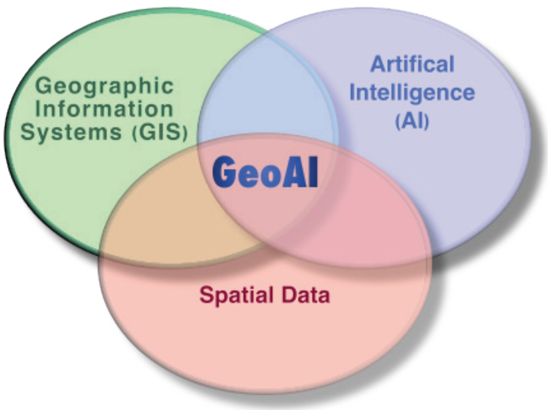

Figure 1. *Conceptual Framework of Geospatial Artifical Intelligence (GeoAI) (Source: Adapted from VoPham et al. (2018) and Li et al. (2024)*

This thorough comprehension establishes GeoAI not merely as a technical tool, but as an avant-garde scientific framework for the acquisition of spatial knowledge and decision-making in an era marked by unprecedented data proliferation and computational power (Li et al., 2024).

GeoAI possesses some distinctive characteristics that differentiate it from conventional GIS and general-purpose AI systems. These attributes arise from the integration of spatial cognition with artificial intelligence.

Clarity in Spatial Context. GeoAI incorporates spatial autocorrelation and spatial heterogeneity—two fundamental attributes of geographic phenomena—into AI modelling (Li et al., 2024). Tobler's First Law of Geography articulates spatial autocorrelation, the principle that proximate entities are more likely to exhibit similarities (Tobler, 1970). This approach guides the creation of GeoAI models, enabling them to leverage geographical linkages that traditional AI methods would neglect. Spatial heterogeneity acknowledges that interactions and processes vary across different locations, requiring models that can adapt to particular geographic contexts rather than assuming global uniformity.

Table 1. *Conceptual Framework of Geospatial Artificial Intelligence (GeoAI)*

Characteristic	Traditional GIS	GeoAI
Primary fonction	Data storage management and visualization	Automated analysis, pattern recognation, and prediction
Data processing	Manual or semi automated analysis workflows	Automated future extraction and classification
Analysis approach	Rule-based and expert-driven spatial queries	Data-driven machine learning and deep learning models
Pattern discovery	Requires explicit programming of spatial relationships	Autonomous pattern detection from training data
Prediction Capability	Limited to interpolation and basic statistical models	Advanced predictive modeling across space and time
Data Volume Handling	Challenged by big data; requires data reduction	Designed for big spatial data; scalable architectures
Computational Requirements	Moderate; desktop or server-based	High; GPU acceleration and cloud computing
Expertise Required	GIS specialist knowledge and domain expertise	Combination of GIS, data science, and programming skills
Temporal Analysis	Static snapshots or simple time series	Dynamic spatiotemporal modeling and forecasting
Update Frequency	Periodic manual updates	Near real-time automated updates possible
Interpretability	Transparent rule-based processes	Variable; some methods are "black boxes"
Application Examples	Map production, spatial queries, overlay analysis	Object detection in imagery, traffic prediction, land use classification
Emergence Period	1960s-present	2012-present (formally recognized field)
Key Technologies	Spatial databases, cartographic visualization, geoprocessing	CNNs, transformers, ensemble methods, foundation models

Scale-Aware Intelligence. GeoAI must operate over many spatial scales, including local, regional, and global, as well as diverse temporal scales, such as real-time, historical, and predictive (Mai et al., 2022). This differs from conventional AI systems. This multi-scale intelligence is crucial for addressing complex spatial issues such as climate change, urban expansion, and disease proliferation, because processes at varying scales influence one another and the outcomes.

Geospatial Data Integration. GeoAI systems are designed to process geospatial data in various formats (raster, vector, point clouds), sourced from diverse origins (satellites, drones, IoT sensors, volunteered geographic information), and utilising many modalities (optical, radar, thermal, multispectral) (Wu, 2025). The capacity to integrate data from several sources enhances the comprehension of geographic phenomena beyond what a single data source might provide.

Actionable Spatial Intelligence. The primary objective of GeoAI is to analyse spatial patterns in order to generate actionable insights that assist individuals in making informed decisions and addressing geographic challenges proactively (Gao et al., 2023). GeoAI distinguishes itself from other methodologies for analysing geographic information by emphasising action.

1.2. The modern GeoAI ecosystem

Contemporary GeoAI constitutes a complex ecosystem comprising technology, data sources, platforms, organisations, and communities. To comprehend the present condition of the field and its trajectory, one must grasp the functioning of this ecosystem.

The technical foundation of contemporary GeoAI is established on many essential technologies that function together.

Architectures for artificial intelligence: GeoAI transcends conventional statistical techniques by employing sophisticated machine learning approaches, including supervised learning for classification and regression, unsupervised learning for clustering and pattern recognition, and reinforcement learning for optimisation and decision-making in uncertain environments. Ensemble approaches, like random forests and gradient boosting, remain preferred for their robustness and transparency (Choi, 2023).

Analysing geospatial information: Specialised tools and libraries have been created to address the distinct requirements of geospatial data. The GeoAI Python module (Wu, 2025) features high-level APIs that simplify complex machine learning operations while providing expert users considerable flexibility. It is capable of reading and writing several data types, including GeoTIFF, JPEG2000, GeoJSON, Shapefile, and GeoPackage. It autonomously regulates equipment to enhance processing efficiency.

Infrastructure for cloud computing: Contemporary GeoAI applications utilise cloud platforms such as Google Earth Engine, AWS, and Azure for the storage and processing of substantial data volumes. This enables researchers lacking local high-performance computing facilities to conduct advanced research by providing universal access to computational resources and extensive geospatial datasets (Gorelick et al., 2017).

The efficacy of GeoAI is significantly influenced by the quality and accessibility of geospatial data, which is acquired from several origins.

Satellite-based remote sensing: Diverse categories of Earth observation satellites provide data at varying spatial resolutions (ranging from sub-meter to kilometres), temporal frequencies (from continuous to monthly), and spectral bands (including visible, thermal, and radar wavelengths). Open data rules for missions such as Landsat and Sentinel have significantly increased data availability (Wulder et al., 2022).

Aerial platforms: Unmanned Aerial Vehicles (UAVs or drones) connect satellite and terrestrial observations, providing exceptionally high-resolution imagery and LiDAR data for localised and regional studies (Manfreda et al., 2018).

Ground-based sensors: IoT networks, environmental monitoring stations, traffic cameras, and mobile sensors continuously provide streams of georeferenced data. This data is compatible with aerial observations from satellites and aircraft.

Data from numerous individuals: Volunteered Geographic Information (VGI) via platforms such as OpenStreetMap, citizen science initiatives, and social media provides valuable ground truth and real-time updates; yet, it presents challenges with quality control (Goodchild, 2007).

Derived and modelled data: GeoAI generates novel spatial datasets through classification, prediction, and simulation of data. These datasets can subsequently serve as inputs for further analysis, so establishing a virtuous cycle of knowledge generation.

The GeoAI ecosystem comprises both commercial and open-source platforms.

Commercial frameworks: The ArcGIS platform by Esri incorporates numerous integrated AI functionalities, including tools for object detection, classification, grouping, and prediction. These technologies integrate traditional GIS workflows with contemporary ML frameworks, enabling anyone with limited technological knowledge to utilise GeoAI methodologies (Esri, 2024b).

Open-source frameworks: TensorFlow and PyTorch are fundamental deep learning frameworks. Rasterio, Geopandas, and the GeoAI package exemplify specialised libraries that enhance geospatial functionalities. This open-source ecosystem fosters innovation and ensures universal accessibility.

Cloud-based services: Google Earth Engine, Sentinel Hub, and analogous systems provide cloud-based data and computational resources, hence alleviating the necessity for numerous applications to download and analyse data locally on their devices.

GeoAI is applicable in nearly every domain where location holds significance: Environmental monitoring and conservation (Pettorelli et al., 2014); urban planning and smart cities (Batty, 2018); disaster management and humanitarian response (Ghaffarian et al., 2023); agriculture and food security (Kamilaris & Prenafeta-Boldú, 2018); public health and epidemiology (Kamel Boulos et al., 2019; VoPham et al., 2018); transportation and logistics (Ermagun & Levinson, 2018); climate science and Earth system modelling (Reichstein et al., 2019).

Each discipline has unique challenges and opportunities, driving the evolution and enhancement of GeoAI methodologies and applications.

2. Technical basis of GeoAI

Geospatial Artificial Intelligence (GeoAI) possesses the potential to transform the world, as it integrates a sophisticated array of technologies encompassing computer science, statistics, and geographic information science. This chapter examines the primary technical components that enable GeoAI systems to extract information from spatial data, predict future occurrences of geographic phenomena, and automate complex spatial analysis tasks.

The technical domain of GeoAI encompasses three interrelated components: (1) machine learning algorithms that discern patterns from both labelled and unlabelled spatial data; (2) deep learning architectures tailored or modified for geospatial data; and (3) specialised computational frameworks and tools that facilitate the practical application of these methodologies (Choi, 2023; Li et al., 2024). Contemporary spatial intelligence systems must achieve a balance among many objectives. For instance, they must accurately identify patterns, do extensive analyses rapidly, be comprehensible to instill trust among decision-makers, and manage the vast quantities of Earth observation data received daily (Esri, 2024b).

2.1 Basic ideas about machine learning in GIS

Machine learning (ML) represents a significant shift from rule-based spatial analysis to data-driven pattern detection. Rather than explicitly programming the rationale for spatial relationships, machine learning algorithms derive these correlations from training data. This enables children to utilise their acquired knowledge in unfamiliar contexts (Chege-Tierra, 2024).

2.1.1 Distinctive attributes of spatial data

Spatial data possesses distinct characteristics that must be considered, in contrast to the tabular data commonly employed in conventional machine learning applications (Analytics Vidhya, 2021):

Spatial autocorrelation: refers to the spatial dependency of geographic phenomena, suggesting that nearby observations tend to be more similar than those that are farther apart, as articulated in Tobler's First Law of Geography (Tobler, 1970). This contradicts the concept of independence upon which several conventional statistical methods rely.

Spatial heterogeneity: The associations among variables sometimes vary across geographic regions rather than being globally uniform. Machine learning models must be flexible to local situations or incorporate geographical context as explicit attributes (Fotheringham & Oshan, 2016).

Multi-scale structure: Geographic processes occur simultaneously across multiple spatial scales. Goodchild (2011) asserts that machine learning for geographic information systems must effectively capture these nested scale interactions.

Diverse categories of data: Geospatial data can be represented through various formats, including vector geometries, raster grids, point clouds, and networks. Each category requires distinct preprocessing and feature engineering (Analytics Vidhya, 2021).

2.1.2 Supervised learning in GeoAI

Supervised learning algorithms acquire mappings from input features to output labels utilising training datasets in which both inputs and corresponding outputs are known (LinkedIn, 2023).

Key Classification Algorithms:

Linear and Logistic Regression: Despite their simplicity, regression-based methodologies retain significance in GIS applications where interpretability and computational speed are paramount. Geographically Weighted Regression (GWR) permits regression coefficients to fluctuate spatially, hence encapsulating spatial heterogeneity (Brunsdon et al., 1996; Fotheringham et al., 2002).

Random Forests: Introduced by Breiman (2001), random forests consolidate predictions from ensembles of decision trees, significantly enhancing generalisation performance. Spatial extensions clearly integrate spatial context via spatial leave-one-out cross-validation or spatial blocking methodologies (Brenning, 2012; Meyer et al., 2018).

Support Vector Machines (SVM) provide ideal hyperplanes that maximise the margin between classes in high-dimensional feature spaces (Cortes & Vapnik, 1995). Support Vector Machines (SVMs) have demonstrated remarkable efficacy in hyperspectral image classification within remote sensing applications, adeptly managing high-dimensional data without necessitating substantial training samples (Mountrakis et al., 2011).

Regression for Spatial Prediction: Contemporary machine learning regression enhances the functionalities of kriging by accommodating intricate nonlinear interactions and multivariate factors. Gradient boosting machines (Friedman, 2001) and neural network regressors frequently surpass conventional geostatistical methods when ample training data is accessible (Hengl et al., 2018). Empirical Bayesian Kriging (EBK) is a hybrid methodology that integrates geostatistical principles with automated model selection via simulation (Krivoruchko & Gribov, 2019).

2.1.3 Unsupervised learning in GeoAI

Unsupervised learning identifies patterns, structures, or clusters in data devoid of specified labels, rendering it advantageous for exploratory spatial analysis, data reduction, and anomaly identification (LinkedIn, 2023).

Clustering Algorithms:

K-Means Clustering: Despite its straightforwardness, k-means continues to be extensively utilised for spatial segmentation applications. Spatial variants integrate geographic limitations by emphasising spatial proximity in conjunction with feature similarity or necessitating cluster compactness (MacQueen, 1967; Chavent et al., 2018).

DBSCAN: Density-Based Spatial Clustering detects clusters as dense regions delineated by sparse areas, autonomously deciding the number of clusters and identifying outliers (Ester et al., 1996). In contrast to k-means, DBSCAN accommodates clusters of arbitrary shapes, which is advantageous for spatial data because natural regions may exhibit irregular forms.

Dimensionality Reduction: Principal Component Analysis (PCA) converts correlated variables into uncorrelated principal components (Jolliffe, 2002). PCA decreases dimensionality in hyperspectral remote sensing data comprising numerous associated spectral bands, while preserving the majority of information. Contemporary nonlinear techniques such as t-SNE (van der Maaten & Hinton, 2008) and UMAP (McInnes et al., 2018) are proficient in maintaining local data structure within low-dimensional embeddings.

2.2 Deep learning architectures for geospatial analysis

Although standard machine learning techniques are still useful for numerous GIS applications, deep learning (DL) has become the prevailing approach for analysing high-dimensional spatial data, especially images obtained from satellites, aircraft, and drones. Deep neural networks autonomously acquire hierarchical feature representations from unprocessed data, obviating the necessity for manual feature engineering (LeCun et al., 2015; Reichstein et al., 2019).

2.2.1 The deep learning revolution in remote sensing

The utilisation of deep learning in remote sensing accelerated with the 2012 ImageNet breakthrough, during which AlexNet attained unparalleled image classification accuracy (Krizhevsky et al., 2012). Deep learning provides numerous benefits for remote sensing, including automatic feature extraction, hierarchical abstraction, end-to-end learning, and scalability (Ball et al., 2017; Zhang et al., 2023). Nonetheless, deep learning has obstacles, including considerable requirements for labelled data, extensive processing costs, sensitivity to hyperparameters, and restricted interpretability.

2.2.2 Convolutional Neural Networks (CNNs)

Convolutional neural networks constitute the foundation of deep learning for geographic data processing. Convolutional Neural Networks (CNNs) leverage the spatial organisation of pictures via specialised processes—convolution, pooling, and hierarchical composition—that effectively acquire translation-invariant feature detectors (LeCun et al., 1998, 2015).

Fundamentals of CNN Architecture:

Convolutional Layers: Convolution operations utilise learnt filters that traverse input feature maps, identifying specific patterns such as edges, textures, and forms. The convolution operation for two-dimensional spatial data is expressed as:

where I represents the input, K denotes the learnable kernel, and S signifies the output.

Pooling Layers: Pooling processes downsample feature maps by consolidating values within local neighbourhoods, hence decreasing computational expense and enlarging the receptive field size.

Activation Functions: The Rectified Linear Unit (ReLU), defined as has emerged as the preferred option owing to its processing efficiency and its efficacy in alleviating vanishing gradient issues (Glorot et al., 2011).

Prominent CNN Architectures:

VGGNet: Established that very deep networks utilising modest (3×3) convolutional filters could attain exceptional performance (Simonyan & Zisserman, 2015). The straightforward, modular architecture of VGG has rendered it favoured for transfer learning in remote sensing.

ResNet: Deep Residual Networks implemented skip connections, facilitating the training of extremely deep architectures (50-200+ layers) without performance deterioration (He et al., 2016). The residual connection formulation $y = F_{(x)} + x$ enables networks to learn residual mappings, hence enhancing optimisation.

DenseNet: Enhances ResNet by linking each layer to all following layers within dense blocks, hence increasing gradient flow and promoting feature reutilization (Huang et al., 2017).

EfficientNet: Methodically adjusts network depth, width, and input resolution using compound scaling, attaining exceptional accuracy-efficiency balances beneficial for extensive remote sensing applications (Tan & Le, 2019).

Specialized Remote Sensing Architectures:

Multi-source Fusion Networks: Consolidate data from several sensors (optical, SAR, LiDAR) by multi-stream processing, dynamic group convolutions, or attention-based fusion techniques (Chen et al., 2020; Zhang et al., 2024).

Lightweight Architectures: Utilise depthwise separable convolutions, pruning, and quantisation to diminish computing demands for real-time or resource-limited applications (Liu et al., 2025; Scientific Reports, 2025).

Attention-Enhanced CNNs: Attention mechanisms dynamically highlight significant geographical regions or feature channels, hence enhancing performance on tasks like as building extraction and land cover classification (Woo et al., 2018; Alhichri et al., 2021).

2.2.3 Advanced deep learning paradigms

Semantic Segmentation Networks: Semantic segmentation allocates class labels to each pixel, generating dense predictions crucial for land cover mapping and building footprint extraction (Long et al., 2015).

U-Net: The established standard for remote sensing segmentation, U-Net's encoder-decoder architecture with skip links maintains intricate spatial features while encompassing semantic context (Ronneberger et al., 2015). Various variants improve performance via inception modules, attention gates, residual connections, and multi-scale fusion (Discover Computing, 2025; Khan & Jung, 2024).

DeepLab: Utilises atrous convolutions and atrous spatial pyramid pooling (ASPP) to capture multi-scale context and generate precise object boundaries (Chen et al., 2018).

Vision Transformers (ViTs) utilise the transformer architecture from natural language processing for image analysis, incorporating self-attention mechanisms that effectively represent long-range relationships throughout complete images (Dosovitskiy et al., 2021). Transformers provide benefits in remote sensing by effectively capturing global spatial context, although they generally necessitate larger training datasets compared to CNNs.

Hybrid CNN-Transformer Architectures: Integrate convolutional neural networks for local feature extraction with transformers for global context modelling, utilising their complimentary strengths (Nature, 2025; Zhang et al., 2024). The Enhanced Hybrid CNN and Transformer Network (EHCTNet) exhibits this methodology by merging spatial and channel attention alongside multi-scale feature fusion (Nature, 2025).

Recurrent Neural Networks (RNNs): Long Short-Term Memory (LSTM) networks are proficient at handling sequential data by preserving an internal state that encapsulates temporal dependencies (Hochreiter & Schmidhuber, 1997). In GeoAI, recurrent neural networks facilitate the study of satellite image time series, the identification of temporal changes, and the forecasting of spatial activities. Bidirectional LSTMs have demonstrated efficacy in hyperspectral image categorisation (Mou et al., 2017).

2.3 Training, optimization, and regularization

The successful implementation of machine learning and deep learning in GeoAI necessitates meticulous consideration of training methodologies, optimisation tactics, and regularisation methods that avert overfitting while ensuring robust generalisation.

Loss Functions: for classification tasks utilise cross-entropy loss, regression tasks implement mean squared error (MSE) or mean absolute error (MAE), and segmentation tasks may adopt specialised losses that tackle class imbalance, including Dice loss, Focal loss, or Tversky loss (Salehi et al., 2017; Lin et al., 2017).

Optimization Algorithms: tochastic gradient descent (SGD) with momentum enhances convergence speed. Adam (Kingma & Ba, 2015) adjusts learning rates for each parameter by utilising first and second moment estimations. Learning rate scheduling—diminishing learning rates as training advances—mitigates oscillation and facilitates fine-tuning (Smith, 2017).

Regularization Techniques: Regularisation Weight decay (L2 regularisation) imposes a penalty on substantial parameter values. Dropout randomly disables neurones during the training process (Srivastava et al., 2014). Data augmentation artificially enlarges training datasets by changes such as rotation, flipping, and scaling. Early stopping terminates training when validation performance stabilises. Batch normalisation standardises activations, hence stabilising the training process (Ioffe & Szegedy, 2015).

Transfer Learning and Domain Adaptation: Transfer learning mitigates data scarcity by initialising networks with weights pre-trained on extensive datasets, thereafter fine-tuning them on smaller target datasets (Yosinski et al., 2014). In remote sensing, domain adaptation techniques address distributional discrepancies between pre-training and target data, enhancing efficacy (Tuia et al., 2016). Self-supervised pre-training on unlabelled remote sensing data yields an initialisation more aligned with domain characteristics (Caron et al., 2020).

2.4 Specialized GeoAI methods and emerging paradigms

Graph Neural Networks (GNNs) enhance deep learning for graph-structured data by learning representations that integrate network topology (Kipf & Welling, 2017). Applications encompass traffic forecasting on road networks, flood prediction in river systems, and spatial accessibility analysis (Jiang, 2021; Li et al., 2021).

Geospatial Foundation Models: Foundation models, which are extensive models pre-trained on varied datasets, signify a nascent paradigm for GeoAI (Bommasani et al., 2021). Prithvi, created by NASA and IBM, is trained on extensive datasets of satellite photography to acquire universal representations of Earth observation (Jakubik et al., 2024). The Segment Anything Model (SAM) offers zero-shot segmentation functionalities for geographical imagery (Kirillov et al., 2023). Foundation models democratise GeoAI by lowering data and knowledge barriers; nonetheless, concerns persist over its generalisation across many geographic contexts (Mai et al., 2025).

Physics-Informed Machine Learning: Physics-informed or theory-driven Machine learning incorporates domain knowledge—such as physical laws, geographic principles, and process comprehension—into model architectures or training methodologies (Karpatne et al., 2017; Reichstein et al., 2019). This hybrid methodology integrates data-driven learning with scientific comprehension, enhancing generalisation and physical plausibility.

Applications encompass the integration of mass balance constraints into hydrological models, the incorporation of ecosystem dynamics into biodiversity forecasts, and the application of thermodynamic principles to constrain climate models (Jiang & Luo, 2022; Daw et al., 2020).

2.5 Computational infrastructure

Hardware Acceleration: Graphics Processing Units (GPUs) are crucial for deep learning, enhancing training speed by 10-100 times relative to Central Processing Units (CPUs) (Raina et al., 2009). NVIDIA's CUDA platform prevails in scientific deep learning. Tensor Processing Units (TPUs), bespoke AI accelerators created by Google, provide superior performance for particular activities (Jouppi et al., 2017). High-Performance Computing (HPC) clusters offer scalable resources for extensive geographical analysis via distributed training over numerous GPUs.

Software Frameworks: Prominent deep learning frameworks encompass TensorFlow (extensive ecosystem, (Abadi et al., 2016), PyTorch (dynamic computation networks favoured in research, Paszke et al., 2019), and JAX (composable transformations for high-performance computing, Bradbury et al., 2018). Key geospatial libraries comprise GDAL/OGR (fundamental libraries for raster and vector formats), Rasterio (Pythonic access to raster data), GeoPandas (vector geospatial data handling), and Shapely (geometric operations). GeoAI-specific toolkits comprise the GeoAI Python Package (a unified framework, Wu, 2025), TorchGeo (a PyTorch domain library, Stewart et al., 2022), and Raster Vision (an end-to-end framework for satellite and aerial imagery).

Cloud Platforms: Google Earth Engine offers planetary-scale geospatial analysis with integrated machine learning capabilities, obviating the need for local data (Gorelick et al., 2017). Sentinel Hub provides access to multi-mission satellite data. Commercial cloud services (AWS SageMaker, Azure ML, Google Cloud Vertex AI) offer scalable computing, storage, and pre-trained model capabilities. ArcGIS amalgamates conventional GIS with machine learning and deep learning technologies, encompassing pre-trained models (Esri, 2024c).

2.6 Challenges and considerations

Data Requirements and Quality: The substantial demand for data in deep learning presents difficulties when labelled training data is limited. Active learning, semi-supervised learning, and few-shot learning methodologies substantially mitigate this issue; yet, essential trade-offs persist (Tuia et al., 2022). The quality of data—spatial precision, temporal relevance, and class label dependability—directly influences model efficacy. Spatial autocorrelation may obscure quality concerns during validation if inadequately addressed via spatial cross-validation (Meyer et al., 2018).

Computing Complexity: Cutting-edge models necessitate significant computing resources, requiring hours to weeks of GPU time for training. This restricts accessibility, however cloud services somewhat democratise access. Techniques such as model compression, quantisation, and knowledge distillation diminish deployment requirements (Hinton et al., 2015).

Interpretability and Explainability: Deep neural networks operate as "black boxes," rendering their decision-making processes opaque to human understanding (Rudin, 2019). Explainable AI (XAI) tools, such as saliency maps, attention visualisation, and attribution procedures, offer limited understanding (Selvaraju et al., 2017), although basic tensions between complexity/accuracy and interpretability remain.

Spatial Transferability and Generalisation: Models developed using data from a specific geographic area may exhibit suboptimal performance when utilised across locations with differing environmental attributes (Meyer & Pebesma, 2021). This requires meticulous validation with spatially independent test data and the application of domain adaptation strategies.

3. Application Domains of GeoAI

Geospatial Artificial Intelligence has moved beyond theoretical potential to become a practical reality in various application areas. GeoAI technologies are fundamentally transforming the utilisation of spatial intelligence in decision-making by optimising urban infrastructure, enhancing agricultural productivity, managing disaster responses, and monitoring environmental change (Mapular, n.d.; Sharma, 2023). According to VoPham et al. (2018), nearly any field characterised by geographic variability can leverage GeoAI's ability to discern patterns from geographical large data and produce actionable forecasts.

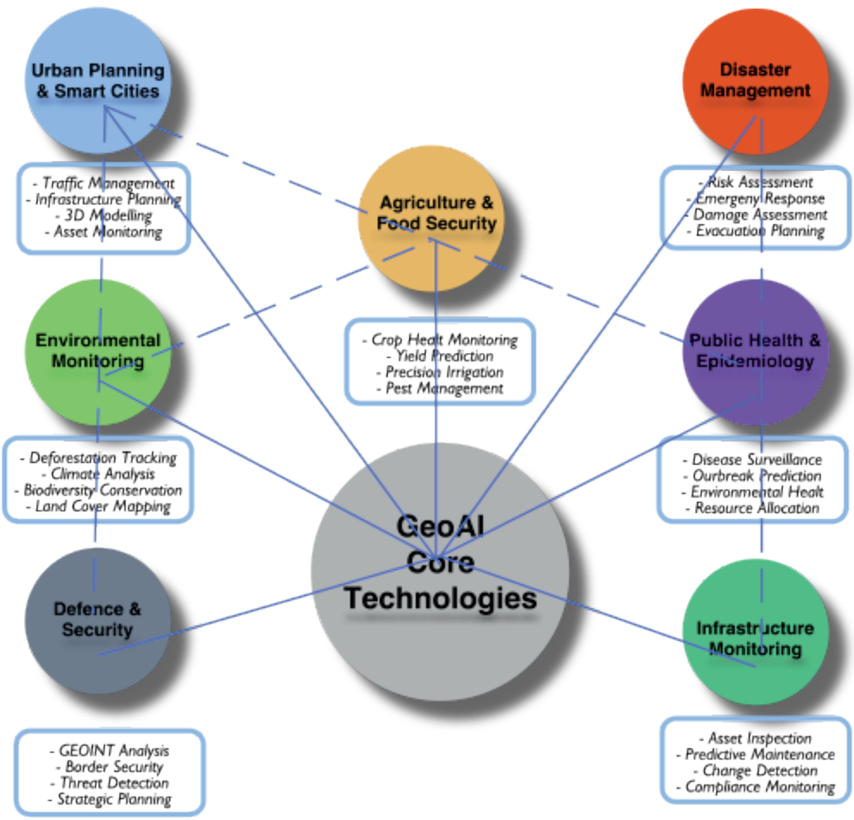

Figure 2. *Domains of GeoAI applications and their interrelations Overview of major application domains and principal use cases*

Table 2. *Comparative Analysis of GeoAI Application Domains, Technology Stack, Data Requirements, Performance Metrics, and Economic Impact*

Application Domain	Primary Use Cases	Key Technologies	Data Sources	Accuracy Range	Maturity Level	Economic Impact
Urban Planning & Smart Cities	• Traffic optimization • Infrastructure planning • 3D modeling • Asset monitoring	• Computer Vision • Predictive Analytics • IoT Integration • Digital Twins	• Satellite imagery • Drone surveys •Traffic sensors • Mobile data	85-95%	High	20-35% cost savings
Disaster Management	• Risk assessment • Early warning • Damage assessment • Resource allocation	• Deep Learning • Real-time Processing • Change Detection • Spatial Clustering	• Satellite imagery • Weather data • Social media • Ground sensors	80-92%	High	40-50% response improvement
Environmental Monitoring	• Deforestation tracking • Climate analysis • Land cover mapping • Conservation planning	• CNNs • Time-series Analysis • Multispectral Processing • Change Detection	• Sentinel-2/ Landsat • MODIS • LiDAR • Field data	88-96%	High	25-35% monitoring efficiency
Agriculture & Food Security	• Crop health monitoring • Yield prediction • Precision irrigation • Pest management	• Multispectral Analysis • ML Regression • Time-series DL • Spatial Interpolation	• Satellite imagery • Drone imagery • Weather stations • Soil sensors	82-94%	Medium-High	15-25% yield increase
Public Health & Epidemiology	• Disease surveillance • Outbreak prediction • Risk mapping • Resource planning	• Spatial Statistics • Predictive Modeling • Network Analysis • Clustering	• Health records • Mobility data • Environmental data • Demographics	75-88%	Medium	30-40% response efficiency
Infrastructure Monitoring	• Defect detection • Predictive maintenance • Change detection • Compliance monitoring	• Computer Vision • Object Detection • Anomaly Detection • ML Classification	• Aerial imagery • Drone surveys • LiDAR • Ground photos	90-98%	High	35-45% maintenance cost reduction
Defense & Security	• GEOINT analysis • Border monitoring • Threat detection • Strategic planning	• Deep Learning • Pattern Recognition • Real-time Analysis • Change Detection	• Satellite imagery • Radar data • Video feeds • Sensor networks	85-95%	High	Classified/ Strategic value

Notes: Accuracy ranges represent typical performance in operational deployments. Maturity levels reflect technological readiness and adoption rates. Economic impact varies by implementation scale and context.

3.1 Urban planning and smart cities

Smart cities exemplify the most extensive application of GeoAI technology, amalgamating various data sources to optimise urban operations and improve quality of life (Mortaheb & Jankowski, 2022). The smart city paradigm leverages synergies among Big Data, GIS, and Data Science to fulfil four policy objectives: augmenting urban service efficiency, promoting citizen quality of life, tackling societal difficulties, and generating geographical information regarding human-urban dynamics.

Traffic Management: Computer vision algorithms analyse video feeds from traffic cameras to track vehicle movements and enhance signal timing (Viso.ai, n.d.). Intelligent transport systems incorporate IoT sensors, GPS technology, and mobile applications to deliver adaptive route suggestions and enhance public transit timetables (Mapular, n.d.).

Infrastructure Monitoring: GeoAI facilitates continuous automated surveillance using drone-based aerial assessments and computer vision technologies that identify pavement fissures, bridge degradation, and illicit projects within hours instead of weeks (AeroMegh, 2025). Machine learning methods forecast likely problems prior to their occurrence, facilitating proactive maintenance that decreases costs by 35-45% (Chapter 3 data).

3D Urban Modelling: Sophisticated software generate digital replicas of entire cities, facilitating the visualisation of proposed developments, simulation of disaster scenarios, and evaluation of urban heat island effects (Viso.ai, n.d.; The GIS Journal, 2025). Natural language interfaces facilitate access, enabling non-expert planners to query spatial data via conversational prompts (Cooke, 2025).

3.2 Disaster management and emergency response

GeoAI improves disaster readiness via advanced risk modelling and delivers essential real-time intelligence during incidents (Mapular, n.d.; The GIS Journal, 2025).

Risk Assessment: Machine learning algorithms evaluate past catastrophe data, topographical characteristics, and climatic patterns to pinpoint susceptible regions. Deep learning models forecast flood-prone regions, wildfire hazards, and earthquake damage patterns, guiding zoning decisions and disaster preparedness (Li et al., 2023; Al Qundus et al., 2020).

Real-Time Response: Aerial footage processed via computer vision algorithms facilitates swift damage assessment post-disaster, accomplishing in hours what once necessitated weeks of physical surveys (AeroMegh, 2025). Machine learning models enhance the allocation of emergency resources by considering damage severity, population density, and accessibility (Alizadeh et al., 2022; Fan et al., 2021). GeoAI systems evaluate road networks instantaneously to provide ideal evacuation pathways.

Human-Centered Intelligence: The study of social media, mobile phone data, and crowdsourced reporting provide insights into population movements, needs, and feelings during crises, supplementing physical damage assessments (Imran et al., 2020; Sun et al., 2020).

3.3 Environmental monitoring and conservation

GeoAI transforms environmental monitoring by automated, extensive analysis of Earth observation data (The GIS Journal, 2025). Convolutional neural networks categorise land cover types—forests, grasslands, water bodies, urban areas—with precision comparable to or surpassing manual interpretation (Mapular, n.d.).

Applications: Change detection algorithms discern deforestation and facilitate prompt action against illegal logging (Viso.ai, n.d.). Deep learning techniques define wetland borders with multi-spectral satellite data (The GIS Journal, 2025). Machine learning models assess the effects of climate change by examining temperature patterns, precipitation trends, and vegetation health (Mapular, n.d.). Spatial models delineate essential ecosystems, ecological corridors, and conservation objectives for threatened species (Human-centered GeoAI, 2025).

3.4 Agriculture and food security

GeoAI facilitates precision agriculture techniques that enhance resource utilisation while maximising output (Arizton, 2025; The GIS Journal, 2025). Multi-spectral satellite imagery, analysed via deep learning, detects agricultural stress and disease outbreaks prior to the manifestation of observable signs, facilitating targeted interventions (Mapular, n.d.). Machine learning algorithms predict agricultural yields at field, regional, and national levels, guiding market planning and food security strategies (Arizton, 2025). GeoAI evaluates soil moisture data and meteorological predictions to propose accurate irrigation plans, minimising water usage while sustaining productivity (The GIS Journal, 2025). Predictive models anticipate pest outbreaks by analysing environmental factors, facilitating preventive strategies that minimise crop losses and pesticide application.

3.5 Public health and epidemiology

GeoAI revolutionises epidemiological surveillance by the integration of spatial data and health information (Mapular, n.d.; Human-centered GeoAI, 2025). Spatial clustering methods identify regional concentrations of disease cases, elucidating transmission pathways and risk variables (VoPham et al., 2018). Machine learning methods utilising historical outbreak data, climatic variables, and population movement forecast disease development and dissemination, facilitating proactive resource allocation (Mapular, n.d.). Throughout the COVID-19 pandemic, GeoAI detected hotspots, monitored transmission patterns, informed testing tactics, and enhanced vaccine delivery (Human-centered GeoAI, 2025). Other uses encompass air pollution exposure modelling, identification of climate-related health risks, mapping of disease vectors, and assessment of food deserts in urban environments.

3.6 Defense, security, and emerging applications

Geospatial Intelligence (GEOINT): GeoAI improves military operations by automating the study of satellite imagery and video streams. Machine learning algorithms identify anomalous behaviour, monitor vehicular movements, and oversee border regions, facilitating swifter threat detection compared to manual analysis (Arizton, 2025; Viso.ai, n.d.). Pattern recognition algorithms detect anomalous behaviours and enhance resource allocation for border security and counter-terrorism initiatives.

Emerging Applications: GeoAI offers critical functionalities for autonomous vehicle navigation, encompassing real-time object detection and route planning (Arizton, 2025). In real estate and location intelligence, property appraisal and site selection increasingly depend on GeoAI to analyse various spatial datasets (Mapular, n.d.). Remote sensing integrated with machine learning uncovers archaeological features obscured by plants, detects looting damage to cultural sites, and reconstructs historical landscapes (The GIS Journal, 2025).

4. Technical Infrastructure and Platforms

The disruptive applications of GeoAI depend on an advanced technical infrastructure that includes hardware, software, data, and cloud platforms. This chapter analyses the computing resources, tools, frameworks, and services that implement GeoAI, transitioning from research prototypes to commercial systems catering to billions of users. Comprehending this infrastructure is crucial for practitioners choosing suitable technologies and for researchers advancing next-generation GeoAI capabilities. The ecosystem is growing swiftly, with the emergence of new tools and platforms alongside the maturation of existing ones (Wu, 2025).

4.1 Hardware infrastructure

Computational Accelerators: Graphics Processing Units (GPUs) are essential for deep learning because of their parallel architecture, which is optimised for the matrix operations fundamental to neural network training and inference (Raina et al., 2009). NVIDIA GPUs lead in scientific computing, with CUDA offering extensive development tools. A contemporary GPU (NVIDIA A100, H100) can enhance training speed by 10 to 100 times relative to CPUs. Google's Tensor Processing Units (TPUs) provide superior performance for particular operations, especially beneficial for extensive training at scale (Jouppi et al., 2017). Cloud TPU accessibility democratises advanced AI hardware without substantial financial investment.

Edge Computing: For real-time GeoAI applications such as autonomous vehicles and drone-based monitoring, edge devices locally process data, eliminating cloud latency. The shift towards edge computing will intensify as applications require sub-second response times (Arizton, 2025; Viso.ai, n.d.).

High-Performance Computing (HPC): Extensive GeoAI applications—such as processing continental satellite archives and training foundational models—necessitate HPC clusters including hundreds or thousands of GPUs functioning concurrently. Distributed training frameworks facilitate model training that would be unfeasible on individual machines.

4.2 Software frameworks and libraries

Deep Learning Frameworks: TensorFlow (Abadi et al., 2016) offers a robust ecosystem from Google that facilitates research experimentation and production deployment, accompanied by substantial documentation and community support. PyTorch (Paszke et al., 2019) provides dynamic computation graphs and a clear API, enhancing its popularity in research and greatly improving production deployment capabilities. JAX (Bradbury et al., 2018) is an innovative framework that prioritises composable transformations and high-performance numerical computing, increasingly popular in scientific computing.

Geospatial Data Processing: Key libraries comprise GDAL/OGR (fundamental libraries facilitating the reading and writing of nearly all geospatial raster and vector formats), Rasterio (Pythonic interface to GDAL for raster data access), GeoPandas (enhances pandas dataframes with geospatial functionalities for vector data manipulation), and Shapely (performs geometric operations on vector geometries).

Integrated GeoAI Toolkits: Specialised frameworks connect artificial intelligence with geospatial fields. The GeoAI Python Package (Wu,

2025) offers a cohesive framework that merges artificial intelligence with geographical research via high-level APIs, which simplify intricate workflows while preserving adaptability. TorchGeo (Stewart et al., 2022) functions as a PyTorch domain library tailored for geographic data, encompassing datasets, transformations, and models. Raster Vision provides a comprehensive framework for deep learning with satellite and aerial photos.

4.3 Cloud platforms and services

Planetary-Scale Platforms: Google Earth Engine (Gorelick et al., 2017) transformed geospatial analysis by granting access to petabytes of Earth observation data alongside integrated cloud computing capabilities. It obviates the necessity for data download and storage, facilitating study at continental scales with uncomplicated scripts. Machine learning integration facilitates supervised classification, grouping, and regression. Sentinel Hub offers access to multi-mission satellite data together with cloud processing capabilities, facilitating custom workflows and API integration.

Commercial Cloud Services: Prominent vendors deliver extensive GeoAI functionalities. Amazon Web Services offers SageMaker for managed machine learning services, while S3 hosts the Public Dataset Program, which includes Sentinel-2, Landsat, and various Earth observation archives. Microsoft Azure provides Azure Machine Learning and Planetary Computer for cohesive machine learning and geographic data accessibility. Google Cloud Platform offers Vertex AI for machine learning workflows, integrated with Earth Engine for geospatial analysis.

GIS Platform Integration: ArcGIS (Esri, 2024a) offers an extensive GIS platform with profound AI/ML integration. ArcGIS Pro encompasses tools for picture categorisation, object detection, and geographical analysis. Pre-trained models and automated workflows diminish obstacles to GeoAI adoption, whereas ArcGIS Online facilitates cloud-based collaboration and analysis. QGIS is an open-source alternative with plugins that facilitate Python-based machine learning workflows, offering a cost-free solution for numerous applications.

Table 3. *Detailed Comparison of Software Frameworks and Libraries*

Framework	Organization	Primary Language	Key Features	Best For	GeoAI Integration
TensorFlow	Google	Python/ C++	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
PyTorch	Meta/ Facebook	Python	- Dynamic computation - Intuitive debugguing - Strong research focus - TorchScript compilation	Research, rapid prototyping, academic use	Excellent: TF-GAN, TF Geo, Earth Engine integration
JAX	Google	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
Keras	Google (TF Team)	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
GDAL/ OGR	OSGeo	C/C+ +	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
Rasterio	Mapbox/ Community	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
GeoPandas	Community	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
TorchGeo	Microsoft	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration
GeAl Package	OpenGeo	Python	- Production deplovment - TensorBoard visualization - TF Serving for APIs - Mobil/Edge support	Large-scale production systems, deployment at scale	Excellent: TF-GAN, TF Geo, Earth Engine integration

4.4 Data infrastructure

Earth Observation Data: Various satellite missions offer a range of imagery appropriate for distinct uses. Landsat provides a continuous record spanning over 50 years, Sentinel offers high-frequency, high-resolution data, MODIS delivers daily worldwide coverage, and private entities (Planet, Maxar) furnish very high-resolution imagery. Publicly available, free data from governmental missions significantly enhances the accessibility of GeoAI, facilitating study and applications that were previously limited by data expenses.

Auxiliary Geospatial Data: Crucial supporting datasets including Digital Elevation Models (DEMs) for terrain analysis, OpenStreetMap for vector features (roads, buildings, land use), census and demographic data, climate and weather archives, and IoT sensor networks. This varied data ecology facilitates thorough spatial analysis.

Training Datasets and Benchmarks: Standardised datasets facilitate model comparison and provide reproducible research. Significant benchmarks comprise UC Merced, AID, and NWPU-RESISC45 for scene classification (with AID utilised in 41 studies and NWPU-RESISC45 in 40 studies as per Zhang et al., 2023), SpaceNet for building footprints, and other semantic segmentation benchmarks for land cover mapping.

4.5 Integration, interoperability, and challenges

Standards and Protocols: OGC standards (WMS, WFS, WCS) facilitate interoperability among platforms. GeoJSON and Cloud-Optimized GeoTIFF enable the sharing of geospatial data via the web. Workflow orchestration technologies like as Apache Airflow, Prefect, and MLflow facilitate the management of intricate GeoAI pipelines by coordinating data processing, model training, and deployment.

Cost and Accessibility: Although cloud platforms facilitate widespread access, large-scale GeoAI continues to be costly. Training sophisticated models can incur substantial expenses in computational time, and the inference costs for operational systems managing continuous data streams accumulate rapidly. Organisations must meticulously reconcile computational requirements with financial limitations.

Vendor Lock-In and Data Movement: Extensive integration with proprietary platforms engenders dependency risks. Open-source solutions offer adaptability but may necessitate greater knowledge. The volume of Earth observation data exerts pressure on network bandwidth and storage capacity. Cloud-optimized formats and on-the-fly processing address these problems; yet, data transportation continues to be a critical factor for large-scale applications.

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