VIEW POINT

GEOSPATIAL INSIGHTS: EXPLAINABLE AI (XAI) IN REMOTE SENSING AND GIS

Abstract

The growing adoption of Explainable AI (XAI) in remote sensing and geographic information systems (GIS), often referred to as GeoXAI, is transforming how users interact with AI-driven geospatial models. GeoXAI enables better understanding, trust, and validation of outcomes from complex "black-box" models, including deep learning in remote sensing. By enhancing transparency and interpretability, it provides clear insights into how predictions—such as classification and detection from Earth observation data—are generated. Widely used XAI techniques in geospatial platforms such as SHAP, LIME, heatmaps, visualizations, and surrogate models provide insights into the spatial and temporal factors influencing model outputs, helping improve accountability, fairness, bias detection, and risk assessment. As demand for transparent GeoAI solutions grows, stakeholders increasingly seek location-specific explanations that support reliable decision-making and build confidence in AI-generated geographic insights before operational deployment.

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The evolution: Traditional GIS -> GeoAI -> GeoXAI

Geospatial intelligence is fundamentally reshaping and evolving through three distinct primary stages:

To begin, the traditional phase of GIS was largely characterized by manual spatial queries, rule-based mapping, and static overlay operations. In this stage, GIS primarily served as a repository for data storage, management, and visualization—offering essential but limited capabilities for spatial analysis.

The second stage, GeoAI (geospatial artificial intelligence), marks a significant way forward. By integrating machine learning and deep learning pipelines with geographic data, GeoAI automates a range of complex spatial tasks. This includes sophisticated processes such as feature extraction, object detection, and predictive modeling, all at a much greater scale and efficiency than was previously possible.

Now, we are entering the era of GeoXAI (geospatial explainable AI), which represents the emerging frontier in GIS. While advanced AI models deliver impressive results, they have often been criticized for their lack of transparency. GeoXAI addresses this challenge by providing human-understandable explanations for the outputs of these spatial models. This step is crucial, as it enables us to trust and interpret the results generated by AI.

Evolving drivers shifting geospatial intelligence

There are several factors fueling this transformation in geospatial intelligence:

- Firstly, we're seeing an explosion of remote sensing data—high-resolution aerial and satellite images, LiDAR scans, drone data, and streams of real-time sensor data are flooding the field with unstructured spatial information. This surge is overwhelming traditional GIS methods, making it clear that new approaches are needed.
- Secondly, machine learning has become indispensable for automating spatial analysis and location trends. Algorithms are now central to tasks like semantic segmentation, which enables automatic interpretation of public utilities and land cover. Additionally, deep neural networks are being leveraged for change detection, allowing us to track objects and monitor urban growth over time with greater precision.

The challenge: The black-box AI limit

GeoAI delivers impressively accurate predictions, but one significant challenge always remains: The deep learning networks (like convolutional neural networks) at their core often function as "black boxes." These systems do not reveal which specific GIS data features or geographic elements are most influential in producing a given spatial output.

This lack of transparency can create substantial hurdles for broader adoption.

Limits trust: Stakeholders naturally hesitate to base critical infrastructure, urban planning, or disaster response decisions on results they cannot independently verify or validate

Bias and error identification: This decision-making opacity can obscure underlying biases. If we can't see into the decision-making process, there's a real risk that models may draw on flawed data or reflect geographic biases, ultimately leading to poor outcomes in real-world scenarios.

Human-in-the-loop validation: Decision-makers, urban planners, and environmental scientists must verify model outputs before deploying resources.

By addressing these transparency concerns, we can help ensure that GeoAI delivers not only accuracy but also reliability and accountability for all stakeholders involved.

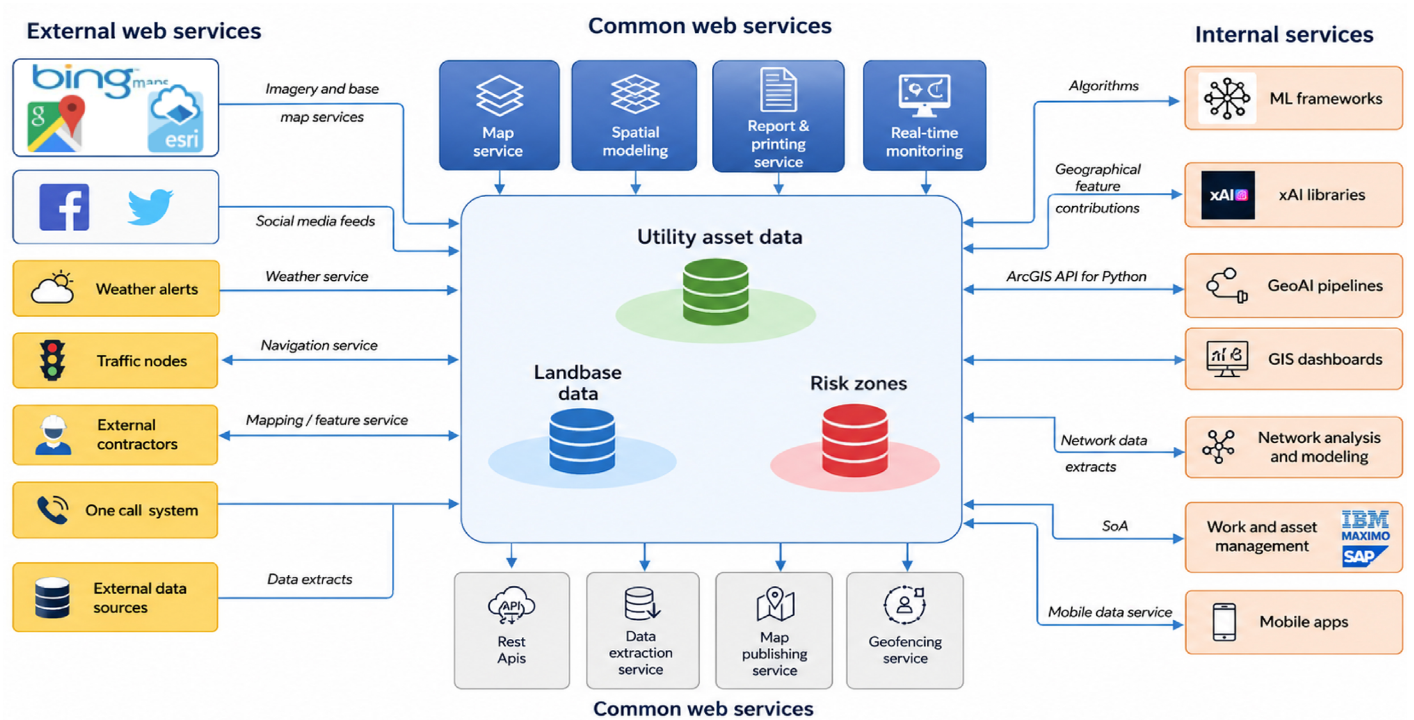
Embracing GeoXAI

Successful transition to GeoXAI is using post-hoc interpretability frameworks such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), deep learning explainability (Grad-CAM and saliency maps), and surrogate models. These powerful tools and models help demystify the inner workings of complex AI models by quantifying feature importance and highlighting exactly how specific spatial attributes contribute to model decisions.

What makes these frameworks even more impactful is their integration into interactive GIS mapping platforms. By doing so, users are empowered not only to visualize mapping results but also to gain direct insight into the decision-making process of AI models. This transparency is essential—it fosters trust and enables users to feel more confident and informed when interacting with these advanced systems.

Architecture: Integrating XAI into GIS systems

Integrating explainable AI (XAI) into GIS systems can significantly elevate our GeoAI solutions. By weaving XAI into our GIS architecture, we open the door to highly transparent and defensible decision-making processes. This approach bridges the gap between advanced spatial analytics and machine learning, empowering stakeholders to not only see spatial predictions but also to understand the specific geographical features that drive those outcomes.



GeoXAI for enterprise GIS

Infosys is in the process of initiating its GIS offerings with explainable AI (XAI) as a foundational framework for its customers, enabling trust, transparency, and governance while addressing the opacity of traditional black-box models in geospatial analytics. By integrating XAI with enterprise GIS and utility asset management, Infosys can translate complex spatial data science into transparent, actionable map-based insights. There are few below mentioned GIS based explainable AI (XAI) innovative approaches that will help analysts to better understand why an algorithm assigns risks or patterns to certain geographies and thus embrace spatial models, knowing they have a clear grasp of the factors influencing outcomes in various locations.

Core XAI frameworks for GIS

- **Trust layer for GeoAI solution offerings:** This validates machine learning predictions in areas like predictive maintenance or site selection by exposing exactly which geographic variables drove the model's output.
- **Automated error resolution traceability:** During GIS data migration, AI algorithms will only automatically identify spatial connectivity errors and overlapping assets. But XAI visually deciphers spatial relationships causing these map anomalies. This allows business to understand the reasons behind any dataset alterations, rather than trusting automated migrations blindly.
- **Spatial governance mechanism:** It will maintain regulatory compliance and promote ethical AI process by meticulously documenting spatial logic, actively minimizing bias, and ensuring operational transparency across systems

Enterprise & platform integration

- **Enterprise GIS integration:** This connects spatial AI directly with leading mapping platforms like ArcGIS, ensuring visualization within the tools.
- **Asset systems:** They will assist in bidirectional sync with platforms like IBM Maximo allowing business to seamlessly map AI-generated risk predictions to physical infrastructure —including pipelines, grids, and facilities—streamlining asset management and risk response.
- **Cloud platforms:** This helps with scaling AI model training across distributed cloud environments (e.g., AWS, Azure) while maintaining centralized geospatial governance.

Visual interpretability techniques

- **Map-based visual explanations:** Transforms standard XAI outputs into interactive GIS layers.
- **Spatial feature importance:** Visualizes the weight of various spatial features (For e.g., proximity to water, soil type, or elevation) directly on the map.
- **Satellite heatmaps:** Overlays attribution-based methods (calculating the influence of every individual pixel or feature that will be applied on satellite imagery to pinpoint the exact pixels) that contributed to a model's classification or change detection. By doing this, it becomes much clearer which regions of the satellite image influenced the model's decision, making the results more interpretable and actionable.

Looking ahead in GeoXAI, the enterprise application perspective

1. Spatial explainability framework

At the enterprise level, Infosys can extend its GeoAI platform by integrating geospatial explainable AI (GeoXAI) frameworks that embed post-hoc interpretability techniques such as SHAP, LIME, and gradient-based saliency maps directly into geographic workflows. This enables organizations to transform complex "black box" model predictions into clear, actionable, and scientifically grounded insights, improving decision-making, regulatory compliance, and stakeholder trust. Key enterprise use cases include:

- **Pixel-level explainability (satellite imagery)**
  Enterprises leveraging high-resolution satellite imagery—for disaster management, asset monitoring, or environmental analysis—require precise interpretability of model predictions. GeoXAI enables visualization of pixel-level drivers (e.g., spectral bands or spatial edges), helping decision-makers clearly understand features such as damaged infrastructure or vegetation health.
- **Spatial feature attribution (land parcel classification)**
  For applications such as zoning, utilities planning, and infrastructure development, GeoXAI enables attribution of predictions to spatial and contextual features. By integrating SHAP/LIME with geographic variables (e.g., proximity to road networks, elevation, terrain slope), organizations gain a deeper understanding of classification outcomes, supporting more transparent and defensible decision-making.
- **Temporal explainability (change detection reasoning)**
  In use cases such as deforestation monitoring or urban expansion, enterprise solutions can move beyond simple change detection to explain why changes occur over time. GeoXAI frameworks enable tracing historical patterns and identifying key drivers of change, providing actionable intelligence for policy-making and long-term planning.

2. Domain-specific explainability models

At the enterprise level, Infosys can further operationalize GeoXAI through domain-specific explainability components tailored to industry use cases. These components translate complex spatial-temporal machine learning outputs into human-interpretable insights aligned with business workflows, regulatory requirements, and operational decision-making.

Examples of such domain-specific components (not limited to):

Domain	GeoXAI use case	Implementation output

Utilities	· Asset failure prediction explanation
	· Constraint-validation rules engines for legacy data migration
	· Mapping grid infrastructure elements such as pipelines and transformers
		· Overlaying explicit contribution values of these assets on the map such as:
		  ◦ Proximity to high-corrosion soil
		  ◦ historical load stress data
		  ◦ Ambient temperature conditions
		· Enabling data-driven maintenance prioritization based on these insights
		· GeoXAI flags contradictory spatial data before legacy data is migrated

Public sector	Policy impact visualization	· Interactive web-based map interface designed for policymakers
		  ◦ Ability to dynamically toggle different planning or policy variables (such as zoning adjustments and public transit expansion)
		  ◦ Use of color-coded layers to represent outcomes
		  ◦ Display of localized, geographically specific insights
		  ◦ Integration of Shapley values to explain contribution of each variable
		· Application of explainable AI to quantify factor-level influence
		· Assessment of impacts across key urban metrics such as:
		  ◦ Housing affordability
		  ◦ Traffic volumes
		  ◦ Urban sentiment (e.g., livability or public perception)

Insurance	Risk zone reasoning	· Translates spatial risk data (such as satellite imagery, foot traffic, and real-time perils) into interpretable risk forecasting · Development of predictive customer pricing models based on risk profiles · Utilization of automated, satellite-based damage detection systems · Identification of specific damage patterns (e.g., roof destruction, structural impact) to expedite payouts
Energy	Sub-surface data into intuitive models	· Combines drones and satellite data to map spatial risks along pipeline corridors · Sub-surface and reservoir modeling using drilling logs and well completion reports · Interpret geospatial databases for deciphering environmental footprints

Authors

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Sudeep brings 18+ years of experience in GIS, image processing, and spatial data, focusing on GeoAI and AI-based spatial analytics. He has delivered innovative geospatial solutions across corporates, e-governance, and utilities in the US, Africa, and APAC, serving as a trusted GIS SME. His expertise spans solution design, large-scale program delivery, and business development for complex geospatial engagements, with strong techno-commercial acumen in driving AI-enabled, data-driven decision-making.

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Sonal heads the delivery for GIS and digital marketing operations at Infosys BPM. With overall 20 + years of experience, Sonal is leading operations and delivery across multiple global engagements. Her focus has been on driving process excellence, digital enablement, and process transformation – while enhancing GIS data governance and enterprise-wide geospatial decision support for our clients.

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