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ARTIFICIAL INTELLIGENCE IN EARTH SCIENCE: A GEOAI PERSPECTIVE

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ABSTRACT

GeoAI, or geospatial artificial intelligence, has transformative potential for Earth science by integrating geospatial data with artificial intelligence to enhance environmental monitoring, predictive modeling, and decision-making. This commentary, based on the Greg Leptoukh Lecture at AGU 2024, explores the evolving role of GeoAI in addressing pressing challenges—from environmental change in the Arctic to disaster response in hurricane-prone tropical regions. It highlights advancements in GeoAI-driven analysis of multimodal Earth observation data, ranging from structured remote sensing imagery to semi-structured data and natural language texts. The integration of knowledge graphs and generative AI further strengthens GeoAI by enabling seamless integration of cross-domain data, semantic reasoning, and knowledge inference. By bridging informatics and domain expertise, GeoAI is shaping a more intelligent and actionable digital future for Earth science.

***K*eywords** GeoAI · AI · Reproducibility · Generative AI · Knowledge graph

1 Introduction

This is an exciting and challenging era for Earth science. On the one hand, cutting-edge Earth observation (EO) techniques have enabled the generation of massive EO datasets with super-high spatial and temporal resolutions, driving scientific discovery and addressing complex societal problems. On the other hand, integrating and analyzing such data has become a significant challenge due to their large size, discrepancies in coverage and timespan, and diverse formats and modalities. Traditional scientific analysis often encounters the 80/20 dilemma, where 80% of an Earth scientist's time is spent in the pre-science phase—such as data discovery, search, integration, and exploratory visualization —while only 20% is dedicated to actual analysis and discovery [1]. The challenge of utilizing diverse EO data has become increasingly evident as we step into the big data era.

Fortunately, the emergence of new analytical technologies, especially in artificial intelligence (AI) and deep learning, along with rapid advances in computing, has driven progress in Earth science informatics—an interdisciplinary field pioneered by Dr. Greg Leptoukh and other researchers—leveraging informatics and data science to accelerate Earth science discovery. The recent emergence of GeoAI [2], or geospatial artificial intelligence, as a transdisciplinary expansion of AI into "geo" domains, has propelled advances in Earth science informatics and powered all elements of the data-to-knowledge production pipeline (as shown in Figure 1).

So, what is the "Geo" in GeoAI? At its simplest, the "Geo" in GeoAI refers to the geospatial applications of AI. The surge in AI advancements around 2012 was largely driven by its parallelizable and effective feature extraction capabilities for image analysis, making Earth science a natural field for AI applications due to the vast amount of available remote sensing imagery. Over the past decade, pioneering research has leveraged AI to analyze satellite imagery and other remotely sensed data to map environmental changes [3]. For example, AI and deep learning have been used to classify crop types and predict yields [4]. They have also been applied to map floods, landslides, and other disasters, as well as to conduct change detection [5]. In addition, AI has been utilized for large-scale land use and land

Figure 1: A data to knowledge production pipeline of Earth science enabled by GeoAI. Each component in the pipeline faces unique geospatial challenges. Earth observation (EO) data vary in spatial and temporal resolution, format, and geographic coverage, making sharing and integration difficult. Their distribution across multiple sources, often in the deep Web, complicates discovery and search. The multi-dimensional and real-time nature of Earth data (e.g., weather forecasting) presents additional challenges for visualization and analysis. GeoAI plays a central role in addressing these challenges.

cover mapping to produce high-resolution foundational data products [6]. It has also been used to map infrastructure and Arctic permafrost thaw, helping to understand the impacts of environmental change on communities [7].

We call GeoAI a new interdisciplinary field of research, but what makes it unique beyond being just an application of AI in the "Geo" domain? The answer is yes, there are distinct characteristics that set GeoAI apart. In a recent paper by Li et al. [8], the authors outlined key research directions contributing to the advancement of the "Science of GeoAI." One key aspect is spatially explicit modeling, where spatial principles such as spatial autocorrelation and spatial heterogeneity are embedded into AI models to account for both global patterns and locally unique contexts, improving model predictability. Another important direction is multi-source and multimodal modeling, which is particularly beneficial in EO data analysis. Multimodal refers to data from diverse modalities—such as multispectral satellite imagery, numerical simulation outputs, natural language documents (e.g., scientific literature), audio, video, and sensor network observations—that provide complementary perspectives on Earth's changing environment and climate. Leveraging these diverse data types enhances understanding of the area of study.

In addition, spatiotemporal and multi-scale joint learning enables the modeling of Earth system changes in a holistic manner by integrating space, time, and different geographical scales, taking advantage of near-real-time monitoring capabilities to better capture dynamic environmental changes. Finally, geography-informed model training and validation distinguishes GeoAI from other AI models, as research concerning different locations on Earth must account for geographical variations in climate, landscapes, and human factors. These constraints offer a unique opportunity to train and validate GeoAI models, improving their geographical transferability. Together, these elements highlight the uniqueness of GeoAI, not just as an application of AI but as a specialized field that addresses spatial and temporal complexities in Earth science.

A pioneering GeoAI modeling effort in the Earth science domain is the development of Prithvi-EO, a new geospatial AI foundation model trained on time-series EO data with both national and global coverage to distill unique semantic and spectral characteristics of Earth's varying surface [9]. Beyond EO data training, Prithvi-EO is enhanced with both location and temporal embeddings, enabling stronger generalizability and transferability than other task-specific AI models [10]. As a geospatial AI foundation model incorporating data and knowledge from the "geo" domain, it has demonstrated effectiveness across a wide range of geospatial applications, including disaster mapping, multitemporal land use and land cover classification, and above-ground biomass estimation. This further showcases the power of the GeoAI modeling paradigm.

In the next section, I will introduce two interdisciplinary research projects where GeoAI serves as a key tool to support both science and society.

2 GeoAI in Action: Problem Solving in Earth Science

2.1 GeoAI to track permafrost thaw in near-real-time to inform climate actions

The Arctic has undergone significant changes over the past decade, with an accelerating pace of landscape transformation. At the center of this shift is Arctic permafrost — frozen ground that remains at or below 0°C for at least two consecutive years. As temperatures rise, permafrost thaw leads to ground subsidence, triggering environmental changes such as lake drainage, coastal erosion, and increased landslide risk. This process threatens the five million people living in the Arctic, putting communities at risk of critical infrastructure damage and other cascading impacts. To address this, researchers from the Permafrost Discovery Gateway (PDG; [11]) have begun utilizing big data and GeoAI to track permafrost changes in near-real-time, enabling scientific insights to better support community planning and climate adaptation efforts. GeoAI plays a crucial role in tackling several key challenges. First, GeoAI can analyze super-high-resolution satellite imagery to detect indicators of permafrost thaw, such as ground ice conditions and the formation of thermokarst features like retrogressive thaw slumps. To fully capture these landscape changes, multimodal data play a crucial role. For example, permafrost thaw can be better understood by integrating EO data from different modalities—such as elevation data to detect ground collapse, vegetation indices (e.g., NDVI) to assess disruptions in plant cover, and optical or near-infrared imagery to reveal surface alterations.

Figure 2 illustrates a GeoAI-enabled mapping workflow for generating pan-Arctic-scale big data within the PDG. The GeoAI model takes multimodal data and, through deep learning-based feature extraction, transforms the input into representative features known as feature maps. These feature maps are then passed to the feature fusion module [12]. The fused (and enhanced) feature maps are subsequently sent to the decoder to segment or detect phenomena of interest, such as thaw slumps or lake drainage.

As GeoAI models become larger and more complex (e.g., with the use of transformer architectures) and data volumes continue to grow, significant computing resources (e.g., graphics processing units/GPUs) are required to train and deploy these models. While a modest GPU server with 6–8 A5000 GPUs (24GB memory each) can handle regional-scale tasks such as permafrost thaw mapping as discussed in [12], generating predictions at the pan-Arctic scale may require several thousand GPU hours on high-end GPUs such as the A100. The amount of computing resources needed depends on several factors, including the extent of the study area, the desired image resolution, and the choice of GeoAI model (large or lightweight). Balancing the trade-off between achieving optimal predictive accuracy and managing computational demands is therefore a key consideration in the large-scale deployment of GeoAI models.

Beyond mapping, GeoAI can also integrate climate data, topography, and permafrost thaw triggers (e.g., wildfires) to move beyond current observations and enable seasonal forecasting of abrupt permafrost thaw—helping to predict where and when future thaw events might occur. Existing numerical models primarily consider permafrost thaw as a gradual long-term process, with abrupt thaw events not well understood or accurately represented. By leveraging GeoAI's ability to analyze spatial and temporal relationships within large datasets, researchers can make a critical leap forward in permafrost science, improving both understanding and predictive capabilities. This scientific information is crucial for advancing our understanding of Arctic permafrost and supporting Arctic communities affected by its thaw. By providing timely insights into the risk and pace of permafrost thaw, we can help communities plan for village relocation due to thaw-related damage, reinforce critical infrastructure such as the Trans-Alaska Oil Pipeline, and guide the development of new infrastructure to withstand changing conditions.

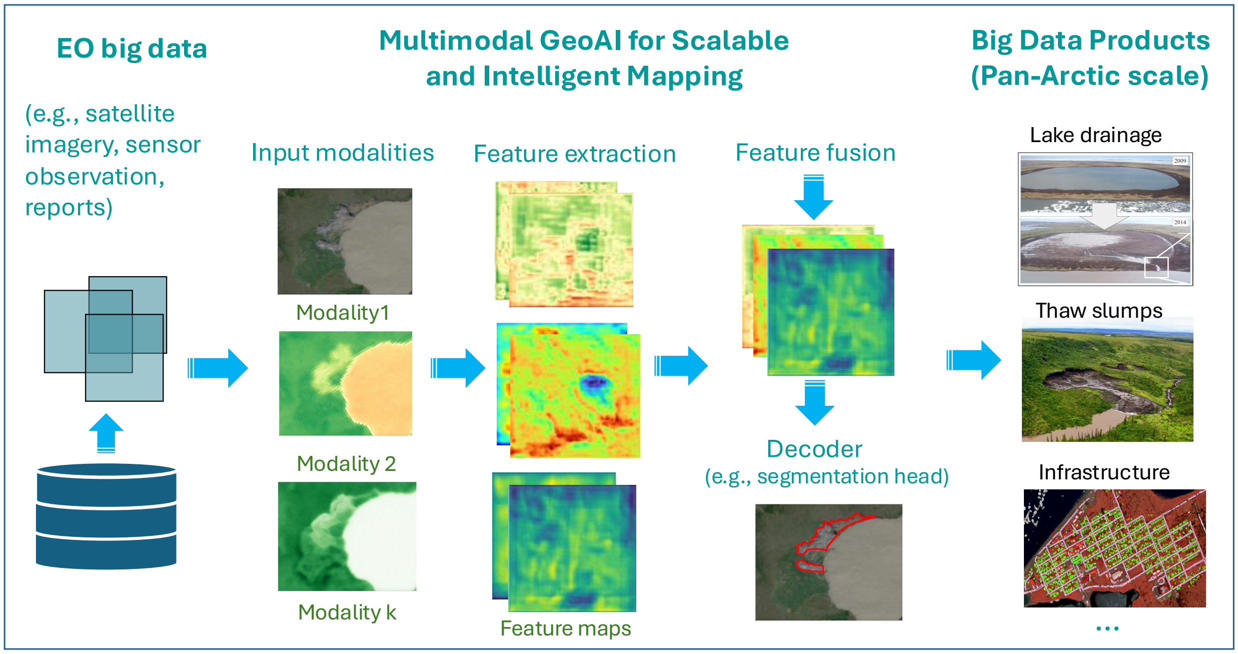

Figure 2: GeoAI enabled intelligent and scalable mapping workflow for permafrost big data generation. Photo credits: Lake drainage (Benjamin M. Jones), thaw slumps (Scott Zolkos), infrastructure (Chandi Witharana).

2.2 GeoAI for building "Geo" knowledge graph to support disaster response and humanitarian aid

Another area where GeoAI can provide significant support is enabling automated and intelligent integration of cross-domain datasets through the development of large-scale knowledge graphs. This research traces back to the early 2000s when Tim Berners-Lee and colleagues envisioned a future internet where the web content would be semantically tagged, making it easily digestible not only by humans but also by machines. This vision, known as the Semantic Web [13], has influenced numerous domains, including Earth science. The integration of Semantic Web principles with Earth science data has been at the forefront of Earth Science Informatics. A well-known example is SWEET ontology (Semantic Web for Earth and Environmental Terminology; [14]), developed by Dr. Robert Raskin and colleagues at NASA JPL, which has greatly facilitated Earth science data search and discovery across multiple information systems. For instance, the SWEET ontology has been used as a knowledge backbone to support semantic disambiguation, query expansion, and cross-domain linked EO data retrieval [15]. It has also been actively adopted by the polar research community to enhance metadata sharing and promote semantic interoperability [16].

A knowledge graph, as a natural extension of ontology-based knowledge representation frameworks like SWEET, connects multidisciplinary data at scale to support rapid decision-making. One of the pioneering efforts in this area is the development of KnowWhereGraph [18], which links and integrates semi-structured and unstructured geospatial information about the Earth and its environment into a unified graph structure. This integration enhances spatial reasoning and enables more effective analysis and decision-making at the intersection of human and environmental systems. Two unique features make KnowWhereGraph stand out from other graph solutions. First, it enables the "Know" feature by combining and linking cross-domain data, information, and knowledge, including the rapid assembly of real-time information during emergencies such as disasters. Second, it enables the "KnowWhere" feature by using location as a key to connect cross-domain data, supporting location intelligence and helping end users make informed decisions.

GeoAI plays a critical role in enabling both features. To enrich the "Geo" knowledge in KnowWhereGraph, GeoAI—particularly geospatial knowledge-guided large language models—has been leveraged to extract geographical entities and their interrelationships (e.g., spatial relations) with high accuracy from natural language text and other data sources. Unlike general-purpose information extraction, GeoAI must instruct large language models to recognize the unique characteristics of geographical entities and develop novel strategies to integrate multi-source information (e.g., gazetteers) for the disambiguation of place names and other geospatial knowledge. GeoAI is also used for graph embedding by incorporating geo-entity types, geometry information, and spatial relations to enrich knowledge representation within the graph [19].

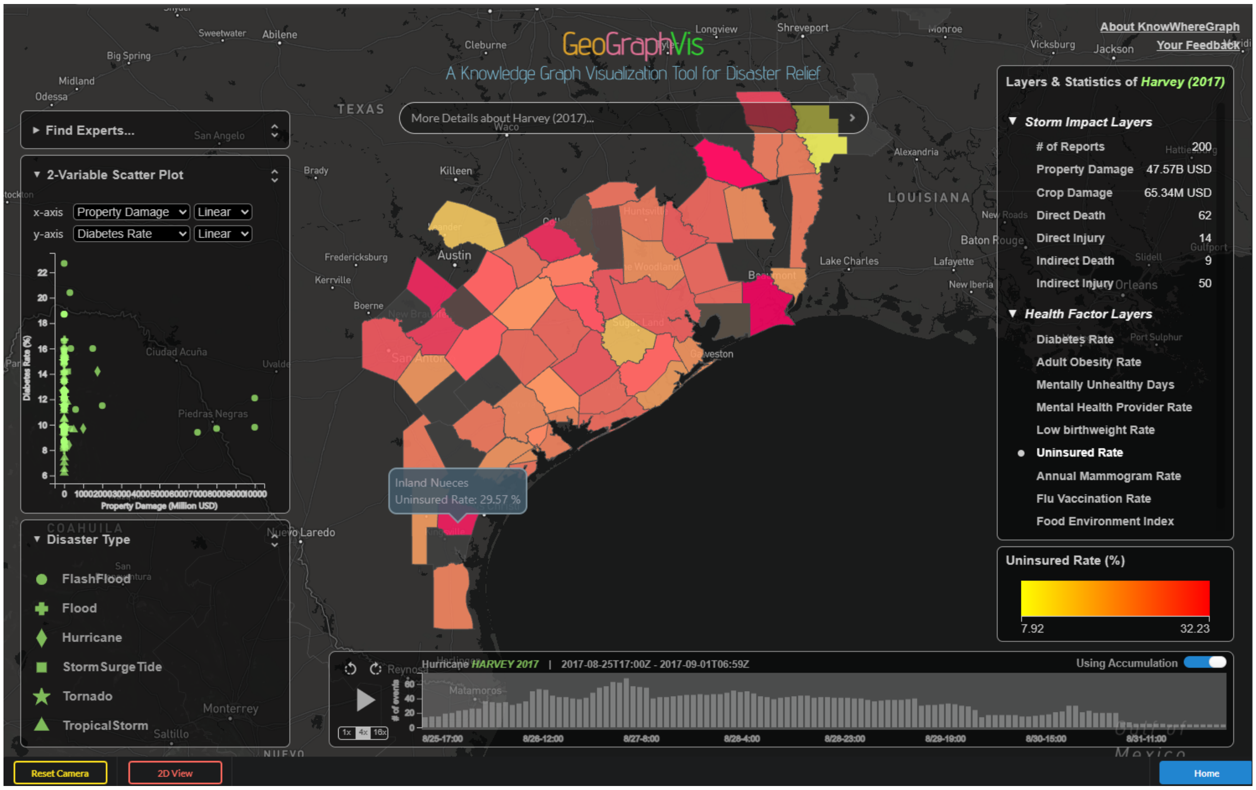

Figure 3: GeoAI and knowledge graph-enabled decision-making tool GeoGraphVis [17] for disaster response. The map in the center displays the uninsured rate in areas impacted by Hurricane Harvey. Other disaster damage information and health factors can also be visualized individually or in combination.

Such a densely connected, location-aware knowledge graph has become a valuable knowledge base for supporting disaster preparedness and response, one of NASA's key application areas. Through novel geovisualization on the front end, as shown in Figure 3, the graph data helps stakeholders develop situational awareness of disaster-affected areas, the damage caused, and cascading events that have occurred. Additionally, it can reveal socioeconomic and health profiles, enabling relief experts to identify vulnerable communities and support evacuation efforts. Beyond this, GeoAI can be further utilized to infer second- and third-order effects, answering "what-if" questions to identify scenarios where different actions may be needed to reduce damages and save lives.

3 Remaining challenges and future research directions

The projects introduced above represent two major subfields of research where GeoAI plays a key role. The Arctic project extends AI's capabilities in image analysis and computer vision to generate permafrost big data, whereas the knowledge graph project enhances AI's power in natural language processing for cross-(geo)domain information integration and spatial reasoning to address critical decision-making questions. Although exciting progress has been made, much research remains to further advance GeoAI to drive scientific breakthroughs and address societal challenges. In addition to ongoing discussions about AI limitations—such as explainability, ethical and responsible AI research, and open AI—I would like to highlight additional points that are critical to GeoAI research for Earth science.

3.1 Systematic scientific validation of GeoAI modeling results

While GeoAI offers immense potential for processing large volumes of observational data to generate scientific data products at unprecedented scale and resolution, there is still a lack of rigorous scientific validation for these products. For example, researchers from the PDG team have created the first pan-Arctic dataset (5TB total) identifying the locations of ice wedge polygons (IWP) by segmenting super high-resolution satellite imagery [20]. This dataset is of great value for assessing ground ice conditions, which are directly linked to permafrost thaw.

From a GeoAI research perspective, evaluation is typically conducted using annotated IWP locations that were not included in model training, allowing performance metrics to be quantified. Yet, from a scientific analysis standpoint, a more systematic validation is required to assess data quality against actual ground-truth observations across the Arctic's diverse landscapes. However, it is important to recognize that this is a very challenging task, as collecting such ground-truth data often requires extensive field or manual work, which is difficult to conduct at scale. Discrepancies may also arise when field data is collected in different years than the satellite imagery used for analysis. To ensure the trustworthiness of GeoAI-generated data for downstream scientific analysis and discovery, it is critical for the Earth science and informatics communities to come together in developing systematic evaluation frameworks. Establishing robust validation methodologies will help bridge the gap between AI-generated results and their real-world scientific applicability.

3.2 Reproducible GeoAI for Earth science

Reproducible Earth science is not a new topic, as the community has long recognized the importance of open science by sharing data, methods, and research outcomes to foster continuous innovation. However, given the complexity of GeoAI models and the significant details involved—such as the data used, potential variance in model parameters, training, fine-tuning, and evaluation methods—it is challenging to make GeoAI research computationally reproducible [21]. The learning curve for GeoAI research, especially in tackling complex problems like climate forecasting, is also quite steep for the scientific community. Toward this end, new approaches to documenting, testing, and ensuring the successful configuration and execution of GeoAI models are needed. Generative AI tools, such as large language models, could potentially assist in automating documentation and reproducibility testing of GeoAI models. An autonomous "reproducibility test" agent could serve two roles: first, automatically generating documentation from existing code and clarifying details through natural language interactions with GeoAI model developers; and second, acting as a testing agent to verify whether, based on the documented information, a model can be successfully set up and produce the expected results. Through this agent-based refinement-retesting paradigm, a significant amount of human effort can be reduced, and the computational reproducibility of GeoAI models can be better ensured.

What is more challenging than computational reproducibility is the replicability—or more precisely, the generalizability—of GeoAI models [22]. A GeoAI model trained on data from one geographic region may yield different prediction results when applied elsewhere due to spatial heterogeneity. In other words, findings in Earth and environmental research, including those in related social science domains, are often difficult to generalize across space and time. Goodchild and Li [22] refer to this limitation as the "weak replicability" of geospatial studies. Because of this, ensuring computational reproducibility—achieving the same results using the same data, model, and study area—becomes even more critical. When adapting an existing GeoAI model, researchers must ensure that the results are fully reproducible under identical settings. At the same time, it is important to recognize that reproducing one study does not guarantee that similar findings will hold under different conditions. This distinction reinforces the need for detailed documentation to clarify the assumptions, constraints, and contextual boundaries of a study, enabling others to better understand and appropriately interpret the results.

3.3 Convergence among generative and deterministic GeoAI for Earth science

In GeoAI for Earth science research, the vast majority of applications have focused on deterministic tasks aimed at extracting important information from EO data. The two projects introduced in Section 2—analyzing satellite imagery and extracting semantic information from semi-structured data or natural language text—both fall into this category. In recent years, the rise of generative AI has introduced new possibilities for GeoAI research. Unlike deterministic tasks, generative AI supports the creation of new content, such as images, videos, text, and natural language responses. This capability could significantly advance Earth science GeoAI research by, for example, automatically generating training images with desired variance and distribution to improve GeoAI model performance in image analysis. It could also be applied to automate scientific workflow generation, an area that Earth science informatics researchers have dedicated significant effort to [23]. Generative AI can also enhance user intent understanding and, when combined with deterministic GeoAI methods (e.g., ranking), enable semantic search for Earth data products across different data centers, such as the Goddard Earth Science Data and Information Science Center (GES DISC; [24]).

However, we must also recognize that generative AI is a double-edged sword. While it offers powerful capabilities, the answers it generates may be fabricated, unlike deterministic tasks where results are directly extracted from existing data. To address this challenge, cross-validation using multiple inputs (e.g., data modalities), independently developed workflows, and diverse solution frameworks (both generative and deterministic) can help verify the reliability of AI-generated outputs. The convergence of generative and deterministic GeoAI approaches could further enhance problem-solving in Earth science by enabling more automated and intelligent solutions.

4 Concluding remarks

AI has undoubtedly driven transformative innovations in Earth science. Rather than attempting to cover all aspects of this evolving field, this commentary offers a GeoAI perspective based on the author's experience. Solving complex Earth science problems in the future will require interdisciplinary teams with diverse expertise, where GeoAI will serve as a key vehicle to bridge the gap between data, science, and actionable solutions. GeoAI researchers will play a critical role as translators, facilitating both the application of AI for Earth scientific discovery and the advancement of AI through geospatial insights. This dual role will enable the development of stronger GeoAI models to better address domain-specific challenges in Earth science and beyond. To effectively contribute to this emerging field, early-career scientists will benefit from training in geospatial analysis, machine learning, remote sensing, and data ethics, alongside domain knowledge in environmental and Earth systems science. Building such interdisciplinary skillsets will empower the next generation of researchers to lead innovations at the intersection of AI and Earth Science.

As GeoAI continues to evolve, ensuring its reliability and broader impact remains a pressing challenge. How can we move beyond accuracy as the primary measure of GeoAI models and ensure they are truly trustworthy in real-world applications? A highly accurate model can still produce results that are biased or difficult to interpret, raising the need for evaluation frameworks that consider robustness, fairness, and explainability. At the same time, can we develop an operationalizable GeoAI research framework that systematically fosters responsible AI—one that prioritizes trustworthiness, sustainability, reproducibility, and interpretability? Establishing such a framework would not only guide technical advancements but also help bridge the gap between research and real-world adoption. To maximize GeoAI's impact, we must ensure that innovations translate into meaningful, lasting benefits. Now is the time for the community to take action—refining evaluation metrics, advancing responsible AI practices, and shaping a future where GeoAI solutions are both powerful and trusted.

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