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INVITED ARTICLE

GeoAI for Science and the Science of GeoAI

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Abstract: This paper reviews trends in GeoAI research and discusses cutting-edge advances in GeoAI and its roles in accelerating environmental and social sciences. It addresses ongoing attempts to improve the predictability of GeoAI models and recent research aimed at increasing model explainability and reproducibility to ensure trustworthy geospatial findings. The paper also provides reflections on the importance of defining the "science" of GeoAI in terms of its fundamental principles, theories, and methods to ensure scientific rigor, social responsibility, and lasting impacts.

Keywords: artificial Intelligence, spatially explicit, AI for science, responsible AI, explainable AI, GeoAI, reproducibility, co-design, ethics, AI for Good

1 Introduction

Artificial Intelligence (AI), especially deep learning, has transformed many science and engineering disciplines because of its outstanding ability to learn and reveal previously unknown patterns and knowledge in a data-driven manner. Geography is an ideal domain to extensively apply and further boost AI research because of the availability of vast, diverse geospatial data, intriguing and complex human-environmental interactions, as well as its central role in enabling location-based analysis. In less than a decade, we have witnessed a rapidly growing interest and progress in Geospatial Artificial Intelligence (GeoAI) research—the transdisciplinary expansion of AI in Geography and its sibling domains in urban, environmental, and social sciences.

So, what is GeoAI? Li [34] defines it as a novel technological solution that integrates AI, geospatial big data, and high-performance computing for solving data- and computation-intensive geospatial problems. This field has gained continuous momentum, driven by strong demands in geography and the rapid advancement of AI. On the one hand, the sheer amount of available geospatial data, ranging from super-high-resolution satellite imagery (centimeter scale) to sensor observational data collected in real time, continues to fuel the need for robust, scalable, and smart analytical capabilities. These capabilities are essential for producing important datasets about the natural and built environment, as well as human activities, which are critical to help us better understand ever-changing environmental, ecological, and social systems and their interactions. On the other hand, the rapid evolution of cutting-edge AI technology, the open science movement, and the seamless exchange and fusion of new (deep) learning strategies across subdomains of AI further offer methodological guidance for strengthening GeoAI [9].

In a broader sense, GeoAI research primarily involves applying off-the-shelf AI models to solve geospatial problems. Indeed, much of this research falls into this category; however, it also features a unique methodological core that sets it apart from general AI research:

Spatially explicit modeling. The explicit incorporation of space and place into AI modeling has become a desired property of GeoAI [13, 24]. Spatial data and processes possess two unique properties: spatial autocorrelation and spatial heterogeneity. Spatial autocorrelation, defined in Tobler's First Law of Geography, reflects the phenomenon that things closer geographically tend to be more similar. This property has guided the design of multiple spatial algorithms, such as spatial clustering and interpolation, as well as GeoAI models. For example, guided by the principle of spatial autocorrelation, researchers [36] developed a weakly supervised deep learning (WSDL) framework by converting a spatial object detection problem into a sequence learning problem, relying on much less ground truth information. This is achieved by serializing 2D data into a 1D sequence and maximizing the preservation of spatial continuity and therefore spatial autocorrelation in the serialized data. Enabled by the WSDL, a significant amount of data annotation cost can be reduced. Experiments on both Earth and Mars feature detection have shown that the spatially explicit GeoAI model outperforms cutting-edge AI models.

Spatial heterogeneity refers to the uncontrolled locational variance and non-stationarity of environmental and social processes on the Earth's surface [1], and this property has been increasingly embedded in the newer generation of GeoAI models [12, 60]. For example, [60] developed a spatial-heterogeneity-aware deep learning framework for mining spatial data. A multivariate scan statistic is applied to identify spatial heterogeneity in the input data and guide the hierarchical spatial partitioning of the study area to train multiple deep learning models. This approach results in stronger model predictions in both mobility pattern analysis and land cover classification compared to other AI models.

Such GeoAI models, integrating the above and other fundamental spatial principles (for example, spatial interaction and the Third Law of Geography [65]), represent a deep fusion of geography and AI and will continue to bring innovation to GeoAI research.

Multi-source, multimodal GeoAI modeling. One distinctive feature of geospatial data is that they are geographically framed [50]. This enables geospatial data collected from different sources to be spatially (and temporally) aligned and integrated to provide a more comprehensive view of a study area. Hence, multi-source GeoAI [56] has become a unique research topic that leverages complementary spatial data to achieve high-accuracy data analysis and spatial modeling. Meanwhile, because geospatial data often include multiple modalities, such as raster, vector, and text, processing them into a coherent representation through techniques such as location embedding [29,41] will further improve the utilization of these multimodal data.

Spatiotemporal and multi-scale joint learning. A shared characteristic among many geophysical and social phenomena, such as hurricanes or a spreading pandemic, is that they are evolving spatial processes. Hence, it is important to consider their spatial and temporal properties simultaneously when modeling such phenomena. Recent efforts [5, 32] to develop large transformer models that can capture the spatial and temporal dependencies within a huge amount of data over long ranges have set an exemplar for GeoAI research. The inherent integration of multi-scale learning in this process captures the spatial hierarchy and compositionality of many spatial features and processes, shedding new light on complex forecasting tasks, such as weather forecasting and climate projections. These tasks are traditionally accomplished with physics-based models, which require massive computing power and long simulation times. Additionally, coupling physical process models with multi-scale deep learning improves process understanding in spatial and Earth sciences [46].

Geography-informed model training and validation. In addition to helping develop spatially explicit models, geography also plays important roles in informing and improving model training and evaluation. For example, existing research has leveraged map projections and cartographic principles to automatically generate training data for map image recognition [20]. Researchers have also utilized OpenStreetMap data to create AI-ready training data to identify buildings and roads from aerial images [17, 26]. For model evaluation, GeoAI research can use different strategies depending on whether the goal of the trained models is to predict within the same geographic area or to predict into new areas. Random cross-validation may be used for predictions without considering the geographical context, whereas spatial cross-validation may be adopted to better assess model performance when the goal is to predict outcomes in untested geographic areas [15, 47, 49].

In the following, we describe use cases showcasing the power of GeoAI over traditional GIS methods in advancing spatial sciences.

2 GeoAI for Science

GeoAI has contributed to a wide range of scientific domains, such as climate modeling [32], environmental epidemiology [53], health care [27], human dynamics tracking [57], remote sensing image analysis [35], land cover and land use change detection [62], sustainable agricultural practices [10], urban planning [43], infectious disease analysis [30], disaster response [66], and supply chain management [25]. This section discusses two recent initiatives where GeoAI plays a crucial role in supporting spatial science. The first use case examines a geospatial AI foundation model that primarily deals with field data (raster data). The second focuses on building an intelligent National Map, emphasizing object-based modeling of space.

2.1 The development of a new geospatial foundation model Prithvi

An exciting development in GeoAI is the move toward building foundation models—models trained on massive geospatial data of various kinds to gain strong capabilities in knowledge representation [22]. Rather than being task-specific, foundation models are designed to be adaptable to a wide range of downstream tasks, from image analysis to question answering in natural language text [61]. As the community witnesses considerable success in large language models (LLMs), such as ChatGPT, developing vision foundation models tailored to detect important phenomena from images and other structured data has fallen behind [38]. First, it is difficult to generalize a fine-grained image analysis task in an image-to-image learning framework, as the output of such tasks varies substantially due to different application needs. The second challenge is the lack of data and computing infrastructure for academic research groups to conduct national- to global-scale analysis of ever-expanding earth observation data. Big-tech companies, which have such a scale of resources, are more equipped to develop foundation models to address problems of commercial value rather than their value to open science.

Fortunately, the National Aeronautics and Space Administration (NASA) and International Business Machines (IBM), along with other partnering research organizations, are spearheading the development of a geospatial foundation model—Prithvi—to transform the management and analysis of geospatial big data. The Prithvi model is built upon an advanced AI architecture called a vision transformer and uses self-supervised learning to reduce labeling costs and scale up the amount of data the model can utilize. A distinctive feature of Prithvi is its geospatial focus—the model is trained on Harmonized Landsat and Sentinel-2 (HLS) imagery in time series, and it has shown stronger domain adaptability and transferability than other AI models for geospatial applications, including flood mapping and wildfire prediction [22, 39]. Another advantage of this research is that both the data and model under development are made open-source and publicly available, fostering the growth of a community to collectively contribute to the advancement of GeoAI modeling capability in this important area.

2.2 GeoAI for building an intelligent National Map

At multiple mapping agencies, such as the United States Geological Survey (USGS) [16], United Kingdom's Ordnance Survey [44], Natural Resources Canada [7], and Geoscience Australia [59], there has been a major effort to build a National Map. This map, or more precisely, a core collection of geospatial data about elevation, hydrography, orthoimagery, geographical names, and more, is an essential element for building the National Spatial Data Infrastructure and supporting a wide range of mapping and modeling applications [2].

However, this process is very time-consuming and often lasts for decades. Taking the USGS topographic map as an example, the original creation process of the Historical Map Collection (HTMC) involved a few hundred cartographers, field scientists, geomorphologists, and managerial staff. They spent multiple years examining online maps to identify the extent of important topographic features, from mountain summits to valleys and ridges, and to recognize the correct geographical extent and type of these features. This effort also required extensive fieldwork and interviews with local and state communities to ensure high accuracy and a semantically consistent definition of terrain features. The Geographical Names Information System (GNIS) database captured many of these features from the HTMC amid long-term efforts to build digital gazetteers detailing attributes of important named features. Despite the database's over one million named features, its geolocation information remains a single point location for all features, regardless of size. This incomplete information has limited the effective use of such data for geospatial analysis [4]. Additionally, the search and identification of important features on the surface of Earth and other planets have also introduced significant challenges for AI in answering the question of "where" [14].

GeoAI, with spatial methods developed specifically for processing many satellite images, historical maps, and other geospatial data, provides an unprecedented opportunity to automate the process toward building an intelligent National Map [52]. Whereas traditional machine learning methods can support the processing of geospatial data or images, the analysis is often limited by geographical extent due to the need for manually distilling important data attributes and rules for recognizing natural or manufactured features. In comparison, large neural network models enable generalizability in pattern recognition and extraction, contributing to much-advanced feature extraction capabilities and the ability for large-scale intelligent analysis. Geospatial deep learning models have been developed to harness high-accuracy LiDAR data from the USGS 3D Elevation Program and airborne interferometric synthetic aperture radar (IfSAR) data for fine-scale hydrologic streamline detection, producing desirable benefits for many scientific domains [48,63]. The leverage and fusion of multi-source geospatial data, as well as the integration of geospatial domain knowledge, are unique to GeoAI research [19]. Georeferencing and rescaling can align and combine datasets of varying spatial resolutions and map projections to further empower such intelligent analyses [3].

3 The Science of GeoAI

Although the propulsion of GeoAI into scientific research in both social and environmental sciences is evident, the readiness to claim GeoAI as a new scientific discipline remains an open question. Below, we discuss topics critical to GeoAI research and what may make it a long-lasting and high-impact scientific discipline instead of a 'local hotspot' in GIScience research.

In terms of research objectives, the science of GeoAI may cover four fundamental pillars: predictability, interpretability, reproducibility, and social responsibility (Figure 1). It

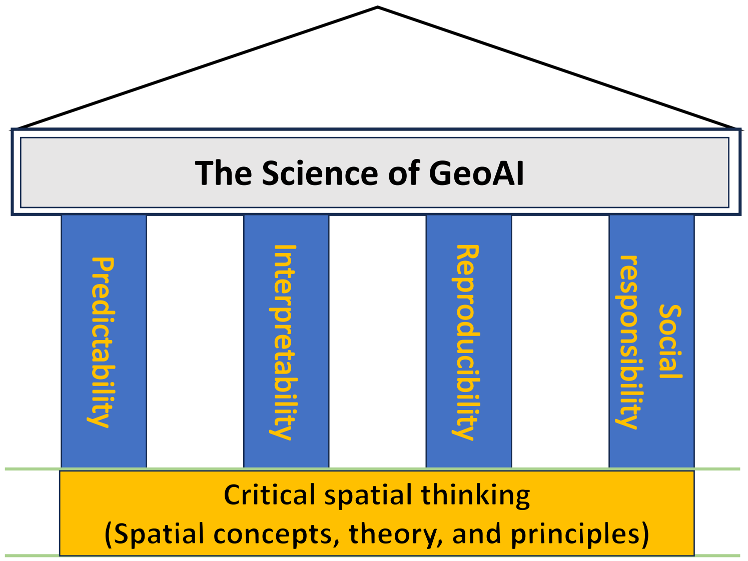

Figure 1: The four pillars of the science of GeoAI

is worth noting that other frameworks, such as the FAIR principles—Findability, Accessibility, Interoperability, and Reusability—as well as the field of data science, aim to address similar issues. However, these pillars have unique interpretations within the GeoAI research context. Advances in these areas within the scientific framework of GeoAI require support and guidance from spatial theory and spatial sciences.

3.1 Predictability

The predictive performance of a model, measured by either accuracy, efficiency, or their combination, is always a primary goal driving the development of new GeoAI methods. A robust method is also an important lens through which we make sense of the geospatial world and make new discoveries. Instead of merely applying AI to geospatial data, a GeoAI model may explicitly incorporate spatial concepts and principles into the modeling process. To assess the "Geo" capabilities in a GeoAI model, it may be worth asking: Are spatial variables such as latitude, longitude, and distance captured in the model? Are the findings differentiable by location and scale? From a spatial modeling perspective, will the predictions or conclusions change when the inputs move to a different study area? The four points discussed in the introduction—spatially explicit modeling, multi-source, multimodal GeoAI modeling, spatiotemporal and multi-scale joint learning, and geography-informed model training and validation—are along these lines advancing GeoAI as a differentiator from general AI research. This not only involves feeding AI with important geospatial problems to solve but also advancing AI modeling with a unique spatial lens.

As GeoAI models are becoming huge and even more complex today, it is important to seek a balance in our design principles between developing big, one-size-fits-all geo-foundation models versus smaller but "smarter" models that excel at task-specific problems. It is also important to leverage spatial knowledge and principles such as spatial autocorrelation and spatial heterogeneity to reduce existing model complexity, helping them 'lose weight' while becoming more robust and effective at answering spatial questions.

3.2 Interpretability

Model interpretability also plays a critical role in GeoAI research. Interpretability is often used interchangeably with explainability in the domain of X-GeoAI (Explainable GeoAI), which aims to provide human-understandable explanations of how a GeoAI model arrives at a decision. Achieving explainability in a GeoAI model is an important step toward building trust in AI-based systems, especially when leveraging them for high-stakes decision-making, such as emergency management. An explainable GeoAI model also offers increased transparency; it can assist researchers in verifying results and findings, identifying new causal relationships, further contributing to the advancement of knowledge, and the development of new theories.

It is worth mentioning that model interpretability and predictability are often competing goals for a GeoAI model. Achieving high model predictive performance often requires the design of complex model architectures, making it difficult to explain the inner logic of the model. This is known as the black box conundrum. Other methods, such as decision trees or geographically weighted regressions (GWR) [6], are built upon simpler mechanisms and are often self-interpretable by reviewing the model summary and the learned model parameters. However, these models may not handle the same amount of big data as do deep learning models; they can hardly achieve the same level of predictability due to a limitation in extracting complex relationships within the data.

Compared to the extensive literature on developing GeoAI models and applications, research on explainable GeoAI is relatively new and requires further investigation. Recent studies have emerged that connect a GeoAI model's prediction results through back-propagation to the input data, identifying important image regions or features that contributed most to the model's decision [18]. There is also increasing research focused on using human-recognizable concepts [31] or class ambiguity indices [33] to understand deep learning behaviors. However, these techniques are not unique to GeoAI. An intriguing development in this field is GeoShapley [40], which employs a game theory approach and treats location as a player in a model prediction game. This framework quantifies the importance of location and its interactions with other variables in a machine-learning model, thereby enhancing the explainability of statistical and black-box machine-learning models. Combining GeoShapley concepts with deep learning models may provide the geospatial community with a new opportunity to explain and enhance the trustworthiness of complex, deep-learning-based GeoAI models.

3.3 Reproducibility

GeoAI model reproducibility concerns whether a piece of GeoAI research is reproducible computationally. Reproducible research ensures that the methods and findings reported in one study can be validated by other researchers. It also allows the data and methodological workflow to be easily leveraged to advance knowledge on the same scientific topic or adapted to address a different research question. Toward this end, reproducibility accelerates scientific research processes and enables researchers to develop new knowledge based on existing findings. Today, reproducibility is often advanced through data and code sharing. However, this merely addresses the reproducibility challenge in GeoAI research. On the one hand, the complexity of a GeoAI model architecture hinders its readability, and even with code sharing, it can still be difficult to comprehend and reuse. On the other hand, GeoAI research involves multiple complex and interconnected procedures, from data preparation to model design, training, fine-tuning, and testing, further challenging the reestablishment and reproduction of the workflow.

Addressing these challenges benefits from the movement toward 'open science.' Well-documented data, workflows, openly shared design principles, and lessons learned are critical for improving code and model comprehension and promoting reuse [28,58]. However, when considering reproducibility from a spatial perspective, namely, whether research findings derived from one study area can be reproduced in another, the issue of replicability arises. Replicability concerns the inferential reproducibility or spatial generalizability of a GeoAI model's findings, which is a key goal in spatial science research. Given the ubiquitous presence of spatial heterogeneity across geospatial data and processes, GeoAI models exhibit only "weak replicability" [15]. That is, although the model structure can remain general, the model parameters will vary when applied to different geographical regions or geospatial datasets.

Recent GeoAI replicability research has developed a 'replicability map' to demonstrate the location transferability of GeoAI model findings for global Mars crater detection [37]. This study uncovers statistically significant findings that the GeoAI model results are more replicable along latitude, and the closer the distance is, the higher the degree of replicability the model will achieve. In contrast, spatial heterogeneity is a dominant factor for experimental results along longitudinal zones, with no strong spatial autocorrelation found in zones that have close spatial proximity. Moving forward, it is worth investigating whether such a finding on one set of data on one planet is replicable to another dataset on Earth or another planet. It is also important to devote research to answer critical questions such as the following: To what degree does spatial heterogeneity affect the replicability of GeoAI models? How does this influence vary across space and time and different spatial processes? Can we identify ways to quantify this influence through a universal mechanism within GeoAI models?

3.4 Social responsibility

Socially responsible AI is another essential element in GeoAI research that complements its scientific and technological facets, as social responsibility materializes GeoAI for the social good. A GeoAI system is more socially responsible when its decisions are fair, transparent, and robust while preserving user privacy, safety, security, and fostering social beneficence.

From a geospatial perspective, there is no doubt about the critical need to protect location privacy in GeoAI research [45]. Interestingly, on one hand, we encourage the integration of location information in GeoAI models to take advantage of unique spatial dimensions; on the other hand, it is important to preserve individual-level location data as they are key to linking multi-source data, which can then be used to infer sensitive personal information. These two aspects are not conflicting, as the former may emphasize large-scale environmental research (over non-sensitive areas), whereas the latter describes studies on human movement and dynamics. Techniques such as obfuscation, anonymization, synthetic data generation, and cryptography have been developed to protect data privacy used in the GeoAI models [42]. Research on how location information can be best embedded and represented in future GeoAI modeling, which combines extensive environmental data with fine-grained human-level information, will offer new insights into socially responsible GeoAI research.

Achieving social responsibility also requires designing GeoAI systems to follow ethical guidelines [51], which govern the ethical use of AI data and algorithms to ensure the system causes no harm to humankind and can, to the maximum extent, reduce bias and discrimination, comply with laws, and protect human rights. Here, a co-design process will help mitigate ethical concerns by involving the local communities in the GeoAI model design and prediction process. By incorporating and adapting local knowledge and practices, the cultural relevance and respectfulness of GeoAI tools can be enhanced. The tools' accuracy and usability can also be improved.

Environmental sustainability is also a critical aspect of social responsibility for GeoAI. Today's AI models, such as LLMs, require massive computational power and high energy costs in their training processes, contributing to a significant carbon footprint and thus risking the planet's environmental sustainability [23]. GeoAI models, especially those dealing with high-resolution spatial data and simulations, can also be computationally intensive. However, by leveraging the spatially explicit nature of GeoAI tasks and domain-specific optimizations, GeoAI research could potentially reduce environmental impact compared to general-purpose AI, thereby becoming more environmentally friendly and socially responsible.

As our research increasingly relies on commercial AI tools, such as ChatGPT, it is important to provide proper training to the geospatial community. Unintentional disclosure of geospatial data to these models may result in misuse and unexpected consequences. GeoAI governance will play a key role in ensuring data privacy and accountability. Going beyond general AI governance, GeoAI governance includes additional layers such as spatial data accuracy, data representation, and the preservation of sensitive locations (e.g., indigenous lands and military bases). As synthetic dataset becomes a valuable source for augmenting a GeoAI model's learning capability, caution must be exercised in discerning deepfake geospatial data [64] to prevent their use in critical spatial analysis and decision-making tasks. Last but not least, it is important to develop clear agreements and licensing terms to ensure explicit permission for the use of copyrighted geospatial data (e.g., proprietary satellite imagery) in GeoAI models and the ownership of their derived products.

3.5 The interconnectivity among the research pillars

Social responsibility is a key principle driving advances in GeoAI research's three other pillars. Improvements in model predictability, interpretability, and reproducibility enhance GeoAI's capabilities and benefits to society, making it more socially responsible. Figure 2 showcases the interconnected research dimensions falling in the science landscape of GeoAI. Interpretability is fundamental—it makes a GeoAI model transparent and inherently more trustworthy. This transparency establishes a vital connection between the model's inner workings and user understanding, fostering reliability and accountability. Reproducibility, another essential aspect of responsible GeoAI, is the foundation of reliability and robustness. The robust nature of a reproducible GeoAI model further ensures the consistency and dependability of its decision-making processes.

In applying these principles, a robust GeoAI model will not only excel in predicting outcomes but will also be reliable and trustworthy. The combination of predictability, inter-

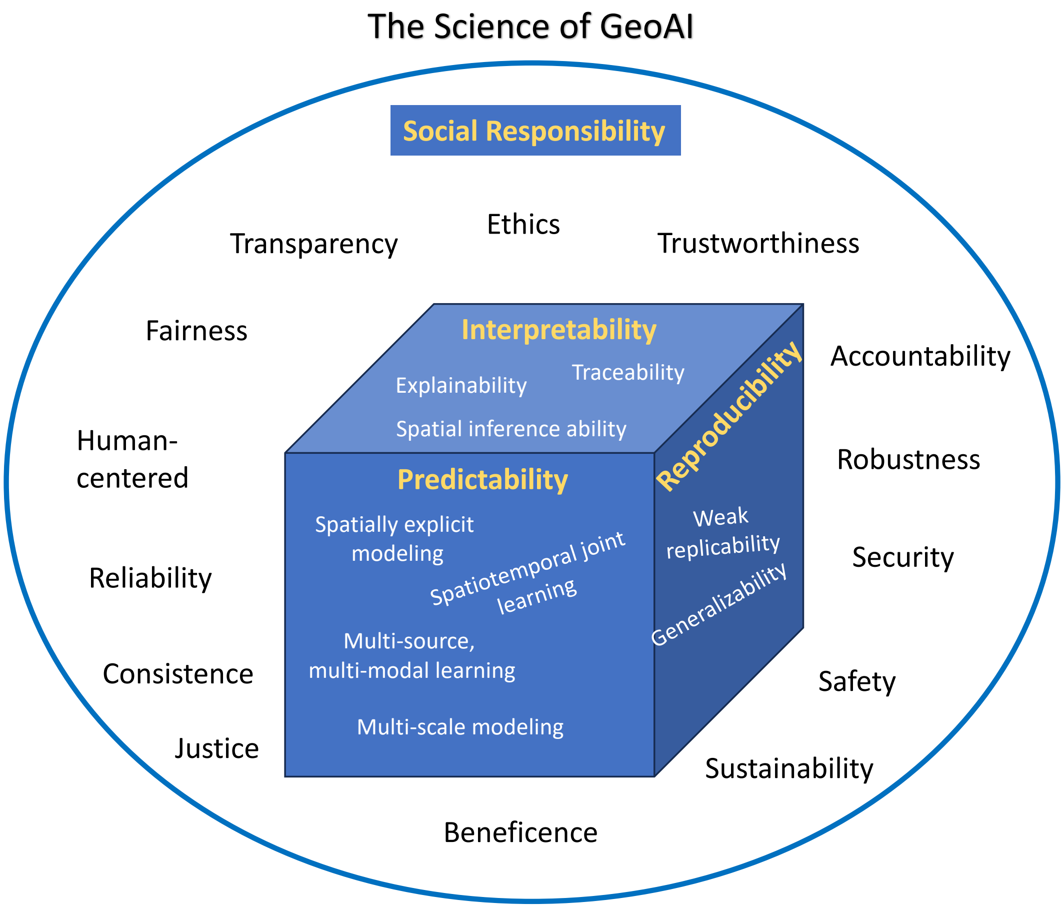

Figure 2: Interconnected research dimensions in the science landscape of GeoAI

pretability, and reproducibility, integrated with social responsibility, makes a GeoAI model extremely powerful for advancing both spatial sciences and practical applications. Models with such capabilities maximize long-term societal impacts and contribute to the greater good.

4 Concluding remarks

Recent growth in GeoAI motivates the present discussion of progress made in advancing spatial sciences through new analytical capabilities that address important data and knowledge gaps in social and environmental research. By summarizing the milestone development of GeoAI methods (for example, spatially explicit modeling, spatiotemporal and multi-scale joint learning), this paper emphasizes the importance of integrating key spatial principles into AI model design to enhance the methodological foundation of

GeoAI. Subsequently, we discussed four interconnected research pillars that shape the science landscape of GeoAI, including predictability, interpretability, reproducibility, and social responsibility.

As we look ahead, there is a critical need to advance GeoAI methods and techniques, enhancing their predictive capabilities with greater reliability and transparency. The recent rapid advancement in AI has been driven by the harnessing of big data and significant computing power. In the same vein, the tremendous potential for advancing GeoAI is likely dependent on and/or synergistic with frontiers in cyberGIS and spatial data science, especially from scientific perspectives [54, 55]. Addressing large-scale and complex problems requires significant advances in theories, methods, and experiments, as well as team science approaches to developing open data, benchmarks, and evaluation methodologies.

To further advance GeoAI, we should continue to embed spatial thinking and convergent thinking into the design of GeoAI models while maintaining a commitment to social responsibility. In light of the growing attention to large commercial AI models, such as ChatGPT, the geospatial community must stay alert as the use of such models will pose overwhelming challenges regarding their interpretability, reproducibility, and social responsibility. Rather than being mere users of these models, we should focus on identifying fundamental geospatial research questions and solutions that leverage their strengths while addressing potential negative spatial and societal impacts. It is important to develop new ways to ingest geospatial knowledge into large models to regulate their reasoning process, as the generative nature of some AI models may result in spatially or topographically incorrect answers [8,21]. Meanwhile, a disclaimer for the use of AI in operational geographic information systems is recommended to keep end users informed and comfortable with their use. In addition, proper training for geospatial researchers on commercial AI models is needed to ensure they do not unintentionally leak important research data to the models or violate any privacy issues.

We should also be aware that many geospatial research projects and problems solved using AI, such as Stanford University researchers' groundbreaking work in using Street View images to infer neighborhood-level social and demographic profiles [11] and Google DeepMind's cutting-edge AI model for medium-range weather forecasting [32], are developed by the general AI community. However, they present opportunities for the GeoAI researchers to make substantial contributions. Hence, we need to remain open-minded and continue conducting outreach to increase other AI researchers' awareness of the value of GeoAI. The national Institute for Geospatial Understanding through an Integrative Discovery Environment (I-GUIDE, http://i-guide.io) supported by the National Science Foundation offers an exemplary model for engaging research communities within and outside the geospatial domains to gain visibility and enhance the impact of geospatial research.

We hope the perspectives presented in this paper will encourage the deepening of GeoAI's support for scientific discovery and contribute to the dialogue advancing the science of GeoAI. Both endeavors clearly require a community effort. Continued collaboration and critical evaluation within the community are essential to ensure that advancements in GeoAI are both scientifically robust and ethically sound.

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