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Review Article

Advances in geospatial analysis in the era of big data challenges and integrating GeoAI techniques

Daniel Asfaw Bekele[1, 2] *and Amare Sewnet Minale*[1]

[1]***Department of Geography and Environmental Studies, Bahir Dar University, Bahir Dar, Ethiopia***
[2]***Geospatial Data ad Technology Center (GDTC), Bahir Dar University, Bahir Dar, Ethiopia***
Correspondent email:daninarm55@gmail.com

Abstract: *The evolution of geospatial analysis from the mid-20th century quantitative geography and regional science to contemporary GeoAI reflects a profound methodological and technological transformation. Early geospatial work relied on statistical and cartographic techniques implemented through geographic information systems (GIS) to map, query, and test hypothesis-driven models of spatial distribution and relationships. The advent of geospatial big data driven by satellite remote sensing, Internet of Things sensors, mobile devices, and social media introduced unprecedented volume, velocity, and variety that exceeded the capacity of traditional, aggregate approaches and conventional computing infrastructure. In response to this, advances in high-performance computing, parallel processing, GPU acceleration, and cloud platforms enabled scalable data storage and processing, while machine learning and deep learning methods were adapted to exploit spatial structure, multi-scale phenomena, and heterogeneous data modalities. GeoAI thus emerged as the integrated application of artificial intelligence to geospatial big data, enabling automated feature extraction, detection of complex spatial and spatiotemporal patterns, and robust predictive modeling at scales previously unattainable. This review synthesizes recent advancements in deep learning architectures and earth observation data fusion to characterize the current state of GeoAI. While GeoAI substantially extends analytical capability, it also raises critical challenges: spatial autocorrelation and scale effects, data quality and representativeness, model interpretability and uncertainty quantification, computational cost, and ethical concerns including privacy and bias. Addressing these issues through theory-informed methods, transparent model design and rigorous data governance will be essential for realizing GeoAI's potential in research and applied domains.*

Keywords: Spatial analysis, big data, GEOAI, quantitative geography, regional studies

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1. Introduction

Geospatial science is a science and an art of collecting, analyzing, and interpreting data related to location and geography. Geospatial science combines elements of geography, environmental science, computer sciences and engineering to collect, analyze, visualize, and interpret geographic data. Essentially, it is about understanding the "where" and "why" of things and using this knowledge to solve real-world problems (Li et al., 2009). At its core, geospatial science seeks to analyze human and physical variables in relation to their spatial location, where identifying spatial relationships is important for understanding how they interact and influence one another using diverse spatial analysis techniques (Paelinck, 2008).

Geospatial analysis, as a cornerstone of spatial science, comprises a range of techniques that help to identify patterns, trends and relationships in geographical data (Berry et al., 2008). The ability to integrate spatial information with other relevant data enable decision-makers with a holistic understanding of complex situations, leading to more informed and effective strategies and plays a role in a range of real-world applications. This includes environmental sciences, urban studies, public health, natural resource management, business sectors, and transportation and disaster risk management to mention a few.

This proliferation of geospatial data from different sources, including satellite imagery, massive datasets from location-based services, real-time sensor networks, and geo-tagged social media, has brought us to an era of unprecedented data availability known as big geospatial data (Li et al., 2020). This geospatial big data presents both range of opportunities and significant challenges for classical analytical approaches. The sheer volume, velocity, variety, veracity, and value of this data necessitate new computational paradigms and analytical techniques capable of handling its complexity and extracting meaningful information efficiently (Lansley et al., 2018).

Concurrently, the rapid advancements in artificial intelligence (AI) particularly in machine learning and deep learning, and alongside improvements in computational capacity with the development of Graphics Processing Unit (GPU) and cloud computing revolutionized the discipline leading to a new version of Geographic Information Science (GIScience) called Geospatial Artificial Intelligence (GeoAI) (Scheider & Richter, 2023). GeoAI, the synergistic integration of AI and geospatial analysis, leverages the power of AI algorithms to automate feature extraction from remote sensing imagery, identify complex spatial patterns in large datasets, predict future spatial events, and even understand human language related to locations (Janowicz, 2023). This convergence enabled the development of sophisticated statistical methods, data mining techniques, and increasingly, machine learning and deep learning algorithms to not only understand past and present spatial phenomena but also to predict future trends and optimize spatial decision-making accuracy.

Therefore, the trajectory from fundamental geospatial analysis to the cutting-edge field of GeoAI, fueled by the rise of big data, represents a significant advancement in our ability to understand and interact with the spatial dimensions of our world. Thus, this literature review addressed the core concepts of geospatial analysis, explored the transformative impact of big data and AI, and assessed the emerging trends and challenges associated with this dynamic in the field, with the aim of providing a comprehensive understanding of how these advancements are shaping research and driving innovative real-world applications across a multitude of domains.

Hence, the overall objective of this literature review is (1) to provide an overview of the evolution of geospatial analysis, from its fundamental concepts to its advancement to current state, and (2) to explore recent advancements in geospatial big data handling, emerging GeoAI applications, and the integration of Artificial Intelligence (AI) and Machine Learning (ML) within geospatial science.

2. Methodology

This literature review was conducted using a regular (narrative) literature review approach. Regular literature review approach is a narrative form of review which is flexible and involves a comprehensive summary and critical analysis of existing literature on a specific topic. Unlike more structured approaches (like systematic reviews), it doesn't follow a rigid, pre-defined methodology for selecting and synthesizing studies. Instead, it aims to provide a broad overview, identify key themes, trends, debates, and gaps in the existing research (Snyder, 2019; Cronin et al., 2008).

It is aimed at capturing both the theoretical foundations and recent developments in the field of geospatial analysis, geospatial big data, and GeoAI. It involved a comprehensive search of relevant scholarly literature across various databases, including Google Scholar, ResearchGate, Science Direct, and PubMed, and supplemented by book repositories such as Library Genesis Zilb and PubBook. The search strategy utilized a combination of keywords, including spatial analysis, geospatial science, geospatial analysis, geospatial big data, GeoAI, machine learning, and deep learning combined with Boolean operators (AND, OR, NOT) to refine the results.

The temporal scope of the review covered literature from any year to establish the historical and theoretical foundations of geospatial analysis, geospatial big data and GeoAI, with particular emphasis on recent publications to capture the current trends and advancements in GeoAI and big geo-data which helps trace the development of the field while highlighting contemporary trends. The review process involved key stages such as identification, where initially search results were screened based on title and abstract relevance to the review objectives, followed by selection, in which the retrieved resources were assessed for the inclusion of predefined criteria, including relevance to geospatial analysis, big geo-data, and GeoAI.

3. Review and interpretations

3.1 Geospatial analysis

In today's data-driven world, the ability to analyze and interpret spatial data has become increasingly vital across various disciplines. Geospatial analysis, which involves the collection, visualization, and examination of geographic data, serves as the cornerstone for more advanced spatial analytics and spatial statistics. It provides the tools and methodologies necessary to understand complex spatial patterns and relationships, enabling researchers to address critical questions in urban planning, environmental management, public health, and beyond (Ma, 2019). It is the quantitative techniques applied to analyze and interpret geographical data which contains location information or spatial references (Smith, 2018). The origins of geospatial analysis lie in developments in the 1950s and1960s of quantitative geography and regional science, which marked a major paradigm shift from descriptive and regional geography to empirical, model-based approaches (Brunsdon & Chalrton, 2007; Murayama & Thapa, 2019).

The 1960s revolution of quantitative geography not only provided sophisticated analytical methods and refined spatial models for development of Geographic Information Systems (GIS) and geospatial analysis, but it also contributed a lot to the basic concepts related to the fundamentals of GIS architecture. The geographical matrix proposed by Berry (1964) led to the attribute table concept of GIS. The abstraction of geographical space based on the point/line/plane concepts proposed by Peter Haggett led to the idea of the vector data model that controls geographical planes with nodes, arcs, and polygons. The methodology of Tobler’s geographical conversion contributed to the development of spatial analytical and paved the way for computer mapping (Murayama & Thapa, 2019). This shift was driven by the growing need to understand spatial patterns and processes using mathematical and statistical techniques (Sui et al., 2015). The emergence of spatial analysis brought tools such as spatial statistics, location theory, and spatial modeling to the forefront of geographic research, enabling more objective and reproducible studies (Murayama & Thapa, 2019; Smith et al., 2021).

The development of GIS in the 1970s and 1980s further expanded the analytical capabilities of geographers by allowing spatial data to be stored, manipulated, and visualized digitally. This is a foundational leap that transitioned geography from a purely observational science to one that could simulate, predict, and analyze complex spatial phenomena (Smith, 2018). The emergence of GIScience further advanced this trajectory by emphasizing not only technical development but also the theoretical and conceptual foundations of geographic representation, spatial data models, and analytical frameworks (Samantha & Wenwen, 2021).

The 1991 National Center for Geographic Information and Analysis (NCGIA) initiative and its publication Spatial Analysis and GIS (1994) formalized spatial analysis within GIS frameworks. The Bristol workshop (1994) and its outcome Modeling in a Spatial Analysis–GIS Environment (1996), alongside the GISDATA program (1993), which produced influential works like Spatial Analytical Perspectives on GIS (1996), expanded the integration of spatial modeling with GIS. Later, interdisciplinary conferences such as GeoComputation (1996) and GIScience (2000) further established geospatial analysis as a core element of computational geography and spatial data science (Murayama & Thapa, 2019). This revolution brought about profound methodological and conceptual shifts. These included transitions: from model-driven to data-driven approaches, from deductive to inductive reasoning, from top-down to bottom-up analysis, from aggregate to disaggregate data, from discrete to continuous representations, from lagged time to real-time considerations, from static to dynamic modeling, from purely quantitative to more qualitative (or integrated) perspectives, and from linear to non-linear thinking (Murayama, 2012; Murayama & Thapa, 2019).

Collectively, these foundational shifts have led geospatial analysis into a new era marked by real-time data, cloud computing, and integration with artificial intelligence. Today, the field is driven by advancements in geospatial big data, GeoAI, and machine learning, enabling more dynamic, predictive, and automated spatial analysis. This evolution continues to expand the scope and impact of geospatial science across diverse disciplines.

3.2. Methodological shifts in geospatial thinking

The development of GIS theory and technology brought profound changes to the ways spatial problems are approached. As Murayama and Thapa (2019) highlight, this evolution marked a major methodological shift as described below:

i. From aggregate to non-aggregate thinking

Aggregate thinking relies on totals and averages, typically summarized by area or district, to analyze regional patterns. In contrast, non-aggregate thinking focuses on individual data points, avoiding reliance on averages like rates or densities. This shift to non-aggregate data reduces distortion from outliers and enables more detailed spatial analysis in GIS.

ii. From model-driven to data-driven

Conventional research relies on deductive reasoning, whereby hypotheses are formulated and data are used to test predetermined models. However, recently there has been growing awareness of the existence of approaches which attempt to inductively build models starting from data acquisition. GIS is increasingly seen not just as a tool to test hypotheses, but to generate theme, discovering hidden patterns like "*a diamond in a mountain of garbage*" (Openshaw, 1991). This data-driven method, similar to fieldwork, emphasizes explaining phenomena through observed data rather than pre-constructed theories, enabling new discoveries and insights.

iii. From pattern recognition to predictive spatial modeling

The qualitative revolution of the 1950s marked a shift from idiographic (descriptive) to nomothetic (empirical) geography, paving the way for spatial analysis. Initially focused on static spatial patterns, spatial analysis evolved to encompass dynamic processes. By the 1990s, GIS advancements enabled the processing of large spatial datasets, facilitating the development of complex models for inductive forecasting, which include hierarchy processes, multi-criteria evaluation, genetic algorithms, cellular automata, and agent-based models. These transformations show a broader trend toward emergence of geospatial big data and GeoAI, where AI techniques are used to manipulate complex, high-volume spatial problems.

3.3. Geospatial big data

The term big data, the buzzword of today and potentially the huge data of tomorrow, first appeared in the scientific community in the mid-1990s, gained popularity around 2008, and became widely recognized in 2010 (Loukili et al., 2022). Big data in 1999 referred to one gigabyte (1 GB). However, today it represents a huge volume of data that is symbolized by exabytes (EB) (1024 petabytes (PB)) or zettabytes (1024 EB). According to the UN Initiative on Global Geospatial Information Management (UN-GGIM), the total amount of data created, stored, retrieved and processed in computer systems around the world in 2024 was 149 zettabytes and forecasted to reach 181 zettabytes by the end of in 2025 which increases by 23.71% in data generation compared to the previous year. These data will increase to more than 394 zettabytes in 2028 with the rate of 2.5 million terabytes per day or 29 terabytes per second globally (Lee & Kang, 2015; Loukili et al., 2022; UN Global Pulse, 2024). As pointed out on the discussion paper of Dempsey (2012) and Hahmann et al. (2011), 80% of the world's data is geographic and possesses a geographic reference which means that a large portion of the world's data is georeferenced and the majority of big data is geospatial in nature leading to the concept of geospatial big data.

Geospatial big data refers to massive datasets with spatial or geographical components, collected from diverse sources such as various satellite and aerial or drone images, Internet of Things (IoT) sensors, street views, social and news media, mobile data, web applications, trajectories of GPS-equipped devices, onsite and portable smart sensors, surveillance vehicles, and crowd sourcing platforms (Lansley et al., 2018). These geospatial big data offer unique insights for geospatial analysis. Satellite and aerial imagery enables large-scale environmental and urban monitoring, while street level images support built-up environment assessments and computer vision applications. Mobile data which include GPS trajectories and Call Detail Records (CDR) reveal human mobility patterns for transportation planning, whereas social media geotags (Twitter, Instagram) capture real-time public sentiment and activity trends. In addition, environmental sensors like air quality sensors and noise sensors provide important data for resource management and policy decisions. Collectively, these sources form a multidimensional framework for analyzing the dynamics of human behavior, urban development, environmental systems, and their interplay (Loukili et al., 2022; Sudmanns et al., 2020; Zou et al., 2024).

Building upon this understanding of the diverse origins of geospatial big data, it is essential to recognize its multifaceted nature. These datasets can be categorized into three primary big data type such as structured data, unstructured and semi-structured data. Structured data is a data presented in a structured schema along with all the required attribute fields. It is in a structured format which is stored in any database management system like relational database management system with geospatial extension (e.g., PostagesSQ). These include GPS coordinates, sensor readings, or satellite images. On the other hand, unstructured data is a data which lacks fixed schema and include diverse data format such as image files, log files, text files, video files, and audio files. The semi-structured data blends both forms, featuring partial organization where the schema is not properly defined, i.e. both forms of data are present. Thus, semi-structured data has a structured form but it is not well defined, a data like, JSON, and CSV (Sudmanns et al., 2020).

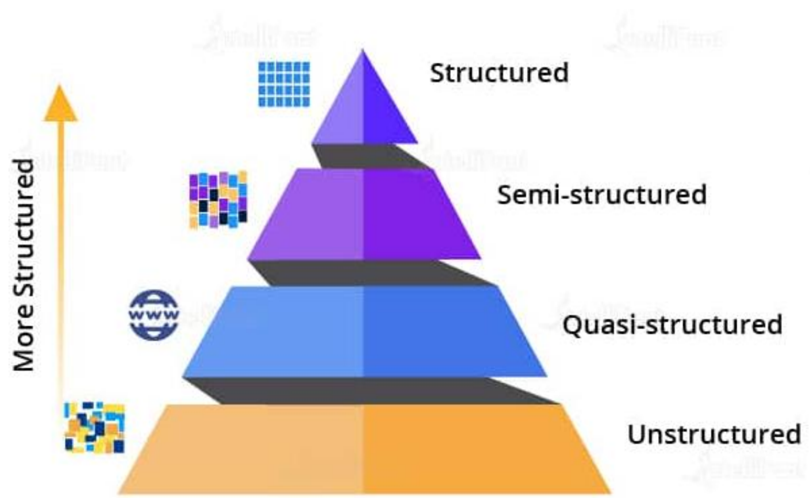

Figure 1. Level of data structure hierarchy in geospatial big data (*Source:* Great Learning, 2023)

These datasets are often multi-dimensional, containing spatial, temporal, thematic, and relational information, which is essential for understanding complex geospatial patterns and interactions across various domains. Therefore, there is a growing interest from academia, government, organizations, and the public in leveraging geospatial big data to observe the dynamics of social, urban, and environmental phenomena, and to understand integrated systems, and support decision-making (Li et al., 2020) and it is a predominant source of innovation, competition and productivity which has resulted in a paradigm shift to data-driven research. Hence, geospatial big data is a spatial data that is big in volume, yet growing exponentially with time and it is so vast and complex that traditional data management system cannot store or process it efficiently (Lansley et al., 2018).

3.3.1. Features of geospatial big data

The complexity of geospatial big data, originating from a multitude of sources, are characterized by several key features which commonly known as the V's of big data. The seven dimensions (7D) (Fig. 2) that characterize big geo-data are volume, velocity, variety, veracity, value, versatile and visualization (Li et al., 2016; Loukili et al., 2022; Sudmanns et al., 2020).

Volume represents the storage and processing of large volume of the data which is produced in a high rate. The zettabyte archives remotely sensed imagery data, ever increasing volume of real-time sensor observations and location-based social media data, vast amount of crowd source data, etc., as well as their continuous increase raise not only data storage issues but also a massive data analysis issue (Li et al., 2016).

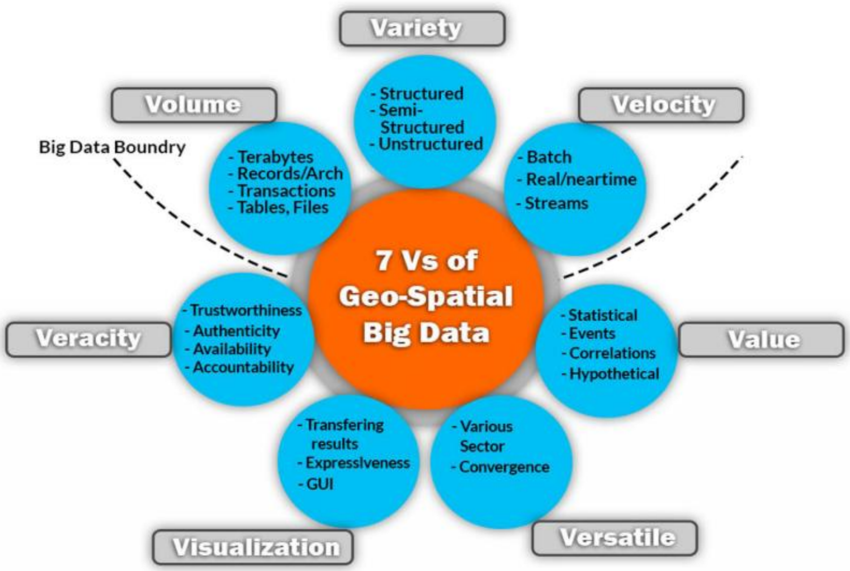

Figure 2. The graphic representation of the 7Vs of geospatial big data (*Source*: Sharma et al. 2025)

Variety represents the composition of diverse data format generated in different sources and in different ways. These data could be map data, imagery data, geotagged text data, structured and unstructured data, raster and vector data which result in complex structures and calls for more efficient models, structures, indexes and data management strategies and technologies (NoSQL or PostgreSQL).

Velocity represents the rate and speed of data generation. Nowadays, the speed of data production is very fast (29 terabytes per second) from satellite observation with frequent revisits at high resolution, continuous streaming of sensor observations, Internet of Things (IoT), real-time GNSS trajectory and social media data. This feature of geospatial big data requires matching the speed of data generation and the speed of data processing to meet demand.

Veracity refers to the reliability, accuracy, and trustworthiness of geospatial big data. As datasets grow in volume and variety, ensuring data quality becomes critical to avoid misleading analyses and flawed decision-making. Hence, the level of accuracy varies depending on data sources, raising issues on quality assessment of source data and how to ‘‘statistically” improve the quality of analysis results a concern in geospatial big geo-data ((Li et al., 2016)).

Visualization provides valuable procedures to impose human thinking into big data analysis. It transforms geospatial big data into intuitive graphical representations, enabling analysts to detect patterns (clusters, outliers, trends) and generate insights. Hence, to provide meaningful insight, the data should be clear and retrievable which is represented by value, the other feature of big geo-data (Fig. 3). Visualization serves as both an analytical tool for hypothesis generation and an effective communication medium for conveying complex spatial relationships to stakeholders (Murayama & Thapa, 2019).

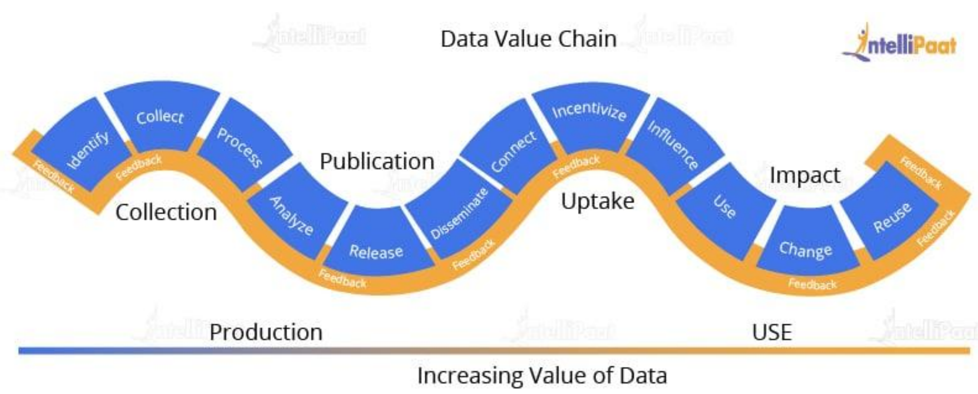

Figure 3. Progressive procedure in big geo-data to extract value data (*Source*: Great Learning, 2023)

Visibility implying the emergence of cloud computing and cloud storage has revolutionized geospatial big data accessibility and processing, enabling capabilities that were previously impossible. Cloud platforms (e.g., Google Earth Engine (GEE), Amazon Web Service (AWS) Geospatial) now allow users to efficiently store, access, and analyze massive datasets without local infrastructure constraints. This shift has replaced the traditional paradigm of bringing the user to the data with bringing the data to the user via scalable, on-demand resources (Sudmanns et al., 2020). Cloud technology is still evolving, and once issues such as data provenance are resolved, big data and the cloud would be mutually dependent and reinforcing technologies.

3.3.2. Spatiotemporal aspects of geospatial big data

In addition to the V's that characterize geospatial big data, there are several spatiotemporal aspects that influence its applicability and reliability in analysis. These include spatiotemporal granularity which refers to the resolution of data in space and time. High granularity like real-time GPS tracking enables fine-scale analysis, while the low granularity such as annual global level datasets provides broader trends (Goodchild, 2013). The other aspect is spatiotemporal scope which represents the geographic and temporal coverage of a dataset, determining whether it suits localized studies such as urban heat islands or global assessments for climate change modeling (Miller & Goodchild, 2015).

The spatiotemporal density is an aspect of geo-big data which measures the distribution of data points, with high density (e.g., IoT sensor networks) improving model accuracy, whereas sparse data may introduce uncertainty (Janowicz et al., 2020). Finally, spatiotemporal bias which arises from uneven representation, such as urban-centric mobile data neglecting rural areas or daytime imagery missing nocturnal phenomena, potentially biasing data-driven insights (Kwan, 2016). Addressing these aspects is essential to ensure robust geospatial analytics, equitable policy-making, and trustworthy machine learning applications in fields like disaster management and smart city planning (Goodchild, 2009).

3.3.3. Challenges and opportunities of geospatial big data

Geospatial data hence exhibits distinctive spatial characteristics compared to a spatial data. The management and analysis of big geospatial data present a unique set of challenges, primarily stemming from its inherent volume, velocity, variety and other Vs. The first challenge is related to storage and access. With its voluminous nature, geospatial big data requires scalable and distributed data storage which is capable of handling massive datasets such as cloud based storage and distributed file systems like Hadoop Distributed File System (HDFS). Lack of such systems resulted in significant bottlenecks (Sudmanns et al., 2020). Besides, efficient indexing and retrieval mechanisms are essential for timely access to relevant datasets which make utilization of geospatial big data difficult.

The second major challenge stem from the heterogeneity character of geospatial big data which causes difficulty in the integration of geospatial big data (Li & Arundel, 2022). Hence big geo-data is composed of diverse datasets with different formats, standards, and quality; and manipulation is complex. This necessitates the development of strong data integration frameworks, including standardized metadata schemas, data quality control procedures, and data harmonization techniques, to ensure interoperability and consistency (Shekhar et al., 2015).

The sheer size and complexity of geospatial big data demand substantial computational resources for effective selection, exploration, and mining is another challenge related to big geo-data. This requires high-performance computing infrastructure, distributed computing platforms like Spark, and load-optimized algorithms to enable fast and scalable processing (Lee & Kang, 2015; Li et al., 2016). These computational resources must be capable of handling the intensive processing demands of complex geospatial analysis tasks such as spatial data mining, predictive modeling, selection, exploration and real-time analytics (Li et al., 2016; Zou et al., 2024). Additionally, hence, geospatial big data often involve the collection and processing of sensitive location data from individuals, raising issues of privacy, which causes problems in safeguarding geoprivacy and ethics (Sudmanns et al., 2020; Zou et al., 2024).

Despite the significant challenges associated with managing and processing geospatial big data, geospatial big data provides multifold opportunities which transform the spatial data manipulation and pattern recognition. This involves the shift from traditional spatial datasets to massive, high-velocity, and diverse geospatial big data which has enabled a paradigm shift in the approaches of spatial phenomena observation, and recognition (Cao, 2022). The opportunity to access real-time data from remote sensing satellites, UAVs, location-based services, and from crowd sourced platforms enables mining data at finer spatial and temporal resolutions than ever before. Furthermore, the advancements in data integration, quality control, and harmonization not only address the integration challenges but also pave the way for the development of more accurate and reliable predictive geospatial models, leading to improved predictions and decision-making (Vopham et al., 2018).

More importantly, the scalability and granularity offered by geospatial big data provides opportunities to reduce difficulties associated with data scarcity, out-datedness and computational limitation. This is because as cloud computing platforms such as GEE AWS, and Microsoft Planetary Computer (MPC) become more accessible, the barriers to entry for advanced geospatial analysis become lower, creating new opportunities for researchers, local governments, humanitarian agencies, and citizens alike (Gorelick et al., 2017; Stevens et al., 2020). Collectively, big geospatial data optimizes revenue and time saving, and represents a major leap forward for geospatial science and its applications in solving complex, real-world problems (Lee & Kang, 2015; Li & Arundel, 2022).

3.3.4. Geospatial big data computational methods

The convergence of big data and geospatial computing has brought challenges and opportunities to GIScience with regard to geospatial data management, processing, analysis, modeling, and visualization. Fundamental to the advancements in geospatial big data computation is the integration of computational thinking and spatial thinking, and the transformation of abstract ideas and models to concrete data structures and algorithms (Li et al., 2020).

The complexity and richness of geospatial big data demand a computational paradigm capable of handling massive volumes of heterogeneous, dynamic, and spatially explicit information. To this end, geospatial analytics has increasingly provided parallel processing and Graphics Processing Unit (GPU) computing, which enable the simultaneous execution of complex operations using both Central Processing Unit (CPU) and GPU architectures. This approach significantly enhances computational efficiency, especially in tasks involving high-resolution imagery, dense spatial networks, or large-scale temporal simulations. Further, in order to speed up the computation, the Spark-based frameworks such as Spatial Hadoop and GeoSpark were developed (Fig. 4). Additionally, the cloud-based computing platform like GEE which is dedicated for big Earth Observation (EO) data have been used in geospatial studies and applications (Li et al., 2016; Li et al., 2020).

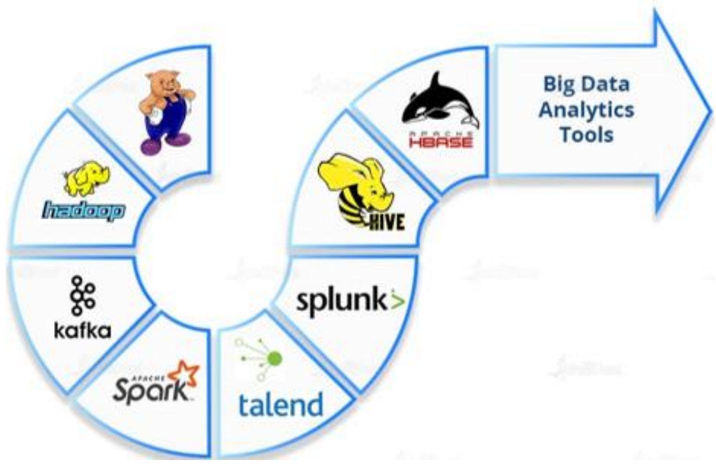

Figure 4. Tools for big data analytics (*Source*: Great Learning, 2023)

These advancements in computational infrastructure have paved the way for the development and application of sophisticated analytical methods for extracting patterns and making predictions from complex, diverse, and often noisy big geospatial datasets. These include Natural Language Processing (NLP), ML and AI spatial analysis and modeling and image processing and computer vision (Fig. 5) (Li et al., 2020; Zou et al., 2024).

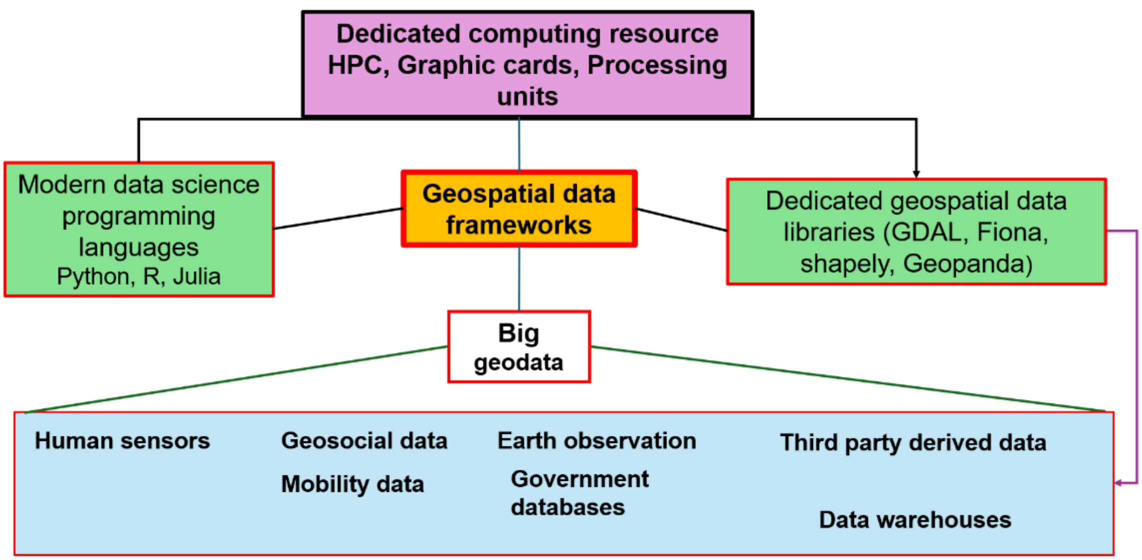

Figure 5. Computing systems and analytics for big geospatial data

The confluence of AI, ML, and powerful computing platforms has fundamentally transformed traditional geospatial analysis. The ability to process massive datasets, coupled with the demand for real-time, predictive spatial insights, has driven the evolution of an automated, intelligence-driven discipline known as GeoAI (Scheider & Richter, 2023). GeoAI, which harnesses these enabling technologies to interpret complex spatial patterns, forecasts dynamic phenomena, and optimizes decision-making across diverse domains representing a significant leap forward in our ability to understand and interact with our environment (Mai et al., 2025).

3.4. Concepts of geospatial artificial intelligence (GeoAI)

Artificial intelligence (AI) is the field of embedding human thinking into computers, or it is creating an artificial brain that mimics the functions of the biological brain (El-Amir & Hamdy, 2020). In the first-generation of AI development, AI focuses on problems that can be formally described by humans. In this stage, AI followed instructions for doing something intelligently. Machines follow humans without changes which is the characteristic features of the first era of AI. Thus, the intelligence of the machine is artificial. That is the machine itself is not intelligent, but humans have transferred their intelligence to the machine in the form of several static lines of code. “Static” means that the behavior is the same in all cases. The machine, in this case, is tied to the human and can’t work on its own. The second era of AI is knowledge-based systems where previous knowledge from experts is given to the machine to recognize objects; however, it was not able to handle uncertainty and operate in complex environment like human do (Gao, 2021). However, despite the progress in AI's evolution from rule-based logic to knowledge-based systems, its ability to handle the inherently spatial, dynamic, and uncertain nature of geographic problems has remained limited. This limitation, combined with the explosive growth of geospatial big data and the increasing availability of advanced computing resources, promoted the emergence of GeoAI domain-specific intelligence (Mai et al., 2025).

These advancement of AI techniques converged with the proliferating geospatial big data and massive computing capability (GPU) and promoted the development of GeoAI or geospatial artificial intelligence (Fig. 6) (Gao et al., 2024). GeoAI at the junction of AI, geospatial big data, and high performance computing (HPC) provided a promising solution technology for data or for computing intensive geospatial problems in highly automated and intelligence way (Li, 2020). The aim of GeoAI is for the machine to gain the intelligence to perform spatial reasoning and analysis like humans. Thus, GeoAI is regarded as a discipline to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics; to advance our knowledge; and to solve problems in human environmental systems and their interactions with a focus on spatial contexts and roots in

GIScience (Gao, 2021; Janowicz et al., 2020). GeoAI evolves as AI has evolved, but it is not simply an application of AI in geography. Instead, GeoAI is an interdisciplinary field that injects spatial theories and concepts to make AI more powerful and suitable for tackling geospatial problems. Theoretically, GeoAI is underpinned by spatial statistics, spatial cognition, and AI principles including pattern recognition, neural networks, and probabilistic modeling. Its foundation lies in blending spatial thinking (the ability to reason about spatial patterns, processes, and relationships) with computational intelligence, offering a new paradigm for geospatial problem-solving across disciplines (Mai et al., 2025). Therefore, it would be pertinent to know about underlining principles of GeoAI, its feature, computation practices as well as geographic domain knowledge to be competent in the area.

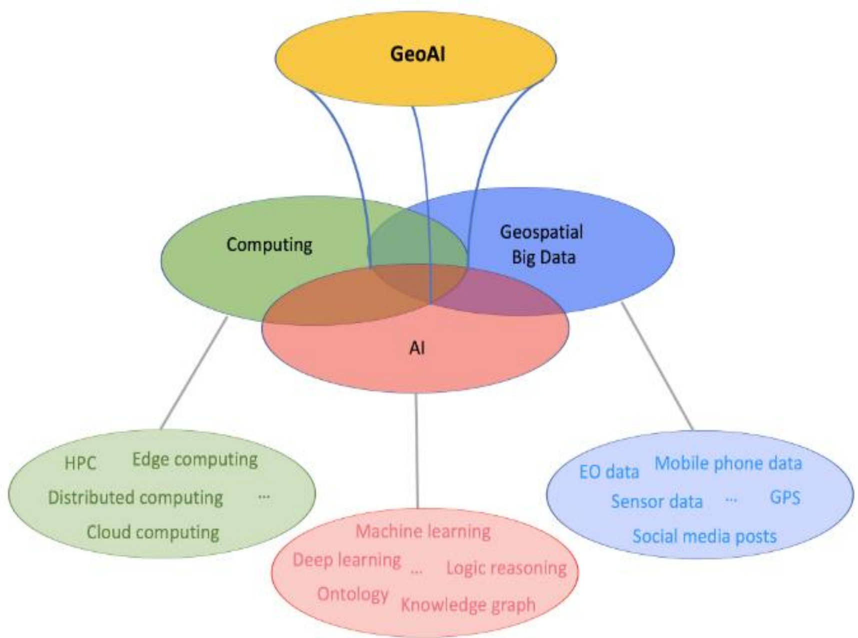

Figure 6. A conceptual, three-pillar view of GeoAI (*Adopted from Li, 2020*)

3.4.1. Historical foundation of GeoAI

Although the foundational ideas of artificial intelligence were introduced as early as the 1950s, most notably by Newell and Simon (1959), the term "Artificial Intelligence" was formally coined by John McCarthy (Mai et al., 2025) and its intersection with geospatial concepts began to take shape in the 1980s where pioneering GIScience scholars started to explore how AI could address geographic problems. Early contributions include Smith's (1984) discussion of AI's cognitive and engineering approaches, and Couclelis' (1986) reflections on AI's potential for theoretical and applied geographic research. A landmark in this convergence was Openshaw and Openshaw's (1997) influential book "Artificial Intelligence in Geography," which laid the foundation for applying AI in spatial analysis and pattern discovery (Gao, 2021; Mai et al., 2025). These early explorations marked the conceptual origins of GeoAI, a field that has evolved significantly through advances in location intelligence and AI.

3.4.2. Philosophical foundations of GeoAI

As described earlier, GeoAI shares the underlying assumptions with geography, AI, cognitive science, and many other disciplines while adding its own perspectives (Janowicz, 2023). The philosophical foundations of GeoAI are derived from the interplay between computational objectivity and geographic subjectivity. Epistemologically, it deals with how machine learning constructs spatial knowledge that shifted from deductive GIS logic to inductive, data-driven generalizations, while struggling with uncertainty in defining fuzzy geographic entities (Janowicz, 2023). Ontologically, it navigates dualisms of absolute vs. relational space, digital environment vs physical realities challenging traditional geographic representations (Budak et al., 2006). Ethically, GeoAI inherits biases from training data, risking reinforcement of spatial injustices, while its surveillance capabilities raise Foucaultian critiques of power in geospatial monitoring. Phenomenologically, it struggles to encode human-place relationships into algorithmic models. These foundations reveal GeoAI not merely as a technical tool, but as a paradigm that redefines geographic reasoning, demanding interdisciplinary scrutiny at the intersection of AI, spatial science, and philosophy (Gao et al., 2024).

3.4.3. Methodological foundations of GeoAI

As an innovation, GeoAI emerged at the junction of geospatial science, big geo-data analytics, and artificial intelligence, representing a methodological evolution from traditional rule-based spatial analysis toward intelligent, automated systems capable of learning and reasoning from complex and large-scale spatial data (Hosen et al., 2023). Basically, GeoAI has two major methodological classes (a) the knowledge-driven (top-down), and (b) data-driven (bottom-up) approaches. Each plays a distinct role in advancing geospatial knowledge discovery, decision-making, and predictive modeling (Li, 2020).

a) The knowledge-driven approach

It refers to the way of solving geospatial problems or making decisions based on structured knowledge rather than relying purely on data or statistics. A knowledge-driven approach is rooted in ontological frameworks and semantic reasoning. An ontological framework is a knowledge representation which provides the conceptual foundation or blueprint for the knowledge structure and specifies how they relate to each other, whereas semantic reasoning is a process of understanding and processing the meaning of information based on the meaning of words, phrases, or symbols in context or semantics (Budak et al., 2006). In the knowledge-driven approach, expert knowledge or domain knowledge plays a central role in guiding decisions or computations (Li, 2020).

Although the knowledge-driven approach is highly interpretable and beneficial in domains where semantic clarity and traceability are crucial like land use, land cover classification or spatial planning, the construction and maintenance of ontologies (guiding rules) are labor-intensive and dependent on domain experts, posing challenges for scalability and adaptability, particularly in fast-changing environments. An ideal example of this method is knowledge based and rule based classifications which are part of machine learning methods (Murayama & Thapa, 2011).

b) The data-driven approach

The data-driven approach, the dominant paradigm in GeoAI, is led by machine learning (ML) and deep learning (DL) techniques because of its outstanding ability to learn and make predictions from massive amounts of data without the need to explicitly program the analytical rules (Li & Arundel, 2022). Deep learning, as a recent breakthrough in machine learning, has transformed data analytics paradigm. It automatically extracts prominent features from the data and differentiate object classes accurately. These models are convolutional neural networks (CNN) and recurrent neural networks (RNNs) which learn from large volumes of spatial data to identify patterns, classify features, and make predictions without explicit programming (Li & Arundel, 2022 Mai et al., 2025). The Machine learning, powered by more traditional, top-down, ontological based GeoAI approaches, solve spatial problems semantically and logical reasoning. Furthermore, the rise of knowledge graphs where semantic networks enriched with AI capabilities offers a promising integration of both methodological strands which support advanced operation (Li, 2020).

Collectively, these methodological advances in GeoAI address critical limitations of traditional geospatial analysis, Hence, GeoAI ability to process multi-source, multi-scale, and multi-temporal spatial data (big geo-data) suited today's challenges in disaster response, urban planning, environmental monitoring, and humanitarian decision-making. Therefore, GeoAI stands as a transformative force that bridges data richness with spatial intelligence, enabling timely, precise, and context-aware insights.

Table 1. Comparison of ML and DL data-driven approaches

Machine Learning	**Deep Learning**
Applies statistical algorithms to learn the hidden patterns and relationships in the dataset	Uses artificial neural network architecture to learn the hidden patterns and relationships in the dataset
Can work on a smaller amount of dataset	Requires a larger volume of dataset compared to machine learning
Better for low-level task	Better for complex tasks like image processing, natural language processing, etc.
Takes less time to train the model	Takes more time to train the model
A model is created by relevant features which are manually extracted from images to detect an object in the image.	Relevant features are automatically extracted from images. It is an end-to-end learning process.
Less complex and easy to interpret the result	More complex and works like the black box interpretations of the result are not easy
It can work on CPU or requires less computing power as compared to deep learning.	It requires a high-performance computer with GPU.

(*Source:* Studocu, 2024)

3.4.4. Application of GeoAI

Blending AI with location intelligence improves operational efficiency and decision-making of geospatial technology; consequently, GeoAI is benefiting multiple areas by providing highly accurate and precise information, accessing real-time insights efficiently and automatically, and being applied across a wide range of areas. This includes urban planning and smart cities, agricultural monitoring, environmental monitoring, disaster risk management, public heath, public safety, transportation, defense and intelligence (Faizuddin & Rahman, 2023; Gao et al., 2024; Liu et al., 2023).

The graphic representation presented in Figures 7, 8 and 9 shows how GeoAI improves operational efficiency and decision-making in smart cities, smart agriculture, disaster management, health and wildlife preservation. More specifically, AI-powered geospatial technologies in urban planning and smart cities simulate urban expansion, optimize land use, and create more intelligent transportation systems, collectively supporting sustainable urban development. In agriculture, integrating GeoAI technology to manage water supply (irrigation), monitoring crop health, evaluate soil quality and application of inputs will improve agricultural productivity and support the practice of precision agriculture.

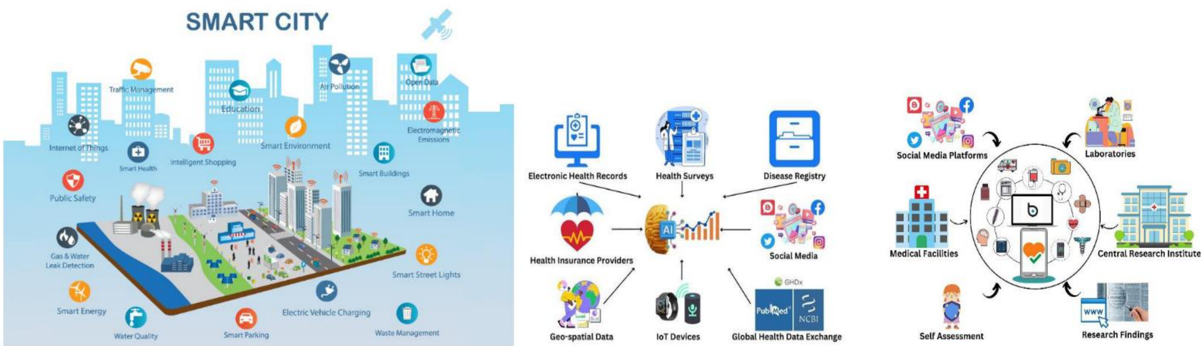

Figure 7. GeoAI application for smart city (left) and public healthcare (right)
(*Source*: Golomb, 2018; Malo, 2023)

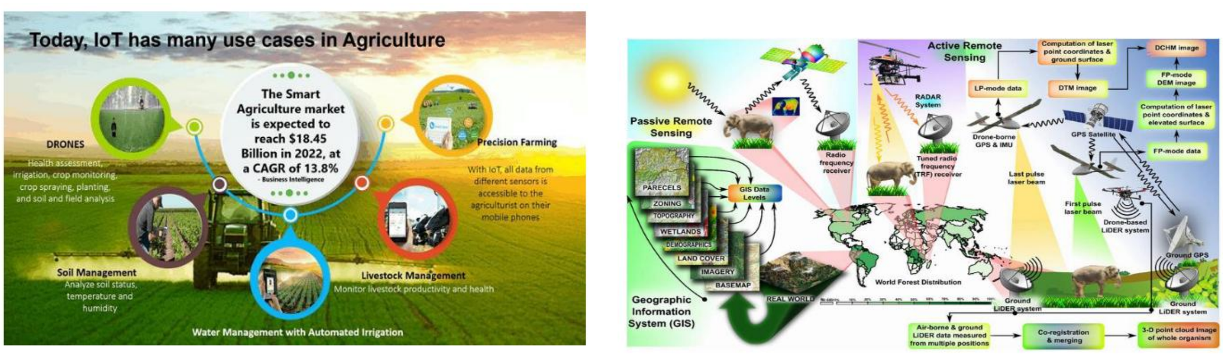

Figure 8. GeoAI application for smart agriculture (left) and wild life preservation (right)
(Source: Agbelusi et al., 2024)

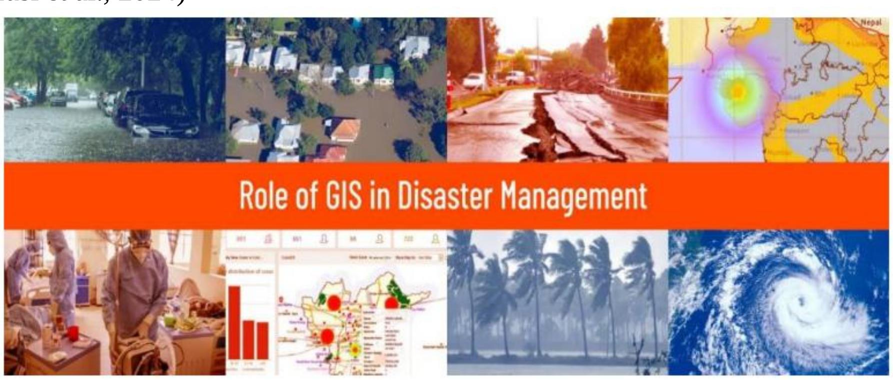

Figure 9. GeoAI application for disaster risk management (*Source*: Rahman, 2025)

GeoAI restructures infrastructure building by forecasting maintenance requirements, optimizing routes, and analyzing topography which help to save costs and increase efficiency. It also aids in wildlife conservation by tracking animal movements, identifying habitat degradation, and using predictive analytics to stop poaching. GeoAI stimulates innovation and promotes sustainable development in a variety of domains by converting geographical data into actionable insights. GeoAI enables dynamic, predictive, and automated decision-making. It enhances early warning capabilities by detecting patterns and anomalies that precede disasters such as floods, wildfires, earthquakes, and disease outbreaks from real-time or near real-time geospatial big data.

3.4.5. GeoAI's future perspectives

The future perspectives of GeoAI are focused on the evolving potential of GeoAI to transform industries, enhance decision-making, and address complex global challenges, driven by advances in AI, data availability, and computational power. As it is discussed by Darwish, (2025) the key future perspectives of GeoAI are:

a) More accurate and real-time predictions: As geospatial data becomes more accessible and AI models improve, GeoAI will be able to deliver real-time predictions and insights. This could be especially important in areas like disaster management, traffic monitoring, and urban planning. GeoAI will also enhance predictions in fields like weather forecasting, climate change modeling, agriculture yields, and population growth by analyzing large-scale datasets and finding patterns more efficiently.
b) Automated geospatial data processing: In the future, GeoAI will involve automating the process of geospatial data extraction. The deep learning models will help to analyze satellite images more efficiently and accurately than ever before. In addition, fusing multi-sensor, multi-model imagery will provide a more comprehensive understanding of phenomenon.
c) Autonomous systems (drones, robots, and vehicles): Autonomous systems such as drones, robots, and self-driving vehicles rely extensively on geospatial intelligence for accurate navigation and real-time decision-making. GeoAI enhances these capabilities by enabling machines to interpret their surroundings, assess road conditions, detect obstacles, and operate safely in complex environments. This is particularly transformative for autonomous vehicles, which must continuously analyze spatial data to adapt to dynamic scenarios.

d) Personalized geographic services: GeoAI is reshaping personalized services by using location and behavior data to tailor experiences. In e-commerce and marketing, it enables businesses to offer region-specific recommendations and predict local consumer trends. It also enhances location-based apps like navigation and fitness trackers by delivering more accurate and context-aware information aligned with users' real-time environments.

e) Global collaboration and open data initiatives: It will strive to expand access to open geospatial data and international cooperation. Public datasets from organizations like NASA, ESA, and platforms like OpenStreetMap will support global efforts in climate action, disaster response, and sustainability. Additionally, crowdsourced data from sensors, smartphones, and social media will enhance the precision and timeliness of GeoAI insights by complementing traditional data sources.

f) Enhanced decision-making and policy planning**:** GeoAI supports smarter policy and planning by modeling urban growth, zoning, and infrastructure needs, enabling data-driven decisions in city development. It also aids disaster preparedness by predicting risks such as floods or wildfires and improving emergency responses. In resource management, GeoAI helps optimize water use, track deforestation, and guide renewable energy deployment, promoting more sustainable and efficient practices.

g) Ethical and responsible AI in GeoAI: As GeoAI expands, ensuring ethical use becomes critical. This includes addressing bias in AI models to prevent unfair outcomes across regions or populations, and protecting personal location data. Governments and organizations will need to establish clear regulatory frameworks to promote transparency, fairness, and accountability in geospatial AI applications**.**

4. Conclusion

The evolution of geospatial analysis has been a dynamic journey, leading to the advent of GeoAI. Initially, geospatial analysis, rooted in the mid-20th century with the emergence of quantitative geography and regional science, was based on traditional statistical and cartographic methods. The basic concepts focused on understanding spatial distributions, patterns, and relationships through tools such as geographic information systems (GIS), which provided capabilities for mapping, querying, and spatial operations. This phase was characterized by a more aggregate, model-driven approach, where analysis was often guided by pre-defined hypotheses and limited by computing power and data availability. The proliferation of geospatial big data marked a critical turning point. The sheer volume, velocity, variety, and other characteristics of data from multiple sources such as satellite imagery, Internet of Things (IoT), social media, and mobile devices overwhelmed traditional analytical frameworks. This large volume of data required basic shift in methodology from static pattern recognition to more dynamic and predictive spatial modeling. The challenges of storing, processing, and extracting meaningful insights from these massive datasets prompted the development of advanced computational methods, including parallel processing, GPU computing, and cloud-based platforms. It was this confluence of geospatial big data and artificial intelligence (AI) that gave rise to GeoAI. GeoAI represents a synergistic integration of AI algorithms and geospatial big data which enables GeoAI to overcome the limitations of traditional analytics by automating complex feature extraction, identifying subtle spatial patterns in massive datasets, and performing advanced predictive analytics that were previously impossible. The development of GeoAI represents the field's evolution toward more intelligent, autonomous and adaptive spatial analysis capabilities. It marks a transition from human-intensive, hypothesis-driven analysis to data-driven, algorithmically-enhanced insights. The trajectory from basic GIS and statistical analysis to the advanced predictive power of GeoAI shows a significant shift in geospatial science.

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