Geospatial Artificial Intelligence for Land Use Change: A Survey

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Abstract

Geospatial Artificial Intelligence (GeoAI) merges artificial intelligence with geospatial sciences, revolutionizing the analysis and prediction of land use changes by integrating geographic data and machine learning. This survey explores the transformative potential of GeoAI in addressing complex spatial phenomena, emphasizing its role in urban dynamics, environmental monitoring, and disaster management. Central to GeoAI are Geospatial Knowledge Graphs, which structure and interpret vast datasets, facilitating sophisticated spatial analysis and decision-making. The survey highlights GeoAI's applications in urban expansion, agricultural systems, and climate change, demonstrating its ability to enhance predictive accuracy and inform sustainable development. Despite challenges related to data quality, computational complexity, and ethical considerations, GeoAI offers innovative solutions for managing spatial data. Emerging techniques, such as deep learning and Bayesian methods, further enhance GeoAI's capabilities, enabling more nuanced analyses of spatial dependencies and interactions. The survey underscores the importance of interdisciplinary collaboration and standardization in advancing GeoAI technologies, promoting their responsible and equitable use. By integrating diverse data sources and refining analytical models, GeoAI not only advances spatial analysis but also plays a critical role in environmental and urban studies, addressing the complex challenges of modern geospatial phenomena. Through these advancements, GeoAI emerges as an essential tool for sustainable land management, offering robust frameworks for predicting and understanding land use changes.

1 Introduction

1.1 Concept of GeoAI

Geospatial Artificial Intelligence (GeoAI) merges artificial intelligence with geospatial sciences, creating a framework for complex spatial data analysis [1]. This interdisciplinary approach employs AI methodologies, particularly artificial neural networks (ANN) and machine learning, to efficiently manage and analyze spatial information [2]. The integration of AI into spatial analysis enhances urban dynamics understanding and promotes sustainable development, showcasing GeoAI's transformative potential in contemporary spatial sciences [3].

At the core of GeoAI are Geospatial Knowledge Graphs (GeoKGs), which are crucial for structuring and interpreting extensive geospatial datasets [4]. These graphs facilitate the organization of spatial information, enabling sophisticated analysis and decision-making. Notably, GeoAI is influencing cartography, where advanced AI techniques are redefining traditional mapping and spatial visualization practices [5].

By leveraging AI capabilities, GeoAI enhances spatial data interpretation precision and explores intricate human-environment relationships. This synergy between AI and geospatial sciences is

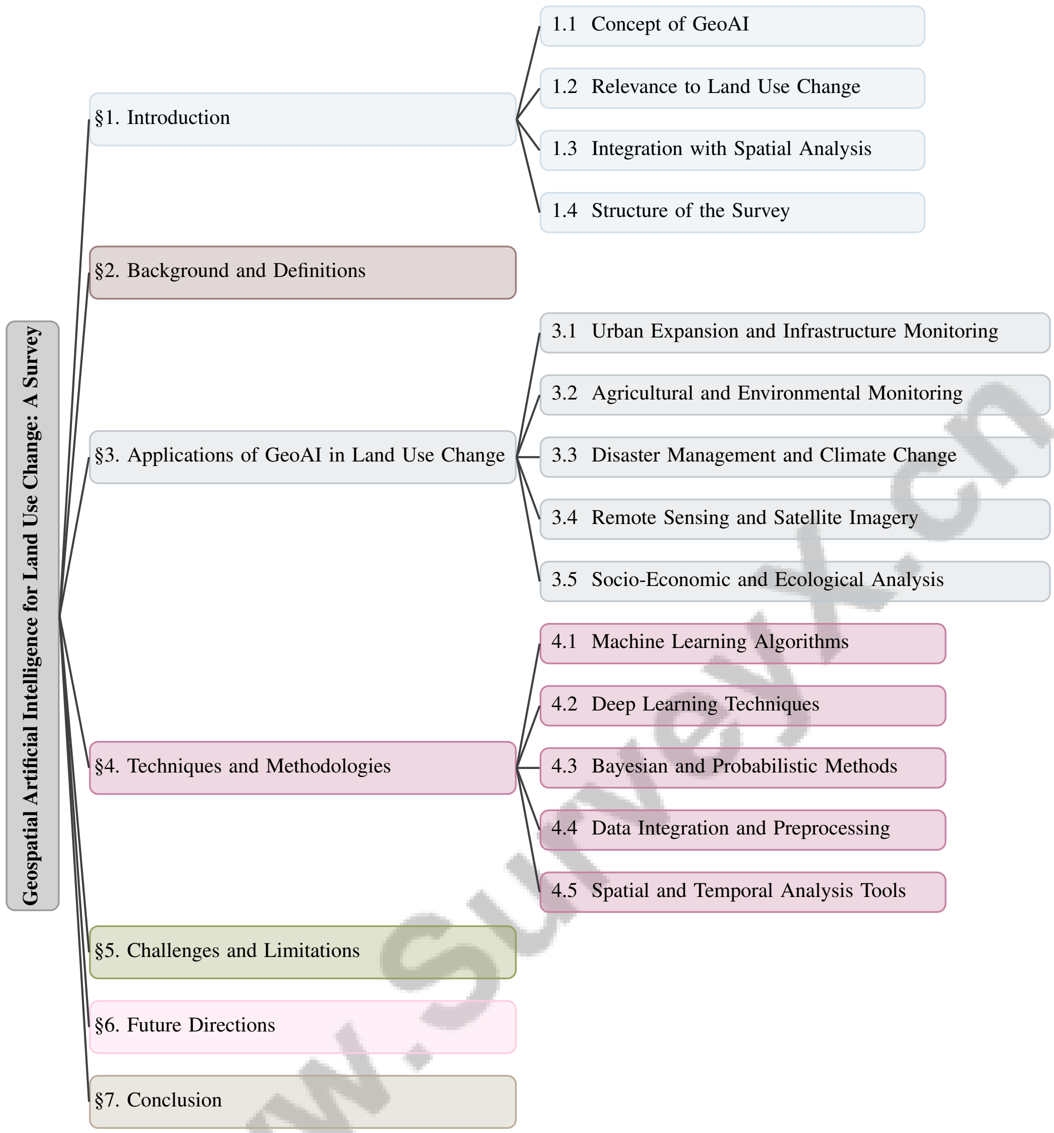

Figure 1: chapter structure

vital for advancing spatial analysis, addressing the emerging opportunities and challenges posed by technological advancements [1].

1.2 Relevance to Land Use Change

GeoAI's integration into land use change analysis is essential for managing and predicting the environmental impacts of human activities. It synthesizes spatial data to tackle societal challenges like urbanization, climate change, and socio-economic transformations [1]. Employing advanced AI methodologies, GeoAI significantly enhances land use change prediction accuracy, outperforming traditional methods that often overlook complex spatial characteristics [2].

A critical application of GeoAI is in interpreting 3D point clouds, which are foundational for various geospatial applications and provide insights into land use dynamics [6]. This capability is vital for urban planning, where GeoAI facilitates decision-making by integrating AI with geospatial data to analyze urban growth patterns and their land use implications [7].

Moreover, GeoAI's role in remote sensing image analysis is underscored by the need for models that perform well across diverse geographical regions, enhancing land use prediction accuracy [4]. This is

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particularly relevant in agriculture, where simulating land-use and cover change dynamics is crucial for understanding economic, environmental, and technological interplays [8].

GeoAI also addresses the limitations of terrestrial biosphere models (TBMs) in representing land-use and land-cover change (LUCC) processes, which are critical for climate change assessments [9]. Its application facilitates a comprehensive understanding of LUCC impacts, improving climate model predictive capabilities.

In environmental sustainability, predicting soil erosion is vital for food security, and GeoAI offers valuable tools for assessing these risks [10]. By leveraging AI techniques, GeoAI enhances land use change prediction, reinforcing its relevance in environmental studies.

As a crucial tool for sustainable land management, GeoAI provides innovative solutions to the complexities of land use change. Its ability to integrate advanced learning techniques tailored for geospatial data further emphasizes its transformative potential in modern spatial sciences [5]. Additionally, monitoring land use/land cover changes (LUCC) around significant infrastructure projects, such as the Three Gorges Dam, highlights GeoAI's necessity in understanding the social and environmental impacts of such developments [11].

1.3 Integration with Spatial Analysis

Integrating AI techniques with spatial analysis is vital for enhancing land use change predictions, improving accuracy and efficiency across applications. This integration is exemplified by AgroDEVS, a model simulating land-use and land-cover change (LUCC) dynamics through behavioral rules reflecting farmer preferences, crop yields, weather, and economic factors [8]. Such models illustrate AI's potential to capture complex interactions within spatial datasets, enhancing predictive capabilities.

Remote sensing has become a pivotal method for tracking land use/land cover changes, particularly in areas like the Three Gorges Reservoir, effectively monitoring environmental transformations [11]. The fusion of AI with remote sensing data enhances the detection and prediction of land use changes, addressing the complexities of spatial datasets.

In the broader spatial analysis context, AI fosters interdisciplinary collaboration, bridging AI technologies and geographical sciences. This is evident in frameworks categorizing research into place representation, spatial analysis, and urban planning [12]. The synergy of AI, machine learning (ML), and deep learning (DL) with geomatics enhances spatial analysis precision, showcasing their application to geospatial data [13]. This is particularly beneficial in urban planning, where AI methods enhance decision-making capabilities through improved data interpretation [14].

Advanced platforms like 3D VRGIS and WebVRGIS employ virtual reality technology to create immersive environments for visualizing and analyzing extensive city data, enhancing spatial analysis capabilities. Hybrid models, integrating satellite images with geographical features, improve land-use change modeling by accurately capturing transition probabilities [15].

In aerial imagery analysis, advanced AI models for segmentation and classification, as demonstrated by the BOSC toolbox, enhance image analysis accuracy and efficiency, providing critical insights into land use dynamics [16]. The convergence of data science and GIS underscores the significance of machine learning and big data technologies in advancing spatial data analysis, facilitating informed decision-making processes [17].

Recent advancements in integrating artificial intelligence with spatial analysis, particularly through Geospatial Location Embedding (GLE) and Spatial Language Models (SLM), highlight the potential for enhancing our understanding of land use changes. These technologies facilitate the assimilation and analysis of complex spatial data, enabling effective management and predictive modeling of land use dynamics. Leveraging AI alongside geospatial big data allows researchers to overcome critical data gaps and cultivate a nuanced comprehension of spatial phenomena, ultimately paving the way for innovative land use planning and policy-making solutions [18, 19]. This integration not only enhances spatial analysis capabilities but also plays a crucial role in addressing modern urban and environmental studies' complex challenges.

1.4 Structure of the Survey

The survey is systematically structured to comprehensively explore Geospatial Artificial Intelligence (GeoAI) and its application in land use change analysis. It begins with the **Introduction**, which defines GeoAI, discusses its relevance to land use change, and outlines the integration of AI techniques with spatial analysis. This section also provides an overview of the survey's organization, guiding the reader through subsequent sections.

Section 2: Background and Definitions delves into foundational concepts, offering precise definitions of key terms such as GeoAI, land use change, and spatial analysis, establishing a clear understanding of their significance in the study context.

Section 3: Applications of GeoAI in Land Use Change explores practical applications, highlighting GeoAI's role in monitoring urban expansion, agricultural activities, disaster management, and climate change. This section draws on recent studies to illustrate GeoAI's diverse applications and benefits in real-world scenarios.

Section 4: Techniques and Methodologies examines the AI techniques and methodologies utilized in GeoAI for spatial analysis. Discussions encompass various advanced methodologies, including machine learning algorithms, deep learning techniques, Bayesian methods, and data integration processes, illustrating the foundational technical aspects of GeoAI applications. These methodologies are crucial for addressing complex challenges in geospatial data analysis and interpretation, facilitating effective AI applications in urban planning, social science, and environmental monitoring [13, 20, 14, 18, 21].

In **Section 5: Challenges and Limitations**, the paper addresses challenges in applying GeoAI to land use change, such as data quality, computational complexity, and ethical concerns, providing a critical analysis of current limitations and potential areas for improvement.

Section 6: Future Directions highlights significant emerging trends and potential research pathways in the evolving landscape of GeoAI. It underscores the necessity of enhancing existing models, fostering interdisciplinary collaboration among geoscientists, computer scientists, and engineers, and addressing ethical considerations to ensure responsible GeoAI advancement. This section reflects on the critical role of breaking down data silos and promoting standardized methodologies to tackle open challenges in GeoAI system design and implementation, ultimately aiming to address pressing societal issues through innovative solutions [20, 18].

The **Conclusion** summarizes the survey's key findings, emphasizing GeoAI's critical role in enhancing our understanding and forecasting of land use changes. It reinforces how GeoAI integrates artificial intelligence with geospatial data, addressing significant challenges and opportunities in various applications such as urban planning and environmental monitoring, thus highlighting its importance in tackling complex societal issues [20, 18, 22]. This structured approach ensures a logical flow of information, guiding the reader through the complexities of GeoAI and its transformative impact on spatial analysis and land use change studies.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Defining Geospatial Artificial Intelligence (GeoAI)

Geospatial Artificial Intelligence (GeoAI) synergizes geographic information systems (GIS) with advanced AI techniques to enhance spatial data analysis [1]. This interdisciplinary approach employs machine learning and deep learning to navigate the complexities of large spatial datasets, extracting valuable insights [4, 2]. GeoAI's efficacy is evident in mapping land use and land cover changes with high-resolution remote sensing, crucial for urban planning and environmental monitoring [11, 3]. Integration with frameworks like S2 Geometry further strengthens geospatial data analysis by facilitating complex dataset manipulation [4].

In agriculture, GeoAI is instrumental through models like AgroDEVS, which simulate land-use dynamics by integrating economic, environmental, and social factors [8]. These models enhance predictive capabilities by capturing intricate dataset interactions. Additionally, GeoAI transforms cartographic design by categorizing research into dimensions of methods and applications, expanding its scope to spatial representation learning, spatiotemporal prediction, and geographic text semantic analysis [5, 1].

2.2 Understanding Land Use Change

Land use change, driven by human activities, alters Earth's surface and functional land use, influenced by socio-economic, environmental, and technological factors [23, 24]. Understanding these changes is crucial for assessing human-environment interactions, vital for resource management and urban planning [14]. Land use alterations can lead to habitat destruction, affect biodiversity, and contribute to climate change by impacting carbon storage and greenhouse gas emissions, necessitating robust monitoring strategies [25, 26].

Technological advancements, particularly AI integration with geospatial analysis, enhance monitoring and prediction of land use changes, allowing for more accurate large-scale assessments [13]. Tailored datasets and high-resolution satellite imagery improve land cover mapping accuracy [27, 11]. However, challenges like the scarcity of labeled geospatial data and limitations of conventional self-supervised learning in capturing spatial semantics persist [28, 29]. Integrating policy frameworks into land use models and reliance on historical patterns for long-term predictions remain ongoing challenges [19].

Socio-economic factors, such as population growth and urbanization, are closely linked to land use change, influencing management practices [30]. In regions with outdated census data, like Nigeria, understanding land use change is crucial for urban planning and resource allocation [31]. Exploring these relationships is essential for developing sustainable land use strategies.

While AI offers significant analytical capabilities, it cannot fully replace human judgment due to the complexity of social interactions and emotions essential for evaluating socio-economic impacts [32]. A collaborative approach integrating advanced analytical techniques with human insight is necessary to address environmental degradation and climate change challenges. By leveraging advanced methods and integrating socio-economic and environmental data, researchers can gain deeper insights into the drivers and consequences of land use change, informing more sustainable environmental policies and practices.

2.3 Spatial Analysis and its Role in GeoAI

Spatial analysis is fundamental to GeoAI, providing insights into land use changes by examining spatial dependencies and relationships within geospatial data [33]. Integrating AI techniques with spatial analysis enhances the exploration of complex spatial patterns, improving decision-making in human geography and enriching the understanding of social dynamics and environmental interactions [12].

Spatial analysis's significance in GeoAI lies in its ability to incorporate spatial dependence, crucial for data interpretation and prediction accuracy enhancement [33]. This is particularly relevant for land use change, where spatial analysis identifies and quantifies changes across scales, from patch-level to landscape-level metrics [25]. These metrics are vital for effective environmental management and urban planning.

The hierarchical structure of S2 cells in GeoAI applications facilitates efficient spatial relationship management, supporting complex querying and analysis tasks [4]. This capability is essential for managing large geospatial datasets, enhancing GeoAI models' predictive capabilities.

Machine learning, particularly artificial neural networks (ANN), significantly advances spatial analysis by modeling complex spatial patterns and interactions [2]. These advancements allow for the integration of spatial lag features into machine learning models, improving prediction accuracy across various applications, including real estate and environmental monitoring.

3 Applications of GeoAI in Land Use Change

Geospatial Artificial Intelligence (GeoAI) is pivotal in tracking land use changes, aiding urban planning, agriculture, and environmental management. This section explores GeoAI's diverse applications, particularly in urban expansion and infrastructure monitoring.

3.1 Urban Expansion and Infrastructure Monitoring

GeoAI enhances urban expansion and infrastructure monitoring through advanced AI methodologies, analyzing spatial patterns and predicting land use changes. Utilizing top-down approaches like ontologies and knowledge graphs, along with bottom-up machine learning techniques such as clustering, classification, and deep learning, GeoAI provides a comprehensive understanding of urban dynamics [18]. In Kuwait, machine learning models automate map updates, enhancing data accuracy for urban planning [14]. The Prithvi model excels in object detection and segmentation, crucial for monitoring urban expansion [27]. Convolutional neural networks (CNN) enhance satellite image processing, facilitating urban landscape change detection [15]. The Multi-task Building Refiner (MT-BR) extracts detailed spatial and attributional information from high-resolution satellite imagery, improving urban dynamics modeling [3].

Building footprint segmentation from high-resolution imagery is crucial for infrastructure monitoring [34]. Long-term car-sharing demand predictive models highlight the need for adaptive urban infrastructure for emerging mobility trends [35]. Accurate demographic data is essential for urban planners, necessitating high-quality population estimates [31]. Heterogeneous sensor databases facilitate environmental parameter monitoring, such as Land Surface Temperature, crucial for assessing urban expansion impacts [28].

The Semantic CV-DCM in Rotterdam uses geo-tagged street-level images for residential location choice monitoring, informing urban planning strategies [7]. These applications highlight GeoAI's transformative potential in addressing rapid urbanization challenges.

As illustrated in Figure 2, the hierarchical structure of urban expansion and infrastructure monitoring underscores the key GeoAI techniques, applications, and data methods. The main categories—GeoAI Techniques, Applications, and Data and Methods—encompass specific tools such as ontologies, machine learning, satellite image processing, and demographic data utilization, showcasing their roles in advancing urban planning and monitoring.

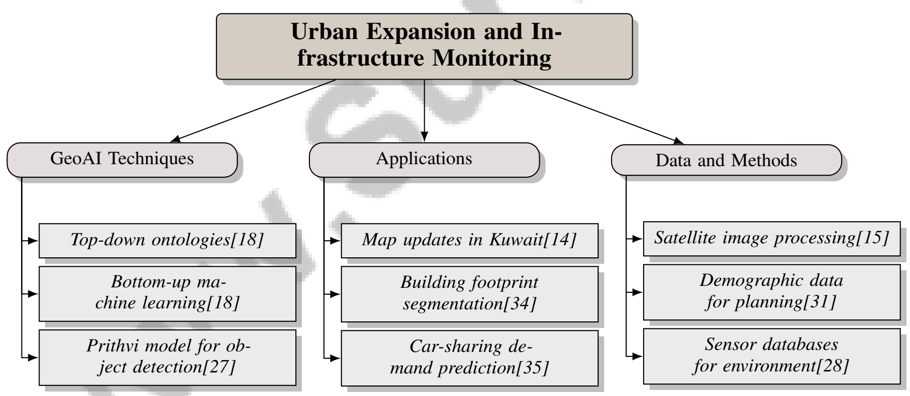

Figure 2: This figure illustrates the hierarchical structure of urban expansion and infrastructure monitoring, highlighting key GeoAI techniques, applications, and data methods. The main categories include GeoAI Techniques, Applications, and Data and Methods, each encompassing specific tools and methods such as ontologies, machine learning, satellite image processing, and demographic data utilization, showcasing their roles in advancing urban planning and monitoring.

3.2 Agricultural and Environmental Monitoring

GeoAI advances agricultural and environmental monitoring by employing sophisticated AI methodologies to analyze complex spatial datasets. The CapsAttn method enhances crop type classification from low-resolution satellite imagery, improving monitoring accuracy [36]. AgroDEVS integrates socio-economic and environmental factors to simulate land-use and land-cover change dynamics, boosting predictive capabilities [8]. Deep learning methods for semantic segmentation, applied in the Three Gorges Reservoir Area, improve land use mapping accuracy, essential for monitoring environmental changes [11]. GeoAI also enhances soil erosion predictions, integrating diverse data sources to mitigate land degradation risks [8]. Through precision agriculture, environmental monitoring, disaster management, and urban planning, GeoAI leverages advanced AI techniques on large-scale geospatial data, promoting sustainable agricultural practices and environmental stewardship [37, 13, 20, 18, 22].

3.3 Disaster Management and Climate Change

GeoAI is crucial in disaster management and climate change assessment, utilizing advanced AI methodologies to analyze complex spatial datasets. Its integration with geospatial data leads to significant advancements in disaster response and climate modeling, showcasing GeoAI's transformative potential [20]. In disaster management, GeoAI enhances mitigation, preparedness, response, and recovery phases [38]. AI techniques improve natural disaster prediction and response, bolstering community resilience. Case studies demonstrate data science and GIS integration, providing robust spatial data analysis tools [17].

The CLVAE method exemplifies GeoAI's flood detection capability, achieving superior performance metrics over traditional techniques [39]. In climate change, the SCALAE method generates realistic satellite imagery conditioned on population data, revealing demographic shifts' impact on landscapes [40]. GeoAI knowledge graphs with spatially and temporally-enabled semantic rules identify causal relationships among disaster events, enhancing understanding [32]. These advancements underscore GeoAI's potential in addressing environmental and climate change challenges, fostering resilient communities through informed decision-making and interdisciplinary collaboration [20, 18, 22, 13].

3.4 Remote Sensing and Satellite Imagery

Remote sensing and satellite imagery are fundamental to GeoAI, providing critical geospatial data for monitoring and predicting land use changes. This data includes various imagery types, such as RGB, thermal, and hyperspectral images, essential for AI algorithms analyzing complex geomatics data. AI integration with remote sensing improves interpretation accuracy and addresses data gaps, advancing spatial phenomena understanding [13, 18, 22].

Smart datasets like the CI-dataset, containing critical infrastructure images, exemplify remote sensing's potential in enhancing GeoAI applications [41]. Hyperspectral imaging technologies, like HSIMamba, demonstrate superior classification performance, facilitating detailed spectral information extraction crucial for land cover identification [42]. The Prithvi model enhances geospatial analysis through self-supervised learning on large datasets, improving land use change predictions [43]. Innovative methods combining neural networks with GIS and remote sensing yield more accurate deforestation predictions than traditional approaches [44]. Spatiotemporal inference methods significantly improve multitemporal very high-resolution satellite images classification accuracy, enhancing temporal analysis [45].

Tools like the BOSC toolbox facilitate actionable insights extraction from aerial images, making advanced remote sensing techniques accessible [16]. Hyperspectral time-lapse data for land-use change detection further exemplifies remote sensing's versatility in GeoAI applications [46]. Recent GeoAI advancements illustrate its transformative potential in managing and predicting land use changes, contributing to effective and sustainable land use management strategies [14, 18, 22, 13].

3.5 Socio-Economic and Ecological Analysis

GeoAI significantly advances socio-economic and ecological research by integrating sophisticated AI techniques with spatial data analysis, enabling automated processing of complex geospatial data and addressing societal challenges across various fields [13, 20, 14, 18, 22]. This integration enhances understanding of interactions between human activities and ecological systems, supporting informed decision-making.

Artificial neural networks (ANN) in GeoAI have improved predictions in spatial information analysis, particularly relevant for socio-economic and ecological studies [2]. Studies highlight human activities' significant influence on Earth's systems, emphasizing ongoing land-use impact monitoring facilitated by GeoAI through advanced spatial analysis techniques [1]. Landscape metrics and pattern-based analysis enhance ecological dynamics understanding, providing insights into land use, climate, and biogeochemical cycles.

Systematic approaches, like the Segment Anything Model (SAM), streamline data labeling and mapping processes crucial for socio-economic and ecological analyses. Leveraging foundation models

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like SAM enables efficient geoparser comparisons, facilitating comprehensive spatial distribution analyses of socio-economic activities and their ecological impacts. Advanced spatial statistical models improve understanding of geographic and non-geographic factors' interactions, enhancing predictions related to environmental and socio-economic variables [47, 33].

Multiresolution tensor learning (MRTL) in GeoAI enhances computational efficiency and interpretability by managing spatial data complexity, achieving significant speedup compared to fixed resolution approaches, and deepening understanding of spatial relationships [48, 49, 21, 50]. GeoAI also evaluates geographic biases in model performances, ensuring accuracy and reliability across diverse contexts. Tools like TorchSpatial advance spatial representation learning (SRL) by integrating various location encoders and introducing innovative evaluation metrics, fostering GeoAI research progress [51, 52, 19, 53, 29].

4 Techniques and Methodologies

Category	Feature	Method
Machine Learning Algorithms	Pattern and Representation Analysis	S2V[54]
	Hierarchical and Multi-level Processing	MRTL[48], MT-BR[3]
	Data Management and Integration	HSDF[28]
	Simulation and Interaction Modeling	AD[8]
Deep Learning Techniques	Efficient Network Design	FRNN[46]
	Spatial Analysis and Monitoring	ML/DL-IPC[6], VFDA[55]
	Dimensionality Reduction	UMLM-UA[56]
Bayesian and Probabilistic Methods	Non-Gaussian Modeling	ELK[50]
	Spatial-Temporal Analysis	BISTAR[57]
	Bayesian Optimization	KOBM[58]
Data Integration and Preprocessing	Compositional and Socio-Economic Analysis	-IT[51], ESMN[59]
	Spatial Data Techniques	P100M[60], GW[61], visGP[62]
	Data Quality Assurance	ANN[2]
Spatial and Temporal Analysis Tools	Spatial Scaling Insights	SCDD[63]

Table 1: This table provides a comprehensive summary of various methods and techniques utilized in Geospatial Artificial Intelligence (GeoAI). It categorizes these methods into machine learning algorithms, deep learning techniques, Bayesian and probabilistic methods, data integration and preprocessing, and spatial and temporal analysis tools, highlighting their respective features and specific methodologies. Such a classification underscores the diverse approaches employed in enhancing spatial data analysis and decision-making processes within GeoAI.

The foundation of Geospatial Artificial Intelligence (GeoAI) is built upon diverse techniques and methodologies that enhance spatial data analysis and decision-making. Table 5 offers a detailed classification of the techniques and methodologies pivotal to the advancement of Geospatial Artificial Intelligence (GeoAI), reflecting their applications and contributions to spatial data analysis. This section delves into various GeoAI approaches, with a focus on machine learning algorithms crucial for extracting insights from complex geospatial datasets and improving predictive accuracy. The following discussions will detail these algorithms and their transformative effects on spatial dynamics and land use changes.

4.1 Machine Learning Algorithms

Machine learning algorithms are central to advancing GeoAI, offering sophisticated methodologies for analyzing intricate spatial datasets. They enhance land use change predictions by utilizing diverse data acquisition technologies, such as RGB, thermal images, and 3D point clouds, and facilitate the integration of geospatial big data with AI. This integration improves decision-making and addresses data gaps in environmental monitoring and disaster risk reduction [20, 2, 13, 18]. These algorithms foster a nuanced understanding of spatial dynamics, crucial for environmental and urban planning.

Artificial Neural Networks (ANN) are pivotal in GeoAI, functioning as computational models that recognize patterns and make decisions based on input data [2]. Their ability to learn from vast datasets enables them to extract insights critical for understanding and predicting land use changes.

The integration of machine learning and deep learning techniques in 3D point cloud interpretation exemplifies their capability to extract features and semantics directly from geospatial data [6]. This is vital for interpreting complex spatial structures and enhancing spatial analysis precision, particularly in urban monitoring.

Multi-resolution tensor learning (MRTL) combines full-rank initialization with multi-resolution learning, achieving efficient and interpretable spatial analysis [48]. This method highlights machine learning's role in providing scalable models for geospatial data analysis.

Space2Vec integrates multi-scale representations to model spatial distributions of Points of Interest (POIs), utilizing sinusoid functions for encoding [54]. This showcases the versatility of machine learning in capturing spatial dependencies, essential for spatial representation and analysis.

The Heterogeneous Sensor Database Framework (HSDF) employs SQL-based queries for data processing, enhancing the integration and interpretation of diverse geospatial datasets [28]. This framework supports efficient data management and real-time monitoring.

In residential analysis, the Semantic CV-DCM utilizes computer vision techniques to enhance understanding of residential preferences, illustrating a novel machine learning application in GeoAI [7]. Similarly, the AgroDEVS model combines agent-based modeling and cellular automata to simulate interactions between farmers and their environment, exemplifying machine learning's role in agricultural land use change analysis [8].

Benchmark tests of various models, including deep learning models like SegNet, U-Net, and PSPNet, alongside traditional classifiers like CART, SVM, and Random Forest, demonstrate the diverse range of machine learning algorithms applied in GeoAI [11]. These models enhance land use mapping accuracy and efficiency, providing critical insights into spatial transformations.

The Multi-task Building Refiner (MT-BR) employs a multi-task neural network architecture to process various building attributes simultaneously, showcasing machine learning's application in urban analysis [3]. This approach improves urban monitoring precision and supports informed decision-making in urban planning.

Collectively, these machine learning algorithms underscore the transformative impact of AI methodologies in GeoAI, providing advanced tools for analyzing and predicting land use changes. This is illustrated in Figure 3, which categorizes machine learning algorithms in GeoAI, highlighting key algorithms, their applications, and notable frameworks that enhance geospatial data analysis and decision-making. By integrating a variety of advanced techniques, GeoAI significantly enhances spatial data analysis accuracy and reliability, crucial for effective environmental and urban planning strategies. This interdisciplinary approach merges insights from computer science, engineering, and spatial science, leading to innovative solutions that address pressing societal challenges [13, 14, 20, 18, 22].

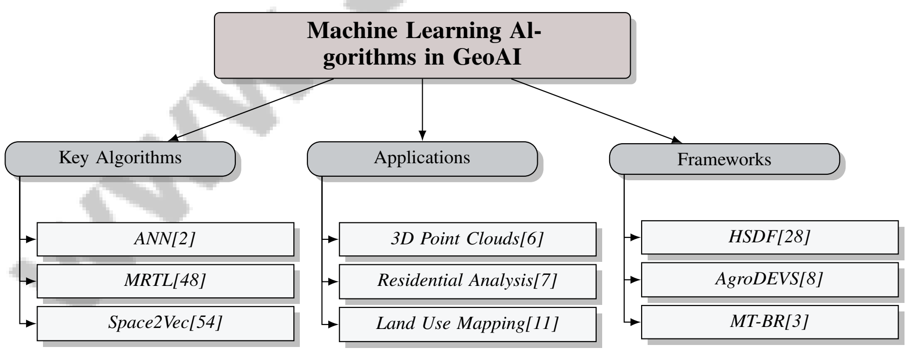


Figure 3: This figure illustrates the categorization of machine learning algorithms in GeoAI, highlighting key algorithms, their applications, and notable frameworks that enhance geospatial data analysis and decision-making.

4.2 Deep Learning Techniques

Deep learning techniques have significantly enhanced GeoAI by introducing sophisticated methodologies for processing and analyzing complex spatial datasets. These advancements facilitate nuanced interpretations of geomatics data, including RGB images, thermal images, and 3D point clouds, addressing critical challenges within the field. The integration of these advanced AI approaches fosters interdisciplinary collaboration among geoscientists, computer scientists, and engineers to tackle significant societal issues through improved geographic knowledge discovery [20, 13]. These

Method Name	Data Types	Application Domains	Analytical Techniques
UMLM-UA[56]	Urban Datasets	Urban Monitoring	Pca, Autoencoders
VFDA[55]	Rgb Images	Urban Monitoring	Faster R-CNN
ML/DL-IPC[6]	3D Point Clouds	Geospatial Applications	Deep Learning Techniques
FRNN[46]	Hyperspectral Data	Land-use Change	Semantic Segmentation

Table 2: This table provides a comparative overview of various deep learning methods utilized in GeoAI, highlighting their respective data types, application domains, and analytical techniques. It illustrates the diverse methodologies employed to address challenges in urban monitoring, geospatial applications, and land-use change analysis.

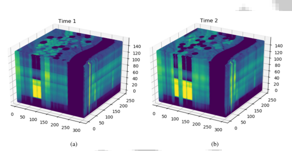
techniques enhance the extraction of meaningful patterns from high-dimensional geospatial data, improving spatial analysis accuracy and efficiency.

Table 2 presents a detailed comparison of deep learning methods in GeoAI, showcasing their application across different data types and domains. Key innovations in deep learning within GeoAI include unsupervised techniques like Principal Component Analysis (PCA) and autoencoders, which extract patterns from high-dimensional urban data [56]. These methods enable data dimensionality reduction while preserving essential information, facilitating efficient urban dynamics analysis.

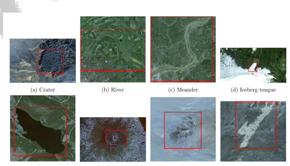
In commercial activity monitoring, deep learning identifies and geo-references visible firms from Google Street View images, creating comprehensive datasets of commercial activity [55]. This application illustrates deep learning's potential to enhance the granularity and accuracy of socio-economic analyses.

The integration of deep learning with 3D point cloud analysis exemplifies its transformative potential in GeoAI. By deriving domain-specific semantics from 3D point clouds without explicit models, deep learning facilitates feature extraction directly from geospatial data [6]. This capability is crucial for interpreting complex spatial structures and enhancing spatial analysis precision, particularly in urban monitoring.

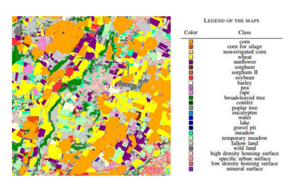
Recent advancements in deep learning techniques are pivotal in enhancing GeoAI capabilities, improving interpretability through methods like saliency maps, fostering interdisciplinary collaboration to address complex challenges, and leveraging vast geospatial datasets to bridge critical data gaps across various fields, including social sciences [20, 21, 18]. By providing sophisticated tools for processing and analyzing complex spatial datasets, deep learning contributes to more informed decision-making in environmental and urban studies, ultimately supporting the development of sustainable and resilient communities.



(a) Time Series Visualization of Two Different Time Points[46]



(b) Geological Features in Satellite Images[21]



(c) Urban Land Use and Land Cover Map[64]

Figure 4: Examples of Deep Learning Techniques

As depicted in Figure 4, the examples illustrate the diverse applications of deep learning techniques across various domains. The first example, "Time Series Visualization of Two Different Time Points," showcases a sophisticated 3D rendering of time series data, allowing for dynamic comparisons between distinct temporal datasets. This visualization highlights deep learning's power in processing and interpreting complex temporal data, as evidenced by color gradients representing data points across a time range of 0 to 300 and spatial coordinates from 0 to 250. The second example, "Geological Features in Satellite Images," demonstrates deep learning's capability to identify and classify geological features from satellite imagery, enhancing our understanding of Earth's geological processes through advanced image analysis. Lastly, the "Urban Land Use and Land Cover Map" example illustrates deep learning's application in urban planning and environmental management by providing a color-coded map categorizing different land uses and covers within an urban landscape. This map aids in visualizing the spatial distribution of various land categories and supports decision-making processes related to urban development and resource management. Collectively, these examples underscore the versatility and transformative impact of deep learning techniques across scientific and practical fields [46, 21, 64].

4.3 Bayesian and Probabilistic Methods

Method Name	Modeling Uncertainty	Spatial Dependencies	Interdisciplinary Applications
ELK[50]	Bayesian Inference	Complex Spatial Dependencies	Diverse Spatial Contexts
BISTAR[57]	Bayesian Inference	Spatial Dynamics	AI Patent Cooperation
KOBM[58]	Posterior Probability	Spatial Characteristics Detection	Ecological Datasets Analysis

Table 3: This table provides a comparative analysis of three Bayesian and probabilistic methods—ELK, BISTAR, and KOBM—highlighting their capabilities in modeling uncertainty, handling spatial dependencies, and their interdisciplinary applications. Each method demonstrates unique strengths in geospatial data analysis, contributing to enhanced GeoAI systems.

Bayesian and probabilistic methods significantly enhance GeoAI's analytical capabilities by providing robust frameworks for modeling uncertainty and spatial dependencies in geospatial data. Techniques like integrated nested Laplace approximation (INLA) and latent Gaussian models enable accurate inference and posterior estimates, crucial for addressing complex geospatial challenges. These approaches facilitate the integration of expert knowledge across spatial scales, overcoming limitations in current geospatial analyses and improving GeoAI systems' effectiveness in addressing critical societal issues [20, 18, 50]. They deepen the understanding of complex spatial phenomena, enhancing the accuracy and reliability of GeoAI applications. Table 3 presents a detailed comparison of selected Bayesian and probabilistic methods, elucidating their roles in advancing GeoAI through robust uncertainty modeling and spatial dependency management.

The ELK method exemplifies Bayesian inference application in spatial analysis, particularly for non-Gaussian responses, thereby improving spatial models' robustness [50]. This approach addresses uncertainties in geospatial data, enabling more accurate predictions and analyses.

Bayesian inference also models the spatial and temporal dynamics of AI patents, capturing cooperation patterns [57]. This highlights Bayesian methods' versatility in understanding intricate interactions between spatial and temporal variables, essential for evolving geospatial phenomena.

Kernel methods enhance GeoAI's predictive capabilities by integrating kernel-based techniques with Bayesian inference [49]. This integration supports precise modeling of spatial relationships, informing decision-making in environmental and urban planning.

The Knuth method, which employs Bayesian principles to derive posterior probabilities of bin parameters, showcases Bayesian and probabilistic methods' application in GeoAI [58]. This approach optimizes data representation, enhancing spatial analyses' interpretability and accuracy.

In population estimation, a Bayesian Hierarchical Poisson Regression model estimates population counts, demonstrating probabilistic methods' application in GeoAI [31]. This framework addresses data scarcity and variability challenges in geospatial contexts.

Collectively, these Bayesian and probabilistic methods underscore advanced statistical techniques' transformative potential in GeoAI. By equipping researchers with tools for modeling uncertainty and spatial dependencies, these methods significantly improve geospatial analyses' accuracy and reliability. This enhancement facilitates informed decision-making in environmental and urban management strategies and supports interdisciplinary applications across geographic information science, environmental science, and socio-economic research. Such methodologies effectively handle complex spatial data, ensuring underlying patterns and relationships are accurately captured and utilized in predictive modeling [47, 17, 52, 65, 33].

4.4 Data Integration and Preprocessing

Data integration and preprocessing are critical components of GeoAI applications, ensuring spatial data analysis's accuracy and reliability. Transforming, organizing, and preparing geospatial datasets are essential for effectively applying artificial intelligence methodologies to analyze and interpret complex spatial phenomena. Advancements in geospatial location embedding (GLE) techniques enhance large language models' (LLMs) capability to assimilate spatial data, contributing to the

Method Name	Data Transformation	Integration Techniques	Preprocessing Strategies
-IT[51]	-IT Mapping	-	Closure Operator
GW[61]	Helper Functions	Modular Structure	Filtering Noise
P100M[60]	Masked Autoencoder Approach	Multi-sensor Data	Novel Approach
ESMN[59]	Census Tract Data	Gis Data Integration	Filtering Noise
visGP[62]	Visibility Graph	Covariance Selection	Filtering Noise
ANN[2]	Data Collection Sources	Integrating Recurrent Networks	Preprocessing Cleaning Data

Table 4: Overview of various data transformation, integration techniques, and preprocessing strategies employed in GeoAI applications. The table highlights methods such as -IT, GW, P100M, ESMN, visGP, and ANN, detailing their distinct approaches to handling geospatial data for improved spatial analysis and model development.

development of Spatial Artificial Intelligence Systems (SPAIS) for nuanced geospatial data analysis [17, 13, 19, 18, 66]. Table 4 provides a comprehensive overview of the methods utilized in data transformation, integration, and preprocessing, which are critical for enhancing the accuracy and reliability of GeoAI applications.

The -IT transformation converts compositional data into Euclidean space, facilitating geostatistical methods' application [51]. This transformation is vital for integrating diverse geospatial datasets, allowing for more precise spatial analysis and modeling.

In geographically weighted analysis, the gwverse package's core provides general helper functions for constructing specialized geographically weighted (GW) modules [61]. This package streamlines spatial data integration and preprocessing, supporting tailored GW model development for enhanced geospatial pattern analysis.

Identifying and filtering data noise, such as spams, bots, and cyborgs, are crucial preprocessing steps. By organizing methods into stages of data collection and noise identification, researchers can effectively classify and filter data using criteria like source metadata fields [67]. This ensures the integrity and quality of geospatial datasets, vital for accurate GeoAI applications.

Integrating land-use information with road networks involves meticulous data preparation, as demonstrated in methodologies that scale global road networks' structure [68]. This integration is crucial for enhancing transportation and urban planning spatial analysis, providing a comprehensive understanding of land use and infrastructure interactions.

Efficient pre-training and fine-tuning of geospatial foundation models are facilitated by novel data sampling and preprocessing methods, addressing satellite imagery's unique challenges [60]. These methods enhance processing and analyzing large satellite data volumes, improving GeoAI models' predictive capabilities.

Defining networks based on census tract data and applying extended models, such as the Schelling model, highlight integrating socio-economic factors into geospatial analyses [59]. This integration supports identifying socio-economic patterns, such as ghetto formation, enhancing urban dynamics understanding.

Organizing methods into stages based on data integration, process interoperability, and application development emphasizes the need for a cohesive approach [69]. This organization ensures effective geospatial data integration and preprocessing, supporting seamless AI methodology application in GeoAI.

The visGP method defines a visibility graph to establish adjacency relationships, essential for integrating and preprocessing spatial data in irregular domains [62]. This method enhances analyzing complex spatial structures, providing a robust foundation for GeoAI applications.

The comprehensive approach involving data collection, preprocessing, ANN model training, and validation is critical for ensuring GeoAI applications' accuracy [2]. This structured methodology enhances spatial analyses' reliability, contributing to informed decision-making processes in environmental and urban studies.

4.5 Spatial and Temporal Analysis Tools

Spatial and temporal analysis tools are integral to advancing GeoAI, providing necessary frameworks and methodologies for examining complex spatial and temporal patterns in geospatial data. These tools significantly improve understanding and predicting land use changes by offering valuable insights into the dynamic interactions between spatial entities over time while accounting for factors like spatial dependence and heterogeneity that influence prediction accuracy across various domains, including environmental and socio-economic contexts [52, 19, 70, 33, 66].

A significant challenge in current research is the lack of comprehensive frameworks for evaluating these tools' effectiveness, compounded by the technical expertise required to leverage their capabilities fully [71]. This limitation emphasizes the need for more accessible and user-friendly tools that can be utilized effectively by a broader range of users, including those with limited technical backgrounds.

The Spatial Correlation Dimension Derivation (SCDD) method exemplifies advanced spatial analysis tools' effectiveness in GeoAI. This method reveals scaling processes inherent in geographical patterns, allowing for a nuanced understanding of spatial relationships [63]. By capturing intricate spatial dependencies, the SCDD method enhances spatial analyses' precision and reliability, supporting informed decision-making processes in environmental and urban studies.

Integrating these tools with AI methodologies facilitates exploring complex spatial and temporal patterns, improving GeoAI applications' predictive capabilities. By offering comprehensive frameworks for analyzing spatial dependencies and temporal dynamics, these analytical tools enhance our understanding of land use changes and their broader implications for environmental sustainability and urban planning. They facilitate integrating diverse datasets—ranging from geospatial to socio-economic variables—allowing for more accurate predictions and informed decision-making. Moreover, emphasizing hybrid methodologies, such as combining machine learning with statistical models, improves predictive accuracy and addresses urbanization's complexities, ultimately supporting sustainable land management practices aligned with global sustainability goals [72, 73, 33].

Feature	Machine Learning Algorithms	Deep Learning Techniques	Bayesian and Probabilistic Methods
Data Type	Geospatial Datasets	High-dimensional Data	Geospatial Data
Primary Application	Land Use Prediction	Spatial Analysis	Uncertainty Modeling
Key Feature	Pattern Recognition	Complex Pattern Extraction	Spatial Dependency Management

Table 5: This table provides a comparative analysis of various methodologies utilized in Geospatial Artificial Intelligence (GeoAI), focusing on machine learning algorithms, deep learning techniques, and Bayesian and probabilistic methods. It highlights the types of data each method is best suited for, their primary applications in spatial analysis, and the key features that distinguish them in the context of GeoAI.

5 Challenges and Limitations

The progression of Geospatial Artificial Intelligence (GeoAI) is impeded by several foundational challenges, primarily revolving around data quality and availability. These issues critically affect the precision and dependability of GeoAI applications, necessitating an exploration of their impacts on spatial analyses. Figure 5 illustrates the hierarchical structure of challenges and limitations faced by GeoAI, categorizing the main challenges into five key areas: data quality and availability, computational complexity, methodological limitations, ethical and privacy concerns, and integration and interoperability challenges. Each category is further divided into specific issues, thereby highlighting the critical areas that require attention to advance the application of GeoAI across various fields. This comprehensive overview not only underscores the multifaceted nature of the obstacles but also serves as a foundation for discussing potential solutions and advancements in the discipline.

5.1 Data Quality and Availability

GeoAI's effectiveness is contingent upon high-quality, accessible data, yet such data is often scarce, particularly in intricate urban settings or detailed land use mapping [2]. Integrating diverse sensor data, crucial for comprehensive analysis, can lead to significant processing burdens, complicating the maintenance of data quality [28]. Traditional data sources like census data frequently lack the granularity needed for precise street-level modeling [7]. Environmental applications face additional challenges due to soil property variability and limited observational data, complicating phenomena predictions such as soil erosion [10, 9]. The scarcity of standardized AI development approaches and limited interdisciplinary collaboration further exacerbate these issues [1]. Overcoming these

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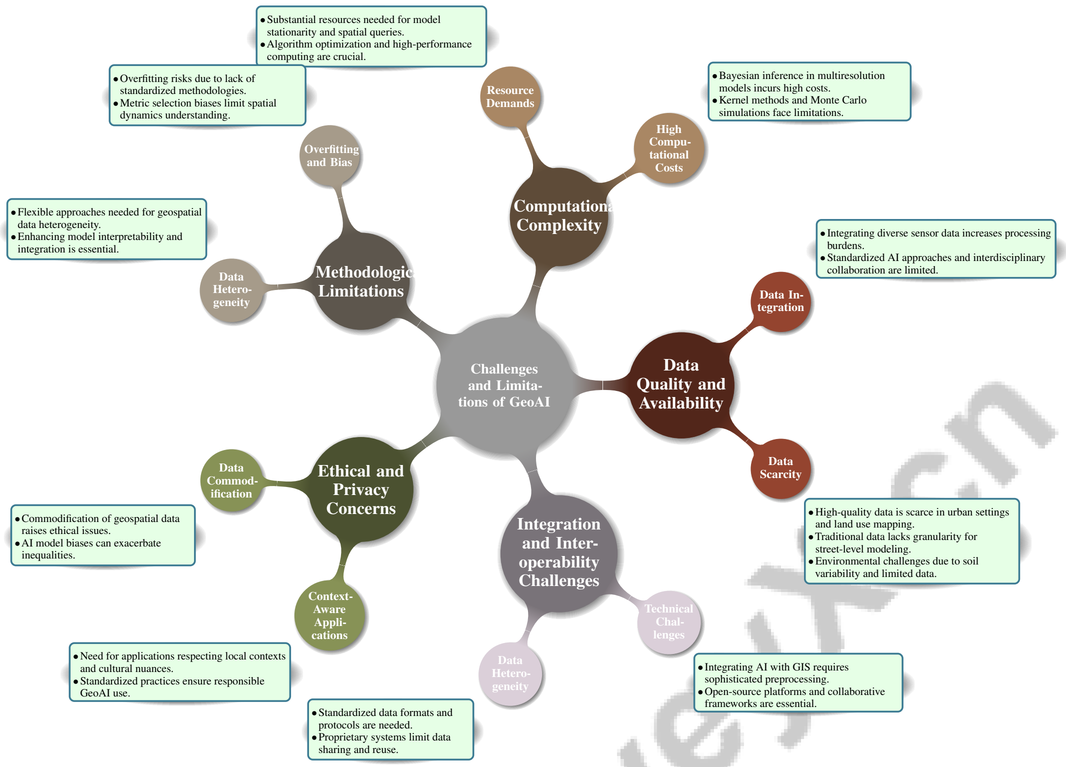

Figure 5: This figure illustrates the hierarchical structure of challenges and limitations faced by Geospatial Artificial Intelligence (GeoAI). It categorizes the main challenges into data quality and availability, computational complexity, methodological limitations, ethical and privacy concerns, and integration and interoperability challenges. Each category is further divided into specific issues, highlighting the critical areas that need addressing to advance GeoAI's application in various fields.

challenges through improved data integration and innovative techniques is vital for advancing GeoAI's role in environmental and urban management.

5.2 Computational Complexity

GeoAI's computational demands present a significant hurdle, especially when processing large datasets and implementing complex models. As illustrated in Figure 6, the figure outlines the computational complexity challenges in GeoAI, focusing on Bayesian inference, resource demands for model stationarity and large-scale queries, and the need for algorithm optimization in kernel methods and Monte Carlo simulations. For instance, Bayesian inference in multiresolution spatial models incurs high computational costs, limiting practical applications [50]. The need for substantial resources to ensure model stationarity and manage large-scale spatial queries further complicates GeoAI's scalability [74, 4]. Kernel methods and Monte Carlo simulations also face computational limitations, particularly with extensive datasets [49, 75]. Addressing these challenges through algorithm optimization and high-performance computing is crucial for advancing GeoAI's capabilities in environmental monitoring and urban planning [13, 20].

5.3 Methodological Limitations

GeoAI's methodological constraints impact spatial analysis accuracy, with overfitting risks and a lack of standardized methodologies being primary concerns [14]. The complexity of landscape interactions and metric selection biases are often inadequately addressed, limiting the understanding of spatial dynamics [25]. Furthermore, outlier detection in high-dimensional datasets remains computationally challenging [65]. Flexible approaches are needed to adapt to geospatial data heterogeneity, and enhancing model interpretability and integration across diverse sources is essential for GeoAI's advancement [20, 18].

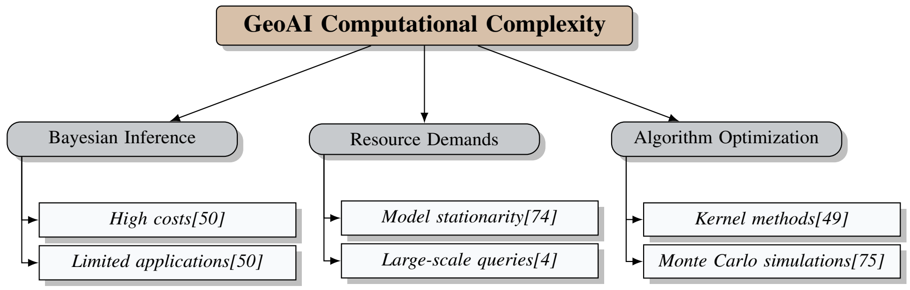

Figure 6: This figure outlines the computational complexity challenges in GeoAI, focusing on Bayesian inference, resource demands for model stationarity and large-scale queries, and the need for algorithm optimization in kernel methods and Monte Carlo simulations.

5.4 Ethical and Privacy Concerns

GeoAI's application raises significant ethical and privacy issues, including the commodification of geospatial data and potential privacy breaches [76]. AI model biases can lead to skewed analyses, exacerbating inequalities [12]. The need for context-aware applications that respect local contexts and cultural nuances is critical [12]. Addressing these concerns through standardized practices and context-aware applications is vital for GeoAI's responsible use, ensuring equitable deployment across diverse geographical settings [20, 18].

5.5 Integration and Interoperability Challenges

The integration and interoperability of GeoAI systems are hindered by the heterogeneity of geospatial data sources, necessitating standardized data formats and protocols [69]. Proprietary systems and data formats limit data sharing and reuse, impeding GeoAI's scalability [69]. Integrating AI with traditional GIS systems poses technical challenges, requiring sophisticated preprocessing techniques [69]. Developing open-source platforms and collaborative frameworks is essential for overcoming these challenges, improving geospatial data accessibility and usability across various sectors [13, 20]. Addressing these integration and interoperability issues is crucial for enhancing GeoAI's capabilities in precision agriculture, environmental monitoring, and urban planning, facilitating interdisciplinary collaboration and tackling significant societal issues [20, 18].

6 Future Directions

6.1 Emerging Techniques and Frameworks

The evolution of Geospatial Artificial Intelligence (GeoAI) is set to be significantly influenced by emerging techniques and frameworks, enhancing analytical capabilities and expanding application domains. Key advancements include refining models like AgroDEVS to incorporate diverse agent behaviors, assessing agricultural policies' impacts on land-use and land-cover change (LUCC) dynamics [8]. Expanding datasets and exploring advanced deep learning architectures are vital for improving classification accuracy in complex environments, such as those around the Three Gorges Dam [11].

Integrating diverse data sources, including social media and multi-sensor imagery, will deepen GeoAI's understanding of urban environments, enabling comprehensive analyses that inform urban planning and management strategies [3]. Enhancing model adaptability to various spatial data types and exploring semi-supervised learning techniques will further bolster GeoAI's robustness and versatility [2].

Ethical considerations are crucial in advancing GeoAI, especially in cartography. Future research must prioritize developing ethical guidelines for transparency and accountability while exploring new applications and refining existing models [5]. Such efforts will enhance the credibility and acceptance of GeoAI technologies across various domains.

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The integration of advanced deep learning architectures and diverse data sources is essential for advancing GeoAI applications. By focusing on these advancements, researchers can leverage artificial intelligence, geospatial big data, and computational capabilities to develop innovative solutions for complex spatial analysis and land use change prediction challenges. This interdisciplinary approach fosters collaboration among geoscientists, computer scientists, and policymakers, ultimately leading to more effective decision-making in precision agriculture, environmental monitoring, and urban planning [20, 18, 22, 13].

6.2 Model Enhancements and Predictive Capabilities

Advancing Geospatial Artificial Intelligence (GeoAI) involves enhancing model robustness and predictive capabilities to address spatial data analysis and land use change prediction complexities. Future research should focus on improving model robustness against bias, exploring novel population distributions, and integrating longitudinal satellite data for better climate change forecasting [40]. This approach will enable more accurate predictions of environmental transformations and their socio-economic impacts.

Refining models like the RFA-CA model is critical for urban growth prediction. By incorporating additional variables, these models can better capture urban expansion dynamics and environmental impacts [77]. Such enhancements will improve urban planning and management strategies, supporting sustainable development initiatives.

In deforestation prediction, enhancing data collection methods, exploring additional environmental factors, and refining neural network architectures are essential for improving predictive performance [44]. These efforts will lead to more effective conservation strategies and environmental management practices.

Optimizing computational efficiency in parameter selection processes is crucial for practical applications in public transportation and other domains. By validating routes and enhancing computational methods, researchers can improve GeoAI models' applicability and reliability in real-world scenarios [75].

Considering spatial autocorrelation and heterogeneity in outlier detection is vital for improving model accuracy and reliability. Outliers, often overlooked, can provide valuable insights into spatial dynamics and should be leveraged to enhance predictive models [65]. Additionally, improving data quality and refining model parameters are critical steps in enhancing prediction accuracy, enabling GeoAI to offer precise insights into land use changes and their environmental impacts [23].

These research directions underscore the need for continuous enhancements to GeoAI models and the integration of diverse data sources. This approach is essential for addressing multifaceted challenges in GeoAI system design and implementation, requiring cross-disciplinary collaboration to leverage advancements in artificial intelligence, geospatial data science, and big data analytics. By breaking down data silos and fostering interdisciplinary engagement, these efforts aim to enhance GeoAI applications' effectiveness in precision agriculture, environmental monitoring, disaster management, and urban planning, ultimately driving significant societal impact [20, 18, 22, 13].

6.3 Ethical Considerations and Socio-Economic Impacts

The future development of Geospatial Artificial Intelligence (GeoAI) requires a thorough examination of its ethical considerations and socio-economic impacts. As GeoAI technologies evolve, integrating AI in geospatial contexts raises critical ethical questions that must be addressed for responsible and equitable use [14]. A significant concern is the ethical implications of urban morphology and its socio-economic impacts, crucial for understanding how GeoAI developments influence urban environments and community structures [78].

Future research should investigate the implications of road expansion on environmental sustainability and the integration of local road networks into broader scaling frameworks [68]. This exploration will yield insights into the potential environmental and social consequences of infrastructure developments, informing more sustainable urban planning practices. Additionally, integrating further data sources is essential for enhancing the understanding of community interactions and their implications for urban policy [79]. By examining these interactions, researchers can better understand socio-economic dynamics within urban areas and develop policies that promote equitable development.

Exploring individual heterogeneity in residential location choices is another critical area for future research, highlighting the diverse preferences and needs of urban residents [7]. Utilizing wider-angle images to capture comprehensive street-level conditions will provide deeper insights into the factors influencing residential decisions, ultimately informing more inclusive urban planning strategies.

Effectively addressing ethical and socio-economic considerations is essential for the responsible advancement of GeoAI, safeguarding individual rights and fostering social justice by promoting inclusivity and collaboration among diverse stakeholders, including geoscientists, computer scientists, and decision-makers to tackle significant societal challenges [20, 18]. By developing standardized practices and context-aware applications, researchers can mitigate potential risks and ensure the responsible use of GeoAI technologies across diverse geographical settings.

6.4 Interdisciplinary Collaboration and Standardization

Interdisciplinary collaboration and standardization are pivotal in advancing Geospatial Artificial Intelligence (GeoAI), fostering the integration of diverse expertise and promoting cohesive framework development. The convergence of insights from scientists, engineers, and policymakers is essential for addressing the complex challenges posed by GeoAI applications [1]. This collaborative approach ensures that GeoAI technologies are developed with a comprehensive understanding of both technical and societal implications, facilitating more effective and sustainable solutions.

Standardization is vital for improving the interoperability of GeoAI systems, facilitating efficient data exchange and integration across diverse platforms, addressing challenges posed by non-standardized AI tool development, and fostering collaboration among geoscientists, computer scientists, and engineers. This effort is crucial for leveraging advancements in artificial intelligence and geospatial big data to solve significant societal problems while breaking down data silos and enhancing research methodologies in the field [20, 52, 18]. Establishing common protocols and data formats supports the scalability and usability of GeoAI applications, ensuring effective deployment in diverse geographical contexts. This is particularly important for promoting the widespread adoption of GeoAI technologies, as standardized practices reduce barriers to entry and facilitate collaborative research and development.

The interdisciplinary nature of GeoAI necessitates incorporating diverse perspectives from geography, computer science, environmental science, and urban planning. By fostering collaboration among these fields, researchers can leverage a wide range of methodologies and insights, ultimately enhancing the analytical capabilities and predictive accuracy of GeoAI systems. This collaborative approach not only enhances the development of GeoAI technologies by integrating insights from diverse disciplines but also ensures that these innovations align with broader societal objectives, including sustainability and social equity, thereby addressing critical data and knowledge gaps and fostering interdisciplinary engagement among researchers, practitioners, and decision-makers [20, 18].

7 Conclusion

The exploration of Geospatial Artificial Intelligence (GeoAI) reveals its substantial impact on advancing land use change analysis and prediction. By harnessing extensive spatial big data, GeoAI enhances computational processes, offering refined models for intricate spatial phenomena. Its application in high-resolution environmental assessments underscores GeoAI's capability to address complex geospatial challenges effectively. The integration of geospatial and temporal data, as demonstrated by innovative frameworks like GNN-RNN, exemplifies the enhancement of predictive accuracy in areas such as crop yield forecasting.

In the realm of disaster management, GeoAI emerges as a critical tool, enabling efficient decision-making and bolstering preparedness and response strategies. This technology enriches the understanding of compound hazards, thereby strengthening urban and environmental resilience. However, the ethical and privacy implications in urban analytics necessitate careful consideration, ensuring that GeoAI applications are developed and deployed responsibly.

The survey highlights the transformative potential of GeoAI in democratizing access to urban big data, facilitating social service delivery and citizen engagement through advanced visualization and analysis platforms. The importance of interdisciplinary collaboration is emphasized, as the continuous evolution of GeoAI technologies demands diverse expertise to unlock their full potential. Sophisticated techniques, such as the visGP method, further illustrate GeoAI's pivotal role in enhancing spatial analysis and understanding land use dynamics.

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