A Survey of Geospatial Data Processing with Deep Learning and Large Language Models

Abstract

Geospatial data, integral to understanding Earth's surface, is enhanced by Geographic Information Systems (GIS) and remote sensing technologies. This survey explores the integration of deep learning and neural networks, including large language models (LLMs) and multimodal learning, in geospatial data processing. These advancements enable complex spatial-temporal modeling and spatial analysis, crucial for applications in AI for geosciences, environmental monitoring, and geospatial intelligence. The survey underscores the significance of raster and vector data formats, alongside natural language processing, in deriving insights and making predictions. It highlights the transformative impact of AI methodologies on geospatial analysis, enabling accurate and efficient data interpretation across various applications. The adaptability of models like Prithvi and GeoGPT exemplifies AI's potential to generalize effectively with minimal labeled data, broadening accessibility to geospatial technologies. Integration of S2 Geometry and REFeD frameworks demonstrates improvements in data processing efficiency and land cover mapping accuracy. The survey also emphasizes the potential of Geospatial Big Data (GBD) mining in urban planning and environmental monitoring, alongside challenges in data retrieval and privacy. Advancements in deep learning and LLMs are poised to revolutionize geospatial data processing, offering unprecedented opportunities for innovation and improvement in geosciences, ultimately shaping the future landscape of geospatial intelligence.

1 Introduction

1.1 Significance of Geospatial Data

Geospatial data is essential for understanding and managing the Earth's surface, serving as a critical resource across various disciplines. In urban planning, it enables the creation of high-resolution building footprint maps, crucial for urban development and disaster management, particularly in rapidly urbanizing areas like Sub-Saharan Africa, where it aids in mapping urban population growth and evaluating socio-economic impacts [1]. The availability of open geospatial data on buildings further supports urban sustainability [2].

In agriculture, geospatial data is vital for generating timely land use/land cover (LULC) maps, which are essential for effective agricultural management and environmental monitoring. The growing demand for improved agricultural yield, driven by population growth and food security concerns, underscores the importance of such data [3]. Additionally, in disaster management, geospatial data is crucial for monitoring flood hazards and enhancing infrastructure resilience, with satellite remote sensing playing a significant role. The integration of advanced deep learning models with Large Language Models (LLMs) represents a breakthrough in real-time flood detection and management, addressing current methodological limitations [4].

Geospatial data is also pivotal in environmental monitoring, disaster response, and climate change analysis, where timely and accurate information is critical [5]. In the real estate sector, it helps
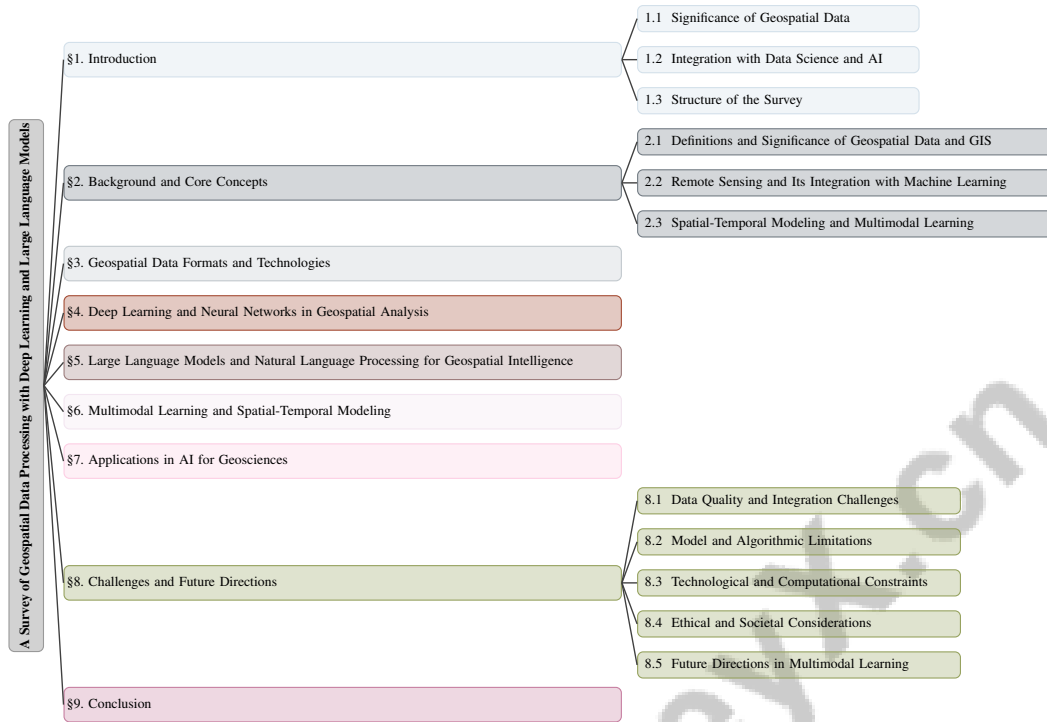
Figure 1: chapter structure

understand geospatial disparities in housing markets, as seen in cities like Paris [6]. Furthermore, it is integral to ecological modeling, particularly in predicting vegetation stratum occupancy from 3D LiDAR point clouds, which is crucial for land management [7].

In humanitarian aid, geospatial data addresses challenges such as landmine detection in post-conflict regions, where accurate data is vital for safety and demining operations [8]. The combination of geospatial data with advanced AI techniques is transforming Geospatial Big Data (GBD) mining, facilitating the extraction of valuable insights from extensive datasets [9]. The exponential growth of geospatial data presents challenges for traditional processing frameworks, necessitating the development of specialized tools for efficient analysis [10].

In ocean dynamics, geospatial data is used to reconstruct sea surface height (SSH) and sea surface temperature (SST) from satellite observations, enhancing the understanding of climate patterns [11]. The limitations of traditional census data, such as poor temporal resolution and the Modifiable Areal Unit Problem (MAUP), highlight the need for more accurate population estimation methods [12]. The increasing volume of geospatial data available on the linked open data cloud also necessitates effective question-answering systems capable of interpreting natural language queries [13].

The diverse applications and critical importance of geospatial data across various domains underscore its indispensable role in advancing scientific understanding and practical applications in geosciences and beyond. The exploration of opportunities and challenges in developing foundation models for geospatial artificial intelligence (GeoAI) addresses knowledge gaps in the application of large-scale pre-trained models in this domain [14]. Moreover, revisiting existing geospatial data handling methods to evaluate their capacity for managing emerging geospatial big data emphasizes the need for innovative approaches [15].

1.2 Integration with Data Science and AI

The integration of geospatial data with data science and AI represents a significant advancement in spatial analysis and decision-making frameworks. This development is exemplified by Geographic Information Systems (GIS) that incorporate data science methodologies to enhance spatial analysis [16]. The synergy between AI and GIS, particularly through Autonomous GIS, utilizes Large

Language Models (LLMs) to automate and improve the collection, analysis, and visualization of spatial data, streamlining workflows and enhancing accuracy [17].

Incorporating domain-adapted LLMs with Earth Observation (EO) systems significantly enhances data integration and analysis, enabling more comprehensive interpretations of geospatial phenomena [18]. The integration of AI into EO addresses global challenges such as environmental monitoring by improving the processing and analysis capabilities of EO data [5]. The interdisciplinary field of GeoAI, which encompasses AI tool development and spatiotemporal data computing, further highlights the transformative impact of AI on geospatial data science [19].

The incorporation of advanced AI techniques into Geospatial Big Data (GBD) mining processes illustrates the importance of merging geospatial data with AI for enhanced analysis [9]. This integration is crucial for addressing the unique characteristics of big data, as emphasized by Li, who advocates for new methodologies to effectively manage geospatial big data [15]. The adaptation of foundation models, which have seen success in language and vision tasks, to the inherently multimodal nature of geospatial tasks presents both opportunities and challenges [14].

Remote sensing techniques have revolutionized agricultural monitoring by providing high-resolution, temporally consistent data that improves population mapping and offers a comprehensive approach to soil analysis. The integration of social media data with remote sensing introduces a novel dimension to geospatial data processing, enhancing the analysis and contextual understanding of spatial events [20]. The EUPEG benchmark facilitates the comparison of various geoparsers, contributing to improved spatial-textual analysis [21].

Addressing the challenges posed by increasingly large and complex spatial datasets requires the adoption of advanced AI and data science methodologies, as noted by Hazra, to overcome computational and storage limitations. The framework proposed by Ning, which enables GIS agents to utilize natural language queries for retrieving and processing geospatial data, exemplifies AI's potential in automating and enhancing geospatial workflows [22]. Zhou's survey emphasizes the necessity for a comprehensive review of Vision-Language Geo-Foundation Models (VLGFMs), which leverage multimodal geospatial data for intelligent models capable of various geo-perceptive tasks [23]. The integration of deep learning with fields such as agriculture, natural language processing, and disaster management further illustrates the role of AI and data science in advancing geospatial data applications [24].

1.3 Structure of the Survey

This survey is organized to provide a thorough examination of the integration of deep learning and large language models in geospatial data processing. It begins with an introduction that emphasizes the significance of geospatial data and its applications, followed by an exploration of how these data integrate with data science and AI for enhanced analysis. The background and core concepts section elaborates on fundamental definitions and the importance of spatial-temporal modeling and multimodal learning in geosciences. Subsequently, the survey delves into geospatial data formats and technologies, discussing the various data formats and the technologies employed in data collection and processing.

The discussion then transitions to the integration of deep learning and neural networks in geospatial analysis, emphasizing advanced models and techniques such as convolutional neural networks (CNNs) for applications in environmental monitoring, urban planning, and disaster management. These methods leverage large-scale satellite imagery and geospatial data to automate land structure classification, enhance urban infrastructure understanding, and improve services like traffic monitoring and weather reporting. By employing state-of-the-art architectures, such as ResNet-50 and Inception-v3, researchers have achieved significant accuracy in identifying and categorizing terrain formations, showcasing deep learning's effectiveness in extracting valuable insights from complex geospatial datasets. Additionally, libraries like TorchGeo facilitate the application of deep learning techniques to remote sensing tasks, enabling more efficient processing and analysis of multispectral imagery [25, 26, 27, 28, 29]. The survey then examines large language models and natural language processing in geospatial intelligence, illustrating how these technologies enhance data interpretation and decision-making. It further discusses multimodal learning and spatial-temporal modeling, emphasizing the integration of multiple data modalities in geospatial applications.

In the applications section, the paper provides an overview of AI applications in geosciences, including environmental monitoring, disaster management, and urban planning, supported by case studies and real-world examples. The survey concludes by addressing challenges and future directions in geospatial data processing with AI technologies, identifying current limitations and potential research opportunities. This structured approach ensures a comprehensive understanding of the current landscape and future prospects of geospatial data processing with advanced AI methodologies.The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Definitions and Significance of Geospatial Data and GIS

Geospatial data refers to information associated with specific geographic locations, encompassing datasets like land use and road networks [30]. Defined by geo-entities—geographic entities with spatially varying contexts [31]—this data, when integrated with Geographic Information Systems (GIS), enhances the management, analysis, and visualization of spatial phenomena, thus improving decision-making across fields [32]. GIS is a crucial platform for collecting, managing, and analyzing geospatial data, facilitating improved urban scene understanding [32].

The importance of geospatial data and GIS is underscored in environmental monitoring and resource management, playing a vital role in mineral deposit estimations [30] and land cover classification, such as categorizing satellite images into vegetation and water classes [33]. However, the heterogeneous nature of geospatial data, including high-resolution imagery and diverse scale changes, complicates dataset aggregation, often leading to inconsistencies in format and quality [34].

The rapid expansion of geospatial data, driven by growing demands for processing power and storage, necessitates timely data analysis [35]. Inefficiencies in acquiring, processing, and visualizing large-scale geospatial data hinder rapid feature discovery essential for effective modeling [36], highlighting the need for advancements in geospatial technologies for diverse scientific and practical applications.

In remote sensing, the LHRS-Align dataset demonstrates the potential of combining diverse data sources, such as Google Earth imagery and volunteered geographic information (VGI) from OpenStreetMap, for enhanced geospatial analysis [37]. The use of hyperspectral data for effective land cover change detection from the PRISMA satellite further emphasizes the significance of high-dimensional data in geosciences [38].

The evolution of GIS technology, driven by advanced processing techniques like machine learning and natural language processing, addresses traditional inefficiencies by enabling diverse geospatial data handling and fostering intuitive interactions for non-professional users. Frameworks like GeoGPT enable autonomous geospatial data analysis through natural language instructions, while computational notebooks enhance reproducibility and integration with modern software, transforming GIS into a more agile platform for managing complex datasets across applications such as disaster management and spatial analysis of unstructured text [39, 40, 21, 16]. The challenge of efficiently processing and analyzing large geospatial data volumes using distributed computing frameworks underscores the need for innovative approaches.

2.2 Remote Sensing and Its Integration with Machine Learning

Remote sensing technologies are pivotal for acquiring and analyzing geospatial data, providing insights for applications like environmental monitoring, land use classification, and disaster management. Satellite programs such as Copernicus generate vast datasets offering comprehensive global coverage essential for modeling and analysis tasks. The integration of machine learning, particularly deep learning, has significantly enhanced remote sensing data processing, allowing sophisticated analyses addressing data volume and complexity, thus tackling challenges like climate change and urbanization [41, 42].

Convolutional Neural Networks (CNNs) have proven effective in managing remote sensing data complexities, improving applications like road network analysis and land cover classification. However, the scarcity of labeled training data remains a significant challenge limiting deep learning models' efficacy in this domain [43]. Innovative models and benchmarks, such as the Multi-dimension Feature Learning Model, integrate high-dimensional geospatial big data with remote sensing images, enhanc-

ing urban region function recognition [44]. The SATIN benchmark evaluates vision-language models' zero-shot transfer classification capabilities across remote sensing tasks, highlighting advanced models' potential in this field [45].

The integration of advanced image processing techniques with machine learning extends to seismic interpretation, automating the process and improving subsurface structure analysis accuracy [46]. Combining remote sensing data with other sources, such as census data through methods like PlaniSphere, enables effective land use and land cover classification and visualization [47]. However, remote sensing faces challenges in domain adaptation, particularly when classifying datasets from different sensors with varying characteristics [48].

Efficient deep neural networks (DNNs) have been developed for real-time semantic segmentation in remote sensing imagery, exemplifying DNNs' integration with remote sensing technologies [49]. Accurate forecasting of soil nitrogen content using multi-modal data from remote sensing images and machine learning methods illustrates these technologies' potential in environmental applications [50].

To efficiently process large Earth observation (EO) data volumes, quantum computing techniques have been explored, addressing classical algorithms' limitations in remote sensing applications [51]. The LHRS-Bench benchmark systematically evaluates multimodal large language models (MLLMs) capabilities in understanding remote sensing images, facilitating model comparisons [37]. Additionally, DeepSPACE, a deep learning-based approximate geospatial query processing engine, leverages autoregressive models to efficiently estimate geospatial data's conditional distributions [35].

The integration of remote sensing technologies with machine learning signifies a major evolution in geospatial data analysis, enhancing GIS capabilities to process vast and complex datasets, improving disaster management, accurate map updates via satellite imagery, and advanced insights through deep learning techniques for various geospatial tasks [27, 52, 16, 53]. This integration enhances data interpretation accuracy and efficiency while expanding remote sensing applications in addressing global environmental challenges. By leveraging comprehensive datasets and advanced analytical techniques, researchers can overcome traditional method limitations and unlock new possibilities in geospatial intelligence.

2.3 Spatial-Temporal Modeling and Multimodal Learning

Spatial-temporal modeling and multimodal learning are crucial in geospatial applications, addressing the challenges of capturing both spatial dependencies and temporal dynamics inherent in geospatial datasets. Traditional data mining methods often inadequately manage the complexities of spatio-temporal data, necessitating advanced modeling techniques that surpass basic feature engineering [54]. This inadequacy is particularly evident in applications like Satellite Image Time Series (SITS) classification, where the temporal dimension is crucial for monitoring dynamic phenomena such as vegetation changes [55].

Advanced frameworks employing Graph Neural Networks (GNNs) have been developed to enhance spatial-temporal modeling, improving scalability and generalization across large-scale datasets [56]. These models are vital for robust spatial-temporal predictions, addressing the need for frameworks capable of handling the vast and varied nature of geospatial data. Additionally, self-supervised learning (SSL) approaches have been proposed to overcome the limitations of task-specific labeled datasets, enhancing deep learning models' generalization capabilities in geospatial applications [57].

Multimodal learning enriches geospatial analysis by integrating diverse data modalities into a unified framework, facilitating comprehensive analyses of complex geospatial phenomena. This integration is exemplified by models leveraging both text and image data, enabling the extraction of low-level, mid-level, and high-level features through deep learning techniques [58]. The development of specialized benchmarks and models, particularly those focused on vision-language geospatial tasks, underscores the need for datasets capable of addressing spatial-temporal dynamics' unique challenges [23].

Generative models, particularly GANs, play a crucial role in addressing data scarcity by generating semantically rich synthetic images, thereby enhancing spatial-temporal modeling capabilities [43]. Moreover, applying tree-based machine learning algorithms to multi-sensor remote sensing data has been proposed to improve the accuracy of environmental predictions, such as soil nitrogen levels, demonstrating the potential of integrating diverse data sources for enhanced geospatial analysis [50].

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The importance of user-friendly tools for spatial analysis, which do not require extensive coding skills, is emphasized as a means to increase accessibility for non-experts, broadening the scope of spatial-temporal modeling applications [36]. These advancements in spatial-temporal modeling and multimodal learning are transforming geospatial analysis, enabling researchers to capture complex spatial patterns and improve decision-making across various applications. By leveraging sophisticated modeling techniques and integrating diverse data modalities, these methodologies enhance the understanding of geospatial phenomena and expand the potential for innovative solutions in geosciences.

3 Geospatial Data Formats and Technologies

Understanding geospatial data formats is fundamental for effective spatial representation and analysis. This section explores the two primary formats—raster and vector—highlighting their unique characteristics and applications. As illustrated in Figure 2, the hierarchical structure of geospatial data formats and technologies encompasses key categories such as geospatial data formats (raster and vector), remote sensing technologies (platforms, applications, and data integration), and data collection and processing frameworks (frameworks, technologies, and advancements). Each category is broken down into subcategories and details, demonstrating their unique characteristics and applications in urban planning, environmental monitoring, and geospatial data analysis. This examination sets the stage for a deeper discussion on geospatial data technologies in the subsequent subsection.
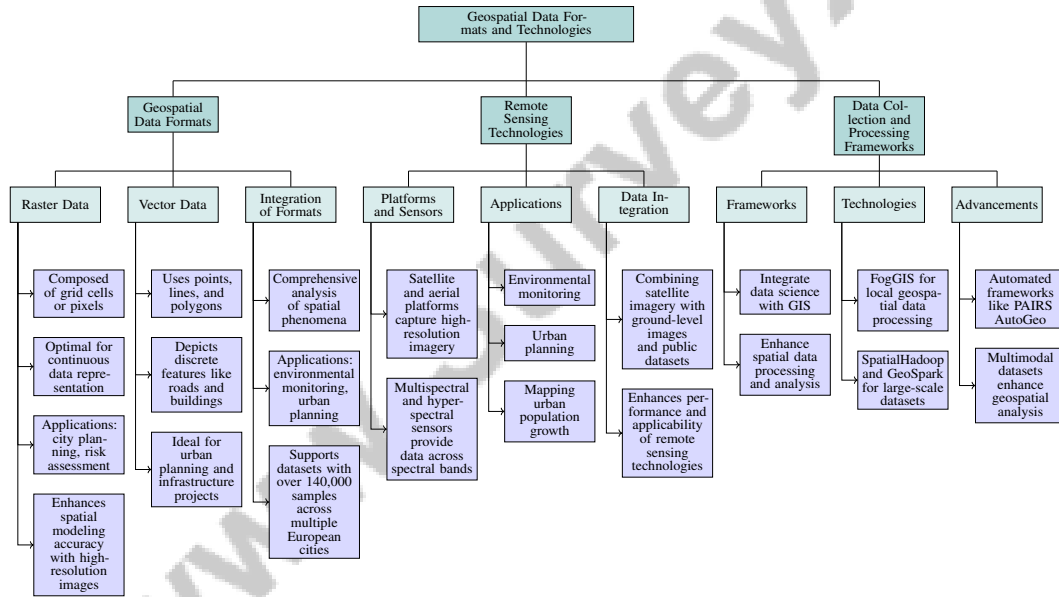

Figure 2: This figure illustrates the hierarchical structure of geospatial data formats and technologies, highlighting key categories such as geospatial data formats (raster and vector), remote sensing technologies (platforms, applications, and data integration), and data collection and processing frameworks (frameworks, technologies, and advancements). Each category is broken down into subcategories and details, demonstrating their unique characteristics and applications in urban planning, environmental monitoring, and geospatial data analysis.

3.1 Geospatial Data Formats

Geospatial data is chiefly represented in raster and vector formats, each serving specific analytical purposes. As illustrated in Figure 3, the hierarchical categorization of these formats highlights their distinct applications and underscores the importance of integrating both for comprehensive spatial analysis. Raster data, composed of grid cells or pixels, is optimal for continuous data representation, essential in applications like city planning and risk assessment [59]. High-resolution raster data, such as 1.2-meter spatial resolution satellite images, significantly enhances spatial modeling accuracy [60]. Conversely, vector data uses points, lines, and polygons to depict discrete features like roads and

buildings, ideal for urban planning and infrastructure projects [2]. Integrating both formats allows for a comprehensive analysis of spatial phenomena, as demonstrated by datasets with over 140,000 samples across multiple European cities, supporting applications from environmental monitoring to urban planning [26]. Advanced frameworks evaluating pre-training and downstream task alignment highlight the necessity of selecting appropriate data formats for complex geospatial challenges [61].

Geospatial Data Formats

Raster Data
- *Continuous data[59]*
- *High-resolution images[60]*
- *Spatial modeling accuracy[60]*

Vector Data
- *Discrete features[2]*
- *Urban planning[2]*
- *Infrastructure projects[2]*

Data Integration
- *Comprehensive analysis[26]*
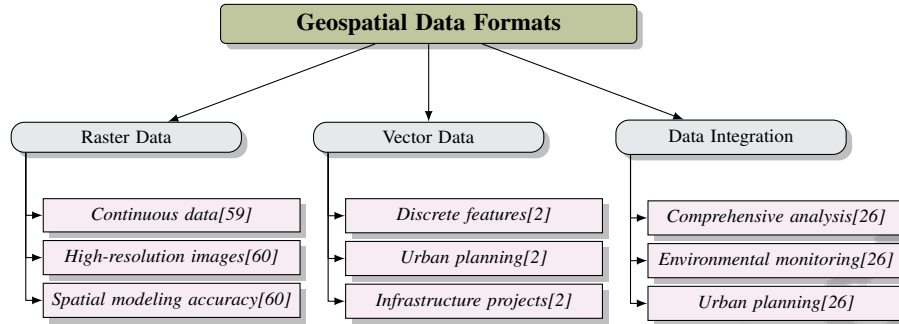- *Environmental monitoring[26]*
- *Urban planning[26]*

Figure 3: This figure illustrates the hierarchical categorization of geospatial data formats into raster and vector data, highlighting their specific applications and the importance of integrating both formats for comprehensive spatial analysis.

## 3.2 Remote Sensing Technologies

Remote sensing technologies are crucial for collecting and analyzing geospatial data, offering insights into environmental and urban phenomena. Utilizing satellite and aerial platforms, these technologies capture high-resolution imagery for applications ranging from environmental monitoring to urban planning. Multispectral and hyperspectral sensors on satellites like Sentinel and Landsat provide data across spectral bands, vital for detailed land cover classification [62]. Data from Planet Labs Inc., including over 100,000 Amazon basin satellite images, exemplify remote sensing's extensive use in environmental studies [63]. The integration of bi-temporal Sentinel-2 MSI data effectively maps urban population growth, showcasing remote sensing's capability to capture urban dynamics [1]. Curating datasets from sources like BigEarthNet and ForestNet ensures broad geographic and spectral representation, supporting diverse geospatial analyses [62]. The SATIN benchmark integrates data from 27 datasets, exemplifying a comprehensive approach to evaluating remote sensing technologies [45]. Multimodal datasets, combining satellite imagery with ground-level images and public datasets, enhance remote sensing technologies' performance and applicability [64]. These technologies remain vital for geospatial data collection, providing detailed insights essential for addressing complex environmental and urban challenges. Innovations in sensor technology and data integration, such as fusing social media with satellite imagery, promise to enhance remote sensing capabilities and applications [52, 16, 53, 20].

3.3 Data Collection and Processing Frameworks

Sophisticated frameworks are necessary for managing the complexities of geospatial data collection and processing. Integrating data science with GIS, these frameworks enhance spatial data processing and analysis, facilitating intelligent systems that derive insights from geospatial datasets [16]. FogGIS utilizes fog computing for local geospatial data processing, reducing latency and bandwidth usage [65]. SpatialHadoop and GeoSpark provide robust solutions for processing large-scale geospatial datasets, essential for managing data volumes generated by modern technologies [10]. Automated frameworks like PAIRS AutoGeo streamline geospatial AI applications by automating data collection and model training [34]. Categorizing Earth Observation datasets by attributes like volume and resolution aids in managing EO data systematically [66]. Multimodal datasets, such as GAMUS, exemplify enhanced geospatial analysis through diverse data types [67]. Advancing frameworks for geospatial data collection and processing is crucial for realizing geospatial technologies' full potential. These frameworks enable diverse data source integration, enhance user accessibility, and address geospatial big data challenges, improving decision-making and fostering innovation across sectors [68, 40, 16, 15, 20].

(a) A table with three columns and five rows[69]
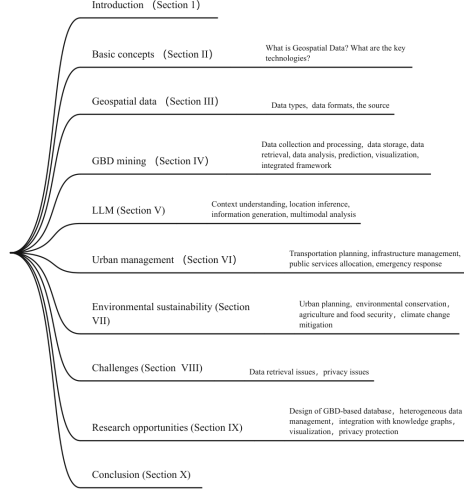
(b) Geospatial Data and Its Applications in Urban Management and Environmental Sustainability[9]

Figure 4: Examples of Data Collection and Processing Frameworks

As shown in Figure 4, understanding various formats, technologies, and frameworks for data collection and processing is crucial for effective applications in urban management and environmental sustainability. The figure illustrates examples highlighting these aspects: a structured dataset for analysis and a mind map outlining geospatial data applications. These examples provide foundational understanding of geospatial data's collection, processing, and application in real-world scenarios, emphasizing its significance in addressing contemporary challenges [69, 9].

4 Deep Learning and Neural Networks in Geospatial Analysis

Category	Feature	Method
Deep Learning and Neural Networks in Geospatial Context	Spatial Encoding and Optimization	DS[35]
	Data Generation and Enhancement	HNUCC[70]
Convolutional Neural Networks for Environmental Monitoring	Spatial Analysis	SPABERT[31], CycleGAN-HDA[48], LSTM-WQP[71], DL-HIA[72], SNFF[50]
Advanced Architectures for Spatial Analysis	Temporal and Spatial Analysis	CTU[73], TempCNN[55], DCVA[38]
	Robust Feature Modeling	EST[56], GFM4MPM[30]
	Quantum and Advanced Operations	Q4EO[51]
	Data Integration Strategies	AHRNR[74], GIS-SfM[75]

Table 1: This table provides a comprehensive overview of various deep learning methods and their applications in geospatial analysis. It categorizes the methods into three primary areas: Deep Learning and Neural Networks in Geospatial Context, Convolutional Neural Networks for Environmental Monitoring, and Advanced Architectures for Spatial Analysis. Each category highlights specific features and methods, demonstrating the diverse applications and innovations in geospatial data processing.

Deep learning, especially the use of neural networks, has significantly advanced geospatial analysis, enabling more accurate and efficient interpretation of spatial data. Table 1 presents a detailed classification of deep learning techniques employed in geospatial analysis, illustrating their roles in enhancing spatial data interpretation and environmental monitoring. Additionally, Table 2 offers a comparative overview of key deep learning methodologies applied in geospatial analysis, emphasizing their distinct features and contributions to the field. These computational techniques address challenges such as data incompleteness and high-dimensional analysis, facilitating improvements in applications like land cover classification and environmental monitoring.

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4.1 Deep Learning and Neural Networks in Geospatial Context

Deep learning is pivotal in geospatial analysis, enhancing methodologies for spatial data interpretation. The Hallucination Network for Urban Land Cover Classification (HNUCC) exemplifies this by using a hallucination network to handle missing data modalities during testing, ensuring effective utilization of training data [70]. In hyperspectral analysis, Deep Change Vector Analysis (DCVA) improves change detection, offering precise insights into environmental dynamics [38]. Convolutional Neural Networks (CNNs), such as the Quanv4EO model, enhance land cover classification accuracy by effectively processing multi-dimensional Earth Observation data [51]. Long Short-Term Memory (LSTM) networks also enhance temporal data analysis, as demonstrated in improved water quality predictions using Sentinel-2 data [71]. Frameworks like DeepSPACE illustrate deep learning's potential in efficient data exploration with minimal memory requirements, crucial for large-scale datasets [35]. These advancements enable innovative applications across environmental monitoring, urban planning, and geographic information systems, enhancing insights from diverse data sources [21, 76, 52].

4.2 Convolutional Neural Networks for Environmental Monitoring

CNNs have revolutionized environmental monitoring by offering advanced methodologies for analyzing complex geospatial datasets. They improve the precision and efficiency of land cover classification and urban land-use detection, automating the identification of intricate urban patterns [52, 26, 77]. Models like ResNet-50 and Inception-v3 achieve high accuracy in classifying geographical land structures [29, 78]. CNNs capture spatial context by forming pseudo sentences that include geo-entities and their neighbors, enhancing semantic segmentation [31]. This is crucial for understanding spatial dependencies, as shown in time-series models predicting Chl-a, SS, and turbidity [71].

As illustrated in Figure 5, the hierarchical structure of CNN applications in environmental monitoring highlights key areas such as geospatial data analysis, advanced architectures, and specific applications in water quality prediction, soil nitrogen forecasting, and environmental change detection. Advanced CNN architectures in hyperspectral image analysis focus on end-to-end classification and multimodal learning, enhancing environmental analysis [72]. Integrating CNNs with techniques like adversarial training ensures accuracy in environmental monitoring tasks [48]. Applications in soil nitrogen forecasting demonstrate CNNs' utility in agricultural management [50]. Overall, CNNs provide robust frameworks for geospatial data analysis, aiding in environmental change detection and informed decision-making [33].
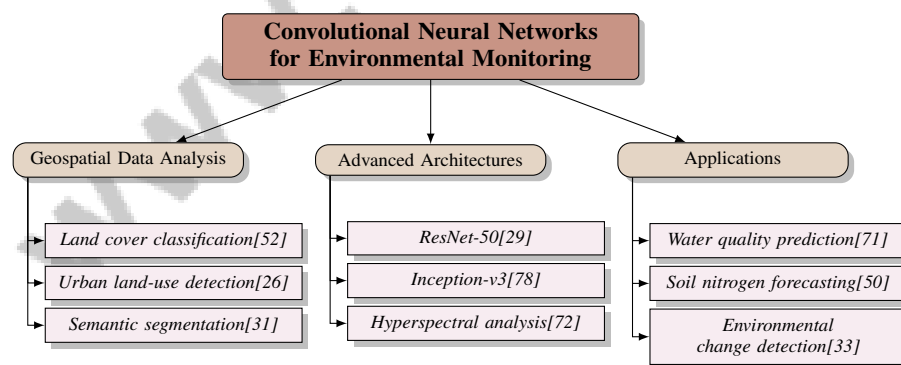

Figure 5: This figure illustrates the hierarchical structure of Convolutional Neural Networks (CNNs) applications in environmental monitoring, highlighting key areas such as geospatial data analysis, advanced architectures, and specific applications in water quality prediction, soil nitrogen forecasting, and environmental change detection.

4.3 Advanced Architectures for Spatial Analysis

Advanced neural network architectures have significantly improved spatial data analysis by addressing geospatial dataset complexities. Temporal convolutional neural networks (TempCNNs) enhance temporal data analysis accuracy by classifying time series data [55]. The GFM4MPM method uses

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a masked image modeling framework to enhance prediction robustness in geospatial analysis [30]. Multi-scale feature generation and band adaptation techniques are crucial for effective geospatial analysis [79]. Automated large-scale reconstruction methods integrate vector-raster data, enhancing scalability [74]. Aligning GIS maps with Structure from Motion (SfM) data improves visual task accuracy [75]. The EasyST framework enhances knowledge transfer robustness using spatio-temporal information bottlenecks [56]. Quantum-inspired operations in CNN architecture, like the Quanv4EO model, improve efficiency [51]. Combining ConvLSTM, Time-LSTM, and U-Net enhances geospatial analysis accuracy [73]. Deep learning methods for hyperspectral data change detection outperform traditional methods [38]. These architectures enhance geospatial analysis accuracy, scalability, and applicability, fostering collaboration in humanitarian assistance and disaster response (HADR) [80, 28].

As illustrated in Figure 6, this figure categorizes advanced architectures for spatial analysis into three main areas: temporal analysis, geospatial prediction, and data integration. Each category highlights key methods that enhance geospatial data processing and analysis, thereby transforming the landscape of geospatial studies. The deep learning and neural networks depicted in the figure exemplify these advancements. The Urban Environments Classification demonstrates neural networks' effectiveness in classifying urban areas, which is crucial for urban planning and management. In contrast, the Multi-Task Multi-Modal Model for Zero-Shot Learning showcases a sophisticated approach to addressing diverse geospatial challenges without requiring extensive labeled data. Together, these examples underscore the transformative impact of neural network architectures in extracting meaningful insights from spatial data [26, 80].
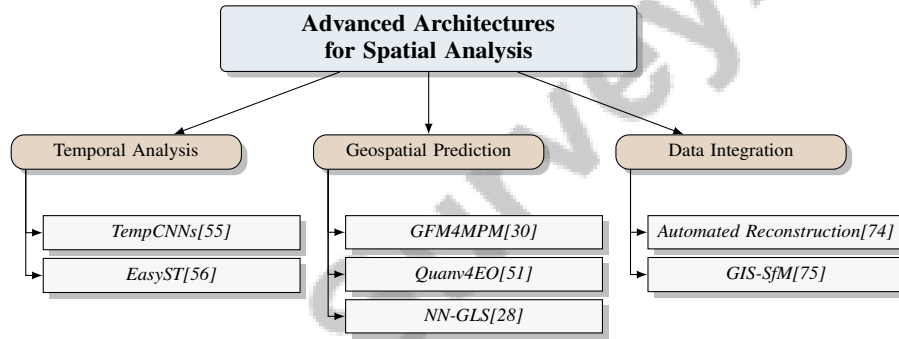

Figure 6: This figure illustrates the advanced architectures for spatial analysis, categorizing them into temporal analysis, geospatial prediction, and data integration. Each category highlights key methods that enhance geospatial data processing and analysis.

Feature	Hallucination Network for Urban Land Cover Classification (HNUCC)	Deep Change Vector Analysis (DCVA)	Convolutional Neural Networks (CNNs)
Data Handling	Missing Data Modalities	Hyperspectral Data	Multi-dimensional Data
Application Focus	Urban Land Cover	Environmental Dynamics	Land Cover Classification
Model Enhancement	Hallucination Network	Change Detection	Semantic Segmentation

Table 2: This table provides a comparative analysis of three prominent deep learning methods utilized in geospatial analysis: the Hallucination Network for Urban Land Cover Classification (HNUCC), Deep Change Vector Analysis (DCVA), and Convolutional Neural Networks (CNNs). It highlights their capabilities in data handling, application focus, and model enhancement, underscoring their roles in addressing challenges such as data incompleteness and high-dimensional analysis in geospatial contexts.

5 Large Language Models and Natural Language Processing for Geospatial Intelligence

The integration of Large Language Models (LLMs) with Natural Language Processing (NLP) is transforming geospatial intelligence by enhancing data interpretation and decision-making capabilities. As the complexity of geospatial data increases, there is an intensified demand for sophisticated analytical tools. This section explores how LLMs are reshaping geospatial intelligence, enabling the extraction of meaningful insights from spatial datasets and facilitating intuitive interactions with complex data.

5.1 Large Language Models and Geospatial Intelligence

LLMs are crucial in merging NLP with complex geospatial data analysis, enhancing data interpretation by generating contextually relevant captions and improving the accessibility of spatial relationships [81]. Tools like ChatMap exemplify the simplification of data interaction, making geospatial information more accessible to non-experts [82]. The GeoLLM-Engine demonstrates LLMs' capabilities in performing complex geospatial tasks, surpassing traditional benchmarks and advancing geospatial analysis sophistication [83]. Benchmarks such as RSGPT-4V further reinforce this by providing frameworks for diverse remote sensing tasks, enhancing model generalization and reasoning [84].

Integrating LLMs into geospatial data analysis propels representation learning, as highlighted in surveys on self-supervised learning in geospatial AI [85]. This integration facilitates nuanced insights, informing decision-making processes and optimizing trajectory management and mining tasks [86]. Geode exemplifies LLMs' potential to respond promptly to complex geospatial queries through natural language processing [87], while ChatGPT integration in flood detection frameworks enhances user interaction via natural language queries [4].

The development of scalable benchmarks for multimodal datasets, inspired by LLM capabilities, underscores their role in generating comprehensive geospatial datasets from public data [88]. These advancements highlight LLMs' significant contribution to geospatial intelligence, enabling efficient data processing, enhanced feature selection, and improved model generalization [89].

5.2 Enhancing Data Interpretation through NLP

NLP enhances geospatial data interpretation by enabling intuitive interactions with complex datasets. By facilitating natural language queries, NLP streamlines data analysis and decision-making, addressing challenges posed by the volume and complexity of geospatial data [87]. Systems like GeoLLM-Engine demonstrate NLP's application in executing complex geospatial tasks, overcoming traditional limitations and improving accessibility for non-experts [83]. ChatMap further illustrates how NLP simplifies data interaction, broadening the user base and enhancing data accessibility [82].

NLP techniques enhance semantic understanding by generating detailed, contextually relevant captions for satellite imagery, as demonstrated by Geode, leading to accurate responses to complex queries [81]. Furthermore, integrating NLP with geospatial data fosters the development of scalable benchmarks for multimodal datasets, essential for training and evaluating advanced geospatial models [88].

The incorporation of NLP into geospatial analysis marks a significant advancement, enabling the extraction of structured geographic information from unstructured texts, such as social media posts and historical archives, using tools like geoparsers. This capability enhances interpretability and efficiency, promoting broader applications of geospatial intelligence. Platforms like EUPEG streamline the benchmarking of geoparsers, while frameworks like GeoGPT empower non-professionals to engage with complex geospatial tasks through natural language instructions [40, 21, 76, 68]. Leveraging NLP techniques enables more effective processing and understanding of geospatial data, leading to enriched insights and informed decision-making across various domains.

5.3 Decision-Making and Semantic Understanding

NLP is vital for enhancing decision-making and semantic understanding in geosciences by facilitating the interpretation of complex geospatial data. By transforming raw geospatial data into actionable insights, NLP improves decision-making across various applications. Integrating NLP with geospatial intelligence allows for translating complex data into comprehensible formats, critical for informed decisions in environmental monitoring, urban planning, and disaster management [83].

NLP enhances semantic understanding by extracting meaningful patterns from large datasets. Systems like Geode exemplify this capability, providing accurate responses to geospatial queries and facilitating informed decision-making [87]. Employing NLP leads to more precise geospatial data interpretation, allowing for a nuanced understanding of spatial phenomena and their implications.

Moreover, integrating NLP with geospatial data fosters the creation of intelligent systems capable of executing complex tasks through natural language queries. This integration streamlines data

analysis and enhances semantic understanding, enabling users to derive critical insights for effective decision-making [83]. The generation of detailed captions for satellite images, as seen in Geode, underscores the significance of semantic understanding in geospatial intelligence, providing users with deeper comprehension of spatial data and its importance [81].

The integration of NLP into geospatial data analysis signifies a substantial advancement, enhancing decision-making and semantic understanding in geosciences. By utilizing advanced NLP techniques, geospatial data can be processed and interpreted with greater accuracy and depth, leading to richer insights and informed decision-making across various fields, including geographic information systems (GIS), thematic mapping, and cognitive geographic concepts. Furthermore, integrating NLP with geospatial semantics enhances interoperability among distributed systems and facilitates the development of intelligent user interfaces, enabling effective communication of complex spatial information [76, 68].

6 Multimodal Learning and Spatial-Temporal Modeling

6.1 Integration of Multimodal Data

Integrating multimodal data in geospatial applications enhances spatial analysis accuracy and efficiency by leveraging diverse sources such as satellite imagery, textual data, and sensor readings. This comprehensive approach is exemplified by Fodor et al., who combine satellite data to improve deforestation and fire detection accuracy, highlighting multimodal learning's role in environmental monitoring [90]. In urban planning, deep learning and GIS synergy is crucial for effective slum mapping, demonstrating multimodal data's transformative potential [91]. The GeoBind framework exemplifies reasoning across multiple modalities, eliminating the need for separate models for each data type [92]. Geode further showcases the integration of various geospatial data types, enhancing spatial information interpretation [87].

Attention mechanisms improve multimodal data processing by enhancing image feature evaluation quality, as demonstrated by Sun et al. [93]. The OmniSat framework consolidates information from multiple Earth Observation modalities, outperforming methods reliant on late fusion or single modalities [94]. In remote sensing, integrating multispectral data with Graph Neural Networks (GNNs) is supported by benchmarks like ViGeo, enhancing geospatial applications [33]. The LocateEarth benchmark offers a comprehensive dataset and robust model for remote sensing object detection, illustrating the significance of integrating diverse data modalities [95].

Incorporating national census data into the Land Use/Land Cover classification process enhances accuracy and reduces reliance on limited field sampling, as shown by Miu et al. [47]. This integration exemplifies the potential of combining structured and unstructured data to improve geospatial analysis precision.

As illustrated in Figure 7, the integration of multimodal data in geospatial applications highlights key applications, data processing techniques, and the benefits of such integration, including enhanced accuracy and interoperability. This integration represents a significant advancement, enabling comprehensive analyses of complex spatial phenomena. By harnessing various data modalities, geospatial applications enhance performance and yield deeper insights into Earth's surface dynamics. This integration bolsters GIS accuracy and reliability, facilitates semantic interoperability among distributed systems, and paves the way for more intelligent user interfaces. Additionally, advancements in NLP and the influx of big geo data, particularly unstructured text from the web, create opportunities for understanding geographic entities and their cognitive representations, enriching thematic maps and geospatial visualizations [76, 68].

6.2 Temporal and Spatial-Temporal Modeling

Temporal and spatial-temporal modeling are crucial for analyzing geospatial data, capturing dynamic patterns and relationships over time and space. These models are vital for applications like urban development, environmental monitoring, and disaster management, where understanding temporal changes is essential. Advanced modeling techniques, particularly those based on convolutional neural networks (CNNs), significantly improve the ability to learn complex hierarchical features directly from raw data, bridging the semantic gap between low-level image features and high-level urban characteristics [60].
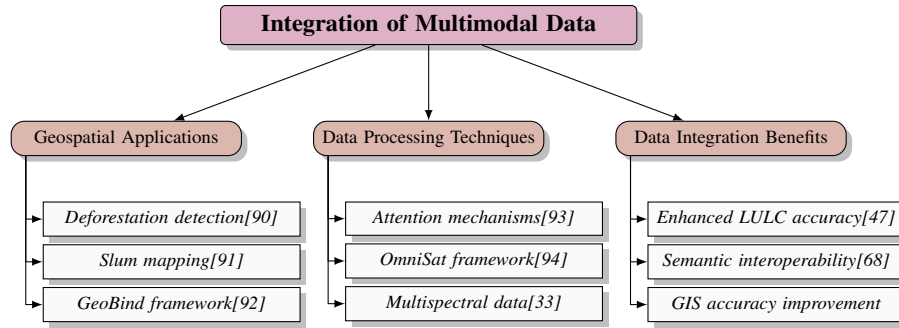
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Figure 7: This figure illustrates the integration of multimodal data in geospatial applications, highlighting key geospatial applications, data processing techniques, and the benefits of data integration, including enhanced accuracy and interoperability.

Frameworks for spatial-temporal modeling often incorporate qualitative spatial representation and reasoning, supported by axioms and principles, facilitating sophisticated analyses of spatiotemporal dynamics [96]. Integrating these principles into geospatial models enhances their capacity to capture and interpret complex spatial-temporal relationships. Machine learning techniques, such as the RESFlow model, boost spatial-temporal modeling efficiency by partitioning data into homogeneous groups, reducing computational complexity, and enhancing processing efficiency [97]. Efficient processing of large volumes of spatial-temporal data is essential for real-time applications and informed decision-making.

Future research should emphasize integrating additional data modalities and developing advanced encoders, like space-time encoders, to enhance existing models' capabilities [98]. By exploiting relationships between different data modalities during training, models can achieve greater robustness against missing data, improving performance across diverse geospatial applications [70]. Advancements in temporal and spatial-temporal modeling techniques are transforming geospatial analysis. Employing sophisticated modeling techniques and synthesizing a wide array of data sources enable researchers to effectively identify and analyze dynamic spatial patterns, enhancing decision-making processes across fields like urban planning—where AI assesses urban green spaces through public opinion analysis—and environmental monitoring, benefiting from improved predictive accuracy by recognizing spatial dependence in geographic and non-geographic contexts [99, 16, 77].

7 Applications in AI for Geosciences

The integration of artificial intelligence (AI) with geosciences has revolutionized various domains, including environmental monitoring, disaster management, urban planning, and agriculture. This section delves into these applications, highlighting AI's transformative role in understanding and managing environmental changes.

7.1 Applications in Environmental Monitoring

AI has redefined environmental monitoring by enhancing analytical capabilities for complex datasets. The synergy between AI and geospatial technologies significantly improves environmental change monitoring, offering superior accuracy and efficiency over traditional methods. Deep learning models, especially convolutional neural networks (CNNs), are adept at processing extensive remote sensing data, enabling the detection of subtle environmental changes critical for effective management [5]. CNNs excel in tasks like land cover classification and urban land-use detection, extracting relevant features from high-resolution satellite images [70]. Their ability to capture spatial context is crucial for understanding environmental dynamics, as demonstrated in deforestation and fire detection through multimodal satellite data integration [90].

AI also improves water quality prediction, leveraging time-series models and Sentinel-2 data to enhance accuracy [71]. In agriculture, AI models combining CNNs and CatBoost forecast soil nitrogen content with high precision, highlighting AI's potential in resource optimization [50]. The integration of AI with remote sensing has enabled real-time monitoring frameworks like Deep Change

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Vector Analysis for enhanced change detection in hyperspectral data [38]. These advancements underscore AI's transformative impact on environmental monitoring, facilitating informed decision-making and effective natural resource management. The field of Geospatial Artificial Intelligence (GeoAI) merges AI with geospatial data, supporting applications in disaster management and climate change analysis. Responsible AI deployment is crucial for ethical practices, data security, and bias mitigation, fostering a comprehensive understanding of environmental dynamics [19, 100, 77, 5].

7.2 Disaster Management

AI technologies are critical in disaster management, enhancing Geographic Information Systems (GIS) and data science frameworks. The integration of AI with geospatial data facilitates sophisticated models for predicting, monitoring, and responding to natural disasters, thus refining disaster management strategies. A case study in Tróia, Portugal, highlights AI technologies' practical benefits in disaster management [16]. AI-driven models, especially deep learning-based ones, are vital for real-time disaster-related event monitoring and prediction. These models analyze vast geospatial data, including satellite imagery and sensor readings, to detect early warning signs of disasters like floods and earthquakes. Advanced machine learning algorithms identify intricate patterns in diverse datasets, including social media content, enabling timely alerts that empower proactive measures to mitigate disaster impacts [101, 8, 102, 103, 77].

AI also enhances resource allocation during disaster response by analyzing geospatial data to identify the most affected areas, prioritize resource distribution, and optimize evacuation routes, significantly reducing casualties and facilitating rapid humanitarian aid deployment [101, 104, 105, 106, 8]. Moreover, AI improves post-disaster assessments by processing high-resolution satellite images to evaluate damage extent, supporting recovery efforts with detailed maps and reports. This information is vital for planning reconstruction activities and optimizing resource allocation [74, 76, 8, 104]. AI in disaster management provides robust tools for predicting, monitoring, and responding to natural disasters, offering cost-effective alternatives to traditional GIS methods and enabling real-time situational awareness and informed decision-making [101, 102, 8].

7.3 Urban Planning and Management

AI has significantly advanced urban planning and management by providing innovative tools that enhance city management efficiency and effectiveness. The integration of AI with geospatial technologies allows urban planners to analyze complex datasets, predict urban growth patterns, and develop sustainable management strategies. AI techniques, particularly deep learning models, facilitate the extraction of meaningful insights from large urban data volumes, supporting informed decision-making in urban planning [70]. AI applications in urban planning include models that integrate diverse data sources, such as satellite imagery, census data, and sensor readings, to capture a comprehensive view of urban dynamics. This multimodal approach enables accurate urban environment modeling, allowing planners to assess land use patterns, monitor infrastructure development, and evaluate urbanization impacts on the environment. By leveraging AI, urban planners can identify optimal locations for developments, optimize transportation networks, and enhance public service delivery, contributing to sustainable and resilient urban environments [47].

AI technologies also address urbanization challenges like traffic congestion, pollution, and resource management. By analyzing real-time data from various sources, AI systems can predict traffic flow, optimize public transportation routes, and reduce emissions, improving air quality and minimizing carbon footprints [2]. Integrating AI with Geographic Information Systems (GIS) enhances urban planning capabilities through advanced spatial analysis and visualization tools. AI-powered GIS platforms enable planners to simulate urban scenarios, evaluate potential impacts of planning decisions, and engage stakeholders in the planning process, facilitating collaborative planning that aligns urban development with community needs [16]. AI's role in urban planning and management is transformative, offering robust solutions to urbanization challenges and supporting the development of sustainable, livable cities. By leveraging advanced AI technologies, urban planners can create comprehensive, data-driven strategies that stimulate economic growth while enhancing environmental sustainability and social well-being. This approach allows for the analysis of citizens' opinions on urban green spaces through natural language processing and assessment of urban land use patterns using satellite imagery and deep learning, significantly enhancing urban life and promoting equitable resource access in rapidly urbanizing environments [102, 17, 77, 26].

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7.4 Agricultural Applications

AI plays a transformative role in agriculture, enhancing practices and productivity through advanced data analysis techniques and remote sensing technologies. The integration of AI with geospatial data enables sophisticated agricultural monitoring systems for timely and accurate land use/land cover (LULC) mapping, utilizing satellite-based remote sensing data from missions like Sentinel-1 and Sentinel-2 [107]. AI applications in agriculture include using CNNs to analyze high-resolution satellite imagery for accurate crop type classification and health assessment. This approach enhances land classification efficiency and supports sustainable practices by enabling precise monitoring of soil moisture and crop conditions. Advanced deep learning techniques have improved classification accuracy, even for smaller, resource-efficient networks, providing farmers with actionable insights that contribute to increased crop yields and effective resource management [108, 26, 109, 29, 3].

AI technologies facilitate real-time monitoring of environmental conditions, such as soil moisture and nutrient levels, critical for effective agricultural management. By integrating sensor data with AI models, farmers gain actionable insights into soil health and can implement precision agriculture techniques that optimize resource use and minimize environmental impact. This approach enhances crop productivity through advanced techniques like satellite imagery analysis and machine learning while fostering sustainable practices by reducing irrigation reliance and minimizing crop loss risks due to extreme weather conditions [64, 110, 77, 3, 20]. AI also encompasses advanced forecasting and risk assessment, where machine learning algorithms leverage historical data, satellite imagery, and sensor inputs to predict future agricultural trends and identify potential challenges. This integration aims to enhance water efficiency, reduce irrigation reliance, and increase crop yields, thereby minimizing crop loss risks due to drought and extreme weather. By utilizing multimodal data sources—including satellite data, ground truth, and climate records—AI-driven farm management systems evolve into real-time platforms offering actionable insights and decision support, contributing to sustainable agricultural practices and the United Nations' Sustainable Development Goal of Zero Hunger [64, 77, 3]. The integration of AI with geospatial technologies in agriculture offers robust solutions for enhancing agricultural practices and productivity. By leveraging AI's advanced capabilities alongside Earth observation technologies, the agricultural sector can significantly improve efficiency, sustainability, and resilience. This integration facilitates precise monitoring of land use and crop health through satellite imagery and remote sensing data while aiding informed decision-making to address the global challenge of feeding an ever-growing population. AI-driven analyses optimize resource allocation and improve agricultural practices, contributing to more sustainable food systems worldwide [66, 64, 110, 77, 5].

8 Challenges and Future Directions

8.1 Data Quality and Integration Challenges

Geospatial analysis faces significant challenges due to data quality and integration issues, particularly stemming from the heterogeneity of datasets and the complexity of synthesizing diverse sources. The scarcity of rich, annotated datasets limits method generalizability, especially in hyperspectral image analysis [111, 72]. The integration of environmental variables and satellite data can introduce inaccuracies, adversely affecting soil nitrogen estimation [50] and water quality predictions [71]. A lack of reliable ground truth data complicates the validation of change detection methods [38].

High computational demands and latency are also major hurdles for real-time applications, necessitating algorithms tailored for resource-constrained devices [49]. The resource-intensive nature of geospatial data presents barriers to clustering technique implementation, limiting scalability [36]. Programming complexity in large-scale geospatial processing, such as SIMD intrinsic functions, deters developers and requires significant redesigns [112]. Maintaining precision in high selectivity queries demands substantial sample size increases [35].

Scalability diminishes with increasing missing modalities, leading to exponential growth in model complexity [70]. Improved optimization targets are needed for predicting extreme temperature values [73]. Addressing these challenges requires innovative solutions to enhance data accessibility and develop robust AI models for efficiently processing large-scale geospatial data. This includes tackling non-standardized approaches, inadequate platforms, and fostering multidisciplinary collaboration. Advancements like integrating large language models in tools such as GeoGPT show promise in

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reducing barriers for non-professionals managing complex geospatial tasks, while research into geospatial big data emphasizes the importance of advanced AI techniques for meaningful insights and addressing data retrieval and security challenges [19, 40, 9].

8.2   Model and Algorithmic Limitations

Current models and algorithms in geospatial data processing face several limitations that hinder their applicability and efficiency. A significant challenge is the dependency on accurately labeled data for supervised learning, which is often scarce and costly, affecting tasks like building segmentation [113]. Models such as XGeoML encounter computational efficiency issues, particularly with large datasets or real-time analyses [114].

Frameworks integrating deep learning models, as discussed by Cresson, require critical parameter provision and fail to account for internal memory consumption, crucial for large-scale datasets [115]. Prototypes like GeoSPARQL+ experience performance overheads, deterring extensive application adoption compared to systems like POSTGIS [59].

ViT-based architectures struggle with high-resolution data and long-range dependencies, leading to information loss and reduced accuracy [116]. Sensitivity to hyperparameter choices and initialization methods can significantly affect model robustness [117]. Some explainable AI methods provide interpretability but may not yield high-resolution outputs and incur substantial computational costs [118]. The DSTL approach faces increased computational time and complexity with larger dictionaries [119].

Localized convolutional neural networks require increased computational resources due to the complexity of learning local features, extending training times [120]. Methods like CycleGAN may struggle with extreme domain divergence cases [48]. Quantum-inspired models like Quanv4EO face challenges with large quantum circuits needed for Earth Observation image processing [51].

Addressing these limitations requires developing more efficient algorithms and models capable of navigating geospatial data challenges. This involves integrating diverse multimodal data sources and optimizing computational resources for enhanced processing efficiency and scalability. Platforms like EUPEG facilitate benchmarking and comparative analysis, streamlining deployment and leading to more effective data processing and insightful geospatial analyses [93, 76, 21].

8.3   Technological and Computational Constraints

Geospatial data processing faces significant technological and computational constraints impacting analytical method efficacy and scalability. High computational demand for training sophisticated models, especially those using generic self-supervised learning techniques, necessitates substantial resources, hindering scalability and efficiency [57]. Automation of segmentation processes, as in tools like EcoMapper, yields competitive results but involves substantial computational overhead, creating resource allocation and processing speed challenges [121].

Satellite data limitations in measuring soil moisture, particularly in dense vegetation, snow cover, or extreme dryness environments, exemplify technological constraints, leading to inaccuracies [122]. Automated large-scale reconstruction of past landscapes faces challenges in distinguishing linear features like roads, highlighting the need for improved feature differentiation techniques [74].

Overcoming these technological and computational limitations requires innovative advancements in hardware and software solutions, enhancing processing capabilities for managing geospatial big data's volume, variety, and velocity. This dual approach integrates modern computational tools, such as computational notebooks and high-performance computing platforms, improving workflow efficiency and facilitating advanced algorithm application in geospatial tasks. Intelligent interfaces and frameworks like GeoGPT democratize geospatial analysis access, allowing non-professionals to engage with complex operations through natural language instructions [68, 39, 40, 123, 15]. This includes optimizing algorithms for efficiency, developing more accurate sensing technologies, and improving data processing framework scalability to accommodate growing geospatial data volume and complexity.

8.4 Ethical and Societal Considerations

AI integration in geospatial data processing raises significant ethical and societal challenges. A primary concern is AI model bias, leading to skewed interpretations and decisions, especially in predominantly English-speaking regions, necessitating more inclusive AI systems [31]. Data privacy is another critical concern, particularly with increasing social media data incorporation in geospatial applications. Geoinformation harvesting from social media raises user consent and data veracity questions, underscoring robust privacy protections and ethical guidelines' necessity.

Addressing geo-privacy and bias mitigation challenges ensures AI deployment in geospatial contexts does not disproportionately affect vulnerable communities. This involves developing standardized AI tool creation approaches, fostering interdisciplinary collaboration among geoscientists, computer scientists, and engineers, and integrating ethical considerations into AI applications. Such efforts enhance AI's effectiveness in understanding complex human-environment interactions, contributing to equitable resource access and responsible technological advancements [19, 102, 27].

The ethical implications of generating synthetic satellite imagery are noteworthy, as these technologies could be exploited for misinformation or malicious purposes, necessitating detection methods to counteract potential misuse [124]. The lack of standardized methodologies in GeoAI research complicates the ethical landscape, hampering uniform concern addressing across applications [100].

Automated GIS data cleaning and processing techniques raise ethical questions regarding transparency and accountability. As these techniques become more prevalent, exploring their implications on data integrity and reliability is crucial [16]. Developing trustworthy AI systems prioritizing ethical considerations ensures AI benefits in geospatial data processing are realized without compromising societal values.

8.5 Future Directions in Multimodal Learning

The future of multimodal learning in geospatial applications promises significant advancements, particularly in optimizing real-time data processing and enhancing model capabilities across diverse environments. Developing robust algorithms for real-time processing is essential for managing geospatial big data's dynamic and voluminous nature [36]. Enhancing real-time processing capabilities, especially in frameworks like FloodLense, can improve prediction accuracy by incorporating additional environmental factors [4].

Expanding datasets and improving model capabilities in diverse urban environments are critical, including exploring more complex geospatial data interactions to enhance models like ChatMap [32]. Integrating Synthetic Aperture Radar (SAR) interferometry with self-supervised learning techniques can enhance model performance and adaptability, particularly in rapid response scenarios like landslide detection [125].

Future research should focus on developing integrated models addressing multiple security threats and enhancing federated learning for data privacy in geoscience applications [103]. This approach ensures geospatial data processing remains secure and privacy-preserving as data complexity and analytical tasks increase.

Incorporating additional frameworks and more diverse datasets can enhance benchmarks like Spatial-Hadoop and GeoSpark, facilitating comprehensive geospatial data processing capability evaluations [10]. Improving data quality control mechanisms and expanding frameworks like PAIRS AutoGeo for complex geospatial analyses will enhance model accuracy and applicability [34].

Refining deep learning models for remote sensing image retrieval and exploring emerging trends in feature representation and similarity metrics are crucial for advancing geospatial analysis [58]. Expanding self-supervised learning frameworks to other geoscience tasks and refining geological process modeling methods will further enhance geospatial model capabilities [30].

Future research will focus on improving alignment and instructional dataset quality and refining training strategies to enhance Multimodal Large Language Models' (MLLMs) capabilities in remote sensing image interpretation [37]. Integrating quantum classifiers post-quanvolution layers and exploring quanvolution filter training can also enhance performance [51].

Developing new geostatistical generalization error estimators and improving spatial coordinate treatment in learning models will address current gaps and enhance geospatial analysis precision

[126]. Future research will extend methods to handle multiple missing modalities efficiently and explore transfer learning to enhance model performance [70]. Pursuing these innovative pathways, future research in multimodal learning for geospatial applications can significantly enhance model adaptability, efficiency, and robustness, advancing geosciences and the broader field of geospatial intelligence.

9   Conclusion

The survey reveals the transformative influence of deep learning and large language models (LLMs) on geospatial data processing, highlighting their potential to revolutionize geosciences. The adoption of advanced AI methodologies has markedly enhanced geospatial analysis capabilities, facilitating more accurate and efficient data interpretation across diverse applications. For instance, models like Prithvi showcase their adaptability and effectiveness across various resolutions and regions, illustrating AI's capacity to generalize with minimal labeled data [127]. Furthermore, the implementation of GeoGPT for processing geospatial tasks via natural language input significantly lowers entry barriers for non-experts, thereby expanding the accessibility and applicability of geospatial analysis [40].

The incorporation of S2 Geometry into Geo Knowledge Graphs (GeoKGs) has led to substantial enhancements in data processing efficiency and query performance, paving the way for scalable management of large-scale geospatial data [128]. Similarly, the REFeD framework improves land cover mapping accuracy by integrating historical and recent data, underscoring the value of temporal data in geospatial applications [110]. In urban planning, convolutional networks applied to satellite imagery analysis have significantly advanced methodologies and understanding of urban environments globally [26].

The potential of Geospatial Big Data (GBD) mining to reshape urban planning and environmental monitoring is evident, alongside the necessity to tackle challenges related to data retrieval and privacy [9]. The Desk-AId system enhances humanitarian mine action efforts by refining landmine risk assessment through geospatial data and advanced machine learning techniques [8]. Additionally, the narrative-centered framework proposed by Bhatt et al. augments GIS's capability to analyze and interpret dynamic geospatial phenomena, reinforcing the significance of narrative approaches in geospatial analysis [96].

Moreover, the integration of OpenStreetMap data markedly enhances the accuracy of semantic labeling in remote sensing applications, achieving a 2.5

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