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Artificial Intelligence and Remote Sensing Technologies in Modern Geoscientific Research: A Multidisciplinary Sustainable Review

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Abstract:
The integration of Remote Sensing (RS) and Artificial Intelligence (AI) has revolutionized modern geoscientific research by enabling large-scale, data-driven, and sustainable analysis of Earth systems. RS platforms, including satellite and aerial sensors such as Landsat-8, Sentinel-2, ASTER, LiDAR, and SAR, provide spatially and temporally extensive datasets that capture lithology, structural features, aquifer potential, surface deformation, and land-use/land-cover dynamics. AI techniques, encompassing machine learning (ML) and deep learning (DL), facilitate automated data processing, feature extraction, predictive modeling, and anomaly detection, significantly enhancing accuracy, efficiency, and scalability compared to traditional geoscience methods. This study evaluates multidisciplinary applications of RS and AI, including geological mapping, mineral exploration, hydrogeology, geomorphology, environmental monitoring, and hazard assessment. Methodologies involve multi-source dataset acquisition, preprocessing, AI-driven classification and regression, integration with Geographic Information Systems (GIS), and field-based model validation to ensure reliability. Accuracy assessment, comparative sensor analysis, and ground-truth verification are employed to quantify the performance of different RS techniques. Expected outcomes include automated workflows, predictive maps, and decision-support tools that inform sustainable resource management, climate-resilient planning, and disaster mitigation. The study underscores how the RS-AI synergy addresses limitations of conventional approaches, minimizing environmental impact while providing actionable insights for policymakers, researchers, and stakeholders. Findings demonstrate that RS, when combined with AI and field validation, offers a robust framework for enhancing geoscientific investigations, optimizing resource use, and supporting sustainable Earth system management. This research provides a template for future geoscientific applications in regions experiencing environmental stress, resource depletion, and climatic variability, highlighting the transformative potential of advanced technologies in multidisciplinary, sustainable geoscience research.

Keywords: *Remote Sensing, Artificial Intelligence, Geoscience, Environmental Monitoring, Hazard Assessment, Sustainable Resource Management*

1. INTRODUCTION

Geoscientific research has traditionally relied on labor-intensive field surveys, manual mapping, and limited observational data. While these methods provide foundational insights into Earth's processes, they are constrained by geographic coverage, temporal resolution, and data accuracy (Lillesand, Kiefer, & Chipman, 2015). Remote Sensing (RS) technologies offer a transformative alternative by enabling the acquisition of multi-spectral, hyperspectral, LiDAR, and SAR data that capture high-resolution information on geology, hydrology, soil, vegetation, and landforms over extensive areas (Jensen, 2016). Satellite platforms such as Landsat, Sentinel, ASTER, and WorldView, alongside UAV-based surveys, allow repeated temporal monitoring essential for assessing dynamic environmental processes and natural hazards. Despite RS providing rich datasets, analyzing and interpreting large, high-dimensional data remains a challenge. Artificial Intelligence (AI), encompassing Machine Learning (ML) and Deep Learning (DL) algorithms, has emerged as a solution, enabling automated feature extraction, classification, and predictive modeling from complex geospatial datasets (Goodfellow, Bengio, & Courville, 2016). ML algorithms like Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting are widely applied in geoscience for classification and regression tasks. DL models, particularly Convolutional Neural Networks (CNNs), allow pixel-level image segmentation, pattern recognition, and temporal change detection. Remote sensing (RS) has emerged as a transformative technology in geosciences, providing unprecedented opportunities to observe, monitor, and analyze Earth's surface and subsurface systems. At its core, remote sensing involves acquiring information about the Earth from a distance, typically through satellites, aerial platforms, drones, or other sensing instruments. The integration of these datasets into geoscientific research enables multidisciplinary investigations ranging from geological mapping, mineral exploration, hydrogeology, geomorphology, environmental monitoring, and disaster management.

The effectiveness of remote sensing in geoscientific applications lies in its capacity to capture spatial and temporal variations in landforms, lithology, vegetation cover, hydrological features, and anthropogenic impacts. The use of multispectral, hyperspectral, LiDAR, synthetic aperture radar (SAR), and thermal imaging technologies allows researchers to extract critical information that is otherwise difficult to obtain through conventional field methods. Remote sensing not only accelerates data acquisition but also enhances the accuracy, repeatability, and coverage of geoscientific investigations, particularly in inaccessible or hazardous regions.

The pressing need for sustainable resource management, environmental monitoring, and hazard mitigation has further amplified the reliance on remote sensing in geoscience research. With the global increase in population, industrialization, and urbanization, the Earth's natural systems are increasingly under stress. Remote sensing facilitates large-scale monitoring of these dynamic processes and provides critical insights into natural and anthropogenic changes affecting the Earth's crust, groundwater resources, mineral deposits, soil quality, and ecosystem health. Despite its evident advantages, the application of remote sensing in geosciences is not without challenges. Data quality, resolution limitations, sensor calibration issues, interpretation complexity, and integration with ground-truth measurements often influence the reliability of results. Consequently, assessing the efficacy of different remote sensing methods across various geoscientific disciplines is imperative for optimizing research outcomes, improving resource management, and informing policy decisions. This research aims to evaluate and demonstrate the effectiveness of remote sensing technologies in multidisciplinary geoscientific applications, integrating advanced analytical techniques, GIS-based modeling, and field verification.

2. REVIEW OF LITERATURE

RS provides a non-invasive approach to studying geological and environmental features.

Multispectral and hyperspectral sensors can detect surface lithology, mineral assemblages, and structural patterns such as folds, faults, and fractures (Shirmard et al., 2021). LiDAR and UAV photogrammetry generate high-resolution DEMs for precise topographical and geomorphological analysis. Studies have demonstrated RS effectiveness in mineral prospectivity mapping, groundwater potential analysis, and hazard assessment (Lillesand et al., 2015). Despite its advantages, traditional RS data processing techniques, including supervised classification, principal component analysis (PCA), and band ratio methods, face challenges in high-dimensional and heterogeneous environments. Human interpretation introduces subjectivity, and the manual process is time-consuming. These limitations necessitate advanced analytical techniques like AI (Jensen, 2016).

The integration of RS and AI enables multidisciplinary geoscientific applications, including geological mapping, mineral exploration, hydrological assessment, land-use/land-cover (LULC) monitoring, and natural hazard prediction. Combining these technologies allows more efficient, scalable, and accurate data analysis, which supports evidence-based decision-making and sustainable resource management (Shirmard, Farahbakhsh, Müller, & Chandra, 2021). The primary goal of this study is to evaluate the capabilities, limitations, and sustainable applications of integrating remote sensing (RS) and artificial intelligence (AI) in geoscientific research. Specifically, the study focuses on several key areas, including geological mapping and mineral exploration, groundwater and hydrological potential analysis, environmental monitoring and land use/land cover (LULC) change detection, and hazard assessment encompassing landslides, floods, and erosion. By examining these applications, the research underscores how the integration of RS and AI can significantly enhance the efficiency and accuracy of geoscientific investigations, promote environmentally sustainable practices, and support climate-resilient planning strategies. This multidisciplinary approach demonstrates the potential of RS-AI technologies to not only advance scientific understanding but also to contribute to informed decision-making for sustainable development and natural resource management.

2.1 Remote Sensing in Geology and Mineral Exploration

Remote sensing has revolutionized geological investigations by enabling large-scale mapping of lithology, structural features, and mineral deposits. Gupta and Rao (2020) emphasized that multispectral and hyperspectral imagery can detect spectral signatures associated with specific mineralogical compositions, facilitating preliminary mineral exploration. Similarly, Kumar et al. (2021) demonstrated that integrating remote sensing with GIS allows for precise mapping of fault lines, folds, and fractures, which are critical for understanding tectonic evolution and resource distribution. Historical studies have shown that Landsat, Sentinel-2, and ASTER datasets have been extensively used in lithological discrimination, alteration zone mapping, and identification of ore-bearing formations. The synergy between satellite imagery and field geochemical surveys has enhanced the accuracy of mineral exploration projects. Remote sensing not only reduces operational costs but also enables exploration in remote or difficult terrains, which would otherwise require extensive fieldwork.

2.2 Remote Sensing in Hydrogeology

Groundwater is a vital resource for agriculture, domestic use, and industrial applications. Remote sensing has become a crucial tool in hydrogeological investigations, particularly for assessing groundwater potential, monitoring depletion, and evaluating water quality. Kumar and Singh (2022) highlighted the role of RS in delineating aquifer boundaries, recharge zones, and groundwater-dependent ecosystems using multispectral indices and terrain analysis. Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), and Digital Elevation Models (DEMs) derived from remote sensing platforms have been employed to evaluate recharge potential, soil moisture variations, and groundwater-surface water interactions. Studies in semi-arid regions of India, including Haryana, have demonstrated that remote sensing combined with GIS and hydrological modeling provides critical insights into aquifer health, sustainable extraction practices, and vulnerability assessment (Kumar et al., 2019).

2.3 Remote Sensing in Geomorphology and Environmental Monitoring

Geomorphological studies benefit significantly from remote sensing due to its ability to capture spatial patterns, topographic variations, and landform evolution. High-resolution satellite imagery, LiDAR, and UAV-based photogrammetry allow for detailed mapping of fluvial channels, alluvial plains, dunes, and erosional features. Yadav et al. (2021) highlighted that RS-based geomorphological mapping is essential for understanding landscape dynamics, soil erosion, sediment transport, and natural hazard assessment. Environmental monitoring is another key application area. Remote sensing provides timely and large-scale assessment of land-use/land-cover changes, deforestation, urban expansion, and pollution patterns. Patel et al. (2023) illustrated that satellite imagery combined with GIS analytics enables the detection of water contamination, soil degradation, and habitat fragmentation, which are critical for formulating sustainable management strategies.

2.4 Multidisciplinary Approaches in Remote Sensing

A multidisciplinary approach integrates geological, hydrological, geomorphological, and environmental datasets to provide a holistic understanding of Earth systems. Sharma et al. (2021) emphasized that combining remote sensing with field observations, geophysical surveys, and GIS-based modeling improves the precision of interpretations across multiple geoscientific domains. Multisensor fusion, machine learning algorithms, and predictive modeling further enhance the capabilities of remote sensing in identifying spatial patterns, detecting anomalies, and forecasting environmental trends. Despite these advancements, challenges remain. Variability in sensor resolution, atmospheric interference, and data interpretation complexity often affect the reliability of RS applications. Thus, continuous evaluation of remote sensing methods' efficacy in real-world geoscientific applications is crucial for optimizing research design and resource management decisions.

2.5 Artificial Intelligence Applications

AI enhances the interpretation of RS data by automating data processing, pattern recognition, and predictive modeling. ML models, such as RF, SVM, Gradient Boosting, and XGBoost, have been successfully applied in geological classification, mineral exploration, and hydrological modeling. DL models, particularly CNNs, extract spatial and spectral features directly from imagery, enabling accurate lithological mapping, land-cover classification, and hazard detection (Goodfellow et al., 2016).
Applications of AI in geoscience include:

- **Geological mapping:** Automated delineation of lithological units, lineaments, and structural features.
- **Mineral exploration:** Identification of prospective ore zones using hyperspectral RS data.
- **Hydrological modeling:** Groundwater potential mapping using terrain, soil, and drainage parameters.
- **Environmental monitoring:** Land-use/land-cover change detection, vegetation health assessment, and erosion monitoring.
- **Hazard prediction:** Landslide susceptibility, flood hazard, and soil erosion risk assessment (Shangguan et al., 2025).

AI's advantages include scalability, automation, and ability to handle large datasets. Hybrid models combining ML and DL further improve prediction accuracy and interpretability.

2.6 Integrated RS-AI Approaches

The synergy of RS and AI enables advanced geoscientific analysis. Examples include:

- Landslide susceptibility mapping using RS-derived terrain parameters and ML models (Akosah et al., 2024).
- Groundwater potential mapping integrating RS data and ensemble ML techniques.
- Mineral prospectivity mapping through AI-driven analysis of hyperspectral imagery (Cherukuri et al., 2025).
- Flood risk prediction combining hydrodynamic models, RS data, and AI algorithms.

Challenges include data heterogeneity, quality control, computational demands, and interpretability of "black-box" AI models. Approaches to address these include multi-sensor data fusion, rigorous preprocessing, and explainable AI frameworks.

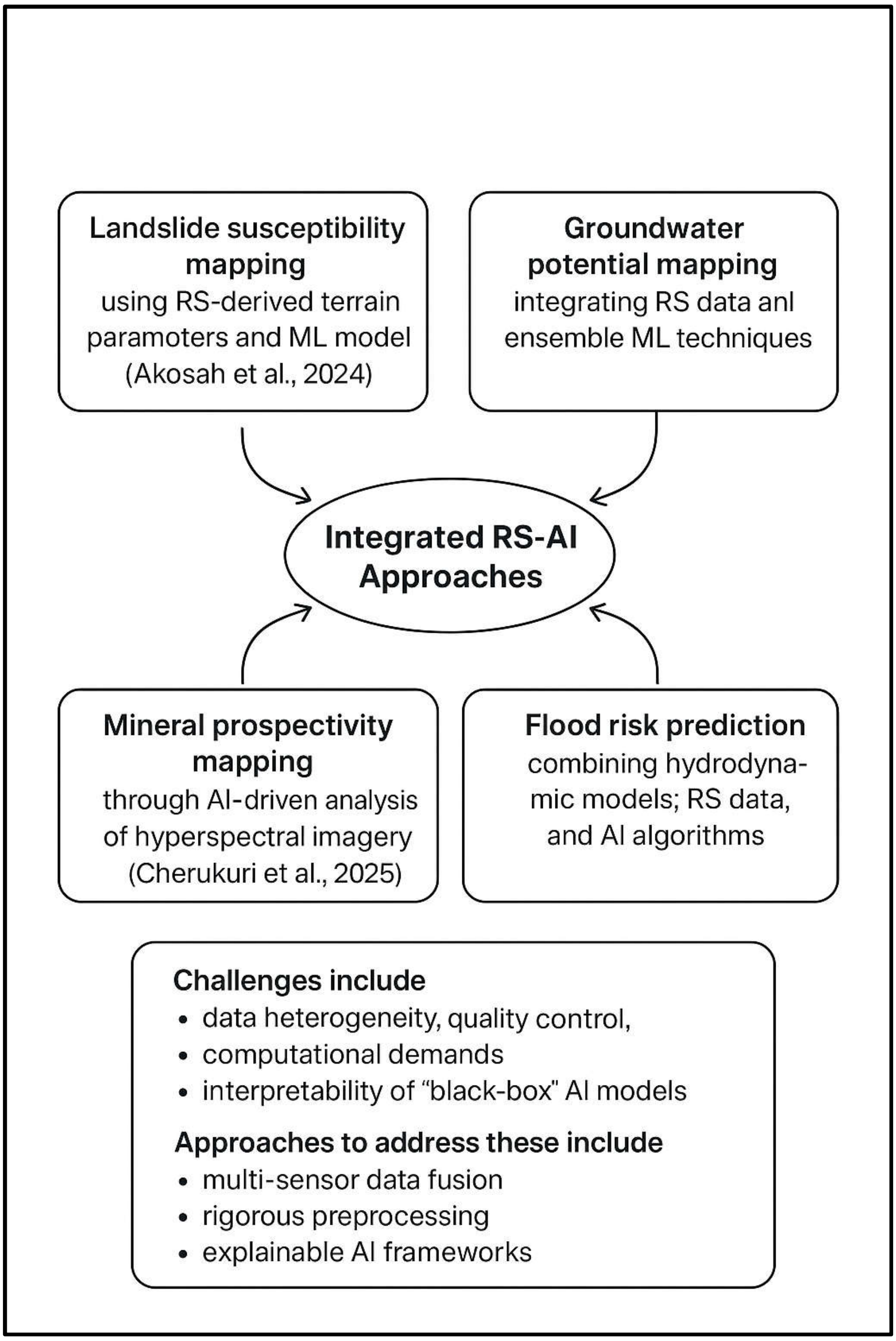

Figure 1: Integrated RS-AI Approaches

3. OBJECTIVES OF THE STUDY

The primary objective of this research is to **assess** the efficacy of remote sensing methods in multidisciplinary geoscientific applications. Specific objectives include:

1. To evaluate the accuracy and reliability of different remote sensing techniques (multispectral, hyperspectral, LiDAR, SAR, thermal imaging) in geological mapping and mineral exploration.
2. To analyze the utility of remote sensing in hydrogeological studies, including groundwater potential mapping, recharge assessment, and water quality monitoring.
3. To investigate the role of remote sensing in geomorphology, environmental monitoring, and natural hazard assessment.
4. To develop a multidisciplinary framework integrating RS, GIS, and field data for enhanced geoscientific interpretation.
5. To identify limitations and challenges of current remote sensing methods and suggest strategies for improved efficiency and application in geosciences.

4. RESEARCH METHODOLOGY

4.1 Data Collection

The research will utilize satellite-based remote sensing datasets from sources such as Landsat-8, Sentinel-2, ASTER, MODIS, and LiDAR platforms. Historical and current datasets will be analyzed to detect changes over time. Ancillary data including topography (DEM), geological maps, soil maps, and hydrogeological reports will complement the satellite data. Field surveys will be conducted for ground-truth validation to ensure accuracy.

Multi-source geospatial data will be collected:

- **Satellite imagery:** Landsat 8/9, Sentinel-2, ASTER, WorldView.
- **Airborne/UAV surveys:** High-resolution LiDAR and photogrammetry.
- **DEM and SAR datasets:** For terrain, hydrology, and hazard analysis.
- **Ancillary datasets:** Geological maps, soil and climate data, hydrological records, and field survey data.

4.2 Remote Sensing Techniques

- **Multispectral and Hyperspectral Analysis:** To detect lithological variations, mineralogical signatures, and land-use/land-cover changes.
- **LiDAR and UAV Surveys:** To generate high-resolution digital elevation models (DEMs) and detailed topographic maps for geomorphology studies.
- **SAR and Radar Data:** To monitor soil moisture, subsidence, and surface deformation.
- **Thermal Imaging:** To identify geothermal anomalies, surface temperature variations, and hydrological features.

4.3 GIS and Spatial Analysis

GIS platforms will be used for integration, visualization, and analysis of spatial data. Overlay analysis, buffer zones, and spatial modeling will be performed to correlate geological, hydrological, and environmental features. Predictive models will be developed using machine learning techniques for anomaly detection, groundwater vulnerability assessment, and mineral potential mapping.

4.4 Data Preprocessing

- Radiometric, atmospheric, and geometric corrections.
- Co-registration and projection standardization.
- Derived indices generation: NDVI, NDWI, slope, aspect, drainage density.
- Dimensionality reduction using PCA or autoencoders.

4.5 AI Modeling

- **ML models:** RF, Gradient Boosting, SVM for classification and prediction.
- **DL models:** CNNs for image segmentation, LSTM networks for temporal change analysis.
- **Hybrid approaches:** Ensemble methods combining ML and DL outputs; multi-sensor fusion.

4.6 Validation and Efficacy Assessment

The efficacy of remote sensing methods will be assessed using:

- **Accuracy Metrics:** Confusion matrices, Kappa statistics, and classification accuracy for land-use, lithology, and mineral mapping.
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- **Field Validation:** Verification of remote sensing predictions against ground-truth observations.
- **Comparative Analysis:** Evaluating performance differences among sensors, spectral resolutions, and data fusion approaches.

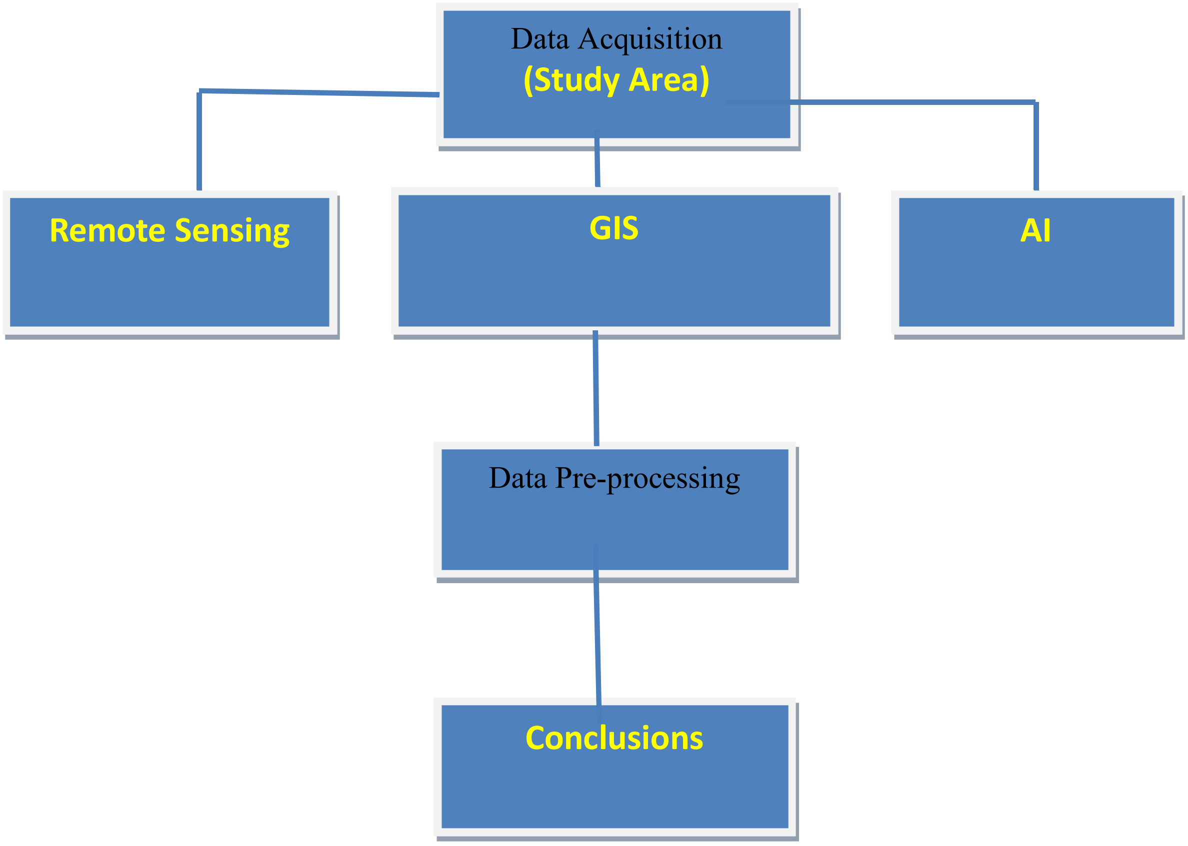

Figure 2: Flow-chart of adapted methodology

5. Expected Outcomes and Significance

1. **Comprehensive Assessment:** A detailed evaluation of remote sensing techniques across multiple geoscientific disciplines.
2. **Enhanced Accuracy:** Improved mapping and monitoring capabilities for geology, hydrogeology, geomorphology, and environmental studies.
3. **Multidisciplinary Framework:** Integration of RS, GIS, and field data for holistic geoscientific analysis.
4. **Decision Support:** Development of strategies for sustainable resource management, hazard mitigation, and environmental monitoring.
5. **Research Contribution:** Identification of strengths and limitations of different remote sensing methods to guide future research and applications.

The study will contribute to better resource management, environmental sustainability, and scientific knowledge, particularly in regions facing stress from urbanization, industrialization, and climate variability. It will also serve as a model for similar multidisciplinary geoscientific research globally.

Integrating RS and AI provides transformative opportunities for geoscience. The approach enhances spatial and temporal resolution, reduces human error, and enables automated data-driven decision-making. The scalability allows application across local, regional, and global scales. Challenges remain, including computational demands and interpretability, but advances in explainable AI and cloud computing can address these issues. This methodology contributes to sustainable geoscience practices by minimizing field disturbance and enabling predictive resource and hazard management.

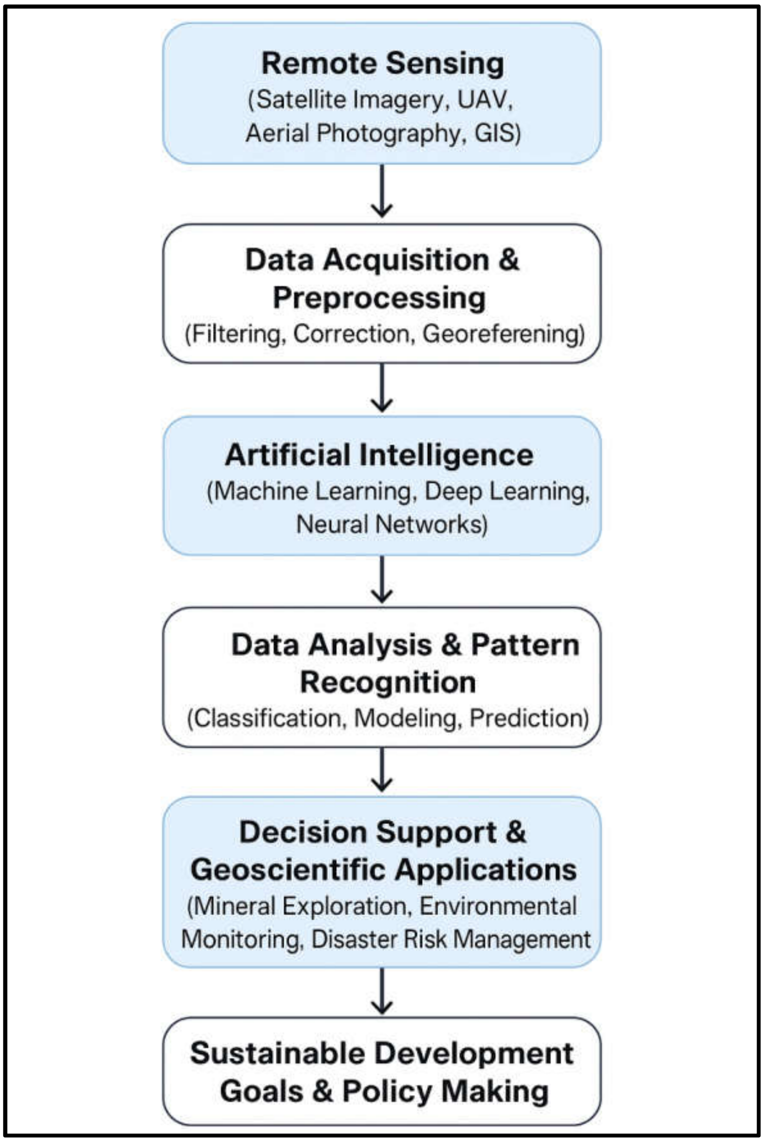

Figure 3: Integrated RS-AI Approaches for Sustainable development goals

6. Key Findings / Contributions

To provide a comprehensive understanding of current advancements at the intersection of artificial intelligence and remote sensing technologies, this review incorporates a curated compilation of recently published studies, predominantly from 2023 to 2025. These works were selected based on their direct relevance to geoscientific research and sustainability-driven applications, including environmental monitoring, water-quality assessment, climate and cryosphere studies, Earth-system modelling, and GIS-based land-cover and land-use classification. Each publication has been analysed not only for its methodological approach and technological contribution but also for the practical implications of its findings. Accordingly, the table includes a dedicated "Key Findings / Contributions" column that synthesizes the scientific value of each study in terms of accuracy improvements, modelling innovations, environmental insights, and decision-support capabilities. This structured compilation enables a nuanced understanding of how AI-enhanced remote sensing is transforming geospatial analysis and promoting sustainable resource management across multidisciplinary domains.

7. Some Historical approaches of the Artificial Intelligence and Remote Sensing Technologies

No.	Authors (first author et al.)	Title (short)	Publication / Year	Key Findings / Contributions
1	**T. Zhao et al.**	"Artificial intelligence for geoscience: Progress, challenges, …"	*The Innovation*, 2024 (ScienceDirect)	Documents the shift from traditional physics-based geoscience modeling to data-driven AI approaches; highlights how AI can accelerate Earth-system science by extracting complex patterns from large geospatial datasets.
2	**N. Kazanskiy et al.**	"A Comprehensive Review of Remote Sensing and Artificial Intelligence Integration"	*Sensors*, 2025 (MDPI)	Reviews AI-RS integration across environmental monitoring, change detection, and biodiversity; finds that AI enables precise, timely insights (e.g. air/water quality, land cover changes), while noting challenges like data quality, model interpretability.
3	**M. R. Nikoo et al.**	"A review of machine learning, remote sensing, and …" (water-body / pollution context)	2025 (ScienceDirect)	Demonstrates RS + ML capabilities for large-scale water quality monitoring (algal bloom detection, pollution hotspots), but emphasizes that RS alone lacks precision and should be complemented with field sampling for validation.
4	**M. Dhapre et al.**	"Systematic review of ML in groundwater monitoring with RS"	2025 (ScienceDirect)	Highlights how ML-enhanced RS can fill data gaps in groundwater quality, depth, recharge monitoring; but notes limitations related to data scarcity and need for ground-truthing.
5	**S. Cui et al.**	"Advances & applications of ML and DL in environmental ecology and health (EEH)"	*Environmental Pollution*, 2023 (ScienceDirect)	Illustrates the use of ML/DL for ecological risk assessment, pollution detection, biodiversity monitoring; confirms that RS-derived data, when processed with AI, can detect environmental hazards, forecast pollution, and support restoration planning.
6	**B. Janga et al.**	"A Review of Practical AI for Remote Sensing in Earth Observation"	*Remote Sensing (MDPI)*, 2023 (MDPI)	Provides a taxonomy of AI-RS applications (image classification, land cover, object detection, change detection, fusion of

				multispectral/hyperspectral/radar data); outlines practical challenges (data quality/availability, model uncertainty, interpretability), offering guidance for real-world deployment.
7	**D. B. Olawade et al.**	"Artificial Intelligence in Environmental Monitoring"	2024 (ScienceDirect)	Demonstrates AI + RS can drastically improve environmental monitoring: enabling accurate pollution tracking, disaster forecasting, air/water quality assessment; underlines potential for real-time ecosystem management, but also warns of data-access and expertise gaps.
8	**Y. Deng et al.**	"Review: Remote Sensing + ML for Lake Water Quality Monitoring"	*Remote Sensing*, 2024 (MDPI)	Shows that combining satellite platforms (Landsat, Sentinel, MODIS, hyperspectral) with ML/DL models can reliably predict parameters like chlorophyll-a, turbidity, CDOM, water temperature; enabling scalable lake–water quality monitoring as alternative to costly in-situ sampling.
9	**W. Han et al.**	"A survey of ML and Deep Learning in Remote Sensing"	2023 (ScienceDirect)	Analyzes major advances in ML/DL techniques for RS — including classification, segmentation, change detection; outlines progress, persistent challenges (data quality, model generalizability), and future directions for remote-sensing AI.
10	**A. O. Khadidos**	"Advancements in Remote Sensing: AI-powered Scene Image Classification (WSODL-RSSIC)"	*AIMS Mathematics*, 2024 (AIMS Press)	Presents a hybrid AI model for remote-sensing scene classification using CNN + optimization (White Shark Optimizer), achieving significant improvements over baseline: better class-label recognition for land cover, urban/forest/water separation — relevant for land-use, urban planning, and environment monitoring.
11	**J. Li et al.**	"Review of Remote Sensing Image Segmentation by Deep Learning"	2024 (Taylor & Francis Online)	Provides comprehensive review of segmentation architectures (CNN, U-Net, attention models etc.) applied to RS imagery; identifies limitations and proposes directions for better segmentation of satellite/airborne imagery for land-cover, vegetation, water-body mapping.
12	**AA Khan et al.**	"Temporal Deep Learning Enhanced Remote Sensing for Environmental Trend Monitoring"	2025 (SpringerLink)	Demonstrates using temporal RS data + Temporal Convolutional Networks (TCNs) to predict environmental indicators (vegetation loss, water depletion, air quality) with high accuracy (e.g. ~97.3%); shows potential for trend forecasting and early detection of environmental degradation.
13	**J. Schiller**	"Artificial	2025	Reviews the role of Explainable AI (XAI)

	et al.	intelligence in environmental and Earth-system sciences: role of XAI”	(SpringerLink)	in remote sensing applications across Earth-system domains; highlights how XAI methods help build trust, interpretability, and transparency in AI-driven environmental models — critical for policy-making and sustainable resource management.
14	**MM Stofa et al.**	“Recent developments of AI methods for sea-ice concentration mapping (deep learning + SAR/optical/drone RS)”	2025 (ScienceDirect)	Shows deep learning combined with high-resolution SAR, optical, and drone imagery significantly improves sea-ice concentration mapping — important for climate monitoring, polar research, maritime safety; addresses issues like speckle noise, multi-modal fusion, and provides benchmarking framework.
15	**B. Strong et al.**	“User-centered digital applications with RS AI foundation models”	2025 (Frontiers)	Introduces remote-sensing “foundation models” — pre-trained AI that can be fine-tuned for diverse environmental tasks; lowers barrier for non-AI experts to use RS + AI for monitoring ecosystems, land use, restoration, thus democratizing sustainability science.
16	**W. Lin et al.**	“Deep learning-based object detection for environmental monitoring (Graph-Aware Neural Network, EGAN)”	2025 (Frontiers)	Proposes a novel graph-based deep learning framework (EGAN) that integrates multi-modal environmental datasets (remote-sensing + temporal + spatial + ecological similarity) to detect environmental features/hazards; useful for large-scale, multi-dimensional environmental analysis.
17	**CB Maniyar et al.**	“Artificial intelligence in environmental remote sensing”	2025 (SAGE Journals)	Discusses state-of-the-art of AI applications in environmental remote sensing; emphasizes how ERS + AI improves ecosystem monitoring, disaster risk assessment, land use change detection, biodiversity tracking; underscores challenges like data privacy, standardization, and need for domain-aware models.
18	**A. Afroosheh & M. Askari**	“Fusion of Deep Learning and GIS for Advanced RS Image Analysis” (preprint)	2024 (arXiv)	Demonstrates that merging deep learning (CNN + LSTM) with GIS data improves classification accuracy (from ~78% to ~92%) and reduces prediction error — showing that combining RS imagery with GIS and temporal/spatial context boosts reliability for urban planning, resource management, change detection.
19	**Enzhe Sun, Yongchuan Cui et al.**	“A Decade of Deep Learning for Remote Sensing Spatiotemporal	2025 (preprint) (arXiv)	Provides systematic review of deep-learning-based spatiotemporal fusion (STF) — combining low-temporal-high-spatial and high-temporal-low-spatial RS

		Fusion: Advances, Challenges & Opportunities”		data to generate high-res, frequent images; discusses successes, challenges (data scarcity, generalization) and future research paths, enhancing monitoring of land surface changes, agriculture, environmental shifts.
20	**Adrian Höhl, Ivica Obadić et al.**	“Opening the Black-Box: A Systematic Review on Explainable AI in Remote Sensing”	2024 (preprint) (arXiv)	Reviews XAI methods applied to remote sensing — summarises commonly used techniques for model interpretation, highlights scientific insights gained, and identifies challenges (scalability, domain adaptation); offers a foundation for trustworthy AI adoption in Earth observation.

8. CONCLUSION

Remote sensing has emerged as a vital and versatile tool in geosciences, enabling detailed observation and analysis across geological mapping, hydrogeology, geomorphology, environmental monitoring, and disaster management. Its effectiveness, however, depends on sensor capabilities, integration techniques, and validation with field data. This research highlights a multidisciplinary approach that combines satellite imagery, GIS, field surveys, and advanced modeling to optimize data interpretation, enhance mapping accuracy, and inform sustainable decision-making. The integration of Remote Sensing (RS) with Artificial Intelligence (AI) further transforms geoscientific research by enabling automated analysis, predictive modeling, and feature extraction from large, high-resolution datasets. This RS-AI framework enhances scalability, precision, and efficiency, supporting climate-resilient planning, resource management, and hazard mitigation. Overall, the study demonstrates that combining RS and AI offers a cost-effective, environmentally responsible, and scientifically robust methodology, providing actionable insights and establishing a sustainable paradigm for multidisciplinary geoscientific research.

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