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Integration of Artificial Intelligence and Remote Sensing: Review of the Progress, Problems and Prospects

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Abstract

The integration of artificial intelligence (AI) and remote sensing (RS) has transformed Earth observation (EO) by enabling the automated, efficient, and precise analysis of large and complex datasets. Rapid advances in machine learning (ML) and deep learning (DL) have further enhanced the processing and interpretation of RS data. This review examines the progress, persistent challenges, and future prospects of integrating AI with RS. Relevant literature was identified through searches of Scopus, Web of Science, IEEE Xplore, and Google Scholar using combinations of terms related to AI, ML, DL, and RS. The reviewed literature indicates that AI substantially improves the efficiency and precision of RS data processing and interpretation while expanding opportunities for automation and data-driven decision-making. Nevertheless, the broader adoption of AI-driven RS remains constrained by data quality and heterogeneity, computational demands, limited model generalisability and explainability, and ethical concerns. Future research should prioritise model efficiency, interpretability, and adaptability, alongside multimodal learning, unsupervised and semi-supervised learning, and real-time AI deployment for global-scale applications. This review consolidates current advances and limitations in AI-enabled RS and provides a research agenda for developing more efficient, interpretable, and flexible models for Earth observation applications.

Keywords: Artificial Intelligence; Deep Learning; Earth Observation; Machine Learning; Remote Sensing

INTRODUCTION

Large amounts of multispectral, hyperspectral, radar, and LiDAR data have been produced by the rapid advancements in Remote Sensing in recent decades. Conventional processing techniques frequently have trouble with these large and diverse datasets or capturing non-linear correlations (Kazanskiy et al., 2025). AI provide strong options for feature extraction, categorisation, and prediction. It includes both traditional machine learning and contemporary deep learning. Thus, the integration of Remote Sensing and Artificial Intelligence has paved the way for novel innovations, facilitating the development of more precise, efficient, and automated solutions in many applications (Zhang et al., 2022; Kazanskiy et al., 2025). For example, AI-enhanced methods have significantly improved the accuracy of land cover classification (Jamil Ghilzai et al., 2025). It has also enhanced accelerated disaster response efforts and biodiversity monitoring (Fabbri et al., 1988). Additionally, these progressions are supported by an increasingly rich landscape of available datasets, pre-trained models, and computational tools, which have made AI techniques more accessible within the Remote Sensing field (Sharifi and Mahdipour, 2024).

Despite the aforementioned encouraging advancements, the combination of RS and AI presents new challenges (Organisation for Economic Cooperation and Development [OECD], 2019; Zhao et al., 2024). Problems such as the generalisation of models in different geographical contexts, the transparency of AI algorithms, and ethical challenges related to automated decision-making require thorough examination (Janga et al., 2023). The smooth integration of AI models into certain fields is hampered by issues such as data scarcity, computing demands, data privacy concerns, and the "black-box" nature of AI models. Furthermore, overcoming the divide between expertise in Remote Sensing and technical skill in AI remains a significant hurdle for widespread implementation and effectiveness (Abdelmajeed and Juszczak, 2024).

Although there are numerous surveys on ML or DL in RS, most current literature focuses on specific methods or applications, resulting in a disjointed understanding of the field. Also, previous reviews are typically descriptive and seldom engage in a critical analysis of the relative advantages, drawbacks, and appropriateness of various methods across different RS tasks. So, this paper covers a state-of-the-art and a critical evaluation of advancements, issues, and opportunities related to the integration of Remote Sensing and AI. In doing so, it expands and supports previous studies at a time when AI in RS is developing quickly.

METHODS

This research employed a systematic approach for literature review by utilising searches of titles, abstracts, and keywords across platforms such as Scopus, Web of Science, IEEE Xplore, and Google Scholar. The keywords used were relevant to artificial intelligence, machine learning, deep learning, and Remote Sensing. The specific search terms employed in this study include " AI in Remote Sensing," "machine learning in Remote Sensing image processing," and "deep learning in Remote Sensing image processing".

The search produced a substantial number of articles, which were subjected to exclusion/inclusion criteria. Exclusions were concerned with articles that were not focused on the topic of study. Studies were excluded if they (1) focused exclusively on AI or ML or DL without RS applications, (2) were commentary pieces or conference papers, or (3) lacked methodological detail relevant to RS applications. On the other hand, inclusion criteria covered papers that address AI and its components in relation to RS. Included peer-reviewed journal articles were those published in English between 2020 and 2025 that applied AI, ML, and DL techniques to RS data. Finally, 20 articles were retained, reviewed in full detail, and analysed. This process ensured that the review covered both methodological innovations and real-world applications.

Furthermore, a set comprising 5 pairs of eligibility criteria was applied to ensure scientific accuracy, metadata completeness, language, type of publication, and thematic significance. These criteria, which consist of two main components (inclusion and exclusion) guided the selection process to include studies that meaningfully contributes to understanding the integration of artificial intelligence and remote sensing with emphasis on the progress, problems and prospects. Specifically, the aim of inclusion criteria was to detect relevant studies while exclusion criteria was aimed at filtering out irrelevant, redundant or insufficiently detailed records (Patino & Ferreira, 2018). The set of eligibility criteria used in the study is shown in Table 1:

Table 1. Eligibility criteria used in the screening process of the articles collected for the study.

No	Included	Excluded
1	Papers published between 2020 and 2025	Papers published before 2020
2	Complete bibliographical information	Missing title or author
3	Publication in English language	Publication in other languages
4	Peer-reviewed journal articles	Other publications
5	Direct or indirect relevance to remote sensing and AI	Studies not addressing remote sensing and AI

By and large, this review followed the workflow of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) as illustrated in the following figure 1.

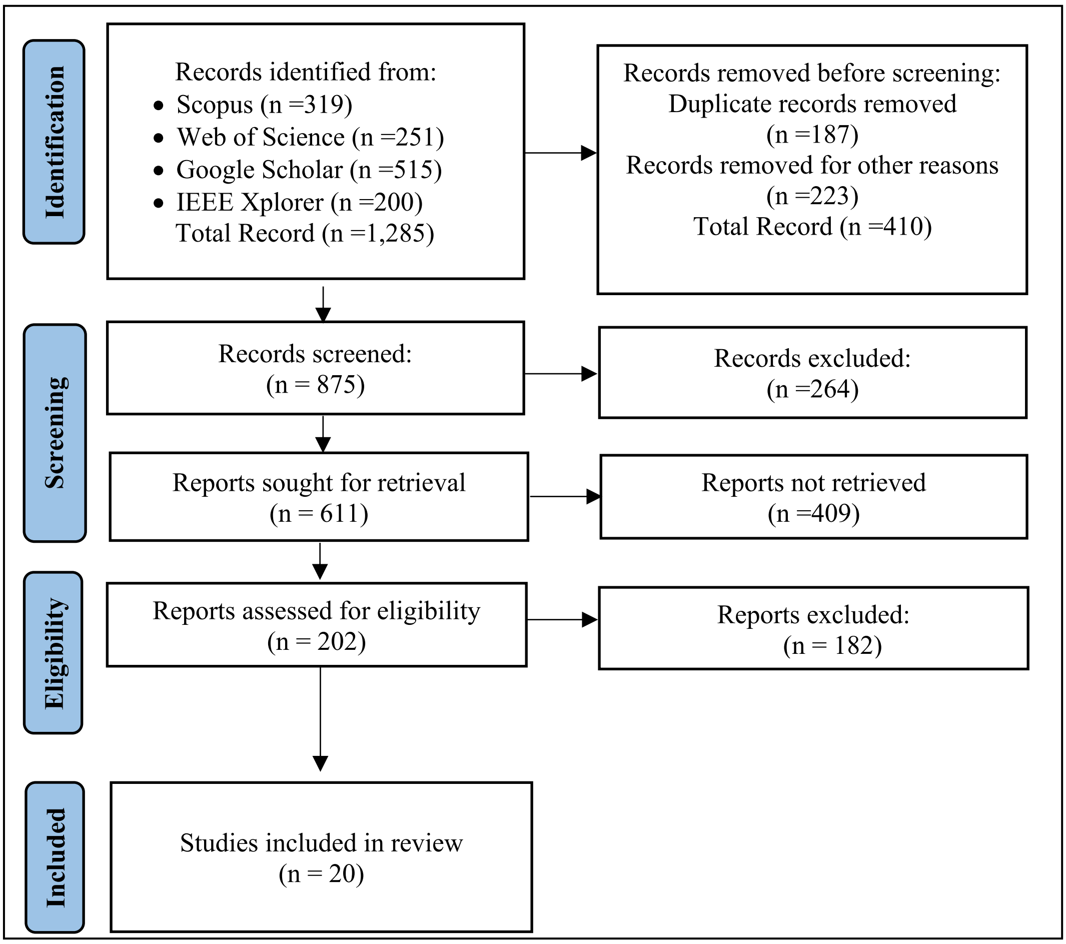

Figure 1. The PRISMA flow diagram illustrating the screening process of the articles included in the study.

RESULTS AND DISCUSSION

Advancement in the Integration of Artificial Intelligence and Remote Sensing

AI is crucial in RS as it advances analysis and understanding of data from various satellite sensors. This is deeply changing our approach to data utilisation. By employing advanced algorithms, AI allows for the derivation of significant and practical insights from large and intricate datasets (Cao, 2025), often surpassing human analytical abilities (Akhyar et al., 2024; Gu and Zeng, 2024). Methods such as computer vision and natural language processing (NLP) lead these innovations. Computer vision specialises in assessing visual information, including satellite imagery, while NLP assists in analysis and interpretation of associated metadata or text descriptions linked to the images (Bashmal et al., 2023).

Through automated feature extraction and analysis, AI greatly improves the effectiveness and precision of RS processes. Conventional techniques for evaluating satellite data, which mainly rely on physics-based models, statistical methods, and visual interpretation, are tedious and often susceptible to human mistakes. In contrast, AI can handle large datasets at remarkable speed, providing high-resolution evaluations within hours rather than weeks or months (Zhao et al., 2024). This automation not only reduces time requirements but also supports nearly instantaneous monitoring and decision-making. For instance, during a natural catastrophe, AI-based systems can swiftly analyse satellite data to pinpoint affected regions, evaluate damage, and assist in rescue missions. Additionally, AI promotes collaboration with other advancing technologies, such as the Internet of Things (IoT) and Geographical Information Systems (GIS) (Miller et al., 2025). This integration amplifies the function of Remote Sensing through dynamic fusion of multi-source data, offering an in-depth understanding of intricate systems. In summary, AI serves not merely as a tool for RS but as a transformative element that revolutionises the potential achievements in Earth Observation (EO) and related fields.

Challenges in the Integration of Artificial Intelligence and Remote Sensing

Even though AI-driven Remote Sensing has made incredible strides, many significant challenges prevent it from reaching its full potential. The ensuing subsections outline a few of these limitation.

Data Quality and Diversity

The Earth has been studied using a variety of satellite remote sensing data, including the DMSP-OLS (Defence Meteorological Satellite Program Operation Linescan System), Landsat TM/ETM/OLS, and the MODIS (Moderate-resolution Imaging Spectroradiometer), etc. However, they often face various obstacles such as interference from noise, incomplete information, and discrepancies in resolutions (Kazanskiy et al., 2025). This arises from the wide range of sensors and platforms utilised for data gathering (Chaurasia et al., 2024). Of course, these complications can affect the precision and dependability of subsequent analyses (Almohsen, 2024). Also, inaccurate analysis and decision-making might result from Remote Sensing data that are inconsistent and of poor quality.

Furthermore, cutting-edge AI techniques, especially DL algorithms, depend on high-calibre, well-annotated datasets to conduct effective training, validation, and testing (Janga et al., 2023a). Nevertheless, the limited availability of standardised, annotated datasets is a major challenge (Santos, 2023) that hinders the creation and assessment of resilient and adaptable AI models. Additionally, the intrinsic diversity of RS data sources—including differences in spatial, spectral, and temporal resolutions—exacerbates the challenge of achieving model generalisation. Tackling these issues will depend on coordinated efforts to enhance data quality (Bernardi et al., 2023; Rangineni et al., 2023), develop thorough annotation standards, and establish benchmark datasets that reflect the varied nature of RS applications.

Computational Requirements

Scalability issues may arise when processing large Remote Sensing data, which require extensive computer resources. Training of sophisticated AI models necessitates substantial resources (computation, memory, & storage). This may limit researchers and organisations that lack access to high-performance computing (HPC) resources (Navaux et al., 2023). Bortnyk et al. (2023) investigated the challenges with AI training, highlighting issues such as data limitations, high computational costs, and the need for robust models. They assessed innovative solutions including the generation of synthetic data, refined neural architectures, and resilience-enhancing techniques, while also stressing the importance of interpretability in AI models.

Model Interpretability and Explainability

Artificial intelligence models, particularly deep learning networks, are often viewed as "black boxes" due to the opaqueness of their decision-making mechanisms (Hassija et al., 2024). A black-box nature is difficult for humans to comprehend. According to Garg et al. (2021), these models generate predictions based on input data, but the user is not privy to the decision-making process. The absence of transparency makes it challenging for users to understand the model's actions, detect biases or errors, and hold the model accountable for its decisions. This poses significant challenges in crucial sectors such as disaster response and military operations, where grasping the rationale behind predictions is just as essential as ensuring accuracy (Dobson, 2023). Relying on a black-box model for important decision-making highlights the necessity for AI systems to provide the process of decision-making they employ (Hassija et al., 2024). In the absence of clear explanations, stakeholders may find it difficult to trust or act on insights generated by AI, particularly in high-stakes situations where decisions can influence human lives and infrastructure. To mitigate this problem, researchers have introduced various interpretability and explainability techniques for models, including feature attribution methods (like SHAP and LIME), attention mechanisms, and surrogate models that simplify complex architectures into more comprehensible representations (Contreras et al., 2024).

Whenever black-box models are brought up in discussions, the need for straightforward interpretations is often the first thought. Interpretability plays a vital role in machine learning. It refers to how well an individual can understand and anticipate the results of an ML model. As AI systems increasingly make decisions that can profoundly influence human lives, the importance of explainability is rapidly rising (Silva et al., 2022). The connection between explainability and artificial intelligence underscores the importance of developing systems that are open, understandable, and reliable, which is vital for their ethical and efficient implementation in different industries (Mohseni et al., 2021). Regulatory frameworks such as the EU's General Data Protection Regulation (GDPR) further emphasise the critical need for explainability, particularly in AI systems that affect people's rights and freedoms. Moreover, ethical and societal dilemmas demand greater attention. It is essential to ensure transparency, accountability, and stakeholder engagement to maximise social benefits while mitigating risks. Improving model interpretability not only increases transparency but also helps identify biases, correct errors, and enhance the model's effectiveness. The quest for explainable artificial intelligence (XAI) in the field of Remote Sensing is gaining momentum, although it remains in its nascent stages (Liu et al., 2023).

Transferability and Domain Adaptation

AI models trained on specific regions or datasets may struggle when used in different environments or datasets due to variability in environmental, atmospheric, and sensor factors. Transfer learning has become a potent method for overcoming these obstacles by applying knowledge from one task (the source domain) to another task (the target domain), even if the two domains have different feature spaces or data distributions (Gholizade et al., 2025). By enabling information transfer across numerous domains, domain adaptation techniques have developed as practical solutions to this issue. This improves the generalisation capabilities of computer and robotic vision systems (Han et al., 2023). However, techniques for domain adaptation, which seek to enhance models' ability to transfer knowledge across different domains, are still emerging in the realm of RS (Tanveer et al., 2023).

The Multimodal Unsupervised Image-to-Image Translation (MUNIT) framework improves domain adaptation by integrating various unsupervised image translation methods. MUNIT is based on the partially shared latent space assumption. Initially, it posits that a content space can be distinct from a style space, both of which are separate from the latent space of images. Furthermore, it assumes that although photographs across different fields may have a common content space, their style spaces are not shared. MUNIT employs disentangled representations to clearly differentiate between content and style, enabling it to generate diverse and realistic translations across multiple domains (Xia et al., 2020). This progress expands its range of applications, enabling better handling of diverse adaptation tasks with increased flexibility and effectiveness (Zhang et al., 2020).

Ethical and Societal Concerns

Ethical dilemmas now exist in relation to AI's impact on society, including privacy concerns under surveillance. Privacy poses a significant challenge because high-resolution remote sensing imagery combined with AI evaluation can unintentionally expose sensitive information about individuals or communities. Future research efforts should address issues such as data privacy (Elwahab et al., 2025), algorithmic bias, and environmental sustainability (Akhtar and Rawol, 2025). It is noteworthy that while these technologies present notable advantages, they also have the potential to alter power relations between governments, corporations, and local communities. Thus, policymakers and researchers should work together to establish guidelines for the ethical use of AI in remote sensing.

With the ongoing development of remote sensing and artificial intelligence, recent technological innovations and expertise have somewhat mitigated previous restrictions in AI and RS integration. However, to fully unlock the transformative potential of AI and RS integration in real-world applications, several key research and development priorities must be advanced. Of course, methodological advancements like multimodal learning, model efficiency, explainability, and collaborative frameworks will play a major role in shaping the future of AI in RS.

Future Outlook

Advances in Data Fusion and Multimodal Learning

Artificial intelligence is poised to significantly advance in integrating data from a variety of sensors and platforms, such as optical, radar, and LiDAR, to generate comprehensive analyses. Utilising multimodal learning approaches can enhance understanding of intricate environmental issues (Ruan, 2024) by leveraging the individual advantages of different data types (Zhang et al., 2024; Berg et al., 2024). Deep learning frameworks play a crucial role in Earth Observation, given the extensive quantities of available Remote Sensing data. Multimodal learning facilitates the integration of various data types, especially when merging images with structured data or data defined by differing spatial and temporal characteristics. However, as the disparities between modalities widen, the fusion process becomes increasingly complex. This renders deep learning models less transparent and harder to explain—an important aspect for critical applications (Li et al., 2022). Gunther et al. (2024) examined how the remote sensing community addresses these challenges, borrowing insights from other fields while highlighting effective methods to improve the interpretability of multimodal deep networks in Remote Sensing contexts.

Improved Model Efficiency Research on lightweight

Advancements in AI frameworks and model compression methods are making remarkable progress (Liu et al., 2025), enabling the deployment of AI models on resource-constrained devices like drones and edge sensors (Dantas et al., 2024). These innovations are anticipated to improve real-time processing capabilities, thereby broadening the use of AI in RS applications (Li et al., 2023). Dantas et al. (2024) explored compression techniques in ML to enhance efficiency in settings with limited resources, such as mobile devices, edge computing, and Internet of Things (IoT) systems. With the growing complexity of machine learning models, their demand for computation is escalating, highlighting the crucial role of compression in maintaining performance while minimising resource usage.

The intricate backgrounds and numerous small targets found in RS images pose significant challenges for object detection. Identifying small objects in RS images poses significant challenges because of elements such as interference and the scarcity of detailed data about the objects (Wang et al., 2025). To tackle these issues, Elhamied et al. (2024) introduced an optimised model to enhance detection performance for small targets. The model began by enhancing the feature extraction stage through the integration of an attention mechanism, thereby improving the quality of the features obtained. A transformer block was added for better representation of the feature map, while a bidirectional feature pyramid network with attention assistance further sharpened the extraction process of discriminative information.

Integration of Unsupervised and Semi-Supervised Learning

Large volumes of training data are necessary for DL and modern machines. However, the percentage of annotated data may still be proportionately low or absent even if the data itself is widely accessible. To tackle the lack of labelled datasets, researchers are investigating unsupervised and semi-supervised learning strategies. These methods leverage unlabeled data to facilitate feature extraction and representation learning, thereby reducing the need for manual labelling. Li et al. (2024) introduced a semi-supervised technique aimed at classifying scenes in remote sensing images, employing prototype-based consistency in conjunction with a large repository of unlabeled images.

The effectiveness of a classification model is enhanced by high-quality labelled samples (Eran et al., 2025), which are often scarce in RS images. To address this challenge, semi-supervised learning approaches leverage both labelled and unlabeled data to elevate classification performance. Kothari et al. (2020) proposed a self-learning semi-supervised classification framework that employs a neural network (NN) as its core classifier.

To overcome the drawbacks of traditional techniques, this model integrates an effective neighbourhood information learning method. Recognising the most pertinent neighbourhood data for unlabeled samples proved essential yet challenging. To address this, two strategies for creating similarity matrices were suggested to enhance NN learning. The initial method collected data on mutual neighbourhoods, whereas the subsequent approach utilised the class-map derived from instances without labels. A classifier that was trained on labelled examples was used to forecast the labels for the unlabeled instances, and the collaborative neighbourhood information obtained from both similarity matrices enhanced the robustness of the proposed model.

Collaborative Frameworks and Open Data Initiatives

Collaborative initiatives such as open-source AI platforms and publicly available RS datasets are fostering innovation and increasing access to important resources. These efforts enable researchers worldwide to engage in the creation and enhancement of AI models (Janga et al., 2023; Kazanskiy et al., 2025). The effective handling, evaluation, and understanding of extensive RS datasets through advanced technologies on RS cloud computing platforms (RS-CCPs) has become increasingly essential (Xu et al., 2022). Large-scale heterogeneous data can be effectively activated and mined via cloud computing. Nevertheless, many existing RS-CCPs primarily focus on improving data storage and computing capabilities for general visual applications. They often overlook critical RS attributes like large image sizes, substantial scale variations, multiple data channels, and the incorporation of geographic knowledge. These limitations can adversely affect the efficiency and precision of computations. To counteract these challenges, Zhang et al. (2023) introduced LuoJiaAI, a platform that integrates a vast sample database (LuoJiaSET) with a tailored DL framework (LuoJiaNET). This platform excelled in five critical RS interpretation tasks: scene classification, object detection, land-use classification, change detection, and 3D reconstruction from various perspectives. Furthermore, LuoJiaAI served as an open-source cloud computing platform for Remote Sensing, adhering to the latest standards from the Open Geospatial Consortium (OGC). Of course, this enabled the development and sharing of Earth-related AI models and products based on standardised datasets.

CONCLUSION

The intersection of RS and AI has revolutionised our approach to analyzing and understanding Earth Observation data, resulting in remarkable progress in areas like environmental monitoring, disaster response, urban development, and agriculture, etc. Techniques driven by AI, especially ML and DL, have greatly enhanced the precision, efficiency, and automation of RS applications. Conventional RS methods, which depended on manual or semi-automated processes, often found it challenging to cope with the increasing volume, complexity, and diversity of data. However, application of AI has transformed the landscape by facilitating advanced feature extraction, classification, object detection, and predictive modelling.

Although the combination of AI and Remote Sensing presents many advantages, several challenges persist that need to be tackled. This is to enhance the widespread use and efficacy of AI within RS. Issues related to data quality, model generalisation, transparency, and computational requirements continue to pose significant challenges. AI systems trained on specific datasets often struggle to extend their functionalities across different geographical areas, weather conditions, and types of sensors, highlighting the importance of robust domain adaptation strategies. Furthermore, the often opaque nature of many deep learning models raises concerns regarding their interpretability and dependability. Implementing Explainable AI (XAI) methods, including attention mechanisms, saliency maps, and rule-based approaches, is crucial to improving the clarity and reliability of AI-powered RS models. Additionally, the increasing reliance on AI surfaces ethical considerations, such as biases present in training datasets, privacy issues linked to high-resolution satellite images, and the potential for misuse of AI-derived insights. Addressing these challenges requires cooperative efforts among RS researchers, AI specialists, policymakers, and professionals from various disciplines.

In the future, studies ought to focus on enhancing the efficiency, interpretability, and adaptability of AI models employed in Remote Sensing applications. Combining traditional physical models with data-driven learning approaches—termed hybrid AI—could bolster model robustness and generalizability. Integrating AI with emerging technologies such as IoT, GIS, and HPC systems will further elevate the capabilities of RS. By addressing existing obstacles and capitalising on forthcoming technological innovations, AI-driven RS is poised to play an essential role in informed decision-making for a more resilient and sustainable world.

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