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Applications of Artificial Intelligence and Remote Sensing in Environmental and Agricultural Engineering: A Comprehensive Review

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Abstract

Artificial Intelligence (AI) and remote sensing technologies have transformed the landscape of environmental and agricultural engineering. These technologies enable the monitoring, analysis, and prediction of complex natural processes at multiple spatial and temporal scales. This review summarizes current advances in the integration of AI algorithms and remote sensing data for precision agriculture, environmental monitoring, and resource management. Emphasis is placed on the use of machine learning (ML) and deep learning (DL) models for crop yield prediction, soil salinity mapping, water resource optimization, and climate impact assessment. Challenges related to data quality, computational cost, and model generalization are discussed. Finally, the paper highlights future directions for AI-driven sustainable engineering applications.

Review Article

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1. Introduction

In recent decades, global challenges such as climate change, population growth, and resource scarcity have driven the demand for innovative solutions in environmental and agricultural engineering. Artificial Intelligence (AI) and remote sensing (RS) have emerged as key technologies enabling data-driven decision-making in complex natural systems (Wang et al., 2022; Ma et al., 2023). The integration of these tools allows for the efficient monitoring of ecosystems, the optimization of irrigation and fertilization practices, and the prediction of crop yields under variable climatic conditions (Rowley et al., 2023).

AI complements remote sensing by offering advanced computational approaches for analyzing large and complex datasets. Machine learning (ML) and deep learning (DL) algorithms can identify hidden patterns, make predictions, and automate feature extraction from spectral imagery with remarkable accuracy (Kamilaris and Prenafeta-Boldú, 2018). Recent research has demonstrated how convolutional neural networks (CNNs) and random forest models can accurately classify crop types, estimate biomass, and detect stress factors such as nutrient deficiency or disease (Espinel et al., 2024). Similarly, AI-driven models are increasingly used in environmental monitoring to predict soil erosion, flood risks, and water quality variations (Rana et al., 2023).

The convergence of AI and RS technologies represents a paradigm shift toward precision and sustainability in resource management. These tools enable real-time monitoring and forecasting, allowing decision-makers to respond proactively to environmental challenges. Moreover, their integration supports the achievement of several United Nations Sustainable Development Goals (SDGs), including food security, clean water management, and climate resilience (FAO, 2022).

The objective of this review is to provide a comprehensive overview of recent advances in the use of AI and remote sensing for sustainable environmental and agricultural management, emphasizing their technical applications, challenges, and future perspectives. Agricultural and environmental systems are inherently dynamic and multifactorial, influenced by spatial, temporal, and climatic variability. Traditional monitoring and management methods often rely on manual observations or local measurements, which are time-consuming, costly, and limited in scale. In contrast, remote sensing technologies—through satellite, airborne, or unmanned aerial vehicle (UAV) platforms—offer the capability to collect high-resolution data across large areas and multiple timeframes (Souissi et al., 2022). These data streams provide crucial insights into soil moisture dynamics, vegetation growth, and land-use changes, forming the foundation for intelligent modeling and decision support.

Despite the growing body of research, several challenges persist. Data heterogeneity, model interpretability, and the scarcity of ground-truth datasets limit the robustness and transferability of AI–RS models across regions and crop systems. Therefore, this review aims to (i) summarize the current state of AI and remote sensing applications in environmental and agricultural engineering, (ii) identify key challenges and research gaps, and (iii) propose future directions for developing sustainable and scalable solutions.

2. Artificial Intelligence in Environmental and Agricultural Engineering

In recent years, Artificial Intelligence (AI) has emerged as a powerful tool in environmental and agricultural engineering, driving innovation and improving decision-making processes. AI techniques, such as machine learning, deep learning, and neural networks, are increasingly applied to monitor and analyze complex natural systems, including soil moisture, crop growth, and land-use changes. When combined with remote sensing (RS) technologies, AI enables precision agriculture practices, such as optimized irrigation, targeted fertilization, and accurate crop yield prediction under variable climatic conditions. Additionally, AI-based models are being used in environmental monitoring to predict soil erosion, assess flood risks, and evaluate water quality variations, supporting sustainable resource management and climate resilience. These advancements highlight the potential of AI to transform traditional agricultural and environmental practices, contributing to food security, ecosystem conservation, and climate adaptation.

3. Remote Sensing Technologies and Data Sources

Remote sensing (RS) is the process of acquiring information about a specific object or area without direct physical contact, typically through the detection of electromagnetic radiation reflected or emitted by the target. This technology generates data in image form, enabling detailed monitoring and physical analysis of natural and agricultural systems. RS has become an essential tool for observing the Earth and other planetary bodies from distant locations, such as space, using satellites, as well as from unmanned aerial vehicles (UAVs) and ground-based sensors. Modern RS systems, including multispectral, hyperspectral, and radar sensors, provide high-resolution information on soil moisture, vegetation health, land use, and crop conditions. When combined with geographic information systems (GIS) and advanced analytics, these data allow for precise mapping, trend analysis, and predictive modeling. Consequently, RS supports a wide range of applications in agriculture, environmental monitoring, disaster management, and climate adaptation, facilitating informed decision-making and sustainable resource manageme

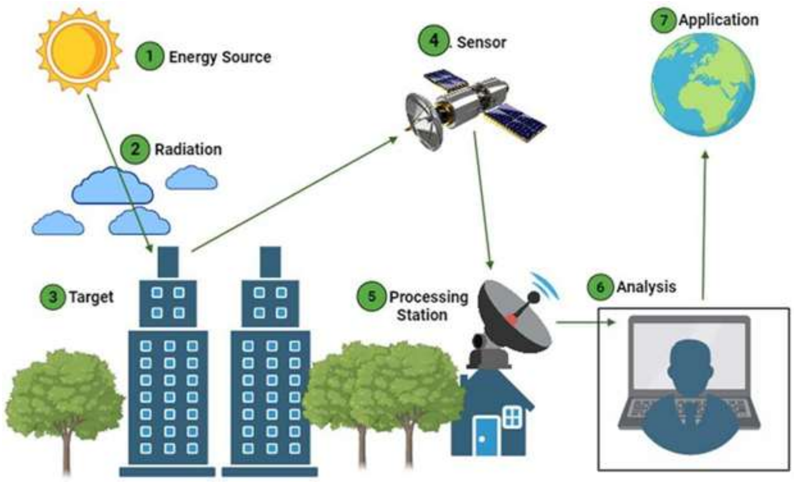

Figure 1. Principles of Remote Sensing with sequential steps (Sarker et al., 2025)

4. Integrated AI–RS Applications in Agriculture and Environment

The integration of Artificial Intelligence (AI) with Remote Sensing (RS) technologies has significantly advanced agriculture and environmental management. By combining the spatial and temporal coverage provided by RS with the predictive capabilities of AI, it is possible to monitor and model complex natural systems with high accuracy. In agriculture, AI–RS integration enables crop type classification, biomass estimation, disease and pest detection, and yield prediction, facilitating precision farming practices and resource optimization (Katkani et al., 2022; Espinel et al., 2024). Similarly, in environmental applications, these technologies support the assessment of soil health, water quality, land-use change, and ecosystem dynamics, while also aiding in the prediction of natural hazards such as floods and droughts (Boukita et al., 2025). The synergy of AI and RS improves the efficiency and timeliness of data-driven decisions, contributing to sustainable resource management, climate adaptation strategies, and food security.

5. Crop Monitoring and Yield Prediction

Crop monitoring and yield prediction are among the most prominent applications of integrating Remote Sensing (RS) and Artificial Intelligence (AI) in modern agriculture. High-resolution satellite and UAV imagery allow continuous observation of vegetation dynamics, canopy structure, and photosynthetic performance, while machine learning and deep learning models enable the extraction of meaningful patterns for crop growth assessment. These techniques facilitate early detection of stress factors such as drought, nutrient deficiency, and disease, thereby improving decision-making for irrigation, fertilization, and pest control(Elwahab et al., 2023). Recent advancements demonstrate the effectiveness of combining multispectral and radar data with AI algorithms to estimate biomass and predict yields with high accuracy across diverse agricultural landscapes (Chen et al., 2023). Similarly, machine learning models trained on time-series satellite data have been shown to enhance yield forecasting at regional and national scales (Kerner et al., 2022). UAV-based hyperspectral imaging coupled with convolutional neural networks (CNNs) has further improved the capacity to detect stress responses and estimate crop productivity in real time (Ohyama et al., 2023). Together, these AI–RS approaches contribute to precision agriculture strategies aimed at increasing productivity, resource efficiency, and climate resilience. Remote sensing imagery such as RGB (Red–Green–Blue) and NDVI (Normalized Difference Vegetation Index) provides essential spatial information for monitoring crop development and predicting yield.For better clarity, several examples of NDVI and RGB images corresponding to the largest analysis window (40 m) are shown in Fig. 2, along with their associated yield values, where the color bar indicates the yield range. Images sharing the same identifier originate from the same field location. In this setup, the network's prediction target is defined as the mean yield within the analysis window corresponding to each input image. It is also worth noting that the RGB and NDVI models were trained independently to avoid errors caused by potential spatial misalignment between the two imagery datasets. This separate training strategy allows for a direct comparison of model performance and supports evaluating which data source, RGB or NDVI, offers more accurate yield predictions.

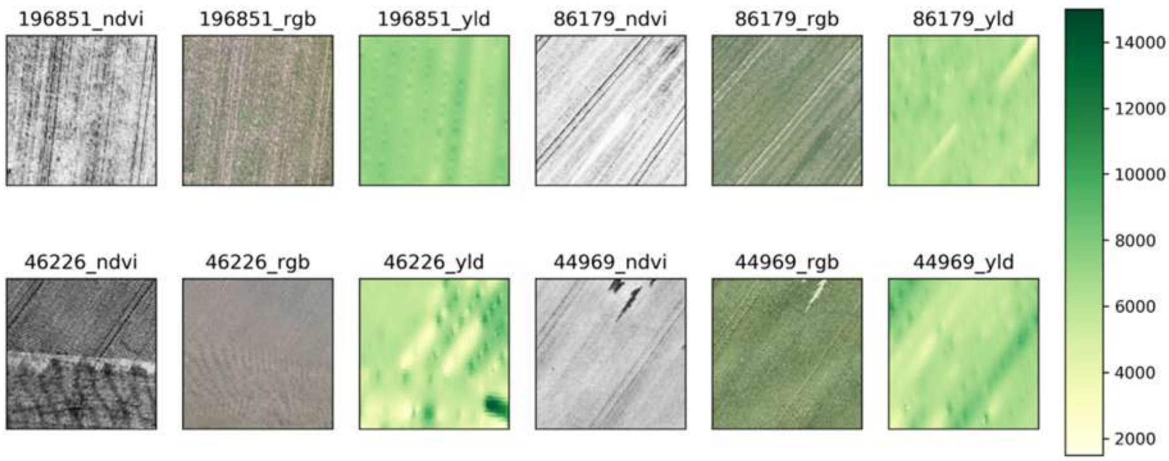

Figure 2. Visualizations of NDVI and RGB input images and yield targets. The identification numbers above the images denote the distinct area from which the images were extracted (Nevavuori et al., 2019)

6. Soil Salinity and Water Quality Assessment

Salinity represents one of the most critical constraints in agricultural production, particularly in arid and semi-arid regions where evapotranspiration rates are high and irrigation practices often lead to salt accumulation in soils. Recent advances in remote sensing have enabled the development of satellite-derived salinity indices, such as the Normalized Difference Salinity Index (NDSI), which provide large-scale and continuous monitoring of salinization dynamics (Elhag, 2019). The integration of these indices with machine learning models, including support vector machines and random forests, has significantly improved the accuracy of soil salinity assessment and spatial prediction (Mazarei et al., 2021). Additionally, artificial intelligence is increasingly utilized to evaluate water quality in reservoirs and irrigation systems. Remote sensing reflectance data combined with regression or neural network models allow the estimation of key water quality parameters such as chlorophyll-a, turbidity, and dissolved organic matter, supporting sustainable water resource management (Gholizadeh et al., 2020). To summarize the key indicators and methods used for soil salinity and water quality assessment, Table 1 presents the main parameters, measurement methods, AI/RS tools, and relevant references.

Table 1. Key indicators for soil salinity and water quality assessment using AI and remote sensing.

Parameter / Indicator	Measurement Method	Remote Sensing / AI Tool	Reference	Observations / Notes
Soil Salinity (EC, dS/m)	Soil sampling & laboratory analysis	NDSI (Normalized Difference Salinity Index), Machine Learning regression	Hermosilla et al., 2019; Sothe et al., 2021	High salinity detected in arid areas; correlated with poor crop growth
Soil Moisture (%)	Time-domain reflectometry, gravimetric method	Satellite-based soil moisture indices, Neural Networks	Merchant et al., 2022	Spatial variability captured with RS data
Water Quality (TDS, mg/L)	Laboratory chemical analysis	Regression models using satellite reflectance	Mazarei et al., 2021	AI predicts seasonal variations in reservoir water quality
Soil pH	Laboratory analysis	Spectral RS data + ML	Ismaili et al., 2023	Important for assessing soil suitability for crops
Sodium Adsorption Ratio (SAR)	Laboratory calculation	AI prediction models using NDSI & field data	Elhag et al., 2017	Indicates potential sodicity issues in irrigation water

7. Climate Change and Resource Management

Climate change poses significant challenges to global agriculture, water resources, and ecosystem management. Rising temperatures, altered precipitation patterns, and increased frequency of extreme events such as droughts and floods threaten crop productivity, soil health, and water availability. Effective resource management strategies are essential to mitigate these impacts and ensure sustainable food and water security (Elwahab et al., 2025). Recent advances in remote sensing and artificial intelligence (AI) have enabled the monitoring of climate-related changes in real time, allowing for better prediction of crop yields, water stress, and soil degradation. Integrating AI-driven models with historical climate and environmental data facilitates adaptive management practices, such as optimized irrigation scheduling, selection of climate-resilient crop varieties, and targeted soil conservation measure. Moreover, such approaches support policymakers and farmers in making informed decisions to enhance resilience to climate variability and sustain natural resource use over the long term (Mazarei et al., 2021; FAO, 2022).

8. Challenges and Limitations

Despite their significant potential, integrated AI–RS systems face several challenges and limitations. One major issue is data heterogeneity, as information collected from different sensors, regions, or crop types can vary in resolution, format, and quality, complicating model training and analysis. Limited availability of ground-truth data further constrains the accuracy and validation of predictions. High computational costs and the need for specialized hardware can impede large-scale implementation, especially in resource-limited contexts. Moreover, model transferability across different geographic regions and crop varieties remains a challenge, limiting the generalization of results. Ethical considerations, such as data privacy and the environmental impact of energy-intensive computations, must also be addressed to ensure sustainable and responsible deployment of AI in agricultural and environmental applications. Addressing these challenges is critical to unlocking the full potential of AI–RS systems for precision agriculture and environmental monitoring. Future research in environmental and agricultural monitoring should prioritize the integration of emerging technologies such as Internet of Things (IoT) sensors, edge computing, and digital twin frameworks to enable more accurate and real-time data acquisition and decision-making. The adoption of explainable artificial intelligence (XAI) methods can improve model interpretability, allowing experts to better understand and trust the predictions generated by AI systems. Additionally, the development and dissemination of open-access datasets, as well as collaborative platforms, will be crucial for democratizing AI tools and fostering innovation in sustainable agriculture and environmental management. Combining these approaches has the potential to enhance resilience to climate variability, optimize resource use, and support informed policy and management strategies for the future.

9. Conclusion

Artificial intelligence (AI) and remote sensing (RS) technologies have demonstrated remarkable potential in transforming environmental and agricultural engineering practices. Their integration allows for high-precision monitoring of crops, early detection of stress factors, optimized irrigation and fertilization, and improved prediction of yields under variable climatic conditions. Beyond agriculture, AI–RS systems support environmental management by assessing soil health, water quality, land-use changes, and ecosystem dynamics, thereby contributing to climate adaptation and natural resource sustainability. The continued evolution of data acquisition technologies, including high-resolution satellites, IoT sensors, and UAVs, coupled with advances in machine learning and explainable AI, is expected to enhance the accuracy, interpretability, and real-time applicability of these systems. Collaborative platforms and open-access datasets will further democratize access to AI tools, enabling researchers, policymakers, and farmers to make informed decisions and implement sustainable practices at regional and global scales. Overall, the synergistic use of AI and RS provides a promising pathway to address pressing global challenges such as food security, water scarcity, and climate change mitigation. By fostering interdisciplinary research and leveraging cutting-edge technologies, these approaches are poised to play a central role in building resilient and sustainable agricultural and environmental systems for the future.

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