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Editorial: Advancements in agricultural monitoring with AI enhanced remote sensing techniques

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Editorial on the Research Topic
Advancements in agricultural monitoring with AI enhanced remote sensing techniques

The integration of artificial intelligence (AI) with remote sensing (RS) technologies is transforming modern agricultural monitoring, offering a new paradigm for accuracy, scalability, and efficiency in data-driven decision making (Fuentes-Peñailillo et al., 2024). By leveraging high-resolution imagery, advanced machine learning algorithms, and increasingly diverse sensor platforms, researchers are now able to capture crop responses to environmental forcing and management interventions in ways that traditional approaches could not achieve (Xing et al., 2025; Omer et al., 2024; Qin et al., 2025). These advances align closely with the broader scope of the LiDAR Remote Sensing Section, where the goal is to harness cutting-edge sensing technologies, whether LiDAR, hyperspectral, UAV-based multispectral, or other modalities, for improved understanding of vegetation structure, function, and dynamics. AI-driven approaches thus provide a unifying methodological framework that can be extended to LiDAR datasets, enabling richer insights into crop physiology, resource use, and ecosystem services (Assimakopoulos et al., 2024; Aghababaei et al., 2025).

The Research Topic, *Advancements in Agricultural Monitoring with AI Enhanced Remote Sensing Techniques*, was conceived as a platform to showcase innovations at the intersection of AI and remote sensing, with a particular emphasis on how these methods contribute new scientific knowledge about crop-environment interactions and management strategies. Rather than focusing solely on improvements in predictive accuracy, the collected studies demonstrate how AI-enabled remote sensing helps unravel the mechanisms by which crops respond to nutrient inputs, climatic variability, and ecological stressors. The contributions highlight both methodological advances and the generation of knowledge with direct implications for sustainable food production, environmental stewardship, and resource efficiency.

The study by Zenonos et al., titled *AI-powered estimation of tree covered area and number of trees over the Mediterranean island of Cyprus*, established the tree-level monitoring framework for Cyprus. Beyond demonstrating high accuracy in crown segmentation and tree counts, the work revealed how forest and peri-urban tree populations vary in response to increasing aridity and fire disturbance in the Mediterranean. These findings generate new ecological knowledge on the spatial distribution of tree resources under climate stress and illustrate how AI-based image analysis can complement LiDAR in building scalable forest carbon inventories.

The study by Menefee et al., titled *Machine learning algorithms improve MODIS GPP estimates in United States croplands*, applied machine learning (AutoML, Stacked Ensemble) to bridge the gap between satellite observations and ground-based carbon fluxes by integrating MODIS GPP products with eddy covariance data from U.S. agroecosystems. Importantly, the study does more than improve GPP accuracy: it demonstrates how different crop systems (maize, soybean) respond to climatic drivers across regions, advancing scientific understanding of agricultural carbon dynamics and resilience under environmental forcing.

Through UAV-based multispectral and RGB imagery, Anku et al., in their article *Remote estimation of leaf nitrogen content, leaf area, and berry yield in wild blueberries*, quantified leaf nitrogen content, canopy structure, and berry yield under controlled fertilization regimes in Nova Scotia. The key contribution lies in revealing the nonlinear responses of blueberry physiology and yield to nitrogen treatments, highlighting thresholds beyond which additional inputs reduce efficiency. This provides new agronomic knowledge on nutrient use in perennial, heterogeneous cropping systems and offers a framework for developing variable-rate fertilization maps.

The final contribution by Crosby et al., titled *What can we learn from a multi-season-stage-variety potato (Solanum tuberosum L.) study using aerial hyperspectral imagery*, demonstrated how nitrogen status and yield can be predicted with stage-specific and cultivar-specific spectral models. The findings reveal that spectral regions most sensitive to nitrogen vary across growth stages and varieties, underscoring that crop responses to nutrient inputs are not uniform. Such insights generate new scientific understanding of genotype–environment interactions and inform more precise management strategies, with potential synergy when combined with LiDAR structural data.

Taken together, the contributions in this Research Topic underscore the multifaceted potential of AI-enhanced remote sensing in advancing agricultural science and practice. Beyond technical gains in predictive accuracy, these studies collectively generate new scientific understanding of how crops and vegetation respond to environmental forcing and management strategies across diverse systems. They highlight that crop–environment interactions are inherently dynamic and context-specific, requiring models that are not only robust but also adaptable to local conditions, cultivars, and management regimes. This reinforces the importance of modular AI frameworks that integrate multi-source data—including spectral, UAV, ground sensors, and LiDAR—to capture both physiological responses and structural attributes of crops. In this sense, the methodological advances presented here are highly complementary to LiDAR-based approaches, which provide critical three-dimensional insights into canopy architecture and biomass that, when combined with spectral and machine learning methods, can yield holistic monitoring of crop function and productivity. Looking forward, the next frontier lies in scaling these scientific advances into operational platforms that can support decision-making for farmers and policymakers, bridging the gap between research innovation and agricultural practice (Dritsas and Trigka, 2025; Liang et al., 2025; Raihan, 2024). As global food demands intensify under mounting environmental constraints, AI-enhanced, multi-sensor remote sensing systems will be indispensable in building resilient, sustainable, and knowledge-driven agricultural systems.

We would like to express our heartfelt gratitude to all the authors who contributed their valuable research to this Research Topic. Their efforts and innovations have significantly advanced the discourse on AI-enhanced remote sensing in agriculture. We also extend our sincere appreciation to the reviewers for their insightful comments and constructive feedback, which ensured the academic rigor of the accepted articles. Finally, we thank the editorial team for their guidance and support in shaping this Research Topic. We hope this body of work will inspire continued interdisciplinary research and innovation at the intersection of artificial intelligence, remote sensing, and agricultural sciences.

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